PDS expansion and dietary choices: Evidence from edible oils in India

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Abstract:

Using large-scale consumer expenditure survey data from the National Sample Survey Office (NSSO), this paper attempts to quantify the extent to which policy interventions in edible oils, particularly palm oil, in the Indian states of Tamil Nadu, Andhra Pradesh and Maharashtra have had an impact on household nutrition. We exploit the cross-sectional variation in the introduction of the intervention on subsidised palm oil to identify the causal effects on household's consumption patterns and caloric intakes thereof. We conduct difference-in-differences (DID) and matched DID analyses for both rural and urban areas separately. Our DID estimation results suggest that, after the policy intervention, an average rural household in the treated district increased its daily caloric intake from palm and other minor oils by 146-154 Kcal relative to an average household in the bordering control district. This translates to an increase of 33-35 per cent from the average baseline consumption of palm and other oils. No such positive effects were however observed for urban areas. In addition, we find that the households reduced their intakes of traditionally consumed coconut and groundnut oils. The estimates from the matched DID are similar in direction and marginally higher than the standard DID estimates for caloric intakes of palm and other oils in rural areas. To capture the changes in group composition over time in a repeated cross-sectional framework, we also undertake the analysis by employing the PSM-DID-RCS estimator. The estimates were close to that found under matched DID estimation using the PSM sample. The results were also robust to heterogeneous treatment impacts and various alternative specifications. The findings from this study have policy implications for the discussion surrounding the expansion of PDS portfolios aimed at addressing the malnutrition problem in India.

JEL Codes: H42, H53, I38, Q11, Q13, Q18

Keywords: Public distribution system, edible oils, difference-in-differences, matched difference-in-differences, calories, India

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1. Introduction

Over the past few decades, India has undergone a rapid transition in its dietary patterns, burden of diseases, and physical activity levels. India is witnessing a decline in caloric intakes alongside rising fat intakes (Siddiqui et al., 2017). There has been a shift from the traditional diets to more 'Westernised diets', which often consist of an increased consumption of vegetable edible oils (Drewnowski & Popkin, 1997; Popkin, 2004). Indian dietary patterns have observed a significant increase in the consumption of edible oils. In most states, there has been an increase in the contribution of oils and fats to overall caloric intakes over time. Edible oils, which are high in caloric content, constitute about 7 per cent of a household's total food expenditure and about 8 per cent of an individual's daily overall caloric intake. These changes in the dietary patterns are also accompanied with an increase in the incidence of burden of overweight/obesity and other non-communicable diseases (NCDs). Recent evidence also suggests that there exists a positive correlation between the share of energy derived from edible oils and measures of overnutrition. It is important to note that most Indian states that are witnessing most rapid increases in their malnutrition burdens are also the ones with better public health infrastructure (Meenakshi, 2016).

The Public Distribution System (PDS) in India has traditionally focused on improving access to cereals, which are a rich source of calories. More recently, the National Food Security Act (NFSA), which encompasses a life cycle approach, has an aim to expand the coverage of PDS to about two-thirds of India's population – 75 per cent and 50 per cent of the rural and urban population, respectively. There has been a consistent increase in the expenditure incurred by the Department of Food and Public Distribution and it spent about Rs. 1.47 lakh crores during 2017-18. The operational responsibility including identification of eligible families, issue of ration cards and supervision of the functioning of fair price shops (FPSs) etc. rests with the state governments. Several state governments such as those of Tamil Nadu, Andhra Pradesh and Chhattisgarh have adopted the 'new style' PDS approach wherein various policy measures have been undertaken to make the PDS delivery system more effective and widen its coverage (Drèze and Sen, 2013).

In the late 2000s, the state governments of Tamil Nadu, Andhra Pradesh and Maharashtra[1] began to provide edible oils, specifically subsidised palm oils as part of their distribution networks. The key objective behind introducing this oil in these states has been to maintain their prices at reasonable levels and to meet adequate demand during peak festive seasons (DFPD, 2008; Downs et al., 2014). India has 5,34,991 FPSs as in June 2019 and about 10 per cent, 6.5 per cent and 5.4 per cent of these were located in Maharashtra, Tamil Nadu and Andhra Pradesh, respectively. These states have also had significantly high incidences of PDS purchases. Andhra Pradesh and

[1] Tamil Nadu introduced fortified palm oil in its special PDS in 2007. Tamil Nadu Government is implementing Universal Public Distribution System (UPDS) and no exclusion is made based on the income criteria. Five types of family cards are issued. Under the special PDS, toor and urad dal, and fortified palmolein oil are being distributed at subsidised prices since 2007. Andhra Pradesh introduced palmolein oil in 2008. Similarly, Andhra Pradesh also has four types of ration cards and palm oil is distributed under PDS since 2008 to BPL families. Maharashtra introduced the supply of palm oil in its PDS in July 2008 and again in August 2009 (probably briefly for festival season) and then again in 2011 (July – Dec).

Tamil Nadu are among the few states that have used their own identification criteria, apart from the criteria specified by the BPL Census, to identify target households and issue ration cards after the introduction of targeted PDS. Tamil Nadu was the only state that maintained its universal PDS system after the unveiling of targeted PDS in 1997 while Andhra Pradesh adopted a quasi-universal approach.

One of the widely used mechanisms that utilises the State's power to promote desired dietary changes is the use of fiscal policy. There has been a growing evidence that fiscal measures have the potential to improve human health and a vast number of countries/governments have deployed them. The rationale behind taxing unhealthy foods or subsidising healthy foods is the established role of price as a driver of dietary choice. Taxation is expected to correct for the negative externalities associated with the excessive consumption of unhealthy foods such as energy-dense foods and sugar sweetened beverages (SSB). Imposition of a tax leads to an increase in the prices of such commodities relative to their true social costs. A wide-ranging variety of European countries has imposed such taxes on saturated fats in Denmark, Finland, Hungary and France. Some of the other Pacific nations, Mexico, United Kingdom, California and South Africa have also levied SSB taxes (Thow et al., 2014; Hagenaars et al., 2017). In view of the finding that fiscal measures play a key role in determining food choices, we aim to evaluate the impact of a subsidy (i.e., opposite of tax) introduced in PDS systems of three Indian states.

In this paper, by employing quasi-experimental methods on large-scale nationally representative survey data, we quantify the extent to which policy interventions in edible oils, particularly palm oils, in the Indian states of Tamil Nadu, Andhra Pradesh and Maharashtra have had an impact on household nutrition. We evaluate the impact of PDS intervention on caloric intakes derived from various oils and the share of calories derived from palm and other oils in overall calories sourced from all edible oils[2]. We find that the introduction of palm oils in PDS led to an increase in daily caloric intake derived from palm and other oils. An average rural household in the treated district increased its daily caloric intake from palm and other minor oils by 146-154 Kcal relative to an average household in the bordering control district. This translates to an increase of 33-35 per cent from its average baseline consumption. No such positive effects were observed for urban areas. In addition, we find that the traditionally consumed groundnut and coconut oils were being displaced. We also undertake the analysis using alternative estimators and specifications. The results from this study have significant implications for the debate surrounding effective functioning and expansion of PDS portfolios aimed at addressing the malnutrition problem in India.

The rest of the paper is organised as follows. We first provide a background on the existing literature in this domain in the next section. We then discuss the details of the policy intervention in the following section. This is followed by a brief discussion about the data sources and

[2] We also evaluated the share of calories derived from palm and other oils in total calories as another outcome variable. The estimation results (not shown here for brevity sake) were on similar lines as that of share of calories derived from palm and other oils in overall calories sourced from all edible oils.

identification strategy and empirical framework employed in sections 4 and 5. Results and discussion are presented in section 6 followed by the concluding remarks and policy implications in the last section.

2. Review of existing evidence on food subsidies and nutrition

The present study contributes to an extensive literature on the impact of food subsidies on nutrition. The literature has largely focused on two key events in the history of PDS reforms - first, the move towards targeted PDS in 1997, and second, on some of the recent reform initiatives taken by different state governments in improving its implementation and functioning. This paper attempts to answer the research questions that fall in the purview of the latter.

Kochar (2005), in her evaluation of the effectiveness of a targeted PDS using the Consumer Expenditure Survey (CES) rounds of the National Sample Survey Office (NSSO), combines the cross-sectional variation in market prices with the variation in programme rules (that consequently generates variation in subsidised prices and quantities) over time and across households. She finds that targeting of PDS did lead to a significant improvement in caloric intakes – albeit with a small magnitude – and lower take-up rates. The study also notes that the value of the programme for both poor as well as non-poor households influences the take-up rates.

Following from Kochar's (2005) analysis, Kaushal and Muchomba (2015) evaluate the relationship between nutrition levels and the size of the PDS subsidy for wheat and rice using the three CES rounds (i.e., 1993-94, 1999-2000 and 2004-05). They instrument for the size of PDS subsidy with the estimated probability of having a Below Poverty Line (BPL) ration card. They find no effect of changes to the PDS in 2002 on nutrition among poorer and rural households. However, the price subsidy did increase the consumption of both wheat and rice, and reduced the consumption of coarse grains. Similar to Kochar's (2005) analysis, here too, the likelihood of being a poor household is imputed and not actually observed.

Using two cross-sections of CES rounds undertaken in 2004-05 and 2011-12, Rahman (2016) compares how outcomes have changed in the two regions of Odisha with differential levels of implicit income transfer – one with a targeted scheme and another with a universal PDS entitlement. The 2004-05 survey period acts as the baseline since a universal PDS in Odisha came into effect in 2008, while the 2011-12 survey captures the post-intervention outcomes. The sample was restricted to rural areas only as the revival of PDS had been more effective in these areas. He exploits this variation in the implicit income transfers over time and finds that the caloric intakes and diet quality improved in Odisha's famine prone Koraput-Bolangir-Kalahandi (KBK) region after the universalisation of PDS in these districts. In another study based on NSSO and India Human Development Survey (IHDS) data, Kaul (2018) assesses the impact of PDS on nutrition using variation in state-specific programme rules and fluctuations in local market prices of subsidised foodgrains. She finds that the households witness an increase in their caloric intakes and the subsidy generates an income effect for the beneficiary households.

Shrinivas et al. (2018) evaluate the impact of state-level changes in the generosity of PDS subsidies with the passage of India's NFSA in 2013. They utilise the respective legal entitlements, as defined by the state governments to account for the endogeneity in PDS purchase decisions, and ration card data reported by the households to arrive at a more precise measure of the PDS parameter. The analysis employs the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT's) Village Dynamics in South Asia (VDSA) panel data of 1300 households (covering 30 villages across eight Indian states) observed over 60 months from June 2010 to July 2015. This data set, however, is limited only to the rural smallholders and is not representative at the national, state or district level. Their identification strategy exploits both cross-sectional and temporal variation in the PDS. The temporal variation comes from 11 policy changes in the PDS entitlements while cross-sectional variation comes from the difference in PDS entitlements across states and the differential expansion in the PDS entitlements for BPL households during the study period. The key findings of their analysis suggest that increases in the generosity of in-kind staple food transfers substantially leads to an improved nutritional status. Staple food subsidies crowd in the consumption of diverse food items, and thereby increase overall food consumption in terms of both quantities as well as total calorie, protein and fat intakes.

The findings from this study pertain to the strand of literature that finds positive impacts of the treatment or intervention. Similar to a few other studies in this strand, we analyse the price variation realised from changes that took place in the PDS of certain states and not in others. Krishnamurthy et al. (2017) find that, relative to the bordering districts, households in Chhattisgarh improved their nutritional intakes after Chhattisgarh initiated a wide range of operational reforms in its PDS framework between 1999-2000 and 2004-05. Some of these changes included the permission to private dealers to run FPSs and enhancement in the quantity of rice procured directly from the farmers for PDS distribution. The policy reforms did lead to an improvement in caloric intakes and dietary quality. The households that were most likely to be eligible for food subsidies mainly drive these results. In addition, they do not find evidence that the households that were least likely to be eligible changed their diets relative to households in the bordering districts (i.e., those that did not experience PDS reforms).

A vast majority of this literature has largely focused either on staples' subsidies or on the shift towards targeting and universalisation of PDS[3]. It is only recently that a few studies have started to assess the impact of state-specific interventions in terms of diversified PDS portfolios and their impacts thereof (Chakrabarti et al., 2018; Rajshekhar et al., 2017). Chakrabarti et al. (2018) evaluate the impact of subsidy on pulses in select Indian states on their consumption and consequently protein intakes using NSSO and VDSA data sets. Their findings indicate that a change in the consumption of pulses because of their inclusion in the PDS, though statistically

[3] In terms of the nutritional outcomes, Tarozzi (2005) also finds no evidence that a longer exposure to high prices affects the weight of children under 4 years of age in Andhra Pradesh.

significant, was of a small order. This impact was not large enough to bring about any sizable difference in either consumption of pulses or total protein intakes. Rajshekhar et al. (2017) undertook an assessment of introduction of millets under PDS in Karnataka. Using focussed group discussions and interviews in certain selected districts of Karnataka, they find that the demand for millets is strong but the lure of taste and ease of cooking rice is stronger.

In line with these studies, this paper evaluates the impact of state-specific PDS reforms relating to diversification of PDS commodities' portfolios on household nutrition. We particularly evaluate the causal impacts of the policy intervention i.e., introduction of subsidised palm oil in the PDS of treated states on household-level nutrient intakes. Over the recent past, palm oil has become an omnipresent part of our diets. India is the largest importer (constituting about 62 per cent of overall edible oils' imports) and consumer (40 per cent of overall edible oil consumption) of palm oil in the world. The relationship between dietary oils, saturated fat and health is quite dynamic as well as complex. The scientific evidence relating to the health impacts of palm oil consumption are although mixed with a tilt more towards adverse health outcomes. An analysis in the Indian context by Basu et al. (2013) estimates that a tax on palm oil could lead to a 1.3 per cent reduction in cardiovascular deaths over the period 2014-23 as long as people do not substitute other oils for reduced palm oil consumption.

3. Distribution of subsidised edible oils in the PDS

This paper aims to evaluate the impact of state-specific policy interventions in PDS on food consumption and thereby the nutritional status of the resident population. We focus our attention particularly on three states i.e., Maharashtra, and two other well-performing states from the Southern India – Tamil Nadu and Andhra Pradesh, which introduced palm oils as part of the special PDS schemes prevalent in these states (Appendix Table A1). Keeping in view the diversity in cultures and food habits amongst Indians, besides the differences in food availability, we undertake the analysis for both rural and urban areas separately.

Palm and other oils account for a maximum of 61 per cent of average energy intakes from edible oil consumption in the rural areas of the three treated states in 2004-05, which increased to 76 per cent in 2009-10. The outcome variables that we analyse consist of consumption of various types of edible oils and the nutrient intakes thereof. The key outcome variables of particular interest are the daily caloric intakes from palm and other oils, and share of palm and other oils in calories derived from all edible oils. The CES data set does not enable a distinction between edible oil purchases made through the PDS, and those made from the market. Further, it is important to note here that throughout the analysis palm and other oils refers to *Vanaspati*/margarine and other edible oils[4]. All the estimation results, therefore, pertain to changes in average oil consumption

[4] Palm oil is commonly used in margarines, *Vanaspati*, shortening and confectionery fats (Imoisi et al., 2015). The NSSO provides the edible oil category-wise consumption data for *Vanaspati*/margarine, coconut, groundnut, mustard

across all households, irrespective of the source of purchase. While PDS participation rates in rural areas did vary across the treated and control states, averaging 57 and 42 per cent in 2004-05 respectively, these differentials remained constant over time (Appendix Table A2). By 2009-10, participation rates had increased by 15 percentage points to 72 and 57 per cent, respectively.

The distribution of subsidised palm oils by Tamil Nadu, Maharashtra and Andhra Pradesh translates into an infra-marginal subsidy[5]. This is suggestive from the back-of-the-envelope calculations that employ the monthly allocations of imported RBD palmolein oil in the three treated states. These allocations are much lower when compared to the usual monthly household consumption of palm and other minor oils, and thus the treated households would have to augment their consumption by market purchases (Appendix Table A3).

4. Data

The analysis relies on consumption data obtained from nationally representative CES rounds conducted in 1999-2000 (55th Round), 2004-05 (61st Round) and 2009-10 (66th Round) by the NSSO. These surveys are stratified by geographical area and location of a household i.e., whether it is situated in a rural or urban area. These also contain household-level information on quantities consumed of a variety of food and non-food items, and the expenses incurred on them.

The present analysis employs unit-record data for over 20,000 households[6] in the treated and control states. The CES surveys also collect information on various socio-economic characteristics such as household size and demographic composition, social group, assets owned etc. We use the food composition tables provided by the Indian Council of Medical Research's National Institute of Nutrition (and used by the NSSO) to convert the quantity of edible oils and other foods into their equivalent caloric values. The nutritional information is estimated only for foods consumed at home, as it is difficult to estimate the same for outside food consumption.

We employ the household survey data collected over a recall period of 30 days[7]. The 2004-05 survey serves as our baseline while 2009-10 survey provides the post-intervention information

oils and other edible oils. The other edible oils category consists of various oils such as palm oil, sunflower oil, linseed oil, gingelly oil, rice bran oil etc.

[5] In theory, the impact of food subsidies depends on how consumers substitute between subsidised and non-subsidised goods. When subsidies are infra-marginal, i.e., when the subsidised quantities are less than the quantities usually consumed by the households, households have to "top up" by making market purchases and the subsidy should lead only to an income effect as long as the marginal propensities to consume from a targeted implicit income transfer are the same as that from cash. On the other hand, if the subsidies are extra-marginal, i.e., the quantity of the subsidised good is greater than the quantity regularly consumed by the households, there would be both income and price effects. The price effects shall only be applicable if the resale of rations is effectively prohibited, or if it takes place below the market price or entails high transaction costs (Gentilini, 2007).

[6] The analysis eliminates outliers in terms of the outcome variables; these constitute less than 1 per cent of the entire sample across both pre- and post-intervention periods. All the estimations are undertaken using Stata 15.

[7] In NSS CESs, there are three ways to measure household's monthly per capita expenditure (MPCE). These include Uniform Reference Period (URP) MPCE, Mixed Reference Period (MRP) MPCE and Modified Mixed Reference Period (MMRP) MPCE. The URP measure collects the information on household consumer expenditure for all the

for the given treatment and control groups. We use these surveys to compare the nutrient consumption in the treated group, i.e., bordering districts of the treated states, to nutrient consumption in the bordering districts of the control states.

5. Identification and empirical strategy

To investigate whether the provision of subsidised palm oil has resulted either in increasing overall edible oil intakes, or in changing the composition of overall edible oil basket in favour of the subsidised oil, this paper exploits the cross-sectional variation in the introduction of the subsidy on palm oil. The identification relies on consumption patterns being similar in neighbouring districts across the state borders such that any differential changes in consumption over time can be attributed to the policy intervention. The 2004-05 survey serves as our baseline while 2009-10 survey provides the post-intervention information for the given treatment and control groups. Figure A1 provides a visual representation of districts assigned as treated (in Tamil Nadu, Andhra Pradesh and Maharashtra i.e., states that introduced subsidised palm oils in 2007 and 2008, respectively) and their bordering districts in neighbouring states that are assigned as controls (in Kerala, Karnataka, Odisha, Chhattisgarh, Madhya Pradesh, Goa, Gujarat, Dadra & Nagar Haveli and Pondicherry). The states, whose districts share borders with Tamil Nadu, Andhra Pradesh, and Maharashtra, did not introduce such an intervention of introducing palm oil in their PDS reforms between 2004-05 and 2009-10.

We use a difference-in-differences (DID) estimator between 2004-05 (when there was no policy of subsidised palm oils) and 2009-10 (by when three states had introduced the subsidised palm oil intervention). Results have been reported for rural and urban areas separately. The DID approach allows for any kind of time-invariant unobserved heterogeneity to be differenced out. A further assumption necessary for identification is that of parallel trends, which we test for by comparing changes between two pre-intervention periods i.e., 1999-2000 and 2004-05.

As discussed later in Section 6, there are small baseline (2004-05) differences in observable characteristics that could influence the consumption decisions. To account for these, a set of matching exercises is undertaken so that each household in the districts of Tamil Nadu, Andhra Pradesh and Maharashtra is matched with corresponding similar households in the bordering districts of control states. A DID estimator is then estimated after matching i.e., a difference is computed for the so derived cross-sectional ATTs in both the pre-and post-intervention periods, and these double differences are averaged across matched subgroups. We term this estimation approach as matched DID. In keeping with the literature, we employ three different types of

items for a reference period of last 30 days. In case of MRP MPCE, household consumer expenditure on items of clothing and bedding, footwear, education, institutional medical care, and durable goods is recorded for a reference period of last 365 days, while expenditure on all other items is recorded for last 30 days. The MMRP measure collects household consumer expenditure on items of food consumption for a reference period of last 7 days, and for all other items, the reference periods used are the same as in case of MRP MPCE. This paper utilises the URP MPCE measure to ensure comparability across different survey rounds.

matching methods (namely, propensity score-based kernel (PSM) and Mahalanobis Distance (MD) matching methods, and Coarsened Exact Matching (CEM) method to evaluate whether the impact estimates vary greatly across them.

In the absence of panel data, another potential concern while using repeated cross-sectional (RCS) data is that there may be compositional differences across the treated and control groups that vary over time. To account for such compositional changes, Blundell and Dias (2000, 2009) propose a PSM-DID-RCS estimator that estimates propensity scores as a function of observable characteristics. These scores are then used to calculate three sets of kernel weights, i.e., over the three control groups – treated before the intervention and non-treated before and after the intervention. In our case, however, over the five-year period there were few, if any, changes in the covariates used in the analysis (see Section 6). Nonetheless, as a robustness check, we also undertake the analysis using the three-way matching PSM-DID-RCS estimator. All these estimation methods are explained in detail in the sub-sections below.

5.1 Identification and potential outcomes framework

Several household characteristics and community features, which may be correlated with the outcome variables, drive the PDS participation. Selection bias can potentially affect the estimation of the true impact of the policy intervention of subsidised palm oil. This bias can arise from both the demand as well as supply side. On the supply side, the intervention can plausibly be a result of targeted rollout by certain states. While, on the other hand, some households may self-select themselves into utilising the PDS for procuring palm oil. These factors can either elevate or attenuate the bias in case of an ordinary least squares estimator depending on the liquidity constraints of the households. This paper attempts to mitigate this bias by exploiting the difference in the timing of inclusion of subsidised palm oil in PDS across states comparing the treated and control states.

The key challenge in impact evaluation studies using observational data rests in constructing a credible counterfactual group, which in this study reflects as to what would have happened had the treated households not received the policy intervention of public distribution of subsidised palm oil. Given that the counterfactual for each individual household cannot be observed or estimated, the methods that the paper adopts thus focus on the average treatment effect on the treated (ATT). The potential outcomes framework or Rubin causal model (Rubin, 1974) underlies this analysis. Formally, let $T = 1$ define the households that are located in the treated districts that have the provision of subsidised palm oil in PDS and $T = 0$ be the non-treated households that do not have such a provision. Let Y_1^T be the potential outcome in the treated state and Y_0^C be the potential outcome in the non-treated state. There are thus two possible potential outcome states for each of the treated and control groups. The average treatment effect on the treated (ATT) (Rosenbaum and Rubin, 1985) is given as:

$$\hat{\tau}_{ATT} = E\,(Y_1^T - Y_0^C \mid T = 1) = E\,(Y_1^T \mid T=1) - E\,(Y_0^C \mid T=1) \quad (1)$$

In our context, $\hat{\tau}_{ATT}$ measures the difference between the expected caloric intakes of households with and without the policy intervention of subsidised palm oil for those households that have access to the intervention. We can observe the outcome for participating households i.e., E (Y_1^T |T=1), but not for those participant households had they not been treated E (Y_0^C |T=1). The researcher only observes one outcome at any given time: the average outcome for households living in states that provide the palm oil subsidy and one for those which do not (Holland 1986). In other words, neither E (Y_0^T| T = 0) is observed, nor is E (Y_1^C |T =1). The literature mainly focuses on programme participants and assumes that the indirect effects on non-participants are negligible (Todd, 2008). While this assumption is not always true, it is often valid for non-contributory publicly funded programmes such as PDS.

As discussed in Heckman et al. (1997), non-experimental methods ideally ought to possess certain desirable features. These include: (i) participants and non-participants should have the same distributions of unobserved characteristics (ii) the two groups should also have the same distribution of observed attributes (iii) same questionnaire is provided to both the groups and (iv) participants and non-participants are placed in same kind of an economic environment. Feature (ii) can potentially be met by adopting an appropriate matching procedure on observables while (iii) and (iv) can be dealt with by making an apt selection of data. For our purposes, the treated and control groups are derived using the same survey rounds and thereby have been administered with the same questionnaires. In addition, the questionnaires are similar across the survey rounds under study. We control for the location effects that somewhat take care of the last feature. Feature (i) is the key challenge in case of observational impact studies and thus requires some further assumptions. Heckman et al. (1997) have shown in their analysis that if requirements (ii) to (iv) are met, then the remaining bias may not be much of a concern in a non-experimental setup.

A vast range of econometric methods are available to identify the missing counterfactual but a standard approach is to use the propensity score matching, as introduced by Rosenbaum and Rubin (1983), with ATT as expressed in equation (1). The basic idea is to impute the counterfactual outcome for the treated units using non-treated units with the same propensity score. To identify the counterfactuals, it is assumed that all the differences between the treated and control groups are derived in a vector X of observable characteristics and that after controlling for these observed covariates, the potential outcomes are independent of the treatment status. This requirement, which is untestable, is the ignorability or conditional independence assumption (CIA). It essentially implies that we can observe and potentially account for all the confounding variables that affect the treatment decision and outcome variables. Another key prerequisite is that of common support condition which requires that the distribution of observed characteristics for non-treated households is similar to that for treated households, such that households with similar characteristics have a positive probability of being treated and not treated. If both the CIA and common support condition hold, then the ATT measure is given as:

$$\hat{\tau}_{ATT} = E\,(Y_1^T|\,T = 1, X) - E\,(Y_0^T|\,T = 0, X) \qquad (2)$$

5.2 Difference-in-differences framework

Given that the procurement of subsidised palm oil from the special PDS by the households can also depend on certain unobservable characteristics such as tastes, preferences etc., the CIA may be too strong an assumption to maintain. Such unobservable characteristics relate to time-variant and time-invariant unobserved heterogeneity and thus cannot be captured by cross-sectional matching methods alone. However, if the pre-treatment data are available and the unobservable factors are time-invariant, then the CIA assumption can be relaxed. To control for such differences, we employ the DID approach. Here, the effect of the unobserved characteristics is differenced out by taking the differences in outcomes before and after the policy intervention. In a DID model, the treatment effect is estimated based on the idea that counterfactual outcome of a treated unit can be approximated by the outcome of that treated unit in an earlier period when it did not receive the treatment intervention. The mean outcome of the treatment group before and after the intervention is compared. The difference between the observed changes in the mean outcomes of the treatment and control groups is the key variable of interest i.e., DID estimate, which is given as:

$$\hat{\tau}_{DID} = E\,(Y_1^T - Y_0^T \mid T = 1) - E\big(Y_1^C - Y_0^C \big| \, T = 0\big) \tag{3}$$

where Y_0^T and Y_1^T are the mean outcomes before and after the intervention, respectively. Similarly, Y_0^C and Y_1^C are the respective mean outcomes for the control group before and after the intervention. The DID estimate can be captured in a regression framework as:

$$Y_{idt} = \beta T_d + \tau_{DID}\,(T_d {*} t_i) + \gamma t_i + \lambda X_{idt} + \mu_d + \varepsilon_{idt} \tag{4}$$

where $Y_{i\,dt}$ is the observed outcome variable for household i in district d at time t. Here d denotes the district as per the 2004-05 prevalent boundaries, T_d is the dummy for treatment region i.e., it is an indicator variable for being a household in one of the 3 treated states, and t_i is the time dummy that takes a value 1 after the introduction of policy intervention and zero otherwise. The outcome variables are the consumption of various types of edible oils and the nutrient intakes thereof. In addition, the proportion of calories derived from palm and other oils in overall edible oils' calories is also considered as another outcome variable. All the outcomes are estimated in both quantity as well as caloric intake terms. We report here only the latter estimates for the sake of brevity. The coefficient on the interaction of time and treatment dummy τ_{DID} is the main variable of interest that gives the impact of PDS policy changes on nutrient intakes. If the increased availability of subsidised palm oil led to higher energy intakes in the treated households, relative to households in the bordering districts, then τ_{DID} should be positive and significant.

We also include district fixed effects μ_d to control for the time-invariant unobserved heterogeneity. These effects absorb cultural norms, habits, food practices and state-level governance factors etc. that would otherwise not get eliminated due to the non-panel nature of the data set. A vector of household-level factors (X_{idt}) such as social group, household size, land possessed, and education of the household head have also been controlled for. We also control for the dependency ratio i.e., proportion of children aged 0-14 in overall working population in the household, and relative price ratio of edible oils with respect to cereals. In addition to these, cross-sectional variation in terms of variables such as wealth measures in terms of ownership of assets that may be correlated with the outcomes is also accounted for. Given that there exists no way to ensure whether a household in a treated district actually purchased subsidised palm oil and a lack of compliance mechanism to evaluate the proper implementation of state-specific policy interventions, the estimates so derived from equation (4) reflect the intent to treat (ITT) and not the ATT of the policy intervention.

We also use the randomisation inference (RI) tests, which are now widely applied to non-experimental data, to determine whether the treatment effects are merely an outcome of chance. As discussed in Conley and Taber (2011), we randomise the assignment of states to treatment and control groups and use τ_{DID} in equation (4) as the test statistic. The null hypothesis here is that the palm oil subsidy had no effect on its consumption and nutrient intakes i.e., $\tau_{DID} = 0$ in equation (4). Ideally, to get the exact distribution one should estimate for all the possible random assignments, but in this case, we employ 2,000 replications as suggested by Young (2018).

The DID approach depends on a relatively less stringent requirement of parallel trends when compared to CIA. Parallel or common trends essentially requires that the unobserved differences between the treatment and control groups are the same over time in the absence of treatment. The validity of the common trends assumption in the pre-intervention period is suggestive of common trends in the treatment period, but it is neither a sufficient nor a necessary condition for the parallel trends condition to hold (Kahn-Lang and Lang, 2019). Statistically, this assumption holds when the DID estimate τ_{DID} is insignificant in the estimated regressions using data from the baseline and earlier periods. We test for the parallel trends assumption parametrically using data from the pre-intervention period i.e., 55th round[8]. Kahn-Lang and Lang (2019) strongly advocate for the use of domain-specific knowledge in justifying the parallel trends assumption.

5.3 Matched difference-in-differences

The DID estimation preferably require panel data wherein the data is available for the same unit both before and after the treatment. A key limitation prevails in terms of the high degree of heterogeneity among the treated and control groups in the absence of panel data. In such a scenario, the units may self-select into the programme as per some unknown rule or may respond differently to macroeconomic changes. Thus, the time-invariant heterogeneity assumption may fail if the group composition changes and the intervention affects the treated and untreated groups differently (Khandker et al., 2009). These compositional differences make it difficult to assume that without

[8] It is important to note here that there are comparability issues across the pre-intervention (1999-2000) and baseline (2004-05) survey rounds, and this may affect the results from our parallel trends assumption. The 55th survey round was based on a different recall period – information relating to food items has been collected from the same households using a recall period of 7 days and 30 days – thus leading to an overestimation of the consumption data. However, this is the best that could be achieved given the data limitations.

the treatment intervention the outcome variables of such units would have the same trend (Imbens and Wooldridge, 2009).

The matched DID approach, as discussed in Heckman et al. (1997, 1998) combines the respective individual advantages and counterbalances some of individual weaknesses of both the methods. It can accommodate the unobserved determinants of the outcome variables affecting the treatment decision as long as these characteristics are constant over time. While PSM controls for the bias related to observable factors, DID controls for the bias related to observable and unobservable time-invariant characteristics. In our estimation strategy, these time-invariant unobserved characteristics would plausibly be the behavioural consumption aspects e.g., tastes and preferences of the households towards particular kinds of edible oils, as well as infrastructural development, agro-climatic conditions etc.

The advantage of the matched DID approach over standard DID regression estimation approach is that it relaxes the linear functional form restriction in estimating the conditional expectation of the outcome variables and reweighs the observations according to the weights used by the matching estimators. Smith and Todd (2005) in their analysis have shown that matched DID estimators control for time-invariant unobservables and are, therefore, more robust compared to other non-experimental matching-based estimators. In this approach, households in the pre-intervention period are ranked based upon their propensity scores and matched across the treated and control groups. The required identifying assumption for this estimator is given as:

$$\mathrm{E}\left(\mathrm{Y}_1^{\mathrm{C}} - \mathrm{Y}_0^{\mathrm{C}} \mid \mathrm{T} = 1, \mathrm{P(X)}\right) = \mathrm{E}\left(\mathrm{Y}_1^{\mathrm{C}} - \mathrm{Y}_0^{\mathrm{C}} \middle| \mathrm{T} = 0, \mathrm{P(X)}\right) \qquad (5)$$

The matching hypothesis is now stated in terms of the before-after evolutions rather than levels. In other words, the control units evolve from a pre to post intervention period in the same fashion as the treatment units would have had they not received the intervention. This assumption alone is not sufficient to estimate the identification of ATT. It also requires the common support condition to be valid for the propensity scores between treated and control states in both the survey periods. This approach is similar to the matched DID estimation as in case of panel data. We first apply a matching estimator to find the non-treated households that were similar to the treated households in terms of observed covariates. A difference is then computed for the so derived cross-sectional $\hat{\tau}_{\mathrm{ATT}}$ as in equation (2) in both the pre-and post-intervention periods, and these double differences are averaged across matched subgroups[9]. We undertake three different matching exercises using Propensity Score-based kernel matching, Mahalanobis Distance (MD) matching, and Coarsened Exact Matching (CEM) method as a measure of robustness of our estimations.

We employ the kernel method for specifying weights in PSM. In this approach, every treated unit is matched with a weighted average of all control units with weights that are inversely proportional to the distance between the treated and the control units. The Mahalanobis distance

[9] Following from Paternoster et al. (1998), we employ the statistical test Z = $(b_1 – b_2)/ (SE_{b1}^2 + SE_{b2}^2)$ ^ 0.5 for evaluating the existence of difference between the two coefficients.

metric is also employed to find a nearest control unit j for each treated unit i using the distance metric $d_{ij} = \| p(x_j) - p(x_i) \|$. In recent years, a new class of Monotonic Imbalance Bounding (MIB) methods e.g., CEM has emerged. This method works without estimating a selection model and applies a stratification matching approach proposed by Iacus et al. (2011, 2012). CEM allows the analyst to ex-ante choose the degree of balancing of covariates and avoids the laborious procedure of ex-post assessment. As has been suggested in the literature (Blackwell et al., 2009), we employ the automated CEM matching method to improve upon other estimation methods; propensity score based kernel matching is undertaken on CEM matched sample to estimate the double differences across subgroups.

5.4 Heterogeneous impacts

Next, we employ various alternative specifications of equation (4) in the context of treatment impact heterogeneity. We first restrict the DID estimation approach to actual PDS users i.e., households who purchase either one or a combination of the three subsidised food commodities i.e., rice, wheat or sugar. We assume here that there is a high likelihood that those households, which purchase either all or at least one of these commodities, are also likely to purchase subsidised palm oils in the treated districts.

Given that there are certain differences in the policy intervention in terms of coverage and quantities entitled across the treated states, we undertake another exercise to capture the heterogeneous impacts of this intervention across states. We do so by estimating an equation like equation (4) but here we use state-specific treatment dummies i.e., AP_{idt}, TN_{id} and MH_{idt}, and state-specific interaction terms in the DID model. This is given as:

$$Y_{idt} = \beta_0 + \tau_{DID1}(AP_{idt} * t_{idt}) + \tau_{DID2}(TN_{idt} * t_{idt}) + \tau_{DID3}(MH_{idt} * t_{idt}) + \beta_1 AP_{idt} + \beta_2 TN_{idt} + \beta_3 MH_{idt} + \gamma t_{idt} + \lambda X_{idt} + \mu_d + \varepsilon_{idt} \quad (6)$$

5.5 Robustness checks

5.5.1 Propensity score matched difference-in-differences in a repeated cross-sectional context

In case of RCS data set, the likelihood that the same household is a beneficiary of the policy intervention in both the survey years is quite low. It is in such a scenario that the combination of matching methods, particularly PSM, with the DID regressions turns out to be helpful. In addition, the identity of future treated and control households is usually not known in the pre-intervention period. There also exists a likelihood that compositional changes do occur and thus differences arise over time among the treated and control households' characteristics. As a robustness check, in our analysis, we adopt the PSM-DID estimator for RCS as suggested by Blundell and Dais (2000; 2009). The estimator is given as:

$$\hat{\tau}^{PSM-DID,RCS} = \sum_{i \epsilon T_1} \{ [Y_{i1} - \sum_{j \epsilon T_0} \tilde{w}^{T}_{ij0} Y_{j0}] - [\sum_{j \epsilon C_1} \tilde{w}^{C}_{ij1} Y_{j1} - \sum_{j \epsilon C_0} \tilde{w}^{C}_{ij0} Y_{j0}] \} w_i \quad (7)$$

where (T_1, T_0, C_1, C_0) are the treatment and control group after and before the treatment or intervention, and $\tilde{w}^{G}_{ijt}$ represent the weight attributed to household j in group G and time t when comparing with the treated household i. These constitute the weights of the three matchings performed. In this setting, for the common support condition to be valid, it is essential to ensure that all the treated units have a counterpart in the non-treated population before and after the treatment intervention. w_i accounts for the reweighting that reconstructs the outcome distribution for the treated sample. This approach has the advantage that the double differencing is undertaken only across treated households that are similar to each other.

5.5.2 Alternative treatment and control groups

Further, two additional counterfactuals of consumption and nutrient intake changes in the absence of state-level policy interventions have been estimated. In the first case, all the districts of Tamil Nadu, Andhra Pradesh and Maharashtra are considered as the treatment but only bordering districts of Kerala, Karnataka, Odisha, Chhattisgarh, Madhya Pradesh, Goa, Gujarat, Dadra & Nagar Haveli and Pondicherry act as the control group. In another specification, complete states of Tamil Nadu, Andhra Pradesh and Maharashtra are considered as the treatment group and the neighbouring states of Kerala, Karnataka, Odisha, Chhattisgarh, Madhya Pradesh, Goa, Gujarat, Dadra & Nagar Haveli and Pondicherry form the control group. We also consider another variant wherein the post-intervention period is considered to be 2011-12 (68th round) instead of 2009-10 (66th round). All the estimates from these three variants largely retain the direction and significance as in case of the main variant. These estimation results are not reported here and can be made available on request to the authors.

6. Results and discussion

This section presents the results and the accompanying discussion for the different estimation specifications employed in the analysis. Table 1 provides the descriptive statistics of the outcome variables used for the main specification in both rural and urban areas. Similarly, Table 2 highlights the differences in the covariates across both treated and control districts. The DID and matched DID estimation results are presented separately for rural and urban areas in Tables 3 and 4, respectively. The subsequent tables provide the estimation results from the analysis undertaken as part of robustness checks for the main specification.

6.1. Descriptive statistics

On an average, household caloric intakes have increased in the rural treated districts between 2004-05 and 2009-10, and vice-versa for urban treated as well as control districts. The households located in the control districts have been consuming more calories when compared to the treated districts; this gap, however, has been narrowing over the years (Figure 1). These differences between the treated and control households are statistically significant. The contribution of edible oils to the overall energy intakes has been rising.

Edible oils contributed about 9 per cent of overall energy intakes in the rural treated households in 2004-05, and saw a marginal increase in their contribution over time. Of the overall edible oils' consumption, a vast majority of it is coming from palm and other oils, and groundnut oil. Given the low relative production costs and high yields, palm oil is a reasonably affordable source of energy but possesses high levels of saturated fats (Cuevas et al., 2019). Its non-aromatic characteristic also makes it a suitable oil for blending purposes. Palm oil however contains about 49 grams saturated fat per 100 grams of oil, as opposed to less than 20 grams in peanut, soybean and rapeseed oils. Consequently, it induces a larger increase in plasma concentrations of total cholesterol and low-density lipoproteins (Basu et al., 2013). Treated districts only observed a marginal consumption of coconut and mustard oils[10].

Table 1 presents the descriptive statistics for the outcome variables in both rural and urban areas. In 2004-05, daily edible oil consumption by an average household was higher in rural treated districts by about 80 Kcal. By 2009-10, calories derived from edible oils increased in both treated and control districts, but the differential between the two groups almost remained the same. However, a sharper picture emerges when one considers the composition of edible oils. There was no statistically significant difference in the calories sourced from palm and other oils across treated and control districts before the introduction of the policy intervention i.e., the distribution of subsidised palm oil. However, by 2009-10 i.e., after the intervention, the population residing in an average rural household in a treated district consumed 183 Kcal more than that consumed among the control districts. This is also evident in terms of the proportion of calories being sourced derived from palm and other oils in overall edible oils; treated districts were ingesting 17 per cent more calories sourced from palm oil than their control counterparts were after the intervention. In contrast, while groundnut oil intakes were higher in the rural treated districts in 2004-05, by 2009-10 these differences became insignificant against a backdrop of lower consumption of groundnut oil over time.

These patterns remain largely similar for urban areas. The treated districts note significantly higher palm oil consumption both in terms of nutrient intakes as well as in proportion terms in 2009-10 after the intervention. There were, however, no significant differences among the treated and control districts for edible oils' intakes. Here also, coconut oil consumption is higher among the control households.

Table 2 presents the differences in the average household covariates among rural as well as urban households located in the treated and control districts. Control variables are utilised to take into account the differences in the characteristics that might affect the outcome variables. In the pre-intervention period (2004-05), household size in the rural treated households was marginally smaller than that in control households. As expected, household size has declined between 2004-05 and 2009-10.

[10] The consumption of mustard oil was however negligible in both treated and control districts, and has thus not been considered in the analysis as a separate outcome variable. A large part of the consumption of coconut oils was driven by control states such as Kerala.

Treated households also had a higher share of rural households from the Other Backward Classes (OBCs) category. As is evident from Table 2, education levels of the household heads were marginally different between the treated and control households in 2004-05. Treated households in rural areas had heads who were relatively less likely to be primary school educated but more likely to receive secondary school education in the pre-intervention period. For urban households as well, marginal differences were noted for educational and social group categories in the pre-intervention period.

In terms of the relative price ratios of edible oils with respect to cereals, we find that the rural control households had lower price ratios compared to the treated households in the pre-intervention period. However, after the introduction of the intervention, treated households had lower price ratios compared to their counterparts in the control group. We further compute the relative price ratios of palm and other oils with respect to groundnut oil, which is the main competing oil in the treated states. Figures 2 (a) and 2 (b) depict these changes separately for rural and urban areas. On an average, these ratios are consistent with the earlier discussed ratios; the unit value ratios of palm and other oils with respect to groundnut oil were nearly the same in rural control and treated districts in 2004-05, the relative price differential increased to favour the treated districts by 2009-10. These pre-intervention differences in the socio-demographic composition between the treated and control districts though significant for some covariates were not that stark.

6.2. Impact estimates: DID

Column 1 of Table 3 (a) reports the simplest DID specification in rural areas, column 2 adds household-level control variables and district fixed effects, and column 3 additionally considers sampling weights. The estimates are almost similar in magnitude and direction across specifications. We focus mainly on the unweighted estimates presented in column 2 while making a comparative assessment across specifications.

The DID estimates suggest that in rural areas the introduction of palm oils in PDS led to an increase in its daily household caloric intake of 146-154 Kcal on an average. This translates into a 33-35 per cent increase from the average baseline consumption of palm and other oils. The intervention led to about 19.4-20 per cent increase in an average rural household’s share of daily calories sourced from palm and other oils in overall edible oils. However, the intervention did not translate into any increase in the overall edible oils’ consumption – the DID estimates are all insignificant. Instead, the intervention led to a substitution of groundnut and coconut oils with the effect being starker for the former. The p values from the RI tests suggest that the effect of palm oil intervention in rural areas are unlikely to be observed as a matter of chance for the daily household caloric share derived from palm and other minor oils in overall edible oils, and daily energy intakes derived from coconut and groundnut oils.

In urban areas (Table 3 (b)), there is no significant impact on the consumption of palm and minor oils, although the signs are, as expected, positive. By 2009-10, coconut and groundnut oils however observed a decline after the intervention; the impact on overall intakes of edible oils is insignificant, as was the case in rural areas. As expected, similar findings are noted with respect to the magnitude and direction of the quantities consumed of different types of edible oils. These results have not been reported here for the sake of brevity. In terms of the p values associated with RI tests, almost all the outcome variables were, however, not significant at the 5 per cent level of significance.

The validity of our DID estimates and subsequent use of these for an appropriate causal interpretation relies on the identifying assumption that the control group of bordering districts is a valid counterfactual for what would have happened to the treated districts in the absence of the policy intervention of subsidised palm oil. This is often referred to as the parallel or common trends assumption. It essentially requires that the unobserved differences between the treatment and control groups are the same over time in the absence of treatment. It is usually tested by checking for the existence of parallel trends in the pre-intervention period. However, as noted by Kahn-Lang and Lang (2019), the presence of parallel trends in the pre-period does not guarantee that these trends would have continued in the absence of treatment. In addition, failure to reject the null hypothesis of non-parallel trends does not confirm the existence of parallel trends. As discussed earlier, it is important to note that there are certain comparability issues across the pre-intervention and baseline survey rounds, and these might affect the parallel trends assumption. We find that there is no violation of the non-parallel trends for all the outcome variables except for caloric intakes derived from coconut oil and overall edible oils in both rural and urban areas at 5 per cent level of significance (Appendix Table A4). The use of our next estimation techniques minimise the concerns relating to the validity of the standard DID estimates.

6.3. Impact estimates: Matched DID

The adoption of the matched DID estimation approach enables us to control for both observed time-variant and unobserved time-invariant heterogeneity across groups. In addition, it corrects for observable pre-existing differences in the treated and control districts by employing only the matched sample with similar characteristics. Tables 4 (a) and 4 (b), respectively provide the rural and urban estimates of the differences based on three matched samples i.e., the kernel PSM, MDM and PSM using CEM samples in rural and urban areas, respectively. As discussed in the literature, we use the CEM matched sample to improve upon other matching methods; we employ propensity score based matching on the CEM matched sample. The results are in line with the earlier DID estimates. The balancing tests for the quality of matching estimates for PSM using CEM sample are given in the Appendix Figure A2.

Table 4 (a) presents the estimates of the differences arrived at by estimating the pre-post differences on the rural matched samples. The estimates from the kernel PSM sample are similar in direction and marginally higher than DID estimates for palm and other oils. Except for overall edible oils' caloric intakes by an average rural household, all the outcome variables are significant and have the expected sign. All the estimations rely on automatic selection of bandwidth for both the pre- and post-intervention periods. The findings are also in line for the MDM and CEM samples. In addition, we report the estimates considering sampling weights in column (2). For urban areas as well (Table 4 (b)), one can observe that there has been an increase in the intakes of palm oil and other minor oils and a displacement of coconut and groundnut oils after the policy intervention. The estimates for palm and other oils are marginally higher for PSM and MDM samples, and are significant unlike the unmatched DID estimates. Except for overall edible oils' caloric intakes by an average urban household, all the outcome variables are significant.

6.3. Impact estimates: DID in the context of treatment heterogeneity

We now shift our attention to the heterogeneous impacts of the treatment status on outcome variables. For this, we first restrict our analysis only to the PDS users i.e., households who purchase either one or a combination of the three subsidised food commodities i.e., rice, wheat or sugar. We assume here that there is a high likelihood that those households, which purchase either all or at least one of these commodities, are also likely to purchase subsidised palm oils in the treated districts. The participation rates in both the treated and control districts in rural areas has increased almost at the same rate across the survey rounds. As in case of earlier estimates, the DID estimates (Table 5 (a (i))) reveal that the policy intervention has led to an increase of daily caloric intake of 137-185 Kcal coming from palm and other oils in an average rural household in the treated district relative to the ones in bordering districts. The PDS users residing in rural areas increased their caloric intakes derived from palm and other oils by about 137 Kcal, which is lower as compared to the 147 Kcal increase undertaken by the overall rural sample. However, the PDS users in the treated districts had about 20 per cent increase in their overall edible oils' calories coming from palm and other oils. Similar to the overall mean estimates, substitution effects are noted for groundnut and coconut oils among PDS users with the effects being starker for groundnut oil.

In case of urban areas (Table 5 (b (i))), no increase is observed in terms of the absolute daily calories derived from palm and other oils for an average household. However, about 18 per cent increase is noted in terms of its overall edible oils' calorie share. Caloric intakes derived from groundnut and coconut oils also declined with the effects being starker for the former.

The paper also analyses the state-specific heterogeneous impacts of the intervention on all the outcome variables (Tables 5 (a (ii))) and 5 (b (ii))). Just as in earlier tables, column 1 does not control for covariates, district fixed effects and sampling weights while the last column takes into account all of them. The introduction of palm oil in PDS across these states has led to the largest increase in daily household caloric intakes derived from such oils in Maharashtra followed by Tamil Nadu and Andhra Pradesh. The increase in palm oil, though positive, is not significant for Andhra Pradesh. However, a decline in calorie intakes from all edible oils and groundnut oil is observed in Andhra Pradesh. It is also important to note here that Andhra Pradesh had introduced the scheme chiefly for its BPL households. Tamil Nadu has a universal PDS system with as high as 96 per cent (85 per cent) rural (urban) households being a PDS user. Andhra Pradesh has a quasi-universal coverage with 87 per cent (48 per cent) rural (urban) households being PDS users in 2009-10. Maharashtra also had more than two-thirds of its rural households as users of PDS.

In terms of the share of daily rural calories attributed to palm and other oils in calories derived from all edible oils, one notes that the largest increase was observed for Tamil Nadu followed by Maharashtra. Both groundnut and coconut oils were being substituted after the intervention. Coconut oil is most displaced in rural Tamil Nadu followed by Andhra Pradesh and Maharashtra. While for groundnut oil, Tamil Nadu was replacing it the most followed by Maharashtra. This could be a consequence of the higher taste preferences for these two oils among the Southern states compared to Maharashtra.

In case of urban areas, households in Tamil Nadu and Andhra Pradesh have reduced their intake of coconut oil but no increase in the consumption of subsidised palm and other oils is noted. Maharashtra witnessed an increase in the intake of subsidised palm and other oils alongside a decline in the consumption of coconut and groundnut oils. It also observed about 7.7-9.8 per cent increase in the calorie share sourced from palm and other minor oils in overall calories derived from all edible oils.

6.4. Robustness checks: Propensity score matched difference-in-differences in a repeated cross-sectional context

The matched DID estimation methods employed thus far do not take into account any differential changes in the composition of covariates over time. In addition, the likelihood of the same unit receiving the treatment over time is quite low in a RCS framework. As noted above, when such compositional changes occur, a matched DID estimation in the context of RCS as proposed by Blundell and Dias (2000, 2009) should be utilised. The PSM-DID-RCS estimator uses the kernel PSM technique in conjunction with DID estimation and ensures that the treated units have a counterpart in the non-treated population before and after the policy intervention. As it emerges, however, there were only a few compositional changes in the distribution of the covariates across the two survey rounds. As can be seen from Tables A5 (i) and A5 (ii) in the Appendix, there exist some minor changes in the group composition of the treated and control households over time in terms of social group, education, relative price ratios etc. in both rural and urban areas.

Tables 6 (a) and 6 (b) present the impact estimates from the PSM-DID-RCS estimator, which takes into consideration the possibility of such differential changes in the distribution of covariates, separately for rural and urban areas. Not surprisingly, the magnitudes of the impact estimates (and their statistical significance/insignificance) are quite close to that found under matched DID estimation using PSM sample, and reported in Table 4 (a). For example, while the matched PSM-DID estimate for the daily average household caloric intake of palm and other oils is 156 Kcal in rural areas, the PSM-DID-RCS estimate for the same is 159 Kcal. This is also applicable for the share of calories derived from palm and other oils in overall edible oils, and household calorie intake sourced from groundnut oil. Similar patterns also emerge from urban areas. An average urban household in the treated district increased its daily caloric intake from palm oils relative to the one in neighbouring bordering district by about 82 Kcal under matched

PSM-DID estimate while the same was 83 Kcal for the PSM-DID-RCS estimate. The reduction in the daily household caloric intake coming from groundnut oil was marginally higher for the PSM-DID-RCS estimator than the matched DID using kernel PSM sample.

There are a few limitations of the findings of this study. First, measurement error is a potential threat in case of analyses undertaken using consumption surveys. The quantities consumed and expenditures incurred thereof are self-reported, and there exists no mechanism to evaluate whether this potential bias is a concern for our sample. Second, the implicit prices so derived are the unit values that are subject to a similar measurement error. Third, we assume that there are no spillover effects on non-beneficiaries in the treated states. This essentially implies that there are no inclusion errors or ghost participants, and that participants do not share the subsidised commodities with non-participants. It is important to point out that we make no claims regarding the generalizability of these results at the national level.

Some of the other caveats relate to data availability. We cannot consider the impact of the policy intervention on direct health outcomes such as obesity. Another key limitation of CES data set is that it does not provide the quantity purchased or expenditure incurred on non-staple commodities such as edible oils, pulses etc. that are distributed through the PDS. In addition, such kind of information with respect to states is not consistently available from any other source as well.

7. Conclusion and policy implications

In the past few decades, low-income countries such as ours have predominantly used the food safety net programmes (e.g., PDS) to address their food security concerns. Significant body of work has largely established the effectiveness of such programmes in enhancing household welfare. Although there have been concerns about the effectiveness of PDS across states, this paper provides evidence that policy reforms in the PDS of three states led to an improved household nutrition. In the late 2000s, the state governments of Tamil Nadu, Andhra Pradesh and Maharashtra began to provide edible oils, specifically palm oils in their PDSs. Using large-scale nationally representative household survey data set, we exploit the cross-sectional variation in the introduction of the subsidy on palm oil. The identification relies on consumption patterns being similar in neighbouring districts across the state borders of Tamil Nadu, Andhra Pradesh and Maharashtra, such that any differential changes in consumption over time may be attributed to the policy intervention. We implement the DID and matched DID estimation methods to evaluate the causal effects of the policy intervention (i.e., ATT) on household nutrition in the treated states. We also undertake another matched DID estimation exercise given the RCS nature of our data set.

We find evidence of a positive impact of the policy intervention of subsidised palm oils on the daily caloric intakes derived from palm oils and in terms of their contribution to overall edible oils' calories for the beneficiary households. An average rural beneficiary household, relative to a bordering non-beneficiary household, noted an increase of 146-154 Kcal in its daily household caloric intake derived from palm and other oils. This translates into a 33-35 per cent increase from the average baseline consumption of palm and other oils. The intervention led to about 19.4 - 20 per cent increase in the share of daily household calories sourced from palm and other oils in overall calories attained from all edible oils. After the intervention, an average treated household also reduced its consumption of groundnut and coconut oils relative to the control household. Heterogeneous impacts of these treatment effects have also been assessed. The estimates from the matched DID are similar in direction and marginally higher than the standard DID estimates for palm and other oils' caloric intakes. The urban areas also noted a marginal positive increase in matched DID estimations. The estimates from the PSM-DID-RCS estimator were quite close to that found under matched DID estimation using the PSM sample.

The results of this study have some important policy implications. First, it adds to the limited extant literature that evaluates the impact of state-specific interventions in terms of diversified PDS portfolios and their impacts thereof on household nutrition. Second, the distribution of subsidised palm oil might enable achievement of food security goals but it could also have significant impacts on the rising NCDs burden in the country in the near future. In the wake of the fact that India is anticipated to have the largest number of cardiovascular deaths by 2020[11], it is vital that all the advantages and disadvantages of such a policy intervention are adequately evaluated. Given the plausible substitution of traditionally consumed relatively heathier oils by palm oil, it is suggested that saturated fats in Indian diets might be considered to be replaced with healthier polyunsaturated fats. This would help to curb the rapidly rising health inequities, and have indirect effects that go beyond the consumption aspects. The incentives to promote healthier oils would aid not only the domestic producers but also ensure in promoting sustainable nutritional security.

[11] According to the World Health Report 2002, cardiovascular diseases (CVDs) will be the largest cause of death and disability in India by 2020 (Nag & Ghosh, 2013).

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TABLES AND FIGURES

Table 1: Descriptive statistics by treatment status at household level

	Round 61 (2004-05)			**Round 66 (2009-10)**		
Rural	Treated	Control	Difference (T-C)	Treated	Control	Difference (T-C)
Daily household calorie intake from palm and other oils (Kcal/hh/day)	438 (45.93)	390 (39.98)	48 (60.56)	652 (52.48)	469 (58.72)	183** (78.33)
Daily household calorie share from palm and other oils in overall edible oils (%)	60 (5.39)	62 (4.70)	-1.32 (7.11)	76 (4.54)	59 (6.20)	16.85** (7.64)
Daily household calorie intake from groundnut oil (Kcal/hh/day)	264 (34.03)	123 (27.07)	141*** (43.25)	180 (34.41)	111 (29.08)	69 (44.81)
Daily household calorie intake from coconut oil (Kcal/hh/day)	3 (0.94)	101 (30.91)	-98*** (30.77)	4 (1.38)	152 (44.34)	-148*** (44.13)
Daily household calorie intake from edible oils (Kcal/hh/day)	707 (28.93)	626 (35.83)	80* (45.81)	837 (36.63)	750 (36.86)	87* (51.69)
Number of observations	8662	6715	15377	6602	4971	11573
	Round 61 (2004-05)			**Round 66 (2009-10)**		
Urban	Treated	Control	Difference (T-C)	Treated	Control	Difference (T-C)
Daily household calorie intake from palm and other oils (Kcal/hh/day)	500 (55.49)	442 (45.90)	58 (71.63)	652 (50.34)	523 (59.02)	130* (77.17)
Daily household calorie share from palm and other oils in overall edible oils (%)	60 (6.03)	51 (3.13)	9.46 (6.75)	75 (5.02)	59 (6.59)	16.01* (8.24)
Daily household calorie intake from groundnut oil (Kcal/hh/day)	325 (59.59)	296 (65.88)	29 (88.37)	188 (37.84)	209 (57.13)	-21 (68.17)

Daily household calorie intake from coconut oil (Kcal/hh/day)	5 (1.05)	82 (39.29)	-78** (39.10)	7 (1.82)	97 (50.49)	-91* (50.26)
Daily household calorie intake from edible oils (Kcal/hh/day)	837 (49.78)	839 (95.38)	-3 (107.04)	865 (59.38)	848 (60.09)	17 (84.03)
Number of observations	6369	4485	10854	5406	4032	9438

Significance levels: * < 10% ** < 5% *** < 1%; Standard errors in parentheses; the differences pertain to sample weighted differences in mean outcomes.

Table 2: Differences in covariates among the treated and control districts by treatment status at household level

Rural	**Round 61 (2004-05)**			**Round 66 (2009-10)**		
Variable	Treated	Control	Difference (T-C)	Treated	Control	Difference (T-C)
Household size	4.19 (0.08)	4.6 (0.11)	-0.406*** (0.130)	4.13 (0.08)	4.6 (0.10)	-0.464*** (0.132)
Social group (Base category: Scheduled Tribes) Scheduled Castes	0.18 (0.01)	0.16 (0.02)	0.022 (0.020)	0.18 (0.01)	0.13 (0.01)	0.047** (0.020)
Other Backward Classes	0.51 (0.03)	0.37 (0.03)	0.136*** (0.045)	0.56 (0.03)	0.42 (0.04)	0.140*** (0.049)
Others	0.2 (0.03)	0.23 (0.02)	-0.036 (0.034)	0.16 (0.02)	0.19 (0.02)	-0.033 (0.033)
Relative price ratio of oils to cereals	6.72 (0.18)	6.67 (0.16)	0.053 (0.242)	5.45 (0.25)	5.78 (0.27)	-0.333 (0.366)
Education level of household head (Base category: Not literate) Less than primary	0.09 (0.01)	0.11 (0.01)	-0.023* (0.013)	0.12 (0.01)	0.14 (0.01)	-0.017 (0.017)
Primary	0.15 (0.01)	0.15 (0.01)	-0.002 (0.016)	0.16 (0.01)	0.16 (0.01)	-0.003 (0.017)
Middle	0.13 (0.01)	0.16 (0.01)	-0.028 (0.017)	0.14 (0.01)	0.16 (0.02)	-0.015 (0.021)
Secondary	0.08 (0.01)	0.06 (0.01)	0.016* (0.009)	0.1 (0.01)	0.08 (0.01)	0.016 (0.011)
Higher secondary and above	0.06 (0.01)	0.06 (0.01)	-0.001 (0.010)	0.07 (0.01)	0.08 (0.01)	-0.004 (0.010)
Assets index	0.13 (0.04)	0.15 (0.09)	-0.025 (0.098)	0.13 (0.06)	0.07 (0.11)	0.058 (0.119)
Dependency ratio	54.55 (1.64)	56.81 (2.32)	-2.268 (2.828)	44.98 (1.64)	51.86 (2.32)	-6.882** (2.832)

Land possessed (in hectares)	0.7	0.81	-0.113	0.67	0.67	-0.005
	(0.07)	(0.09)	(0.110)	(0.06)	(0.08)	(0.100)
Number of observations	8662	6715	15377	6602	4971	11573
Urban		**Round 61 (2004-05)**			**Round 66 (2009-10)**	
Variable	Treated	Control	Difference (T-C)	Treated	Control	Difference (T-C)
Household size	4.09	4.29	-0.207	3.82	3.92	-0.096
	(0.08)	(0.10)	(0.127)	(0.12)	(0.06)	(0.131)
Social group (Base category: Scheduled Tribes) Scheduled Castes	0.16	0.11	0.045^{***}	0.13	0.09	0.033
	(0.01)	(0.01)	(0.017)	(0.01)	(0.02)	(0.026)
Other Backward Classes	0.49	0.34	0.147^{**}	0.53	0.4	0.13
	(0.06)	(0.04)	(0.070)	(0.07)	(0.05)	(0.082)
Others	0.32	0.49	-0.172^{**}	0.31	0.46	-0.144^{*}
	(0.06)	(0.04)	(0.069)	(0.07)	(0.05)	(0.087)
Relative price ratio of oils to cereals	5.21	4.95	0.26	4.37	3.52	0.855^{**}
	(0.15)	(0.15)	(0.215)	(0.28)	(0.27)	(0.383)
Education level of household head (Base category: Not literate) Less than primary	0.06	0.07	-0.005	0.07	0.05	0.015
	(0.01)	(0.01)	(0.015)	(0.01)	(0.01)	(0.014)
Primary	0.15	0.12	0.030^{*}	0.11	0.1	0.014
	(0.01)	(0.01)	(0.017)	(0.01)	(0.02)	(0.021)
Middle	0.17	0.19	-0.019	0.16	0.19	-0.025^{*}
	(0.01)	(0.01)	(0.017)	(0.01)	(0.01)	(0.015)
Secondary	0.16	0.16	-0.001	0.18	0.17	0.014
	(0.01)	(0.01)	(0.014)	(0.01)	(0.01)	(0.016)
Higher secondary and above	0.26	0.29	-0.036	0.31	0.38	-0.066
	(0.02)	(0.02)	(0.028)	(0.02)	(0.04)	(0.042)
Assets index	-0.07	0.07	-0.134	-0.07	-0.13	0.06
	(0.06)	(0.11)	(0.128)	(0.08)	(0.12)	(0.147)
Dependency ratio	47.13	44.31	2.814	39.62	38.64	0.98
	(1.37)	(2.64)	(2.962)	(1.25)	(2.01)	(2.355)
Land possessed (in hectares)	0.11	0.15	-0.041	0.13	0.13	-0.007
	(0.02)	(0.05)	(0.053)	(0.03)	(0.02)	(0.034)
Number of observations	6369	4485	10854	5406	4032	9438

Significance levels: * < 10% ** < 5% *** < 1%; Standard errors in parentheses; the differences pertain to sample weighted differences in covariates.

Table 3 (a): Differences in growth of consumption between bordering districts of rural Tamil Nadu (TN), Andhra Pradesh (AP) & Maharashtra (MH) and bordering districts of control states (2004-05 & 2009-10): DID estimation

	Daily household calorie intake from palm and other oils (Kcal/hh/day)			Daily household calorie share from palm and other oils in overall edible oils (%)			Daily household calorie intake from groundnut oil (Kcal/hh/day)			Daily household calorie intake from coconut oil (Kcal/hh/day)			Daily household calorie intake from edible oils (Kcal/hh/day)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Diff-in-diff	154***	146***	146***	19.50***	19.39***	19.94***	-72**	-88***	-93***	-65***	-61***	-52***	10	-10	-5
	(49.05)	(46.34)	(44.03)	(4.20)	(4.01)	(4.11)	(29.15)	(29.02)	(30.05)	(18.42)	(15.91)	(15.15)	(36.64)	(31.86)	(32.45)
District fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control variables	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sampling weights	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
P value (RI)	0.1700	0.1030	0.1420	0.0225	0.0115	0.0295	0.0265	0.0120	0.0005	0.1505	0.0695	0.1075	0.8820	0.8330	0.9210
R-squared	0.040	0.430	0.460	0.026	0.412	0.451	0.036	0.286	0.310	0.139	0.614	0.618	0.025	0.55	0.529
Observations	26950	25898	25898	26562	25850	25850	26950	25898	25898	26950	25898	25898	26950	25898	25898

Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are clustered at the district level. Control variables include household size, social group, relative price ratio of oils to cereals, education level of the household head, total land possessed, dependency ratio, assets index and district fixed effects. We estimate the standard errors clustered by state using randomization inference on our test statistic i.e., coefficient on the interaction of the treatment indicator and a Post variable using 2,000 replications.

Table 3 (b): Differences in growth of consumption between bordering districts of urban TN, AP & MH and bordering districts of control states (2004-05 & 2009-10): DID estimation

	Daily household calorie intake from palm and other oils (Kcal/hh/day)			Daily household calorie share from palm and other oils in overall edible oils (%)			Daily household calorie intake from groundnut oil (Kcal/hh/day)			Daily household calorie intake from coconut oil (Kcal/hh/day)			Daily household calorie intake from edible oils (Kcal/hh/day)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Diff-in-diff	78	68	97	11.18**	10.13**	8.98*	-53	-60*	-60	-40***	-33**	-28**	-5	-17	17
	(47.59)	(49.34)	(62.90)	(5.01)	(4.74)	(5.40)	(36.15)	(34.06)	(41.22)	(13.37)	(13.08)	(13.49)	(40.06)	(37.97)	(57.52)
District fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control variables	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sampling weights	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
P value (RI)	0.3675	0.3020	0.2845	0.1265	0.1095	0.1830	0.1255	0.1750	0.3135	0.2630	0.0910	0.1775	0.9460	0.6820	0.7640
R-squared	0.023	0.345	0.322	0.025	0.296	0.268	0.023	0.236	0.235	0.092	0.609	0.625	0.005	0.548	0.567
Observations	20292	18831	18831	19277	18782	18782	20292	18831	18831	20292	18831	18831	20292	18831	18831

Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are clustered at the district level. Control variables include household size, social group, relative price ratio of oils to cereals, education level of the household head, total land possessed, dependency ratio, assets index and district fixed effects. We estimate the standard errors clustered by state using randomization inference on our test statistic i.e., coefficient on the interaction of the treatment indicator and a Post variable using 2,000 replications.

Table 4 (a): Matched DID estimation

	Daily household calorie intake from palm and other oils (Kcal/hh/day)		Daily household calorie share from palm and other oils in overall edible oils (%)		Daily household calorie intake from groundnut oil (Kcal/hh/day)		Daily household calorie intake from coconut oil (Kcal/hh/day)		Daily household calorie intake from edible oils (Kcal/hh/day)	
Rural										
PSM Kernel										
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Difference (Post –Pre)	156***	199***	20***	25***	-86***	-75***	-71***	-86***	-7	32*
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
MDM										
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Difference (Post –Pre)	158***	160***	20***	21***	-89***	-97***	-65***	-56***	-3.39	0.82
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
PSM using CEM sample										
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Difference (Post –Pre)	176***	182***	22***	24***	-76***	-43***	-82***	-90***	13	42**
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Following from Paternoster et al. (1998), we employ the statistical test $Z = (b_1 - b_2)/ (SE_{b1}^2 + SE_{b2}^2)$ ^ 0.5 for evaluating the existence of difference between the two coefficients of pre- and post-intervention periods.

Table 4 (b): Matched DID estimation

	Daily household calorie intake from palm and other oils (Kcal/hh/day)		Daily household calorie share from palm and other oils in overall edible oils (%)		Daily household calorie intake from groundnut oil (Kcal/hh/day)		Daily household calorie intake from coconut oil (Kcal/hh/day)		Daily household calorie intake from edible oils (Kcal/hh/day)	
Urban										
PSM Kernel										
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Difference (Post –Pre)	82***	59**	11***	10***	-59***	-78***	-38***	-16	-9	-26
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
MDM										
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Difference (Post –Pre)	83***	54*	11***	6***	-74***	-73***	-41***	-15*	-23	-27
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
PSM using CEM sample										
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Difference (Post –Pre)	88***	16	13***	8***	-76***	-83***	-40***	-17	-23	-78***
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Following from Paternoster et al. (1998), we employ the statistical test $Z = (b_1 - b_2)/ (SE_{b1}^2 + SE_{b2}^2)$ ^ 0.5 for evaluating the existence of difference between the two coefficients of pre- and post-intervention periods.

Table 5 (a (i)): Differences in growth of consumption among PDS users between bordering districts of rural TN, AP & MH and bordering districts of control states (2004-05 & 2009-10): DID estimation

	Daily household calorie intake from palm and other oils (Kcal/hh/day)			**Daily household calorie share from palm and other oils in overall edible oils (%)**			**Daily household calorie intake from groundnut oil (Kcal/hh/day)**			**Daily household calorie intake from coconut oil (Kcal/hh/day)**			**Daily household calorie intake from edible oils (Kcal/hh/day)**		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Diff-in-diff	185*** (46.61)	137*** (41.19)	139*** (44.46)	22*** (5.30)	20*** (4.53)	20*** (4.77)	-38 (29.75)	-76*** (28.61)	-82** (35.56)	-86*** (26.72)	-60*** (17.11)	-50*** (16.05)	55 (36.77)	-3 (30.29)	0.107 (34.28)
District fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control variables	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sampling weights	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.035	0.478	0.503	0.025	0.450	0.49	0.035	0.342	0.388	0.142	0.584	0.589	0.023	0.512	0.502
Observations	15357	14951	14951	15324	14924	14924	15357	14951	14951	15357	14951	14951	15357	14951	14591

Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are clustered at the district level. Control variables include household size, social group, relative price ratio of oils to cereals, education level of the household head, total land possessed, dependency ratio, assets index and district fixed effects.

Table 5 (b (i)): Differences in growth of consumption among PDS users between bordering districts of urban TN, AP & MH and bordering districts of control states (2004-05 & 2009-10): DID estimation

	Daily household calorie intake from palm and other oils (Kcal/hh/day)			Daily household calorie share from palm and other oils in overall edible oils (%)			Daily household calorie intake from groundnut oil (Kcal/hh/day)			Daily household calorie intake from coconut oil (Kcal/hh/day)			Daily household calorie intake from edible oils (Kcal/hh/day)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Diff-in-diff	94 (68.72)	88 (53.49)	66 (68.76)	15** (7.65)	18*** (5.57)	17** (6.78)	-7 (49.41)	-59** (29.04)	-82* (44.96)	-80*** (29.00)	-53** (21.16)	-46** (20.76)	19 (46.61)	-16 (30.42)	-63 (46.19)
District fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control variables	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sampling weights	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.034	0.455	0.449	0.038	0.396	0.355	0.031	0.286	0.259	0.165	0.618	0.639	0.015	0.541	0.558
Observations	7495	7286	7286	7482	7276	7276	7495	7286	7286	7495	7286	7286	7495	7286	7286

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the district level. Control variables include household size, social group, relative price ratio of oils to cereals, education level of the household head, total land possessed, dependency ratio, assets index and district fixed effects.

Table 5 (a (ii)): State-specific impacts on caloric intakes in rural areas

Rural	Daily household calorie intake from palm and other oils (Kcal/hh/day)			Daily household calorie share from palm and other oils in overall edible oils (%)			Daily household calorie intake from groundnut oil (Kcal/hh/day)			Daily household calorie intake from coconut oil (Kcal/hh/day)			Daily household calorie intake from edible oils (Kcal/hh/day)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
DID (TN*Year)	120** (45.92)	140*** (43.11)	146*** (40.76)	30.12*** (5.65)	30.81*** (5.37)	33.56*** (5.66)	-66** (29.61)	-79** (30.51)	-96*** (32.16)	-57*** (18.81)	-51*** (15.98)	-44*** (15.36)	-11 (30.48)	2.38 (29.21)	-1 (29.43)
DID (AP*Year)	22 (50.35)	25 (49.34)	33 (47.95)	13.97** (5.70)	13.86** (5.41)	15.10*** (5.35)	-36 (40.1)	-50 (39.03)	-58 (39.30)	-66*** (18.4)	-61*** (15.56)	-54*** (15.00)	-87** (36.16)	-92*** (31.53)	-85*** (31.50)
DID (MH*Year)	294*** (58.86)	278*** (58.40)	283*** (54.98)	18.71*** (5.29)	18.82*** (5.07)	17.91*** (5.00)	-109** (49.36)	-134*** (47.69)	-133*** (45.30)	-68*** (18.47)	-66*** (16.56)	-54*** (15.49)	110** (49.87)	70 (43.28)	88* (44.77)
Year 2009-10	80** (39.23)	73** (36.34)	70** (33.54)	-3.89 (3.08)	-4.26 (2.90)	-4.38 (2.98)	-27 (17.17)	-17 (17.17)	-5 (20.68)	67*** (18.37)	60*** (15.38)	53*** (14.95)	128*** (27.13)	124*** (25.08)	125*** (25.02)
AP	-5 (74.76)	-129*** (22.31)	-46* (25.96)	-2.20 (10.04)	- 42.63*** (2.23)	- 38.32*** (2.91)	189*** (71.26)	454*** (16.3)	449*** (20.87)	-136*** (39.31)	30*** (7.23)	27*** (7.63)	36 (38.27)	226*** (13.76)	301*** (17.45)
TN	-174*** (57.24)	25 (23.77)	55** (25.05)	-17.88* (9.38)	- 22.38*** (2.97)	-9.01*** (2.88)	166*** (52.06)	200*** (18.11)	189*** (17.52)	-131*** (39.46)	69*** (8.40)	28*** (9.29)	-151*** (40.55)	162*** (15.52)	135*** (17.61)
MH	297*** (66.55)	164*** (25.400	353*** (28.93)	14.17** (6.85)	-8.24*** (2.29)	1.00 (2.74)	166*** (57.27)	341*** (21.9)	69*** (22.48)	-134*** (39.33)	20*** (5.64)	28*** (8.16)	320*** (51.48)	389*** (19.47)	334.4*** (22.66)
Constant	393*** (37.25)	-6 (47.04)	-17 (51.33)	58.27*** (4.61)	84.31*** (2.58)	82.92*** (3.63)	129*** (28.10)	-200*** (34.34)	-176**** (32.91)	138*** (39.31)	-53*** (17.52)	-53*** (16.71)	672*** (34.55)	-140*** (35.08)	-121*** (37.37)

District fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control variables	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sampling weights	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.138	0.435	0.467	0.059	0.041	0.455	0.039	0.287	0.311	0.139	0.614	0.618	0.120	0.553	0.533
Observations	26950	25898	25898	26562	25850	25850	26950	25898	25898	26950	25898	25898	26950	25898	25898

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5 (b (ii)): State-specific impacts on caloric intakes in urban areas

Urban	Daily household calorie intake from palm and other oils (Kcal/hh/day)			Daily household calorie share from palm and other oils in overall edible oils (%)			Daily household calorie intake from groundnut oil (Kcal/hh/day)			Daily household calorie intake from coconut oil (Kcal/hh/day)			Daily household calorie intake from edible oils (Kcal/hh/day)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
DID (TN*Year)	20 (50.74)	44 (53.01)	67 (66.69)	12.90* (6.79)	13.25** (6.58)	12.99* (7.12)	-20 (37.95)	-25 (37.61)	-24 (39.41)	-33** (13.54)	-25* (12.78)	-23* (13.23)	-25 (42.52)	1 (42.25)	18 (59.38)
DID (AP* Year)	16 (71.50)	6 (80.23)	-2 (72.05)	11.07 (6.75)	9.42 (6.47)	6.12 (6.29)	-51 (61.45)	-52 (61.35)	-4 (53.03)	-42*** (13.33)	-36*** (13.01)	-32** (13.44)	-69 (46.76)	-76 (49.54)	-43 (65.72)
DID (MH* Year)	179*** (52.92)	132*** (50.180	177*** (62.63)	9.81* (4.99)	8.23* (4.62)	7.69 (5.34)	-81* (41.72)	-94** (37.02)	-121*** (45.81)	-44*** (13.80)	-38+ (14.17)	-31** (14.28)	69 (52.41)	13 (39.49)	51 (57.07)
Year 2009-10	121*** (40.58)	135*** (42.33)	107* (57.02)	4.80 (4.40)	4.76 (4.02)	5.25 (4.77)	-77*** (26.76)	-70*** (25.32)	-76** (30.80)	41*** (13.26)	34*** (12.81)	30** (13.22)	77** (34.82)	94*** (34.66)	65 (55.21)

AP	-17 (89.65)	402*** (45.15)	-104** (41.85)	3.39 (10.72)	19.97*** (3.39)	-35.82*** (3.82)	101 (95.45)	96** (37.82)	408*** (33.54)	-95** (36.57)	16*** (4.36)	13* (7.51)	-32 (67.68)	330*** (23.29)	171*** (41.15)
TN	-116* (63.45)	154*** (23.59)	53 (45.99)	1.86 (8.72)	11.57*** (2.77)	-32.41*** (4.50)	13 (66.14)	121*** (16.56)	229*** (27.69)	-91** (36.67)	8 (5.50)	46*** (9.27)	-216*** (69.78)	100*** (14.63)	176*** (36.94)
MH	163 (116.2)	82*** (18.69)	472*** (38.90)	2.91 (10.62)	10.02*** (1.183)	17.01*** (3.35)	219** (93.78)	398*** (19.86)	63** (30.56)	-92** (36.65)	26*** (3.70)	59*** (7.92)	285*** (70.80)	314*** (15.69)	427*** (37.68)
Constant	448*** (47.48)	-47.11 (52.03)	-9.58 (85.970	55.74*** (5.31)	73.10*** (3.69)	77.38*** (6.14)	216*** (52.98)	-187*** (48.13)	-199*** (63.24)	97.89*** (36.55)	- 19.43** (9.52)	- 27.58** (13.77)	786*** (62.58)	-92.21*** (30.07)	-114.5*** (41.85)
District fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control variables	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Sampling weights	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
R-squared	0.063	0.346	0.324	0.025	0.297	0.269	0.038	0.236	0.236	0.093	0.609	0.625	0.108	0.549	0.567
Observations	20292	18831	18831	19277	18782	18782	20292	18831	18831	20292	18831	18831	20292	18831	18831

Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6 (a): Differences in growth of consumption between bordering districts of rural TN, AP & MH and bordering districts of control states (2004-05 & 2009-10): PSM-DID-RCS estimation

	Daily household calorie intake from palm and other oils (Kcal/hh/day)		Daily household calorie share from palm and other oils in overall edible oils (%)		Daily household calorie intake from groundnut oil (Kcal/hh/day)		Daily household calorie intake from coconut oil (Kcal/hh/day)		Daily household calorie intake from edible oils (Kcal/hh/day)	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Diff-in-diff	159***	168***	19.44***	20.38***	-87***	-90***	-62***	-65***	1.23	4.45
	(43.38)	(43.26)	(4.05)	(4.05)	(27.50)	(27.25)	(16.35)	(16.82)	(30.85)	(30.07)
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Bootstrapped S.E.	11.394	11.324	0.968	0.826	7.660	6.605	4.320	4.850	8.080	8.881
R-squared	0.44	0.44	0.42	0.43	0.30	0.30	0.62	0.62	0.54	0.54
Observations	25893	25895	25845	25847	25893	25895	25893	25895	25893	25895

*** p<0.01; ** p<0.05; * p<0.1. Bootstrapped standard errors for DID coefficient has been estimated using bootstrapping (50 replications). PS matching with kernel weights has been used to match the households on household size, social group, relative price ratio of oils to cereals, education level of the household head, total land possessed, dependency ratio, and assets index.

Table 6 (b): Differences in growth of consumption between bordering districts of urban TN, AP & MH and bordering districts of control states (2004-05 & 2009-10): PSM-DID-RCS estimation

	Daily household calorie intake from palm and other oils (Kcal/hh/day)		Daily household calorie share from palm and other oils in overall edible oils (%)		Daily household calorie intake from groundnut oil (Kcal/hh/day)		Daily household calorie intake from coconut oil (Kcal/hh/day)		Daily household calorie intake from edible oils (Kcal/hh/day)	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Diff-in-diff	83*	86*	10.49***	11.00**	-66**	-69**	-30**	-32**	-5.12	-5.71
	(47.57)	(47.85)	(4.71)	(4.63)	(31.14)	(30.34)	(12.09)	(12.49)	(35.09)	(34.48)
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Bootstrapped S.E.	13.812	12.762	1.115	1.228	12.371	14.001	4.224	4.470	9.974	11.400
R-squared	0.35	0.35	0.32	0.32	0.25	0.24	0.62	0.62	0.54	0.54
Observations	18825	18830	18777	18780	18825	18830	18825	18830	18825	18830

*** p<0.01; ** p<0.05; * p<0.1. Bootstrapped standard errors for DID coefficient has been estimated using bootstrapping (50 replications). PS matching with kernel weights has been used to match the households on household size, social group, relative price ratio of oils to cereals, education level of the household head, total land possessed, dependency ratio, and assets index.

Figure 1: Daily household calorie intake (Kcal/hh/day) – Rural areas

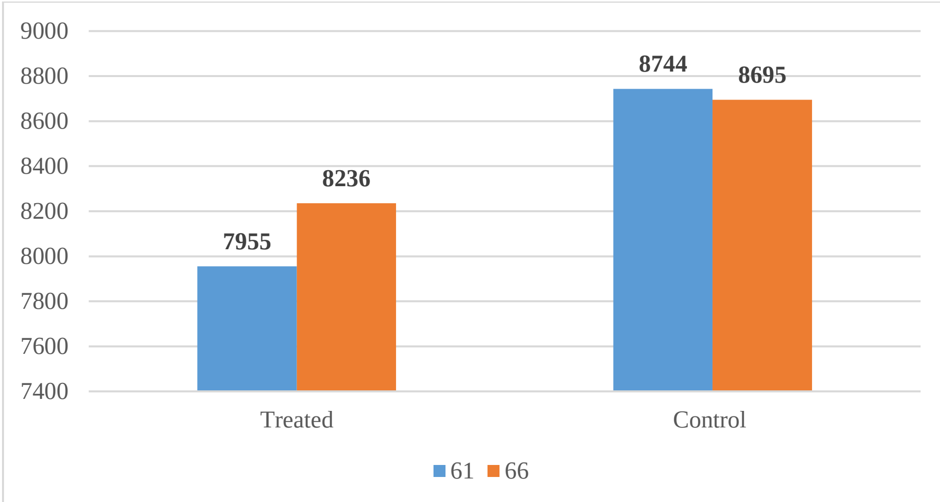
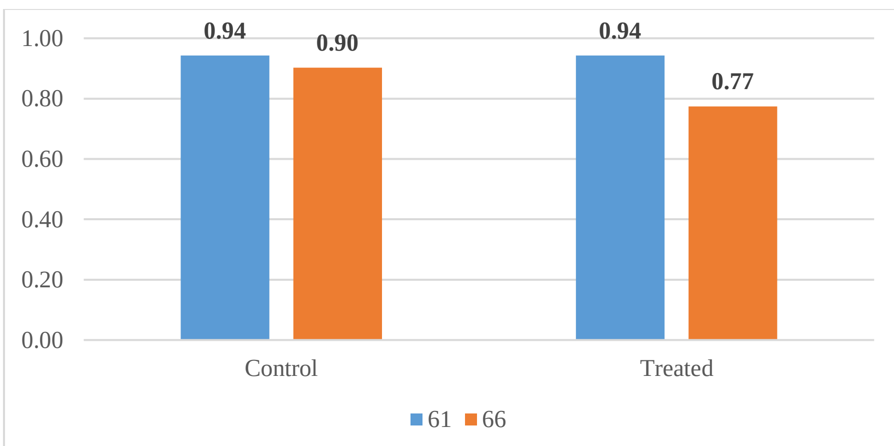
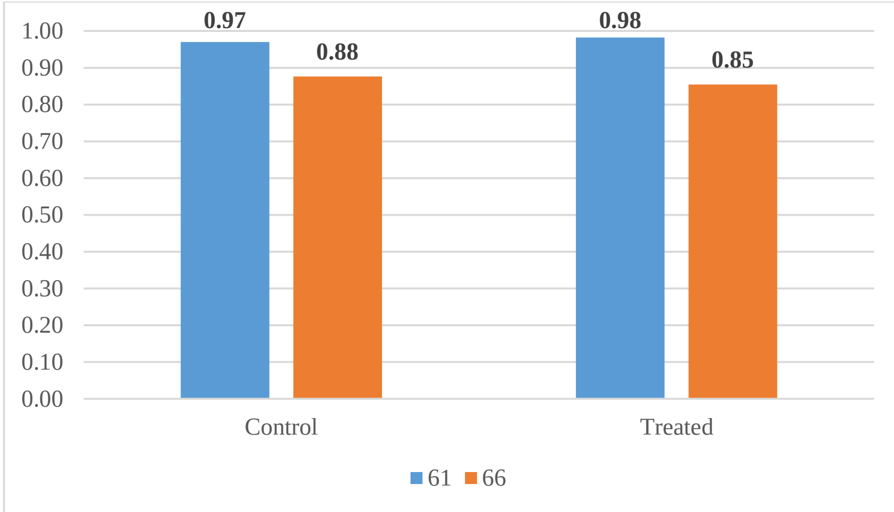


Figure 2 (a): Relative price ratios of palm and other minor oils w.r.t groundnut oil – rural areas



Note: Price ratios have only been computed for those households that had positive consumption

Figure 2 (b): Relative price ratios of palm and other minor oils w.r.t groundnut oil – urban areas



Note: Price ratios have only been computed for those households that had positive consumption

APPENDIX

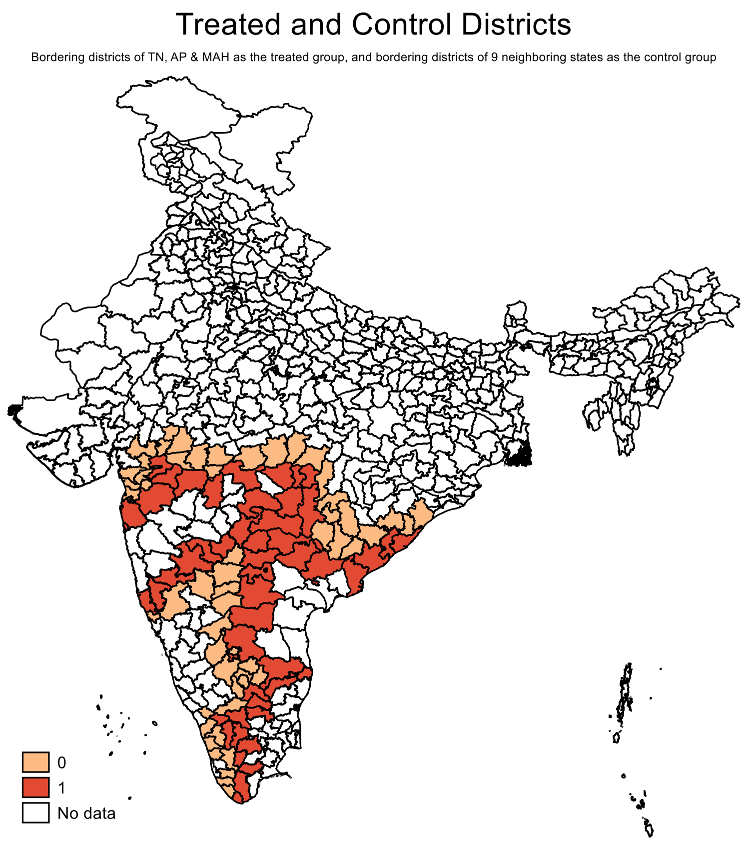


Figure A1: Map of treated and control districts with 2004-05 prevalent district boundaries. Light red (0) refers to the control districts while dark red (1) refers to the treated districts.

Figure A2: PSM using CEM – Match quality

Daily rural household calorie intake from palm and other oils (Kcal/hh/day) during the post-intervention period

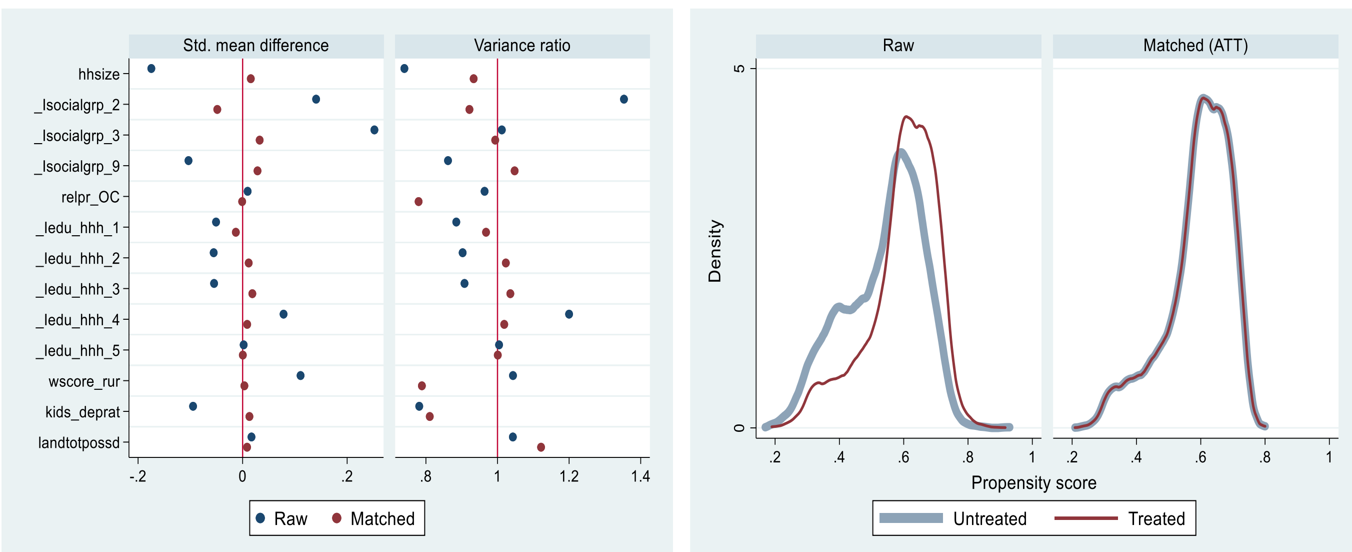


Table A1. Provision of subsidised palm oil in PDS across states

State	Quantity allotted per family per month and issue price per kg/litre	Year of introduction
Tamil Nadu	1 litre; Rs.25/- supplied to the family cardholders under special PDS. Fortified RBD Palmolein oil contains Vitamin A- 25 IU & Vitamin D-2 IU in each gram.	2007
Andhra Pradesh	1 pouch of imported Palm oil; Rs. 40/-per litre (910gms) to the BPL families	June 2008
Maharashtra	1 litre Palm oil to BPL, AAY, APL & Annapurna Beneficiaries; Rs. 42/- per litre with effect from 1 July, 2008 Rs. 35/- per litre with effect from 24 Oct, 2008 Rs.30/- per litre with effect from 27 Aug, 2009 Rs. 45/- per litre with effect from 22 July, 2011	July 2008

Source: Department of Food and Civil Supplies, Government of India; http://www.tncsc.tn.gov.in/PDS.html; http://www.apscsc.gov.in/fin_img2.php; https://www.maharashtra.gov.in/1145/Government-Resolutions; http://mahafood.gov.in/website/english/PDS6.aspx

Table A2: Coverage of PDS participating households across treated and control bordering districts

	Rural		Urban	
	Round 61 (2004-05)	**Round 66 (2009-10)**	**Round 61 (2004-05)**	**Round 66 (2009-10)**
Treated districts of:	PDS_RWS	PDS_RWS	PDS_RWS	PDS_RWS
MH	30.66	46.30	12.09	21.38
AP	64.19	84.75	37.35	46.93
TN	88.27	95.63	74.94	84.60
All 3 states	**56.91**	**72.28**	**39.61**	**48.48**
Control bordering districts of:	PDS_RWS	PDS_RWS	PDS_RWS	PDS_RWS
Orissa	33.78	57.81	13.00	35.00
Chhat	35.68	53.44	19.50	41.41
MP	36.60	49.55	25.07	36.57
Guj	51.25	50.00	11.15	5.42
D&NH	43.75	48.96	26.25	5.21
Kar	54.54	65.79	19.21	28.54
Goa	13.75	55.21	21.01	29.13
Ker	35.32	56.95	28.65	47.31
Pond	65.00	75.78	32.50	45.19
All 9 states	**41.52**	**57.27**	**22.33**	**33.24**

Note: PDS_RWS refers to the participation rates, which are as the proportion of households (%) that purchase either one or a combination of the three subsidised food commodities i.e., rice, wheat or sugar as a proportion of all households in a particular region.

Table A3: Monthly household consumption of palm and other oils in 2009-10 (Kg millions)

State	PDS palm oil allocated	Palm and other oils consumption by overall consumers	Palm and other oils consumption by PDS consumers
TN	15.5	27.7 (1.54*18)	25.5 (1.60*16)
MH	18.2	64.7 (2.91*22.2)	26.1 (3.29*7.9)
AP	20.8	36.4 (1.74*20.9)	27.4 (1.81*15.1)

Note: Palm oil here includes Vanaspati/margarine and other edible oils category. Source: Lok Sabha Starred Question No. 125 and unit-level NSS data. PDS consumer refers to households who purchase either one or a combination of the three subsidised food commodities i.e., rice, wheat or sugar.

Table A4: Testing the parallel trends for the Difference-in-Differences

Dependent variable	Daily household calorie intake from palm and other oils (Kcal/hh/day)	Daily household calorie share from palm and other oils in overall edible oils (%)	Daily household calorie intake from groundnut oil (Kcal/hh/day)	Daily household calorie intake from coconut oil (Kcal/hh/day)	Daily household calorie intake from edible oils (Kcal/hh/day)
Rural					
Parallel trends (trend x treatment)	68 (41.79) [0.107]	0.649 (4.47) [0.885]	-21 (41.18) [0.603]	29 (12.03) [0.018]	81 (26.52) [0.003]
Observations	27964	27924	27964	27964	27964
Urban					
Parallel trends (trend x treatment)	58 (60.76) [0.346]	2.304 (5.118) [0.654]	-17 (59.55) [0.774]	20 (9.36) [0.034]	51 (26.69) [0.061]
Observations	18910	18880	18910	18910	18910

Note: Trend is measured as a continuous variable that takes a value 1 for observations in 1999-2000 and 6 for observations in 2004-05. The coefficient of interaction term is the main variable of interest. Standard errors clustered by state are shown in parentheses and p values are given in square brackets.

Table A5 (i): Compositional changes in rural treated and control households over time

Rural	Treated districts			Control districts		
Variable	**Pre (2004-05)**	**Post (2009-10)**	**Diff (Post – Pre)**	**Pre (2004-05)**	**Post (2009-10)**	**Diff (Post – Pre)**
Household size	4.19 (0.08)	4.13 (0.08)	-0.062 (0.062)	4.6 (0.11)	4.6 (0.10)	-0.004 (0.086)
Social group (Base category: Scheduled Tribes) Scheduled Castes	0.18 (0.01)	0.18 (0.01)	-0.003 (0.013)	0.16 (0.02)	0.13 (0.01)	-0.028** (0.012)
Other Backward Classes	0.51 (0.03)	0.56 (0.03)	0.050*** (0.017)	0.37 (0.03)	0.42 (0.04)	0.046** (0.021)
Others	0.2 (0.03)	0.16 (0.02)	-0.038*** (0.014)	0.23 (0.02)	0.19 (0.02)	-0.040** (0.017)
Relative price ratio of oils to cereals	6.72 (0.18)	5.45 (0.25)	-1.273*** (0.175)	6.67 (0.16)	5.78 (0.27)	-0.888*** (0.253)
Education level of household head (Base category: Not literate) Less than primary	0.09 (0.01)	0.12 (0.01)	0.035*** (0.012)	0.11 (0.01)	0.14 (0.01)	0.029** (0.013)
Primary	0.15 (0.01)	0.16 (0.01)	0.006 (0.013)	0.15 (0.01)	0.16 (0.01)	0.007 (0.013)
Middle	0.13 (0.01)	0.14 (0.01)	0.012 (0.013)	0.16 (0.01)	0.16 (0.02)	-0.001 (0.012)
Secondary	0.08 (0.01)	0.1 (0.01)	0.019*** (0.007)	0.06 (0.01)	0.08 (0.01)	0.019*** (0.006)
Higher secondary and above	0.06 (0.01)	0.07 (0.01)	0.01 (0.007)	0.06 (0.01)	0.08 (0.01)	0.013 (0.009)
Assets index	0.13 (0.04)	0.13 (0.06)	0.004 (0.053)	0.15 (0.09)	0.07 (0.11)	-0.079 (0.093)
Dependency ratio	54.55 (1.64)	44.98 (1.64)	-9.571*** (1.544)	56.81 (2.32)	51.86 (2.32)	-4.957*** (1.911)
Land possessed (in hectares)	0.7 (0.07)	0.67 (0.06)	-0.036 (0.038)	0.81 (0.09)	0.67 (0.08)	-0.145*** (0.053)

Significance levels: * < 10% ** < 5% *** < 1%; Standard errors in parentheses; the differences pertain to sample weighted differences in covariates.

Table A5 (ii): Compositional changes in urban treated and control households over time

Urban	Treated districts			Control districts		
Variable	**Pre (2004-05)**	**Post (2009-10)**	**Diff (Post – Pre)**	**Pre (2004-05)**	**Post (2009-10)**	**Diff (Post – Pre)**
Household size	4.09 (0.08)	3.82 (0.12)	-0.266*** (0.086)	4.29 (0.10)	3.92 (0.06)	-0.377*** (0.088)
Social group (Base category: Scheduled Tribes) Scheduled Castes	0.16 (0.01)	0.13 (0.01)	-0.029* (0.016)	0.11 (0.01)	0.09 (0.02)	-0.018 (0.019)
Other Backward Classes	0.49	0.53	0.041	0.34	0.40	0.058*

	(0.06)	(0.07)	(0.031)	(0.04)	(0.05)	(0.035)
Others	0.32 (0.06)	0.31 (0.07)	-0.008 (0.026)	0.49 (0.04)	0.46 (0.05)	-0.037 (0.045)
Relative price ratio of oils to cereals	5.21 (0.15)	4.37 (0.28)	-0.839*** (0.192)	4.95 (0.15)	3.52 (0.27)	-1.435*** (0.141)
Education level of household head (Base category: Not literate) Less than primary	0.06 (0.01)	0.07 (0.01)	0.008 (0.009)	0.07 (0.01)	0.05 (0.01)	-0.012 (0.009)
Primary	0.15 (0.01)	0.11 (0.01)	-0.044*** (0.010)	0.12 (0.01)	0.10 (0.02)	-0.028** (0.012)
Middle	0.17 (0.01)	0.16 (0.01)	-0.010 (0.011)	0.19 (0.01)	0.19 (0.01)	-0.004 (0.013)
Secondary	0.16 (0.01)	0.18 (0.01)	0.023** (0.011)	0.16 (0.01)	0.17 (0.01)	0.008 (0.009)
Higher secondary and above	0.26 (0.02)	0.31 (0.02)	0.053** (0.023)	0.29 (0.02)	0.38 (0.04)	0.083*** (0.032)
Assets index	-0.07 (0.06)	-0.07 (0.08)	0.000 (0.065)	0.07 (0.11)	-0.13 (0.12)	-0.193** (0.093)
Dependency ratio	47.13 (1.37)	39.62 (1.25)	-7.506*** (1.491)	44.31 (2.64)	38.64 (2.01)	-5.673*** (1.903)
Land possessed (in hectares)	0.11 (0.02)	0.13 (0.03)	0.014 (0.022)	0.15 (0.05)	0.13 (0.02)	-0.020 (0.039)

Significance levels: * < 10% ** < 5% *** < 1%; Standard errors in parentheses; the differences pertain to sample weighted differences in covariates.