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A Fat Subsidy and its Impact on Edible Oil Consumption: Evidence from India

Jaya Jumrani
E-mail: jaya@econdse.org
Department of Economics
Delhi School of Economics

J. V. Meenakshi
E-mail: meena@econdse.org
Department of Economics
Delhi School of Economics

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CENTRE FOR DEVELOPMENT ECONOMICS
DELHI SCHOOL OF ECONOMICS
DELHI - 110007

A fat subsidy and its impact on edible oil consumption: evidence from India

Jaya Jumrani[*] J. V. Meenakshi[†]

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Abstract[‡]

Nearly one-fifth of adult Indians are overweight or obese. Among potential interventions to address the public health problem this poses, are the so-called fat taxes. While these are yet to be implemented in India at scale, this paper looks at the impact of a negative tax (subsidy) on palm oil that has been implemented in three states—Tamil Nadu, Maharashtra and Andhra Pradesh—to examine the extent to which this policy has had an impact on edible oil consumption. Using consumer expenditure survey data, and a matched differences-in-differences approach, the paper finds that the subsidy on palm oil led to an increase in its consumption, both in rural and urban areas, with effects being more pronounced in rural areas. The increases are also the largest in Tamil Nadu, relative to other states. There was modest impact on overall consumption of edible oils in rural areas of two states; and there is consistent evidence that consumers displaced market-sourced groundnut and coconut oils for palm oil. The paper draws some nutritional implications of this switch.

Keywords: Public distribution system, fat subsidy

JEL Codes: H31, I38, Q18

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[*]Department of Economics, Delhi School of Economics, University of Delhi, Delhi - 110007, India; ICAR - National Institute of Agricultural Economics and Policy Research (ICAR-NIAP), Dev Prakash Shastri Marg, Pusa, New Delhi - 110012. Email: jaya@econdse.org

[†] Department of Economics, Delhi School of Economics, University of Delhi, Delhi - 110007, India. Email: meena@econdse.org

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1. Introduction

India is rapidly going through a nutrition transition. This is reflected in increased incidence of overweight and obesity, and associated non-communicable diseases (Martínez Steele et al., 2017). This transition is also accompanied by dietary changes comprising greater consumption of processed foods (that often have high fat and/or sugar content), poor dietary diversity; a shift to more sedentary lifestyles; and living in an increasingly obesogenic environment. Overweight and obesity rates have seen an increase of between 8 (women) and 10 (men) percentage points over a decade since 2005-06; by 2015-16, 15 percent of rural women and 31 percent of urban women were overweight or obese (NFHS, 2016) (Annexure Figure A1, Panel A).

One factor that has perhaps not yet received much attention in this transition is the role of increased intake of edible oils. This paper attempts to address the extent to which fiscal measures can be effective, by examining the impact of a subsidy on palm oil on consumption of edible oils. The subsidy is provided through the public distribution system (PDS) in three states in India.

But first, some context. In the early 1980s, consumption (calculated as net availability) of edible oils in India (Annexure Figure A1, Panel B) was about 5 kilograms per capita per year, considered inadequate. This remained roughly constant throughout the 1980s, with imports (allowed only by the government) accounting for about one-third of domestic consumption. In April 1994, there was a major policy change that relaxed the state monopoly, and palm oil imports were permitted under an open general license but subject to import duty. Subsequently, other edible oils were also added to the list of permitted imports. After this decanalisation, domestic consumption increased steadily over the next two decades, driven entirely by imports.

By 2010, imports accounted for half of domestic consumption, of which the single largest contributor was palm oil.

As a consequence, fat intakes increased. Data from household surveys indicate that between 1993-94 and 2011-12, consumption of fats increased from 31 to 42 (rural), and 42 to 53 (urban) grams per capita per day (Annexure Figure A1, Panel C). Some states saw more rapid increases than others (especially those that started at a lower base): for example, over this period, fat intake per capita per day in rural Tamil Nadu went up from 25 to 39 grams, and from 27 to 43 grams in rural Andhra Pradesh, increasing by over 50 percent (NSS, 2014). Expressed in terms of calories (the metric used in the rest of the paper), and assuming 9 calories per gram of fat, fats accounted for 17 (rural) and 21 (urban) percent of overall caloric intakes in 2011-12.

Taken at face value, these averages are not large in magnitude, and lie within the recommended dietary guidelines. The Indian Council of Medical Research (ICMR) prescribes that fats account for 15 to 35 percent of overall calories. As noted later, the average intakes likely underestimate overall fat consumption, because processed foods are not captured well by household surveys. Nevertheless, the concern among the nutrition community traditionally has been on inadequate consumption of fats. As Mani & Kurpad, 2016 note, the recommended dietary allowances put out by the ICMR in 1990 and even in 2010 "cautioned that in large parts of India, the major thrust ought to be to increase fat intakes since the major issue at hand was of low intakes of total fat…". The rapidity with which India is undergoing the nutrition transition suggests that there is need for a more nuanced focus.

Fats are comprised of the so-called visible sources (vegetable oils and fats used as cooking media) and invisible sources (that include the fat content of snacks and other processed foods for example). The focus of this paper is on the visible fats. Back-of-the-envelope calculations (combining consumption figures from household surveys and net availability data) suggest that nearly 60 percent of domestic consumption in 2011-12 was in the form of visible fats, with the rest accounted for by invisible fats.

There is global evidence linking the consumption of fat-dense foods and incidence of overweight, obesity and associated co-morbidities (Malik et al., 2013) with attendant implications for public health. For this reason, several countries have attempted to tax unhealthy foods to discourage their consumption and better align prices of such foods with their social costs (Powell & Chaloupka, 2009).

The degree to which such taxes are effective depends on price elasticities, availability of substitutes, and, when levied on manufacturers, the degree to which the tax is passed through to consumers. Critics of such Pigouvian taxes see them as a restriction of personal choice and inappropriate for people who are not at risk of developing obesity. They are often regressive in nature and borne disproportionately by the poor who may spend a larger proportion of their income on such foods than do the rich (Craven et al., 2012). The empirical evidence suggests that such taxes are effective in reducing consumption when the taxes are nutrient specific (for example, are on saturated and trans-fats rather than on a specific commodity),[1] and the resulting change in price exceeds a threshold (Harding & Lovenheim, 2017; Mytton et al., 2012).

Many countries also earmark these tax revenues for health investments. Hagenaars et al., 2017 and Allcott et al., 2019 provide reviews of this literature.

In India, few such taxes[2] have been implemented. Kerala was the first state to impose a 14.5 percent tax on select foods sold by fast food chain outlets in 2016. There are other regulations as well: in 2015, the High Court of Delhi curbed the sale of foods high in fat, salt or sugar within a 50-metre radius of schools. The Food Safety and Standards Authority of India has proposed similar legislation nationwide.[3] Sugary drinks fall in the highest bracket of taxes under the Goods and Services Tax system introduced in 2017. Newspapers often report that some states (such as Gujarat) are contemplating the introduction of fat taxes to help stem the rise in overweight and obesity. It is perhaps no coincidence that these are also the states that have an incidence of overweight/obese adults that is far higher than the national average.

While most of these taxes pertain to the so-called junk foods, there is discussion of extending these to edible oils as well (Basu et al., 2013). As noted earlier, India relies on imports for much of its edible oil needs, the lion's share of which is in the form of palm oil. Basu et al., 2013 predict that a 20 percent tax on palm oil (high in relatively unhealthy saturated and trans-fats) purchases would be expected to avert approximately 363,000 deaths from myocardial infarctions and strokes over the period 2014-23 in India, provided consumers do not substitute other unhealthy oils for reduced palm oil consumption.

Instead of a tax, some Indian states have provided for a subsidy on edible oils. In the late 2000s, Tamil Nadu, Andhra Pradesh and Maharashtra began to provide subsidised palm oil as part of their respective public distribution systems. The stated rationale for this was to maintain prices at reasonable levels and to meet adequate demand during peak festive seasons, especially for the poor, who might otherwise be priced out at such times (DFPD, 2008). The policy was implemented in these states at a time when health concerns related to rising fat intakes and overweight/obesity were not as salient in the public discourse. The policy thus makes for a near-natural experiment to assess the extent to which commodity-specific fiscal measures affect consumption.[4]

The objective of this paper, therefore, is to quantify the impact of the palm oil subsidy (or negative tax) on the consumption of palm, groundnut and coconut oils (the other commonly-consumed edible oils), and edible oils as a whole.

None of the states neighbouring Andhra Pradesh, Tamil Nadu and Maharashtra implemented this policy, and the empirical strategy relies on these differences in policy regimes across states to infer impact. In particular, the estimation is based on a matched difference-in-differences (MDID) approach that compares the changes in outcomes in the three states that introduced subsidised palm oil (treated states) relative to those in neighbouring (control) states. It uses the consumption expenditure surveys (CES) conducted by the National Sample Survey Office (NSSO) for the years 2004-05, as the pre-intervention year, and 2009-10, as the post-intervention period. The comparison focuses only on the districts bordering the three states and their respective neighbours, to account for similar agro-ecologies and food habits.

The first set of outcome variables are the energy (calorie) intakes derived from (a) subsidised palm (b) non-subsidised groundnut (c) non-subsidised coconut and (d) aggregate edible oils. The second outcome variable is the share of palm[5] oil in calories sourced from all edible oils. The CES data do not report palm oil purchases separately – what is reported is *vanaspati* or margarine (of which palm oil is the single largest constituent) and an ‘other oils’ category.[6] Henceforth, we refer to this aggregate of *vanaspati* and other oils as palm oil. Also, throughout this paper, the terms consumption and intakes are used synonymously and refer to calories.[7]

The analysis is disaggregated by rural and urban areas, since overall consumption patterns and ease of access to the PDS vary significantly across the two. A formal test of equality of coefficients across rural and urban regions in the benchmark specification is also rejected by the data.

To provide a preview of the results: the PDS subsidy on palm oil led to an increase in its consumption in absolute and relative terms, both in rural and urban areas, with effects being more pronounced in rural areas. The impact magnitude is higher in Tamil Nadu, relative to the other two states. In part, these increases were effected with households displacing groundnut and coconut oils for palm oil. There were also modest impacts on overall edible oils' intake, but these are salient only in the rural areas of Tamil Nadu and Maharashtra. Finally, there is evidence of modest relative increase in expenditures on ghee and butter in rural areas, and in expenditures on processed foods in urban areas.

The rest of the paper is organised as follows. A brief and selected review of the literature is presented in the next section (section 2). Section 3 details the policy intervention; this is followed by a discussion of data and summary statistics (section 4). The empirical framework is set out in section 5. Results are presented in section 6 followed by discussion and policy implications in section 7.

2. Review of evidence on food subsidies and nutrition

The literature thus far has typically documented nutrition/food intake impacts of the PDS as a whole, and not on commodity-specific PDS interventions (see below for an exception). It has focused either on the policy reform that led to the implementation in 1997 of a switch from a universal PDS to a targeted PDS; or on some of the recent reform initiatives undertaken by different state governments in improving PDS functioning to identify impacts. Nearly all of these studies (unless noted otherwise) rely on the CES of the NSSO, as does the present paper.

In an early paper, Kochar (2005) combines cross-sectional variation in market prices with variation in programme rules (that consequently generate 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 of a small magnitude.

Following from Kochar's (2005) analysis, Kaushal & Muchomba (2015) evaluate the relationship between the size of the PDS cereal subsidy. They distinguish between states where the consumption of wheat and rice is higher than the ration entitlement (income effects should predominate) from those where it is less (substitution effects should matter). They find no effect of an enhanced PDS subsidy on overall calories and protein in either set of states, but do find evidence of substitution within specific foods. In addition, the subsidy translated into a marginal but significant increase in fat intakes in the second set of states.

Based on CES 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 foodgrains during 2002-08 in eight states. She finds that the elasticities for cereal consumption and calories with respect to the value of the subsidy are small. However, the PDS subsidy generated an income effect for beneficiary households and was effective in improving nutrition across several food groups, including lentils, fruits and vegetables, and meat products.

Rahman (2016) examines a policy shift from a targeted PDS back to universal access in the eight famine-prone districts (in the Koraput-Bolangir-Kalahandi region) of Odisha in 2008.

He exploits variation in the levels of implicit income transfer across the two regions—one with a targeted scheme and another with a universal PDS entitlement—and their differential change over time. Restricting his attention to rural areas, he finds that famine-prone districts where the PDS was universalised saw increases in both energy intakes and diet quality.

Shrinivas et al. (2018) evaluate the impact of state-level changes in PDS transfers with the passage of India's National Food Security Act in 2013. Their analysis employs the Village Dynamics in South Asia (VDSA) panel data of 1,300 households and exploits the differential expansion in the PDS entitlements for below poverty line households. Their findings suggest that increases in in-kind staple food transfers crowd-in the consumption of diverse food items, thus improving diet quality.

Krishnamurthy et al. (2017) examine the impact of a range of operational reforms to the PDS that Chhattisgarh undertook between 1999-2000 and 2004-05. These included permission to private dealers to run fair price shops, and a greater reliance on local procurement. They find that the policy reforms did lead to an improvement in caloric intakes and dietary quality, especially for those households that were most likely to be eligible for food subsidies. Their identification strategy relies on comparisons across districts that lie along either side of the state border of Chhattisgarh and its neighbouring states that had not undertaken a similar reform.

Most of the studies reviewed above have considered the impact of the PDS as a whole. It is only more recently that the literature has considered specific components of the PDS and their impact. For example, Chakrabarti et al. (2018) evaluate the impact of a subsidy on pulses in selected Indian states on pulses and protein consumption. Using both the CES and VDSA data, they find that the inclusion of subsidised pulses in the PDS network did not result in substantial increases in overall pulse intakes (the coefficients are significant but small in magnitude).

However, consumption of the subsidised pulses increased, displacing market-sourced pulses. An income effect, however, drove increased consumption of non-pulse sources of protein: for example, the pulse subsidy had a large positive effect on the consumption of fish.

The present paper is similar in approach to the work of Chakrabarti et al. (2018) and that of Krishnamurthy et al. (2017), in its focus on the use of the timing of state-specific policies as a near-natural experiment, and in the use of data from districts on either side of treated and control states to compute impact estimates. In contrast to these papers, however, the estimation strategy in the present analysis explicitly accounts for the repeated cross-sectional nature of the data.

This study also contributes to the literature by examining edible oil subsidies in the PDS and the potential role it may play in influencing overnutrition outcomes; an aspect that has thus far not been examined.

3. Distribution of subsidised edible oils in the PDS

Set up in the mid-1960s, the PDS is a vast network of more than 500,000 fair price shops through which rice, wheat, sugar, kerosene and other commodities are distributed at subsidised prices subject to a maximum (rationed) quantity.[8] The operational responsibility of the PDS, including identification of eligible families, issue of ration cards and ensuring the supply of the requisite quantities of commodities rests with the state governments. State governments can also modify the list of commodities provided through their respective PDS networks.

As indicated in Table 1, in 2007, the state of Tamil Nadu introduced palm oil as part of their PDS, with universal entitlement. Maharashtra first introduced palm oil in its PDS a year later in 2008 for all PDS beneficiaries. Andhra Pradesh also introduced palm oil in its PDS in

2008, but restricted its distribution to households below the poverty line. In 2008, 17 million litres of imported palm oil were allocated to the PDS in Tamil Nadu, and 20 and 23 million litres in Maharashtra and Andhra Pradesh, respectively.[9]

Table 1. The intervention: 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 of Palmolein oil at the issue price of ₹25/- per litre	2007
Andhra Pradesh	1 pouch of imported Palm oil; ₹40/-per litre (910gms) to the BPL families	2008
Maharashtra	1 litre of Palm oil at the issue price of ₹42/- per litre with effect from 1 July, 2008 ₹35/- per litre with effect from 24 October, 2008	2008

Source: Department of Food and Civil Supplies, Government of India and of respective state governments; https://dfpd.gov.in/ 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; Accessed on July 20, 2017.

The intervention provides for a subsidised palm oil packet of approximately one litre to every eligible beneficiary household in each of the treated states. To put this number in perspective: in these states, in 2004-05, 57 percent of households consumed more than one litre of palm oil per month (and 92 percent consumed more than one litre of all edible oils).

The price for the subsidised palm oil ranged from ₹25 per litre in Tamil Nadu in 2007, ₹40 per litre in Andhra Pradesh and between ₹35 and ₹42 per litre in Maharashtra in 2008. One way to examine the extent of price subsidy is to consider changes in relative prices (using unit values): before the intervention, in rural areas, the ratio of unit values of palm oil relative to groundnut oil was nearly unity in these three states, and was marginally lower at 0.93 in the bordering control states. After the intervention, the relative price ratio fell in the treated states by one third, but remained unchanged (0.91) in the control areas. The greatest decline in relative prices was seen in Tamil Nadu, followed by Andhra Pradesh, and Maharashtra. This was largely true in urban areas also, which saw a 20 percent drop in relative prices in treated areas, and a 5 percent drop in control districts.

Given the differences in eligibility criteria and implied magnitude of subsidies across the three states, it is reasonable to expect that outcomes would also vary by state. Another reason to expect heterogeneity in outcomes is that the coverage of the PDS varies as well. The percentage of rural (urban) households that accessed the PDS for purchases[10] varied between 88 (73) percent in Tamil Nadu, 66 (34) percent in Andhra Pradesh and 33 (12) percent in Maharashtra. The expectation therefore is that the impact, if any, would be greatest in Tamil Nadu (with high coverage of PDS, universal entitlement to palm oil and sharpest drop in relative prices). Ranking the other two states *a priori* is not as straightforward, for while Andhra Pradesh had higher PDS coverage than Maharashtra, access to subsidised oil was restricted to below poverty line households in Andhra Pradesh, but was universal in Maharashtra. As it turns out, impacts were higher in Maharashtra.

4. Data and summary statistics

The analysis relies on the nationally-representative CES rounds conducted in 2004-05 (61st round) and 2009-10 (66th round) by the NSSO. The estimation sample consists of nearly 20,000 households in 47 treated districts and 50 control districts. For each household, data is reported on the quantity of food items consumed (in kilograms/litres/numbers) over a recall period of 30 days; food composition tables provided by the ICMR's National Institute of Nutrition are used to convert the quantity of edible oils into their equivalent caloric values.[11]

The delineation of treated and bordering control districts that forms the basis of the estimation is set out in Annexure Figure A2.[12]

Table 2 presents the descriptive statistics for the outcome variables. In rural areas, in 2004-05, daily edible oil consumption in treated districts was higher than in control regions by about 80 Kcal per household per day (henceforth cphpd). By 2009-10, calories derived from edible oils increased in both treated and control districts, but the differential between the two groups remained almost the same. There was no statistically significant difference in average intakes of palm oil across treated and control districts before the introduction of the policy intervention. But by 2009-10, average consumption of palm oil in treated households was 183 cphpd more than that in control households. A similar pattern obtains for the proportion of calories sourced from palm oil in overall edible oils: after intervention, treated districts sourced 17 percentage points more calories from palm oil than their control counterparts. 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. Coconut oil consumption was lower by nearly 100 cphpd in treated households in 2004-05, and fell further to a difference of 148 cphpd in 2009-10.

These patterns remain largely similar for urban areas. The treated districts had significantly higher palm oil consumption both in terms of caloric 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 in overall intakes of edible oils.

Table 2: Descriptive statistics by treatment status and CES round

	Round 61 (2004-05)			Round 66 (2009-10)		
Rural	Treated	Control	Difference	Treated	Control	Difference
Intake of palm oil (cphpd)	438 (45.93)	390 (39.98)	48 (60.56)	652 (52.48)	469 (58.72)	183** (78.33)
Share of palm oil in overall edible oils (%)	60 (5.39)	62 (4.70)	-1.32 (7.11)	76 (4.54)	59 (6.20)	16.85** (7.64)
Intake of groundnut oil (cphpd)	264 (34.03)	123 (27.07)	141*** (43.25)	180 (34.41)	111 (29.08)	69 (44.81)
Intake of coconut oil (cphpd)	3 (0.94)	101 (30.91)	-98*** (30.77)	4 (1.38)	152 (44.34)	-148*** (44.13)
Intake of edible oils (cphpd)	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
Urban	Treated	Control	Difference	Treated	Control	Difference
Intake of palm oil (cphpd)	500 (55.49)	442 (45.90)	58 (71.63)	652 (50.34)	523 (59.02)	130* (77.17)
Share of palm oil in overall edible oils (%)	60 (6.03)	51 (3.13)	9.46 (6.75)	75 (5.02)	59 (6.59)	16.01* (8.24)
Intake of groundnut oil (cphpd)	325 (59.59)	296 (65.88)	29 (88.37)	188 (37.84)	209 (57.13)	-21 (68.17)
Intake of coconut oil (cphpd)	5 (1.05)	82 (39.29)	-78** (39.10)	7 (1.82)	97 (50.49)	-91* (50.26)
Intake of edible oils (cphpd)	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. Cphpd refers to Kilocalories per household per day.

By design, only PDS users had access to the subsidised palm oil. As seen in Annexure Table A1, in 2004-05, rural PDS participation rates in the control districts (46 percent) were substantially lower than in the treated districts (59 percent). Five years later, these had increased by about 20 percentage points in both the treated and control groups. Thus, differential changes in PDS access are not likely to influence impact estimates.

Annexure Table A1 also presents similar comparisons for various socio-economic characteristics. In rural areas, and in the pre-intervention year, treated households had smaller household sizes, a higher representation of other backward castes, and relatively more education. There were no other significant differences. The impact regressions detailed below include these characteristics as control variables. Annexure Table A1 also indicates that these averages did not vary much across time either.

5. Empirical strategy

The paper exploits the state-specificity and timing of the subsidised oil intervention, and examines the changes in outcome variables over time (with 2004-05 as baseline and 2009-10 as endline) across the three treated states and neighbouring states that did not implement this intervention. As noted in an earlier section, the estimation sample is restricted to districts that lie along the borders of the treated and neighbouring states so that the comparisons are across similar agro-ecologies and food cultures.

5.1 DID specification:

The benchmark specification consists of a DID regression:

$$Y_{idt} = \beta PDS_{idt} + \tau_{DID}\,(PDS_{idt}*Post_{idt}) + \gamma Post_{idt} + \lambda X_{idt} + \mu_d + \varepsilon_{idt} \qquad (1)$$

where Y_{idt} is the outcome for household i in district d at time t[13]; PDS_{idt} denotes whether the household resides in a district that provided subsidised PDS oil, and $Post_{idt}$ is a time dummy that takes a value 1 for 2009-10 (post-intervention) and 0 for 2004-05 (pre-intervention). X_{idt} include controls for household-level variables that can affect the outcome.[14] District fixed effects μ_d help account for any time-invariant heterogeneity in cultural norms, food practices and governance factors.

The coefficient (τ_{DID}) is the estimator of impact. The identifying assumption is that of parallel trends: absent the intervention of providing subsidised oils, consumption of all types of edible oil would have evolved in the same way across the treatment and control districts.[15] One way to test for parallel trends involves estimating equation (1) for 1999-2000 (55th round) and 2004-05, and confirming that the estimated τ_{DID} is insignificant. Results reported later support this assumption for most outcomes. While this is not conclusive evidence that parallel trends would persist into the period under study, a search of the literature and newspaper reports suggests that there were no other interventions that could have differentially affected edible oil consumption across these treated and control districts.

Also reported are 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 suggested by Young (2019), the RI is implemented for a subset of 2,000 random assignments.

5.2. Matched DID specification

Another way to address the differences in outcomes in the baseline is to use matching techniques, under the maintained assumption that selection is on observables: in other words, conditional on household characteristics, the treatment can be deemed "as if randomly assigned"; provided there is common support. While matching exercises are typically conducted in a first difference context, matching methods can be combined with DID to estimate impact.

The CES data sets that form the basis of this analysis constitute a repeated cross-section. For such repeated cross-sections, Blundell & Costa Dias (2009) propose a matched DID estimator (MDID-RCS).[16] The procedure involves matching treatment (post) group with the treated (pre) and control (pre and post) households. The three sets of weights corresponding to the matches are then used to estimate the impact using DID. The identification in this case arises from differences (over time) in the unobserved component of potential outcomes being independent of treatment status after conditioning on observables. The additional requirement is that of a common support.

The modified common support condition implies that all the treated households have a counterpart in the non-treated sample before and after the intervention, as well as treated households before the intervention. This helps ensure that the double differencing is undertaken only on comparable groups, and has the advantage of accounting for any compositional changes that may have occurred over time.

The estimator is given as:

$$\hat{\tau}^{\mathrm{MDID-RCS}} = \sum_{i \epsilon P_{t1}} \{[Y_{it1} - \sum_{j \epsilon P_{t0}} \widetilde{w}_{ijt0}^{P} Y_{it0}] - [\sum_{j \epsilon C_{t1}} \widetilde{w}_{ijt1}^{C} Y_{jt1} - \sum_{j \epsilon C_{t0}} \widetilde{w}_{ijt0}^{C} Y_{jt0}]\} w_i \quad (2)$$

where (P_{t1}, P_{t0}) are households in treatment (with subsidised palm oil in PDS) districts in periods 2009-10 (t1, post) and 2004-05 (t0, pre), respectively, and (C_{t1}, C_{t0}) are the corresponding households in control districts. The subscripts (i, j) reference the household, and $\widetilde{w}_{ijt}^{G}$ represent the weights attributed to household j in district G (where G = C or P) in time t1 or t0.

6. Results

6.1. Impact estimates: DID

Column 1 of Table 3 reports the basic DID estimates (with no covariates), column 2 adds household-level control variables and district fixed effects, and column 3 additionally considers sampling weights. For the most part, estimates are relatively unchanged across the three specifications.

In rural areas, the introduction of palm oil subsidy led to an increase in its intake by 146-154 cphpd, on an average, relative to the neighbouring control states. This translated into a nearly 20-percentage point differential increase in an average rural household's share of edible oil calories sourced from palm oil. This increase came at the expense of coconut and groundnut oils, with significant and negative impact estimates. These offsetting magnitudes left overall edible oils' consumption unchanged. The p-values from the RI tests suggest that these significant impacts are unlikely to have been observed merely as a matter of chance.

In urban areas, there is no significant impact on the consumption of palm oil, although the signs are, as expected, positive. The share of palm oil in overall edible oils, however, increased by a statistically significant 10 percentage points more in states with subsidised palm oil than in those without.

The caveat in interpreting these results is that for two outcome variables (overall edible oil consumption in rural and coconut oil in both rural and urban) parallel trends do not hold.

Table 3: DID estimates of impact on intakes of various edible oils, 2004-05 (pre-intervention) and 2009-10 (post-intervention)

	Intake of palm oil (cphpd)			Daily household calorie share from palm oil in overall edible oils (%)			Intake of groundnut oil (cphpd)			Intake of coconut oil (cphpd)			Intake of edible oils (cphpd)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Rural															
Impact	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)
P value (RI)	0.17	0.10	0.14	0.02	0.01	0.03	0.03	0.01	0.001	0.15	0.07	0.11	0.88	0.83	0.92
Parallel trends met		Yes			Yes			Yes			No			No	
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
Urban															
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Impact	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)
P value (RI)	0.37	0.30	0.28	0.13	0.11	0.18	0.13	0.18	0.31	0.26	0.09	0.18	0.95	0.68	0.76
Parallel trends met		Yes			Yes			Yes			No			Yes	
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
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

Robust standard errors, clustered at the district level, in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 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. Cphpd refers to Kilocalories per household per day.

6.2. Impact estimates: Matched DID-RCS

The preferred set of estimation results pertain to the MDID-RCS, and are presented in Table 4.

The magnitudes are similar to the DID estimates. In rural areas the matched DID estimates for palm oil range from 159 to 168 cphpd, which corresponds to 36-38 percent of average baseline consumption of palm oil. It also translates into a differential increase of nearly 20 percentage points in the share of edible oil calories sourced from palm oil. At the same time, there were statistically significant decreases in the consumption of groundnut oil of approximately 90 cphpd, and of coconut oil (approximately 65 cphpd) in treated relative to control households. This substitution meant that overall caloric intakes from edible oils did not change.

The urban MDID-RCS results are broadly the same as in rural areas, and indicate an increased intake of palm oil—both in absolute terms and as a share of all edible oils—at the expense of groundnut and coconut oils. The magnitudes, however, are only half of those seen in rural areas: caloric intake from palm oil increased by 83-86 cphpd. The caloric share of edible oils derived from palm oil increased by 10-11 percentage points more in treated districts than in control areas. As was the case in rural areas, this increase was effected largely by a differential substitution away from groundnut (66-69 cphpd) and coconut (30-32 cphpd) oils, leaving overall edible oils' intake unchanged.

Table 4: MDID-RCS estimates of impact on intakes of various edible oils, 2004-05 (pre-intervention) and 2009-10 (post-intervention)

	Intake of palm oil (cphpd)		Daily household calorie share from palm oil in overall edible oils (%)		Intake of groundnut oil (cphpd)		Intake of coconut oil (cphpd)		Intake of edible oils (cphpd)	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Rural										
Impact	159***	168***	19.44***	20.38***	-87***	-90***	-62***	-65***	1.23	4.45
	(11.39)	(11.32)	(0.97)	(0.83)	(8.44)	(8.88)	(4.32)	(4.85)	(8.08)	(8.88)
Observations	25893	25895	25845	25847	25893	25895	25893	25895	25893	25895
Urban										
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Impact	83***	86***	10.49***	11.00***	-66***	-69***	-30***	-32***	-5.12	-5.71
	(13.81)	(12.76)	(1.12)	(1.23)	(12.37)	(14.00)	(4.22)	(4.47)	(9.97)	(11.40)
Observations	18829	18830	18781	18780	18829	18830	18829	18830	18829	18830
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*** $p<0.01$; ** $p<0.05$; * $p<0.1$. Bootstrapped standard errors in parentheses using 50 replications. Covariates for PS matching with kernel weights include 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. Cphpd refers to Kilocalories per household per day.

Annexure Figure A3 provides graphs of common support, which indicate a large area of overlap.

6.3. Impact heterogeneity by state

To what extent do impact magnitudes vary across states, given the heterogeneity in the implementation of intervention and access to PDS? Table 5 presents MDID-RCS estimates disaggregated for each of the three treated states (and their corresponding control districts). As one might expect, the magnitudes are the highest in Tamil Nadu. Rural households in this state saw caloric intakes from palm oil increase by more than 200 cphpd, and the share in overall edible oils increase by over one-third (relative to increases in neighbouring control households). The increased reliance on palm oil consumption was accompanied by a relative (to control areas) reduction in consumption of groundnut (approximately 100 cphpd) and coconut (approximately 75 cphpd) oils. This translated into a net increase of 40 cphpd in overall edible oil consumption (or 8 percent of baseline levels), unlike the insignificant magnitudes seen when all three states were taken together. In contrast, in rural Andhra Pradesh, there was no significant impact on palm oil intakes, but its share in overall edible oil consumption increased by about 12 percentage points more than in neighbouring districts. This was driven by a relative decline in groundnut oil consumption in Andhra Pradesh; this in turn translated into an unexpected negative impact on the overall consumption of edible oils. As was the case with Tamil Nadu, however, rural Maharashtra also witnessed increased intakes of palm oil and decreased consumption of groundnut oil relative to its neighbours, with a positive impact on overall edible oils. The impact magnitudes for palm oil, however, are smaller—approximately 60 percent of that seen in Tamil Nadu.

In urban areas, the results are weaker. Only Tamil Nadu saw a positive impact on palm oil consumption at the expense of the substitute oils (the magnitudes are half those seen in rural areas), leaving overall edible oil consumption unchanged. All of the impact estimates for Maharashtra (barring caloric intakes from coconut oil) are insignificant (both statistically and economically). The pattern for urban Andhra Pradesh households is the same as that seen in rural areas, with no impact on calories derived from palm oil, but a positive impact on its caloric share in overall edible oils, driven largely by differential trends in groundnut oil consumption.

Thus, the aggregate results presented for rural areas in Table 4 are driven in large part by impacts seen in Tamil Nadu and Maharashtra: there was a switch away from groundnut and coconut oils towards palm oil, which also resulted in overall increases in edible oil intakes. That the magnitude of impact estimates are the higher in Tamil Nadu is not surprising, given the wider reach of the PDS in general, the magnitude of its subsidy, and its universal entitlement.

Table 5: MDID-RCS estimates of impact on intakes of various edible oils, 2004-05 (pre-intervention) and 2009-10 (post-intervention), by state

	Intake of palm oil (cphpd)		**Daily household calorie share from palm oil in overall edible oils (%)**		**Intake of groundnut oil (cphpd)**		**Intake of coconut oil (cphpd)**		**Intake of edible oils (cphpd)**	
Rural										
Tamil Nadu										
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Impact	218^{***}	225^{***}	35.63^{***}	36.59^{***}	-103^{***}	-105^{***}	-75^{***}	-81^{***}	40^{***}	39^{***}
	(13.24)	(11.76)	(1.69)	(2.10)	(12.90)	(10.16)	(8.03)	(8.55)	(14.83)	(14.26)
Observations	8055	8031	8034	8012	8055	8031	8055	8031	8055	8031
Andhra Pradesh										
Impact	8.89	11.60	12.38^{***}	12.68^{***}	-95^{***}	-102^{***}	-3.83	-3.18	-130^{***}	-132^{***}
	(22.36)	(25.25)	(2.06)	(2.26)	(12.22)	(17.21)	(2.67)	(2.28)	(16.16)	(21.72)
Observations	8626	8629	8601	8602	8626	8629	8626	8629	8626	8629
Maharashtra										
Impact	131^{***}	137^{***}	4.22^{***}	4.49^{***}	-47^{**}	-50^{***}	-7^{**}	-7^{**}	74^{***}	77^{***}
	(24.53)	(21.31)	(1.57)	(1.60)	(18.64)	(19.49)	(3.09)	(3.51)	(19.51)	(19.57)
Observations	9923	9911	9920	9908	9923	9911	9923	9911	9923	9911
Urban										
Tamil Nadu										
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Impact	114^{***}	125^{***}	18.02^{***}	19.27^{***}	-84^{***}	-84^{***}	-20^{**}	-31^{***}	9	9
	(13.41)	(18.22)	(1.77)	(1.74)	(12.35)	(9.62)	(9.50)	(8.21)	(14.08)	(13.28)
Observations	7401	7416	7388	7402	7401	7416	7401	7416	7401	7416
Andhra Pradesh										
Impact	4.07	12.14	6.14^{**}	6.63^{**}	-73^{***}	-78^{***}	-3.24	-2.98	-84^{***}	-82^{***}
	(32.85)	(27.87)	(2.69)	(2.66)	(23.63)	(25.55)	(2.69)	(2.63)	(22.59)	(20.04)
Observations	4514	4503	4488	4477	4514	4503	4514	4503	4514	4503
Maharashtra										
Impact	-19	-24	-1.57	-1.76	34	32	-7^{**}	-7^{***}	37	27
	(32.79)	(27.07)	(1.84)	(2.08)	(24.13)	(24.16)	(2.85)	(2.50)	(22.66)	(20.74)
Observations	7262	7276	7252	7267	7262	7276	7262	7276	7262	7276
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*** p<0.01; ** p<0.05; * p<0.1. Bootstrapped standard errors in parentheses using 50 replications. Covariates for PS matching with kernel weights include 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. Cphpd refers to Kilocalories per household per day.

What may explain the contrary-to-expectation results in Andhra Pradesh? One reason could be that the entitlement to the subsidised palm oil was only available for below poverty line households. Restricting the estimation sample to the poorest tercile (ranked by total household expenditure)[17] suggests that this is certainly part of the explanation. Annexure Table A2 shows that the poorest tercile in rural areas did switch towards palm oil away from groundnut oil, but there was no impact on overall edible oils.

6.4. Impact on other outcomes

The evidence above suggests that in rural areas, the policy of providing subsidised palm oil led to a clear substitution away from groundnut and coconut oils, with modest effects on aggregate edible oil intakes (apparent only when states are examined individually). Might the subsidy have instead led to changes in intakes of preferred but more expensive and infrequently consumed butter and ghee? Or on intakes of invisible fats, as captured by expenditure on processed foods?

As indicated in Table 6, for calories derived from ghee and butter, the impact magnitudes, while positive, are not significant. However, the magnitudes for expenditures on ghee and butter are significant, with greater (relative) increases seen in urban areas as compared to rural areas. Purchases of processed foods were positively impacted in urban areas, but not in rural areas (the rural coefficient is positive but insignificant). As a caveat, note that it is well documented that the CES does not adequately capture expenditures on processed foods, and foods consumed outside the home, so the impact on expenditures on processed foods presented in Table 6 likely represent an underestimate. Relying on household panel data for urban India, Law et al. (2019) document large increases in purchases of salty snacks, sweet snacks (and also of vegetable oils) between 2013 and 2017.

Table 6: MDID-RCS estimates of impact on other outcomes 2004-05 (pre-intervention) and 2009-10 (post-intervention)

	Intake of ghee and butter (cphpd)		Expenditure on ghee and butter (₹/hh/day)		Expenditure on processed food (₹/hh/day)	
	(1)	(2)	(1)	(2)	(1)	(2)
Rural						
Impact	0.089	0.043	0.044**	0.04**	0.004	0.016
	(0.30)	(0.22)	(0.02)	(0.02)	(0.06)	(0.05)
Observations	25893	25895	25893	25895	25893	25895
Urban						
Impact	0.464	0.476	0.127***	0.126***	0.191**	0.222**
	(0.72)	(0.74)	(0.04)	(0.04)	(0.09)	(0.11)
Observations	18829	18830	18829	18830	18829	18830
Sampling weights	No	Yes	No	Yes	No	Yes

*** p<0.01; ** p<0.05; * p<0.1. Bootstrapped standard errors in parentheses using 50 replications. Covariates for PS matching with kernel weights include 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. Cphpd refers to Kilocalories per household per day.

6.5. Robustness checks

By 2011-12, Maharashtra had withdrawn the subsidy on PDS oil, but another state, Goa introduced it in its PDS. Since another round of the CES is available for 2011-12, as a robustness check, the impact analysis was undertaken using this 2011-12 data as the post-intervention period, with the treatment group now including Tamil Nadu, Goa and Andhra Pradesh, and the neighbouring (control) districts redefined accordingly.

As indicated in Table 7, all the results for rural India go through. Palm oil consumption increased by 181-191 cphpd relative to control districts. Groundnut and coconut oils' consumption decreased by approximately 120 and 72 cphpd respectively, leaving overall edible oil intake changes unaffected. These are comparable in magnitude to those presented in Table 4. In urban areas as well, the increase in palm oil consumption is significant, and, as before, by a lower magnitude than in rural areas. The only difference lies in the perverse impact on urban aggregate edible oil intakes.

Table 7: MDID-RCS estimates of impact on intakes of various edible oils, 2004-05 (pre-intervention) and 2011-12 (post-intervention)

	Intake of palm oil (cphpd)		Daily household calorie share from palm oil in overall edible oils (%)		Intake of groundnut oil (cphpd)		Intake of coconut oil (cphpd)		Intake of edible oils (cphpd)	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Rural										
Impact	181***	191***	28.16***	28.92***	-117***	-120***	-71***	-72***	-9	-4.47
	(13.11)	(13.34)	(1.27)	(1.18)	(7.86)	(10.50)	(7.58)	(6.65)	(10.74)	(11.92)
Observations	16430	16434	16390	16394	16430	16434	16430	16434	16430	16434
Urban										
Impact	84***	85***	13.98***	14.65***	-104***	-103***	-28***	-33***	-43***	-45***
	(13.65)	(14.27)	(1.26)	(1.38)	(10.23)	(11.01)	(6.58)	(5.42)	(12.73)	(13.36)
Observations	12204	12191	12161	12150	12204	12191	12204	12191	12204	12191
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*** p<0.01; ** p<0.05; * p<0.1. Bootstrapped standard errors in parentheses using 50 replications. Covariates for PS matching with kernel weights include 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 Cphpd refers to Kilocalories per household per day.

As a falsification check, impact estimates were recomputed using different sets of treatment and control households.[18] The results are as expected, and are available on request.

Thus, these results are robust across various specifications, and rest on the maintained assumption of no differential trends in unobservable confounds across the treatment and control states, conditional on household characteristics. Further, given the implementation of the PDS, it is unlikely that households could cross state borders to take advantage of the subsidy. While this does not rule out the possibility of cross-border resale, that the impact estimates are nevertheless significant suggests either that the transaction costs associated with such a resale are high, or that as a consequence the impact estimates are attenuated at worst.

7. Summary, discussion and implications

This paper attempted to analyse the implications of a negative tax policy—of providing subsidised palm oil—on intake of edible oils. The results indicate that the policy led to an increase in the consumption of palm oil by a substantial magnitude. In rural areas, the increased intakes represent a 38 (23) percentage point increase from baseline consumption levels of palm oil (overall edible oils). There is consistent evidence that the subsidy induced a substitution away from groundnut and coconut oils that are not sourced from the PDS, along with a modest positive net impact on overall edible oil consumption in two states. In addition, consumer spending on ghee and butter increased in rural areas. Consistent with expectations, impact magnitudes are highest in states with universal PDS entitlement and larger subsidy price differentials.

The pattern of impact in urban areas is similar, although the magnitudes are lower than in rural areas (with no effect on overall intakes of edible oil; however, there was a greater increase in the amount spent on processed foods). That the rural impact is higher is not surprising given that incomes are lower, and that the rural magnitude of price difference between PDS palm oil and its competing oils was nearly twice that in urban areas. In a pan-India study, Kumar et al. (2011) find that the poor are far more sensitive to price changes, with a price elasticity of demand of all edible oils of -0.78, while for the richest groups, the magnitude is -0.38. Basu et al. (2013) find that for a 1 percent increase in the price of palm oil there is a 0.67 percent rise in groundnut oil consumption (but not in coconut oil consumption). Furthermore, rural consumers are far more price sensitive: Gaiha et al. (2013) estimate that in 2004, the price elasticity for oil was -0.35 for rural and -0.12 for urban consumers.

The finding of substitutions among various edible oils is consistent with that presented in Kaushal & Muchomba (2015) and in (Chakrabarti et al., 2018). The latter study finds that a subsidy on specific pulses caused consumers to switch from market-sourced to PDS-subsidised pulses, similar to the case here. This is also in line with some of the international literature on taxes on fats (for example Bíró, 2015).

What are the nutritional implications of a switch away from groundnut and coconut oils towards palm oil? Palm oil is high in saturated fats, with a content of 49 grams of saturated fat per 100 grams. In comparison, groundnut oil is lower (17 grams) and coconut oil higher (87 grams) in saturated fats. Therefore, a switch away from groundnut toward palm oil, all else being equal, would be unhealthy. Singh et al. (2014) indicate that among Indians, increased consumption of palm oil has translated into higher intakes of trans-fats, and associated higher prevalence of coronary artery disease. While a more detailed discussion of the nutritional implications of a switch from groundnut to palm oil is beyond the scope of this study, it is important to recognise that India does not yet have a comparative advantage in vegetable oil production, and will need to rely on imports to meet its needs (see also the discussion in Cuevas et al., 2019). Notwithstanding progress in domestic production, palm oil is the cheapest to import and will be hard to substitute at least in the short term. However, soybean oil is emerging as a competitor, the imports of which have increased in recent years. Soybean oil is low in saturated fats (at 16 grams); a more diversified import portfolio is likely healthier.

There is therefore need to refocus the policy discourse not just on the quantity but also on the quality of fat intake. Policies such as fat taxes or subsidies that are designed to influence dietary choices will need to account for the composition of fats, span across commodities to account for possible substitutions, and more generally consider the overall balance between carbohydrates, proteins and fats, underscoring a call to this effect made by Mani & Kurpad (2016).

This analysis shows that fiscal measures can be effective in influencing consumer behaviour, although the impacts of subsidies and taxes need not be symmetric. However, the design of any tax policy will need to be nuanced. The co-existence of overweight/obese and undernourished individuals is a feature of India's nutrition transition, and there is a clear fat intake-income gradient. In 2011-12 (the latest year for which CES data are available), the poorest one-third of rural households consumed less than 2000 kilocalories per capita per day, of which fats accounted for less than the recommended minimum of 15 percent (caveats again on under-reporting of processed foods). In contrast, the richest one-third of households derived one-quarter of calorie intakes from fats (with intakes of >60 grams of fat per capita per day, far higher than recommended amounts). Any policy intervention will need to address both types of needs, and be holistic in its nature.

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ANNEXURE

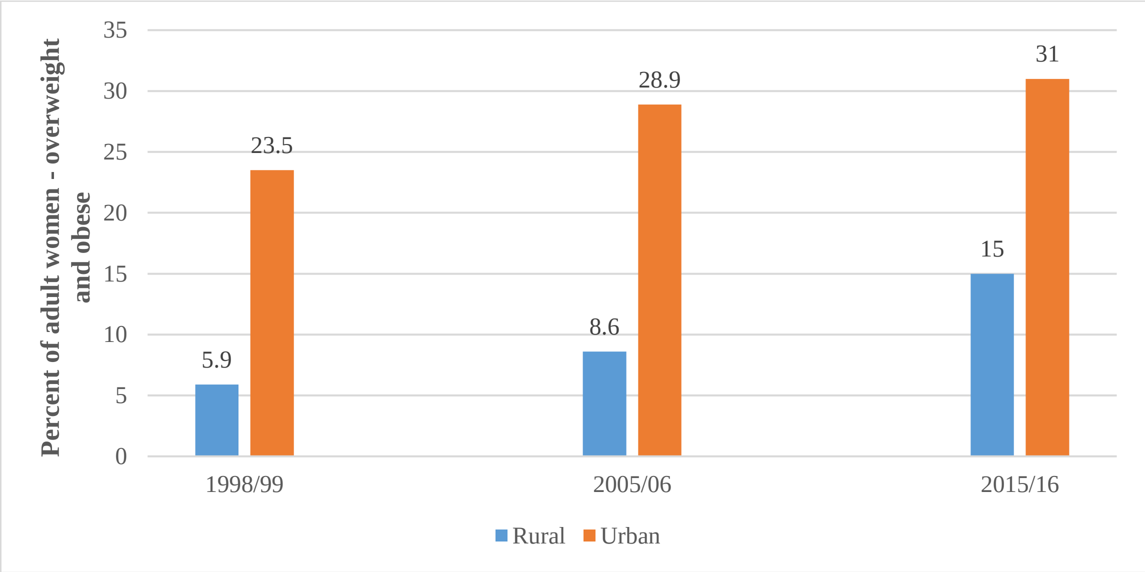

Figure A1 (Panel A): Incidence of overweight and obese women, 1998-99 to 2015-16

Source: National Family Health Survey Reports (1998-99; 2005-06; 2015-16); Ministry of Health and Family Welfare, Government of India

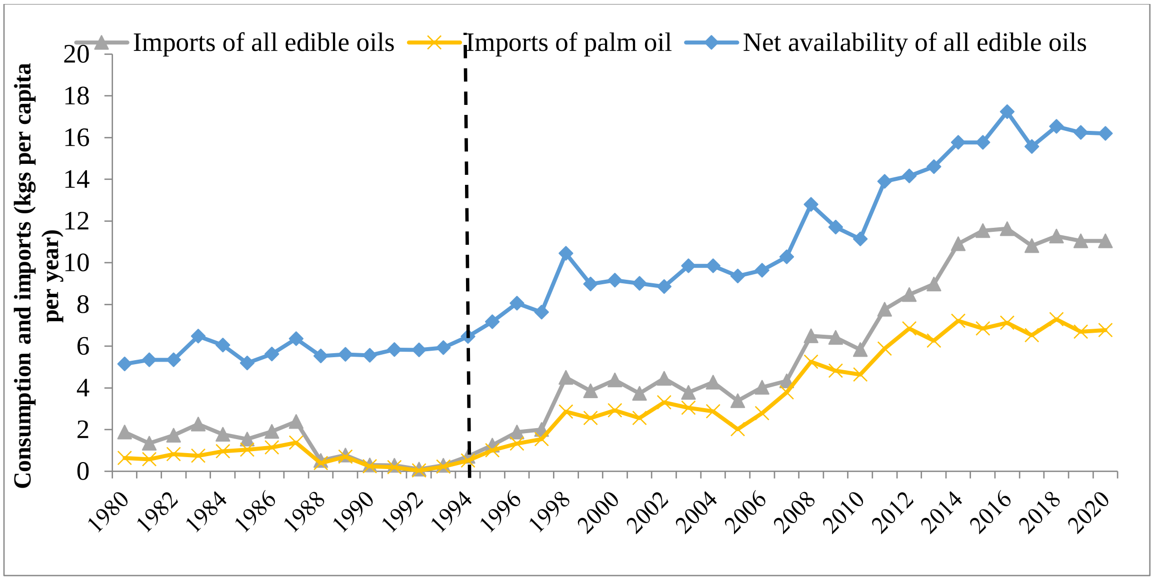

Figure A1 (Panel B): Consumption and imports of edible oils, 1980 to 2020

Source: Production, Supply and Distribution Online Tables, Foreign Agricultural Service, United States Department of Agriculture (USDA); https://apps.fas.usda.gov/psdonline/app/index.html#/app/downloads
Note: Dashed vertical line represents the start of decanalisation of edible oils.

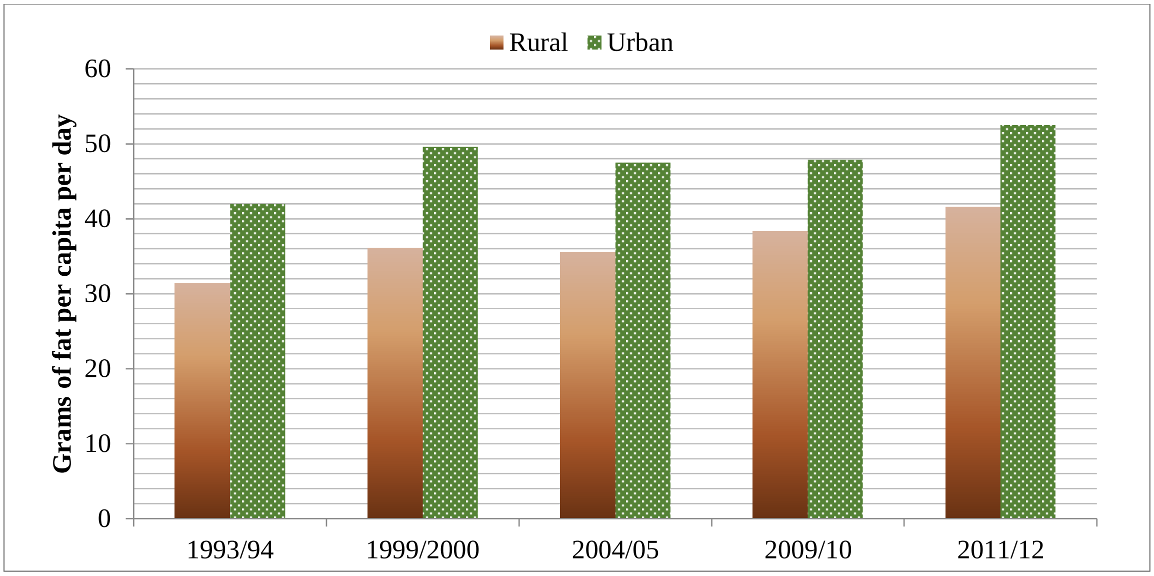

Figure A1 (Panel C): Fat intake, 1993-94 to 2011-12

Source: Nutritional Intake in India, 2011-12 (68th Round); October 2014, National Sample Survey Office, Ministry of Statistics and Programme Implementation, Government of India

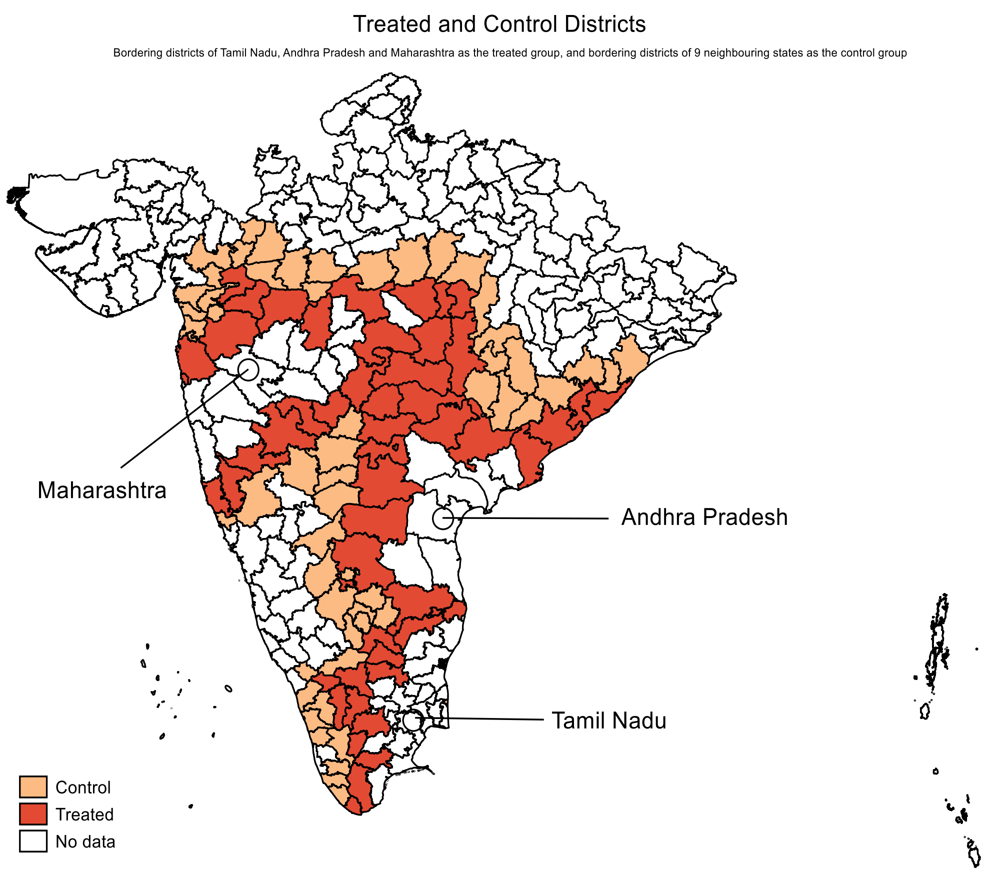

Figure A2: Map of treated and control districts with 2004-05 prevalent district boundaries.

Rural *Urban*

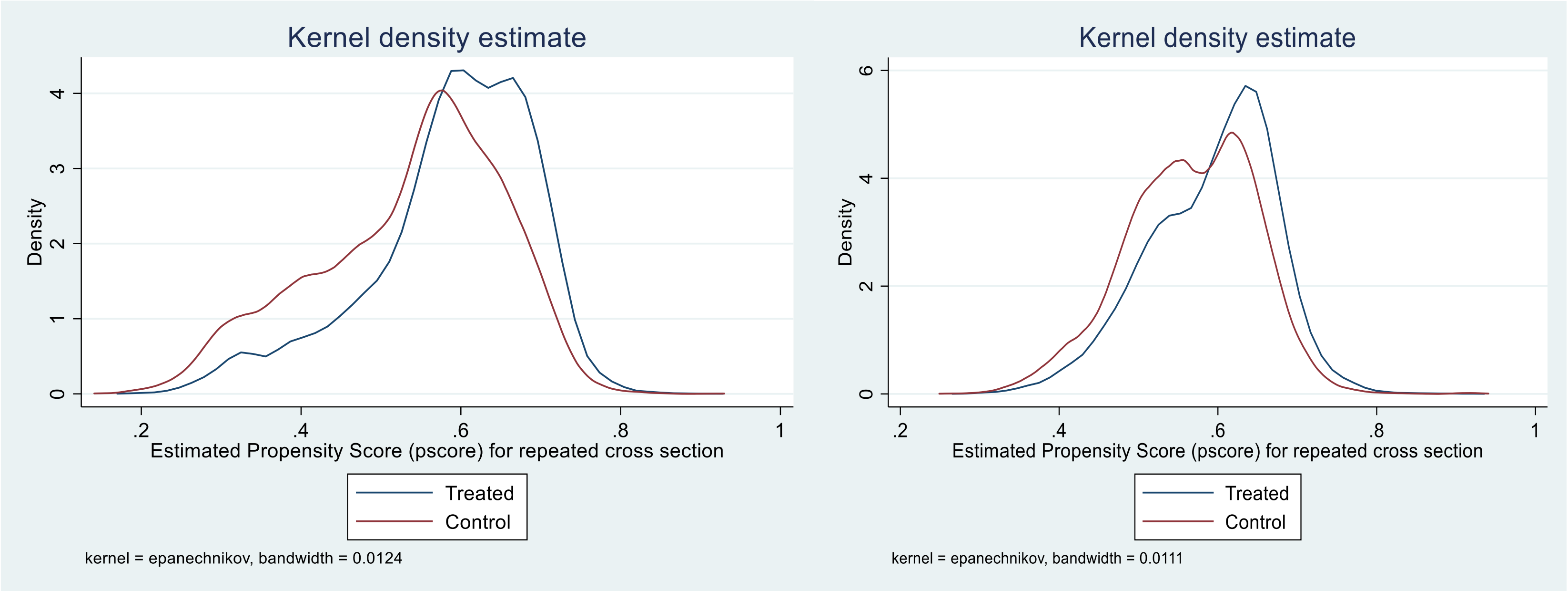

Figure A3: Area of common support for treated and control households

Table A1: Differences in covariates among the treated and control districts

	Pre - Round 61 (2004-05)			Post - Round 66 (2009-10)			Treated districts	Control districts
Rural								
Variable	Treated	Control	Difference (T-C)	Treated	Control	Difference (T-C)	Diff (Post – Pre)	Diff (Post – Pre)
PDS participation rate (percent)	59 (3.47)	46 (2.78)	13*** (4.424)	78 (2.91)	67 (2.54)	11*** (3.844)		
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)	-0.062 (0.062)	-0.004 (0.086)
Social group: 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)	-0.003 (0.013)	-0.028** (0.012)
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)	0.050*** (0.017)	0.046** (0.021)
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)	-0.038*** (0.014)	-0.040** (0.017)
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)	-1.273*** (0.175)	-0.888*** (0.253)
Education level of the household head: 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)	0.035*** (0.012)	0.029** (0.013)
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)	0.006 (0.013)	0.007 (0.013)
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)	0.012 (0.013)	-0.001 (0.012)
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)	0.019*** (0.007)	0.019*** (0.006)
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)	0.01 (0.007)	0.013 (0.009)
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)	0.004 (0.053)	-0.079 (0.093)
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)	-9.571*** (1.544)	-4.957*** (1.911)
Land possessed (in hectares)	0.7 (0.07)	0.81 (0.09)	-0.113 (0.110)	0.67 (0.06)	0.67 (0.08)	-0.005 (0.100)	-0.036 (0.038)	-0.145*** (0.053)
Number of observations	8662	6715	15377	6602	4971	11573	15264	11686

Table A1 Continued: *Urban*								
	Pre - Round 61 (2004-05)			**Post - Round 66 (2009-10)**			**Treated districts**	**Control districts**
Variable	Treated	Control	Difference (T-C)	Treated	Control	Difference (T-C)	Diff (Post – Pre)	Diff (Post – Pre)
PDS participation rate (percent)	36 (6.46)	17 (2.27)	18*** (6.811)	47 (7.84)	23 (5.78)	24*** (9.689)		
Household size	4.09 (0.08)	4.29 (0.10)	-0.207 (0.127)	3.82 (0.12)	3.92 (0.06)	-0.096 (0.131)	-0.266*** (0.086)	-0.377*** (0.088)
Social group: Scheduled Castes	0.16 (0.01)	0.11 (0.01)	0.045*** (0.017)	0.13 (0.01)	0.09 (0.02)	0.033 (0.026)	-0.029* (0.016)	-0.018 (0.019)
Other Backward Classes	0.49 (0.06)	0.34 (0.04)	0.147** (0.070)	0.53 (0.07)	0.4 (0.05)	0.13 (0.082)	0.041 (0.031)	0.058* (0.035)
Others	0.32 (0.06)	0.49 (0.04)	-0.172** (0.069)	0.31 (0.07)	0.46 (0.05)	-0.144* (0.087)	-0.008 (0.026)	-0.037 (0.045)
Relative price ratio of oils to cereals	5.21 (0.15)	4.95 (0.15)	0.26 (0.215)	4.37 (0.28)	3.52 (0.27)	0.855** (0.383)	-0.839*** (0.192)	-1.435*** (0.141)
Education level of the household head: Less than primary	0.06 (0.01)	0.07 (0.01)	-0.005 (0.015)	0.07 (0.01)	0.05 (0.01)	0.015 (0.014)	0.008 (0.009)	-0.012 (0.009)
Primary	0.15 (0.01)	0.12 (0.01)	0.030* (0.017)	0.11 (0.01)	0.1 (0.02)	0.014 (0.021)	-0.044*** (0.010)	-0.028** (0.012)
Middle	0.17 (0.01)	0.19 (0.01)	-0.019 (0.017)	0.16 (0.01)	0.19 (0.01)	-0.025* (0.015)	-0.010 (0.011)	-0.004 (0.013)
Secondary	0.16 (0.01)	0.16 (0.01)	-0.001 (0.014)	0.18 (0.01)	0.17 (0.01)	0.014 (0.016)	0.023** (0.011)	0.008 (0.009)
Higher secondary and above	0.26 (0.02)	0.29 (0.02)	-0.036 (0.028)	0.31 (0.02)	0.38 (0.04)	-0.066 (0.042)	0.053** (0.023)	0.083*** (0.032)
Assets index	-0.07 (0.06)	0.07 (0.11)	-0.134 (0.128)	-0.07 (0.08)	-0.13 (0.12)	0.06 (0.147)	0.000 (0.065)	-0.193** (0.093)
Dependency ratio	47.13 (1.37)	44.31 (2.64)	2.814 (2.962)	39.62 (1.25)	38.64 (2.01)	0.98 (2.355)	-7.506*** (1.491)	-5.673*** (1.903)
Land possessed (in hectares)	0.11 (0.02)	0.15 (0.05)	-0.041 (0.053)	0.13 (0.03)	0.13 (0.02)	-0.007 (0.034)	0.014 (0.022)	-0.020 (0.039)
Number of observations	6369	4485	10854	5406	4032	9438	11775	8517

Significance levels: * < 10% ** < 5% *** < 1%; Standard errors in parentheses; the differences pertain to sample weighted differences in covariates. Reference category for: education level of the household head – Not literate; social group – Scheduled Tribes.

Table A2: MDID-RCS estimates of impact on intakes of various edible oils, 2004-05 (pre-intervention) and 2009-10 (post-intervention), poorest expenditure tercile for Andhra Pradesh and bordering control districts

	Intake of palm oil (cphpd)		Daily household calorie share from palm oil in overall edible oils (%)		Intake of groundnut oil (cphpd)		Intake of coconut oil (cphpd)		Intake of edible oils (cphpd)	
Rural										
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Impact	109*	137**	17.53***	20.73***	-139**	-186***	-8.12	-5.32	-41	-56
	(64.36)	(66.24)	(6.13)	(6.79)	(58.62)	(63.74)	(6.80)	(6.10)	(34.86)	(39.38)
Observations	2548	2556	2538	2545	2548	2556	2548	2556	2548	2556
Urban										
Impact	51	52	12.85***	11.15**	-143**	-140***	-0.04	-0.03	-82*	-76*
	(60.40)	(62.73)	(4.57)	(5.46)	(60.12)	(49.38)	(0.06)	(0.03)	(43.08)	(43.53)
Observations	1288	1309	1301	1301	1288	1309	1288	1309	1288	1309
Sampling weights	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*** $p<0.01$; ** $p<0.05$; * $p<0.1$. Bootstrapped standard errors in parentheses using 50 replications. Covariates for PS matching with kernel weights include 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. Cphpd refers to Kilocalories per household per day.

Endnotes

[1] Nutrient-specific taxes cover a broad range of commodities, and are therefore less prone to substitution effects that may be seen in individual foods (a tax on butter may induce shifts to purchase of other sources of fat, for example).

[2] Temptation goods such as tobacco and alcohol have long attracted taxes. However, the empirical literature on such sin taxes on India is limited. One example is John (2008), who suggests that structure of Indian sin taxes was unlikely to significantly discourage consumption. This is because tax rates are highest (33-60 percent) on cigarettes (with rural consumption of less than 1 stick per month), but only 9 percent on bidis, which are consumed by most people (rural consumption of 32 sticks per month).

[3]https://www.foodnavigator-asia.com/Article/2019/11/19/Four-years-in-the-making-Will-FSSAI-s-ban-on-junk-food-activities-near-schools-prevail

[4] While some states also provide subsidised sugar through their public distribution systems, assessing its impact is not feasible because, given the coverage of this policy, construction of a suitable counterfactual is difficult.

[5] We also evaluated the share of calories derived from palm oil 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 oil in overall calories sourced from all edible oils.

[6] In addition to palm oil, the other oils category consists of sunflower oil, sesame oil, soybean oil, rice bran oil and rapeseed oil. The overall edible oils comprise of palm oil (*vanaspati*/margarine and other edible oils), coconut oil, groundnut oil, and mustard oil.

[7] It is possible groundnut and coconut oils also contain some palm oil, as it is blended into these in small quantities. It is not possible to estimate how much of palm oil enters diets in this way; there are specified limits on blending.

[8] The PDS now operates under the National Food Security Act of 2013, but the analysis in the paper predates this.

[9]As reported in Lok Sabha, Starred Question No. 125, Answered on 27.10.2008.

http://164.100.47.194/Loksabha/Questions/QResult15.aspx?qref=67006&lsno=14

[10] Refers to purchase of cereals or sugar, for which data are separately reported.

[11] Estimated intakes of edible oils pertain only to the food items consumed at home. While meals taken outside the home also contain fat, given the present focus on PDS subsidy, they are not taken into account in this analysis.

[12] These neighbouring states and union territories include Chhattisgarh, Dadra and Nagar Haveli, Goa, Gujarat, Karnataka, Kerala, Madhya Pradesh, Odisha and Puducherry.

[13] Districts are defined according to the 2004-05 boundaries.

[14] These include land possessed, an index of asset ownership, dependency ratio (the proportion of children aged 0-14 in overall working population in the household), relative price ratio of edible oils with respect to cereals (which are computed from unit values and are therefore household specific).

[15] Heckman et al. (1997) identify four sets of desirable features that non-experimental methods (such as the DID used in this paper) should ideally attain: (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 (i) is a maintained assumption in the DID formulated as unchanged evolution of differences across treated and control districts; (ii) is accounted for by a matching exercise; (iii) is met since the NSS schedules were the same across all states, and were not modified between the two survey rounds. The focus on border districts goes some way in addressing feature (iv).

[16] MDID-RCS is estimated using the Stata `diff` command (Villa, 2016).

[17] The 2004-05 survey provided information on whether the household possessed a BPL card, but the 2009-10 survey did not. The estimation sample is based on the poorest tercile since in 2004-05, 80 and 70 percent of households in this tercile had a BPL card in 2004-05, in rural and urban areas respectively.

[18] First, 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 Puducherry 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 Puducherry form the control group.