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Abstract

The production and consumption of nutri-cereals (NCs), more commonly known as coarse cereals, offer significant benefits enhancing soil, human, and livestock health, yet their adoption remains limited. This study aims to investigate NC consumption in the backdrop of free grains interventions to the poor through various schemes, particularly, Pradhan Mantri Garib Kalyan Anna Yojana (PMGKAY). Despite various promotions given to the NCs especially millets in recent years (e.g., National Year of Millets, 2018; International Year of Millets, 2023), the NSSO's HCES 2022-23 data shows the decline in the per capita consumption of the NC and an increase of per capita rice and wheat among the rural consumers who have access to PMGKAY. Based on a causal evaluation framework, the treated households are those not availing free rice and wheat while the control are those who avail free grains within the sample of major NC-consuming states and households reporting access to PMGKAY. Propensity score matching technique is used to analyze the impact based on the average treatment effect on the treated and inverse probability weighted regression adjustment is additionally used to account for potential confounding from observed covariates. The results reveal that the households not consuming free grains but had PMGKAY access consumed 12 percent more NCs than the matched control group, clearly indicating NCs are substituted away by access to free grain consumption among all those households that had the habit of NC consumption. The control group though gain marginally in protein intake and a larger gain in calories from rice and wheat but lose out on the micronutrient consumption from NCs, thereby adversely affecting nutritional diversity. These findings underscore the urgent need for a policy shift that integrates NCs into food security programs, thereby promoting both dietary and nutritional diversity and mitigating the adverse effects of over-dependence on refined cereals.

Keywords: *Nutri-cereals; Free grains; Food security*
JEL Codes: *I14, I15, I18*

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INTRODUCTION

While urbanization and declining poverty rates in India have spurred moderate improvements in rural incomes, malnutrition and lifestyle diseases continue to rise, leaving many rural areas nutrition insecure (Popkin et al., 2012; Meenakshi, 2016). Rural economic growth has largely depended on the monocropping of cereals such as rice and wheat or the cultivation of cash crops, which has led to an over-reliance on these staples (Pingali, 2015). The production and consumption of Nutri-Cereals (NC), more commonly known as coarse cereals (CC) offer significant benefits enhancing soil, human, and livestock health yet their adoption remains limited (MSSRF, 2017; Pingali et al., 2019; Makkar et al., 2019). The major NCs include jowar, bajra, ragi, small millets, barley, and maize.

NCs are an integral part of the lives of the poor in Asia and they are rich in protein and micronutrients and have implications on their health and nutrition. Nutrient composition data underscores the importance of NCs: for instance, one kilogram of rice provides 14,910 KJ of energy, 79.4 grams of protein, 74.9 mg of calcium, and 6.5 mg of iron, whereas one kilogram of bajra delivers 14,560 KJ of energy, 109.6 grams of protein, 273.5 mg of calcium, and 64.2 mg of iron (NIN, 2017). This shows the importance of NCs in providing macro as well as micro nutrients. These grains are highly nutritious, gluten-free, and non-acid-forming, possessing unique dietary properties that help prevent a range of post-translational diseases, including diabetes, cancer, cardiovascular disorders, and celiac disease. Moreover, millets contribute to the regulation of blood pressure, blood sugar levels, and thyroid function (Saini et al., 2021). Additionally, these are nutritionally superior to other cereals such as rice and wheat and they include more protein, amino acids and anti-oxidants (Kaur et al., 2014; Devi et al., 2011). Despite these functional benefits, their utilization based on nationally representative survey data, on the one hand shows a decline among the traditional consumers while on the other hand, an increase in consumption among those who understand the health benefits is not adequately captured (Priya et al., 2024).

The significance of these crops becomes particularly evident in contexts where undernutrition, overnutrition, and micronutrient deficiencies coexist which is commonly observed in developing countries such as India (Meenakshi, 2016). Micronutrient deficiencies, a critical burden, arise from inadequate intake or poor absorption of essential vitamins and minerals such as iron, zinc, iodine, and vitamin A, which are vital for proper growth and health (Ritchie and Roser, 2017). The National Family Health Survey – 5 (NFHS) highlights this concern, showing an alarming rise in anaemia prevalence, especially among women and children, underscoring the persistence of micronutrient deficiencies as a public health crisis. Jumrani (2023) notes that such deficiencies are often rooted in dietary patterns characterized by inadequate diversity and a heavy reliance on calorie-dense but nutrient-poor staple foods. Recent evidence further indicates that there is reduction in the intake of micro nutrients such as iron and zinc due to the decrease in the intake of cereals in especially the states such as Rajasthan which is a NC-consuming state (Kapoor et al., 2024).

NCs formed an important part of the poor person's diet due to their lower price per nutrient relative to rice and wheat (Deaton and Dreze, 2009; Government of India, 2014). Reduced availability of NCs and consequent pressure on their prices is having an adverse effect on the poor consumers. The decline in the intake of coarse grains reduces variety in diet, which is not considered a healthy development. The decline in the demand for coarse cereals causes adverse impact on the farmers (producers) in highly uncertain environments, who face severe constraint to shift to other crops (Chand and Kumar, 2002).

The Government of India (GoI) has therefore started initiatives to promote millets in light of the significance of NCs in order to attain the objectives of environmentally sustainable development and nutrition security. GoI designated 2018 as the "National Year of Millets" and the United Nations designated 2023 as the "International Year of Millets" (WFP India & NITI Aayog, 2023). Despite recent promotions for NCs, particularly millets, the Household Consumption Expenditure Survey (HCES) data for 2022–2023 indicates a continued decline in the per capita (PC) consumption of NCs among the major NC-consuming states. More importantly, the most recent HCES 2022-2023 survey differs from earlier consumption surveys. The recent survey collects data on specific types of millets only for the states where NCs are traditionally consumed, leaving out a couple of states such as Madhya Pradesh and Maharashtra, which are historically recognized for their cultivation and consumption of NCs.

Meanwhile the GoI has introduced Pradhan Mantri Garib Kalyan Anna Yojana (PMGKAY) in 2020 to provide free ration to the marginal households (around 80 crores) in the wake of COVID-19. The scheme provides 35 kg of food grains per Antyodaya Anna Yojana (AAY) household per month and 5 kg of food grains per person per month in case of Priority Household (PHH).[1] This in turn has implications on the food basket of the households, mainly affecting the consumption of the other cereals such as NCs. Furthermore, the government has agreed to provide free food grains under PMGKAY for the next five years, starting

[1] Priority Household (PHH) cards are ration cards issued to vulnerable households who are not classified as the poorest (AAY) but still need support, entitling each member to 5 kg of subsidized foodgrains per month (See https://mahafood.gov.in/scheme/priority-house-holds/).

on January 1, 2024, following the effective implementation of the program addressing poverty and food security (Government of India, 2024). The scheme showed successful performance in reducing poverty and food security. Even if the program has been implemented successfully, it is still unclear whether the goals it seeks to accomplish now will still be important in the future. Although the government has made action to encourage the use of millets, the diet is still primarily focused on rice and wheat, which perpetuates dietary monotony. Given the importance of NCs, it is important to understand the reason behind the reduction in these crops and the role of policies such as PMGKAY.

The rest of the paper is structured as follows: it begins with a review of the relevant literature, followed by the discussion on the data and empirical strategy. The paper concludes with a detailed discussion of the results and conclusion.

LITERATURE REVIEW: THE ROLE OF FOOD POLICIES

Food policies, particularly those pertaining to staple crops and nutrition security, are vital in determining patterns of production, access, and consumption among nations. Historically, the goal of policy interventions in India has been to guarantee calorie sufficiency by providing subsidies for cereals like wheat and rice. However, diverse and nutrient-dense alternatives like NCs have frequently been displaced by these cereals. Recent research shows how these policies have enhanced food security but they also had unanticipated adverse consequences on health outcomes.

Drèze and Sen (1990) emphasize that food policies such as the provision of subsidized or free grains play a crucial role in shaping consumer behaviour, particularly among poorer households facing food insecurity and energy deficiencies. However, the nature of nutritional challenges is evolving, with increasing prevalence of malnutrition manifesting not only as undernutrition but also as obesity and non-communicable diseases. Therefore, in the design and implementation of food policy interventions, it is essential to distinguish between contexts characterized by caloric shortages and those where diets are inadequate due to protein and micronutrient deficiencies.

The impact of food subsidies on consumption patterns has been widely studied, particularly in the context of the Public Distribution System (PDS) in India. There are two different arguments related to the impact of food policy interventions. Firstly, in a positive way, changes in food consumption due to policy interventions are often disaggregated into income and substitution effects due to price changes (Bhargava et al., 2008). The increased income due to cheap subsidized cereals will increase the consumption and the real money can be utilized to buy fruits, nuts, vegetables and meat etc. Shrinivas et al. (2018) and Ghosh et al. (2021) found that subsidies increased staple cereal consumption encouraging dietary diversification due to increased disposable income and improved macro nutrient intake. Jha et al. (2011) show that increase in individuals benefiting from PDS tend to have more protein and micronutrient intakes. According to Umanath et al. (2021), PDS plays a crucial role in providing food security to low-income households by ensuring access to staple grains like rice and wheat at subsidized prices. Nonetheless, this system of subsidies might inadvertently affect dietary choices by promoting increased intake of cheaper staples at the expense of more nutrient-dense foods. Because of this, low-income households might have a less diverse diet, which would limit their consumption of vital micronutrients.

Unfavorably, food policies incentivize only staples while crowding out alternative, more nutrient-dense foods, undermining the nutrition-sensitive food system (Pingali et al., 2016). Foods that are subsidized increase the relative cost of nonsubsidized foods, which incentivizes consumers to shift from the latter to the former. This substitution may have a major detrimental effect on diet composition and individual health outcomes if food subsidy schemes are not nutrition-sensitive. This makes sense since households that are relatively impoverished are more likely to rely on less expensive but unhealthy options or spend a greater portion of their income on food consumption (Abay et al., 2021). This is a serious issue, especially for a country like India that is going through an epidemiological shift from the predominance of communicable diseases to the rise in non-communicable diseases (NCDs).

NITI Aayog (2016) in their study examined the impact of PDS in food consumption patterns and nutritional outcomes. The study used the data on the use of PDS from NFHS 3, Annual Health Survey (AHS), and the District Level Health Survey (DLHS) couldn't find any relation between the access of subsidized grains and the decline of malnutrition also noting that a skewed dietary composition from increased consumption of cereals at any given income level and also found that the lower consumption of milk and lower proportion of expenditure on foods such as fruits, diary, meat and nuts. Similarly, Kaushal et al. (2015) made a study by using consumption data from National Sample Survey Office (NSSO) different rounds to understand the effect of food price subsidy and its amount on the consumption pattern and nutrition. The analysis is conducted by first estimating how Targeted Public Distribution System (TPDS) affects food price subsidies, and then estimating how nutrition and consumption patterns are affected by a rise in subsidies due to TPDS. They found that the lower price of wheat and rice reduced the consumption of NCs which is the unsubsidized staple food. Meanwhile, the estimates of the effect of food price subsidy on calorie and protein intake are statistically insignificant; however, there is a modest increase in fat intake.

Abay et al. (2022) shows evidence for associating government subsidies with increased overweight and obesity prevalence in low- and middle-income countries. Using World Development Indicators data by World Bank and Demographic and Health Survey (DHS) data, they found that higher subsidy spending is associated with increasing overweight and obesity, particularly among poorer households, which are more sensitive to food price changes and more likely to benefit from subsidies. To provide robust estimates, they've employed a fixed effects model that accounts for time, country, and other time-varying factors. Another study by Bartell et al. (2021) employed longitudinal data from the Young Lives survey, and found that higher intake of sugar and rice was substantially associated with access to PDS subsidies. Using two-stage linear probability models, the study reveals that there was no discernible decrease in stunting and that a higher daily intake of rice was associated with a lower height-for-age z-score (HAZ). They also note that PDS families had less dietary diversity than non-PDS households. These results point to possible unforeseen effects for child development outcomes, indicating that although the PDS increases calorie access, it may also bias diets toward less expensive staple foods with little nutritional variety.

Khera (2010) and Desai (2015) both draw attention to the ways that India's extensive food subsidy programs may inadvertently reduce the dietary diversity within cereals. Using data from the India Human Development Survey and using propensity score matching technique, Desai (2015) concludes that having access to subsidized grains through the PDS decreases dietary diversity and does not improve child nutrition because households with PDS access typically spend more on inexpensive cereals and less on nutrient-dense foods like milk and fruits. According to Khera's (2010) primary survey data from Rajasthan, the PDS causes households to switch from nutrient-rich NCs to subsidized wheat, but it has no apparent effect on overall cereal consumption.

The results of the aforementioned studies show both convergent and divergent conclusions regarding how food policy influence nutritional security in India. Differences in the type of data used i.e., primary survey data versus secondary datasets as well as methodological approaches undertaken i.e., from straightforward descriptive studies to more rigorous causal frameworks like quasi-experimental designs are few reasons the drive of these similarities and differences. While certain studies (e.g., Drèze and Sen, 1990; Khera, 2010) emphasize how effective policy interventions are at enhancing food security and access, others (e.g., Pingali et al., 2016) indicate persisting inequalities in nutritional outcomes brought on by an over reliance on calorie-based staples. On the other hand, even while cereals account for the majority of daily intake and are consumed more frequently than foods high in micronutrients, such as fruits, vegetables, and nuts, a major drawback of much of these studies is the little attention paid to dietary diversity within the cereal basket. This disparity is important since, in India, staples account for the majority of household consumption and agricultural policy interventions. However, many studies have not fully examined the potential of NCs to improve nutritional security within this staple framework.

NCs play an important role in improving nutritional outcomes of children. The two studies by Anitha et al. (2019, 2022) highlight the superiority of millets over other staple crops in enhancing nutrition. A systematic review and meta-analysis by Anitha et al. (2022) emphasized the role of millet-based diets in combating malnutrition, particularly among children. These diets significantly improved key anthropometric measures, such as height, weight, mid-upper arm circumference, and chest circumference, compared to rice-based diets over periods ranging from 3 months to 4.5 years. These gains were primarily attributed to the substitution of rice with millets in the diet. Furthermore, a randomized controlled trial (RCT) conducted in Karnataka by Anitha et al. (2019) demonstrated the nutritional advantages of millets. The study analysed nutrient intake in treatment and control groups and found that incorporating millets into the Mid-Day Meal scheme significantly reduced stunting and improved Body Mass Index (BMI) among children. The study ensured the statistical comparability of the treatment and control groups at the baseline. This randomization helps to remove selection bias and allows for a credible causal estimate of millets' nutritional benefits, such as reductions in stunting and improvements in BMI among children.

The studies by Ramaswami (2023) and DeFries et al. (2018) highlights the significant decline in millet consumption in India has contributed to a notable reduction in iron intake, with the sharpest decrease observed among the lowest income quartile. The study by DeFries et al. (2018) adopted consumption data and health data from NFHS and used a mixed effect model for the study. The findings underscore the potential of millets in supporting growth, though further research is needed to tailor dietary programs for different age groups across Africa and Asia. The *Poshan* 2.0 program of the Ministry of Women and Child Development emphasizes the use of millets in take home ration and hot cooked meals for Pregnant Women, Lactating Mothers and Children below 6 years of age since they are rich in protein, essential fatty acids, vitamins and minerals (Government of India, 2023).

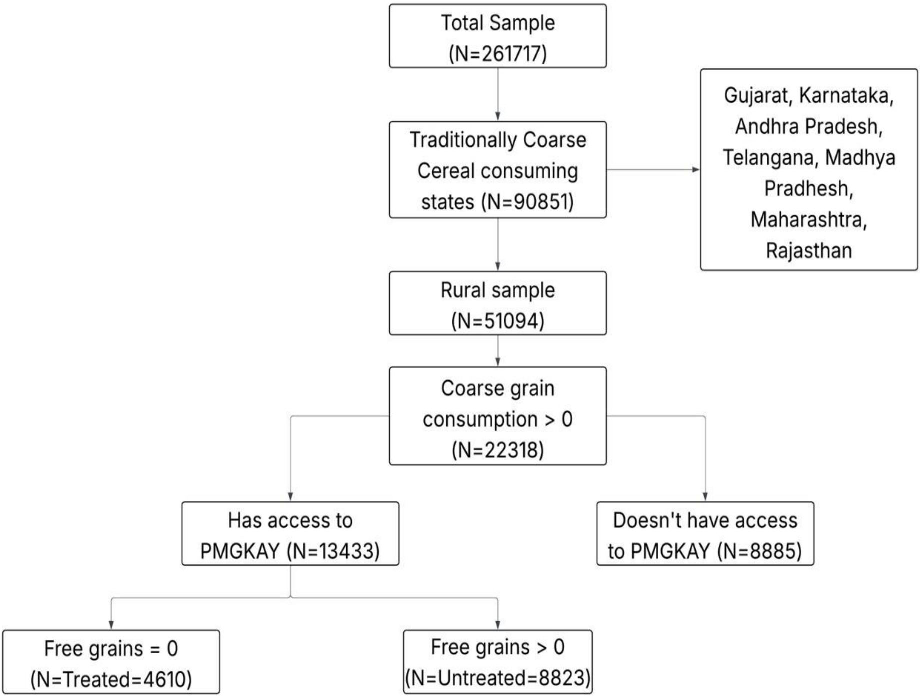
Dietary diversity within the cereal basket is particularly important in rural economies, where cereals form a major part of the daily diet. NCs, in particular, offer higher nutritional value at a lower cost compared to other nutritious food items such as fruits and vegetables. Moreover, NCs have significant policy relevance due to their longer shelf life and minimal seasonal variation in availability compared to nutritionally dense perishables like fruits and vegetables and can address nutritional security of the very young children to the elderly (Devi et al., 2011; Government of India, 2014; Mohanty, 2024).

Crucially, majority of the prior studies does not distinguish between subsidized food grains that households purchase at a very nominal price under the PDS and completely free grain programs (such as PMGKAY), where the entire quantity is supplied freely. In the case of PMGKAY, the quantity provided is the only factor that matters to households, as there is no out-of-pocket expenditure. This, in turn, could further intensify substitution effects away from NCs. Despite this, there is limited causal evidence on how the PMGKAY which provides free rice and wheat affects household consumption of NCs in India. Since cereals make up a large portion of daily diets, even slight modifications to the cereal basket can have significant consequences on nutrition security. While many studies measure the overall dietary diversity across food groups, very few look at how policy-driven price distortions specifically change the proportion of NCs consumed by households in rural areas. Thus, leveraging this gap, this study attempts to find the impacts of large-scale food policies, such as PMGKAY, on the consumption of NCs among the rural households. The notion behind considering only rural areas stems from the previous studies which demonstrated considerable disparities in grain intake between rural and urban areas (Rao et al., 2006; Pingali et al., 2019). According to NSSO's HCES reports 2011-12 and 2022-23, while urban households mostly rely on market purchases for staples like NCs, rural households tend to rely more on home production. Still, rural areas continue to exhibit significant reliance on NCs, particularly among low-income households. However, it is observed that the consumption of millets has declined more sharply in urban areas due to shifts toward refined cereals. Nevertheless, due to a lack of dietary diversity, poorer purchasing power, and a reliance on diets high in cereals, nutrition insecurity continues to be more prevalent in rural India.

DATA AND METHODOLOGY

In order to examine the hypothesis of the how much a free grain program focussing on rice and wheat reduces NC consumption among households that usually prefer to consume NCs, this study uses the nationally representative NSSO HCES for the year 2022-23. The survey covers detailed information on food and non-food items, durable goods, services, and consumption from own production or free collection. The NSSO HCES 2022-23 has methodological changes compared to the earlier rounds, which induce comparability challenges over time. In the HCES survey 2022-23, the quantity and value of millets such as ragi, jowar, and bajra have been aggregated with barley and maize under a single category called coarse cereals. This makes it difficult to analyze the individual consumption trends of specific millets, which were separately recorded in the NSSO Consumption Expenditure Survey (CES) 2011-2012. The NSSO HCES 2022-23 found that NCs are not consumed uniformly across all the states. Data on quantity and value of each NC has been provided only for a limited number of states, such as Rajasthan, Punjab, Haryana, Gujarat, Andhra Pradesh, Tamil Nadu, Kerala, Karnataka, Telangana, and Uttar Pradesh. This limits the possibility of a comprehensive national comparison of NC consumption trends because disaggregated data on NCs for other important states, such Maharashtra and Madhya Pradesh, which are major NC consumers, are not available (Anand, 2024; Manna, 2024; MOSPI, 2024).

Figure 1: Exclusion Criteria for Sample Selection



Exclusion criteria

To validate the sample to be used for assessing the impact of PMGKAY on the consumption of NCs, a systematic exclusion criterion has been designed. The initial sample consisted of 261,717 households, which was subsequently tapered to 90,851 households in the states of Gujarat, Karnataka, Andhra Pradesh, Telangana, Madhya Pradesh, Maharashtra, and Rajasthan, which are known to traditionally consume NCs. The sample was further narrowed to rural households, yielding 51,094 observations, because the PMGKAY program's implementation and uptake, as well as the NC consumption, are more prevalent in rural areas.

To ensure relevance to the outcome of interest, households with positive coarse grain consumption (N = 22,318) have been retained in this rural subsample. Among these, 8,885 households did not report having access to PMGKAY, whereas 13,433 households did, making up the analytical sample. Within this sample, those who have access to PMGKAY but did not receive free grains were classified as treated (N = 4,610), whereas those who did receive free grains were classified as untreated (N = 8,823).

Empirical Strategy: Propensity Score Matching

To assess the causal impacts of any program, the RCTs are treated as the gold standard in the literature. RCT estimates the causal impacts with minimal bias, where participants are assigned randomly to control and treatment groups (Pocock and Elbourne, 2000). However, political sensitivities, financial constraints, ethical issues, and logistical challenges make RCTs impractical in the vast majority of circumstances (Angrist and Pischke, 2008; Baker, 2000; Imbens and Woolridge, 2009). Thus, to deal with this challenge, various quasi-experimental methods are implemented to understand the causal impacts of the program. In India, the effects of extensive social programs have been estimated using several quasi-experimental techniques. For instance, Azam (2016) uses panel data and matching techniques to assess how the Rashtriya Swasthya Bima Yojana (RSBY) social health insurance system affects household financial burden.

The observational datasets have been largely used in the research, particularly when examining the effects of extensive development initiatives (i.e., programs implemented at a national- or state-level). The major issue that arises when examining the observational data is that of confounding variables, where participants in treatment and control groups are likely to differ. Hence, differences in the pertinent outcomes might not be the result of a real treatment impact but rather of changes in the baseline circumstances (Dehejia and Wahba, 2002; Heckman, Ichimura, and Todd, 1997; Rosenbaum and Rubin, 1985). Thus, in order to minimize confounding bias, the Propensity Score Matching (PSM) technique has been employed to estimate the causal impact of the PMGKAY program. The PSM technique ensures that the treated and untreated households are as similar as feasible because the PMGKAY scheme's beneficiaries are mostly found in the lowest socioeconomic strata. As PMGKAY subsidies are not distributed at random, disparities in observable traits like income, household size, caste, or educational attainment could skew simple mean comparisons. Thus, by pairing households from the treated group with control group, PSM lessens selection bias and offers a more reliable assessment of the program's impact.

Matching similar individuals representing both samples based on their confounding factors is the basic premise behind determining the difference between the treated and control samples. The likelihood that an individual will receive a treatment contingent on a number of confounding characteristics is known as the propensity score. Propensity score is frequently estimated using the logistic or a probit regression function (Brookhart et al., 2006; Zhang et al., 2014). By combining the confounding variables into a single indicator, the propensity score estimated from logit or probit regression makes matching easier and aids in identifying the treatment group and its counterfactual group. Here the study uses probit model and this can be expressed as:

$$P(D_i = 1|X_i) = \boldsymbol{\Phi}(\boldsymbol{X_i'\beta}) \qquad i = 1, \dots, N \qquad (\mathbf{1})$$

The binary treatment indicator, D_i, takes the value 1 if household i receives the free grains and 0 otherwise. The set of observed covariates for household i is represented by the vector $\boldsymbol{X_i}$. The function $\boldsymbol{\Phi}(.)$ is the cumulative distribution function (CDF) of the standard normal distribution, and the term β indicates the appropriate vector of coefficients to be calculated. In this study, the propensity score for household i $(i = 1, \ldots, N)$ represents the estimated probability, $p(X_i)$, based on a discrete choice model that the household will take the free grains of $(D_i = 1)$ rather than not taking the free grains $(D_i = 0)$ conditional on their observed vector of covariates $\boldsymbol{X_i}$ such as Monthly Per Capita Consumption Expenditure (MPCE), household size, education level, social group, marital status etc.

Now, due to matching on estimated propensity score, an approximate balance for all confounding variables is produced by matching respondents with comparable estimated propensity scores, and unbiased estimates of the treatment impact are provided by differences in outcomes across groups with similar propensity scores (Austin, 2011; Umanath et al., 2021) (see Figure 2 representing overlap assumption). Heckman et al. (1998) and Dehejia and Wahba (2002) indicate that when matching is performed with precision, PSM can closely approximate experimental conditions. Moreover, through matching, we ensure that the treatment assignment is conditionally random, thus satisfying the unconfoundedness assumption of the PSM. Furthermore, adjusting for the propensity score $p(X_i)$ is theoretically analogous to adjusting for the full set of covariates X_i (Rosenbaum and Rubin, 1983). Therefore, using HCES data, this study uses the PSM technique to evaluate the pure impact of the PMGKAY on the consumption of NCs and nutrient intake.

PSM is estimated in the following steps: First, a logit or probit regression is estimated where the likelihood of being in the treatment group is regressed on the set of various socio-economic household characteristics. Second, using the estimated propensity scores, a matching procedure is performed. In order to match similar individuals from treatment and control groups, various methods are used: Nearest-Neighbour Matching (NNM), radius matching, Mahalanobis matching, kernel matching, etc. For this analysis, NNM with a caliper distance of 0.001 is used, as this matching procedure is widely used in the literature. The observations with very high propensity scores are eliminated from the sample as they would induce bias in the model. Thus, after the matching procedure is done, the quality of matching has been tested using the kernel density plots and the mean absolute standardized bias (MASB).[2] The standardised bias for the jth covariate can be expressed as:

$$SB^{U}_{j,x} = \frac{100(\bar{X}_{j,T} - \bar{X}_{j,C})}{\sqrt{\frac{s^2(x_{j,T})+s^2(x_{j,C})}{2}}} \tag{2}$$

$$j = 1, \ldots\ldots, J$$

And,

$$SB^{M}_{j,x} = \frac{100(\bar{X}_{j,T,M} - \bar{X}_{j,C,M})}{\sqrt{\frac{s^2(x_{j,T})+s^2(x_{j,C})}{2}}} \tag{3}$$

$$j = 1, \ldots\ldots, J$$

In this case, the standardized bias for a given covariate x before matching is represented by $SB^{U}_{j,x}$, and the same measure after matching is shown by $SB^{M}_{j,x}$ (see equations 2 and 3). The variance (squared standard deviation) of covariate x within the treatment group is denoted

[2] *pstest* command in Stata provides the MASB for both matched and unmatched samples.

by the term $s^2\left(x_{j,T}\right)$, while the variance within the control group is denoted by the term $s^2\left(x_{j,C}\right)$. Because the standardized bias is unit-free, it offers a scale-independent method of determining whether there is still an imbalance between the treatment and control groups following matching (Kumar, 2012) (see Figure 3 representing standardized bias of the covariates before and after matching).

The mean of these absolute standardized biases for every covariate is known as the MASB (see equations 4 and 5). It shows how much imbalance remains overall. The MASB before matching is

$$MASB^U = \frac{\sum_{j=1}^{J}\left|SB_{j,x}{}^U\right|}{J} \qquad (4)$$

$$j = 1, \ldots\ldots, J$$

And MASB after matching is

$$MASB^M = \frac{\sum_{j=1}^{J}\left|SB_{j,x}{}^M\right|}{J} \qquad (5)$$

$$j = 1, \ldots\ldots, J$$

where J is the total number of covariates. A lower MASB after matching indicates better balance and thus a higher quality match.

In order to account for any selection bias in observational data, this study uses the inverse probability weighted regression adjustment (IPWRA) method to estimate the Average Treatment Effect on the Treated (ATT). The expected difference in outcomes between the treatment and the counterfactual scenario for those units that actually received the treatment has been defined as the Average Treatment Effect on the Treated (Rosenbaum and Rubin, 1985; Imbens and Wooldridge, 2009). ATT is estimated to account for selection bias into the treatment, which could lead to a potential bias if unaccounted for in the observational data. According to this study, the ATT is the expected difference, conditional on actually choosing the free grains $(D_i = 1)$, between the per capita NC consumption of households that choose to take them (Y_1) and what their consumption would have been if they had not (Y_0). The ATT can be expressed as:

$$ATT = E[Y_1 - Y_0 | D_i = 1] \tag{6}$$

The *teffects ipwra* command in Stata is used in this study to estimate the Average Treatment Effect on the Treated. This command creates a doubly robust estimator by combining Inverse Probability Weighting and Regression Adjustment. This indicates that if either the outcome model or the propensity score model is appropriately specified, the estimated effect stays constant. In order to create a pseudo-population in which the likelihood of receiving the treatment is unaffected by observed characteristics, the IPW estimator reweights the sample, while the regression adjustment directly controls for the covariates in estimating the outcome. Each observation is assigned a weight that is the inverse of the estimated probability of receiving the treatment in order to mimic the random assignment. Under the IPWRA framework, it is allowed for the covariates used in the outcome model of this study to differ somewhat from those used in the propensity score estimate because the estimator stays the same if either the outcome model or the treatment model is appropriately stated (Wooldridge, 2010; Chesnaye et al., 2022; Słoczyński et al., 2022). While the outcome model in this study incorporates variables that impact household NC consumption, the treatment model employs pre-treatment variables to explain the likelihood of receiving free grains. When randomization is not feasible, IPWRA is especially helpful for assessing how program's like PMGKAY affects household NC consumption.

The natural logarithm of the total quantity of NC consumed per capita serves as the dependent variable in this study, reducing distribution skewness and aiding in the interpretation of the estimated coefficients in percentage terms. Studies such as Bhargava et al. (2008), Deaton (2018), Jumrani (2023), and Umanath et al. (2021) are considered to determine the major control variables in the model. Several demographic variables such as gender, age, social group, education, and marital status of the household head have been controlled. Household characteristics like household size, household consumption unit, child and elderly proportions, along with economic variables - log of monthly per capita consumption, landholding and its square, wealth quintiles and income derived from major activity are also controlled.

The wealth index based on household asset ownership is used to create the wealth quintiles in this study. Ownership of a television, radio, cell phone, bicycle, motorbike, truck, animal cart, refrigerator, and ownership of house are among the assets taken into account. These binary asset indicators are subjected to Principal Component Analysis (PCA), which produces a continuous wealth index that is used to categorize households into quintiles. In the price calculation for wheat, rice, and NCs, the total value was divided by its total quantity to determine the unit price, which was set to zero in the case that no consumption was reported. These prices were then averaged at the cluster (FSU), regional, and state levels to account for local price variations and smooth household-level reporting differences. This ensures that each household was given a representative price even when there were missing or zero values. Prices are derived using the aggregate quantities and corresponding values based on the HCES data. For the calculation of proportions of each age groups, number of people in each relevant group was divided by the total size of the household to determine the proportion of children, working-age adults, and elderly people. In order to quantify the impact of various income sources on the likelihood of the outcome of interest, the principal income source type of the family is included. Including them accounts for heterogeneity in livelihoods, which may affect the dependent variable or treatment assignment. Additionally, PDS grain access is also included in the analysis.

RESULTS AND DISCUSSION

The all-India rural consumption pattern in Table 1 shows that in 2011 per capita NC consumption was 2.5 kg per month and it has reduced to 1.84 kg per month in 2022 based only on the NC-consuming states. It is observed that rice and wheat continued to be an indispensable part of the food basket of Indians and there is clear preference for either rice or wheat as the dominant cereal; while, the type of NCs vary across states. In most of the traditionally NC-consuming states, the consumption of rice and wheat has remained more or less stable, while the consumption of NC has seen a sharp decline. However, some states like Telangana, Andhra Pradesh, and Madhya Pradesh show a noticeable decline in the consumption of wheat or rice along with the NCs over the past decade and the reason for this will be examined separately.

Table 1: PC Cereal Consumption (kg/ month) in 2011 and 2022, Rural

State	Year	Coarse Cereals	Rice	Wheat
Rajasthan (Bajra, Maize)	2011	4.8 (0.19)	0.41 (0.02)	9.5 (0.12)
	2022	3.4 (0.06)	0.4 (0.007)	8.8 (0.04)
Madhya Pradesh (Maize, jowar	2011	3.3 (0.32)	2.4 (0.08)	8.7 (0.12)
	2022	1.5 (0.04)	2.6 (0.02)	6.7 (0.02)
Gujarat (Bajra, Maize)	2011	3.4 (0.11)	2.1 (0.07)	3.7 (0.11)
	2022	2.1 (0.03)	2.6 (0.02)	4.2 (0.03)
Maharashtra (Jowar, Bajra)	2011	2.7 (0.06)	3.4 (0.06)	4.6 (0.06)
	2022	1.8 (0.01)	3.02 (0.02)	4.2 (0.02)
Andhra Pradesh (Jowar, Ragi)	2011	1. 0 (0.05)	10.8 (0.10)	0.57 (0.01)
	2022	0.6 (0.01)	8.5 (0.03)	0.4 (0.006)
Karnataka (Jowar, Ragi)	2011	2.8 (0.05)	6.03 (0.09)	1.2 (0.02)
	2022	2.0 (0.01)	5.9 (0.03)	1.2 (0.01)
Telangana (Jowar, Ragi)	2011	1.4 (0.13)	11.1 (0.13)	0.6 0.02)
	2022	0.9 (0.02)	9.4 (0.06)	0.5 (0.009)
All rural NC-consuming States	2011	3.05 (0.05)	6.3 (0.03)	4.8 (0.03)
	2022	2.03 (0.01)	3.9 (0.01)	4.4 (0.01)

Source: Author's Estimates from CES 2011-12 and HCES 2022-23. Note: Standard deviations are in the parenthesis.

NC consumption, with states exhibiting varying preferences for particular varieties of NCs. According to NSSO HCES reports, for instance, Madhya Pradesh and Maharashtra consume more Jowar in addition to Maize or Bajra, whereas states like Rajasthan have historically consumed more Bajra and Maize. Jowar and Ragi are preferred in Andhra Pradesh, Karnataka, and Telangana. The inclusion of millets in the PDS and the imposition of a Minimum Support Price (MSP) are two examples of policy interventions that have been shown in recent works to influence these trends in different ways across states (Raju et al., 2018).

To ensure comparability between treated and untreated groups, 13,389 households on common support make up the final analytical sample. The estimates of the discrete choice probit model are reported in Table A1 in Appendix and the predicted probability from this estimates the propensity score. The kernel density map in the figure 2 shows the distribution of estimated propensity scores for the treated and control groups in PSM or any other matching framework. The propensity score values, or the estimated likelihood of receiving the treatment given the observed covariates, are presented on the x-axis. The density or the number of units that fall within each range of propensity scores, appears on the y-axis. This plot's main objective is to determine whether the treated and control groups have enough overlap, or common support. There is less chance of inaccurate estimations or bad matches when there is enough overlap, which indicates that good matches can be found. There is a significant overlap in this case, as the treatment group's mean propensity score is 0.37 and the control group's mean is 0.32. This overlap strengthens the validity of the causal inference by guaranteeing that the estimated treatment effect is based on similar observations.

Figure 2: Estimated Propensity Scores

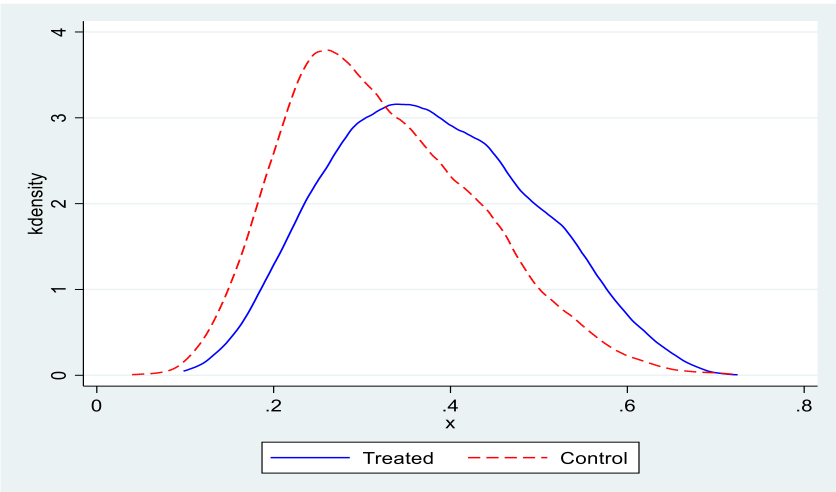
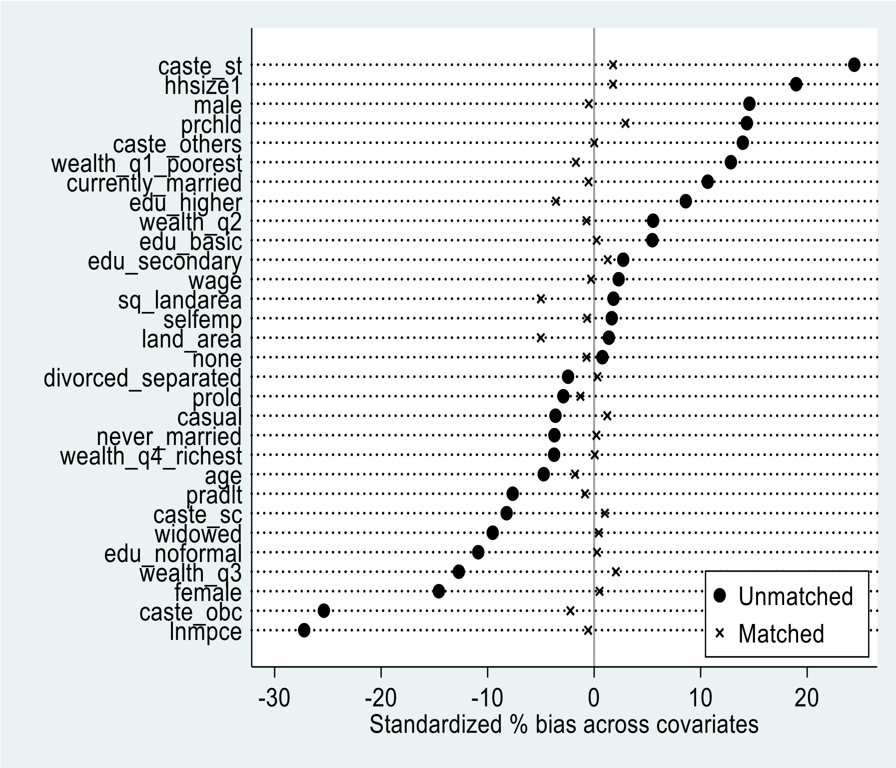


Figure 3: Standardized Bias



The standardized mean differences and the graph for each covariate are generated using *pstest* command in Stata software before and after propensity score matching (see Figure 3). Prior to matching, the black dots indicate significant bias in several covariates, with normalized differences reaching ±20 percent for a number of variables, including household size and scheduled tribe, suggesting that the treatment and control units differed systematically on these attributes. Following matching, nearly all covariates shifted significantly closer to zero, (shown as *) indicating that the matching process was successful in balancing the observed traits between groups. Specifically, there was a significant improvement in covariate balancing, as evidenced by the mean bias dropping from 9.2 percent prior to matching to just 1.3 percent as reported by the *pstest* command in Stata following matching (see equations 4 and 5). Reducing this bias guarantees that the two groups are comparable and that the estimated treatment effect is not influenced by confounding differences. Overall, this shows that the matching process was successful in reducing selection bias brought on by observable covariates, which increased the validity of the causal estimations.

Summary Statistics: Control and Treatment Households

The type of NC consumption varies across states as shown in Table 1. Each state consumes a specific NC or a couple of them and Table 2 provides the per capita (PC) NC consumption per month in quantity for the treated (not consuming free rice or wheat from the PMGKAY in spite of its access) and the control (consuming rice and/or wheat from the PMGKAY). It can be observed that the average PCNC consumption per month is about 2.25 kg for the treated and 2.05 kgs for the control. In the treated group, intake of some specific NCs (such as Jowar and Ragi) is lower than that of other NCs (such as Bajra and Maize). This suggests substitution within NCs, as households choose between varieties instead of uniformly increasing all NC grains consumption. The decrease in Jowar and Ragi is partially offset by an increase in the consumption of Bajra and Maize, which results in a modest net gain in overall NC consumption. Such trends are typical when relative prices or availability are altered by regional factors or policy initiatives. As a result, the figures do not contradict one another; rather, they represent changes in the NC category as a whole.

Table 2: Comparison of Mean PC Cereal Consumption Quantities

Per capita consumption (Qty in kg)	Treated group	Untreated group	Difference
Rice	2.7 (0.04)	4.81 (0.04)	-2.04***
Wheat	4.43 (0.04)	2.88 (0.03)	1.55***
Nutri-Cereals			
Jowar	0.09 (0.007)	0.5 (0.01)	-0.41***
Bajra	0.8 (0.03)	0.6 (0.02)	0.18***
Ragi	0.04 (0.004)	0.4 (0.01)	-0.41***
Small millets	0.0 (0.0)	0.001 (0.0)	-0.001**
Maize	0.3 (0.02)	0.08 (0.0)	0.31***
Barley	0.005 (0.0)	0.003 (0.0)	0.002*
Total NC consumption	2.2 (0.03)	2.05 (0.02)	0.20***
Observations	4610	8823	

Source: Author's Estimates from HCES 2022-23.
Note: (1) *** $p<0.01$, ** $p<0.05$, * $p<0.1$. (2) Standard Deviations in parenthesis. (3) The NC types are based on state specific consumption excluding the States of Maharashtra and Madhya Pradesh as disaggregate data is not available.

Table 2 compares the mean PC consumption of rice, wheat, and NCs for the treated and control groups. The test of hypothesis shows the difference among both groups is statistically significant for rice, wheat, and NCs. These variations reveal that households accessing free grains tend to substitute towards wheat and away from rice, while the impact on NC consumption is positive but relatively small in magnitude. However, these results reflect simple mean differences and do not control for other household characteristics, which are incorporated in the subsequent matching and regression analyses.

The Table 3 shows the Summary statistics of variables by treatment status which demonstrates notable variations in the mean price paid for NCs, wheat, and rice. The treated group is getting NCs and wheat at cheaper rate. These households pay lower average prices, most likely as a result of their local sourcing or own production to supplement market purchases. The mean price of rice, on the other hand, is about the same for both groups, suggesting that price variation is more noticeable for NCs and wheat. Additionally, the percentage of NCs obtained from the PDS is low for both categories, confirming that the PDS primarily provides wheat and rice with very little coverage for coarse cereals. There is a significant association between treatment status and PDS intake of rice and wheat, in particular, around 78 percent in the treated group receive rice and wheat through the PDS, compared to only 18 percent of households in the untreated group.

Table 3: **Summary statistics of variables by treatment status**

Variable	Variable type	Total Sample	Treated group	Untreated group
Characteristics of Household head				
Age	Continuous	50.96 (13.39)	50.54 (13.7)	51.1 (13.2)
Gender				
Male	Categorical	0.85 (0.35)	0.88 (0.31)	0.83 (0.37)
Female	Categorical	0.14 (0.35)	0.11 (0.31)	0.16 (0.37)
Education				
No formal education	Categorical	0.43 (0.49)	0.40 (0.49)	0.45 (0.49)
Basic education	Categorical	0.35 (0.47)	0.36 (0.48)	0.34 (0.47)
Secondary education	Categorical	0.17 (0.37)	0.17 (0.38)	0.16 (0.37)
Higher education	Categorical	0.04 (0.19)	0.05 (0.22)	0.03 (0.18)
Marital status				
Never married	Categorical	0.01 (0.10)	0.009 (0.09)	0.01 (0.11)
Currently married	Categorical	0.82 (0.38)	0.85 (0.35)	0.81 (0.39)
Widowed	Categorical	0.15 (0.36)	0.13 (0.34)	0.16 (0.37)
Divorced	Categorical	0.00 (0.07)	0.004 (0.06)	0.005 (0.07)
Demographic variables				
Proportion of children (0-14 years)	Continuous	0.19 (0.20)	0.21 (0.21)	0.18 (0.20)
Proportion of adults (15-54 years)	Continuous	0.59 (0.28)	0.57 (0.27)	0.60 (0.28)
Proportion of elderly (>54 years)	Continuous	0.21 (0.28)	0.20 (0.28)	0.21 (0.28)
Household size	Continuous	4.65 (2.29)	4.9 (2.4)	4.4 (2.1)

Table 3 continued...

Household consumption unit	Continuous	3.75 (1.87)	4.0 (1.9)	3.6 (1.7)
Socio-Economic variables				
Caste ST	Categorical	0.20 (0.40)	0.26 (0.44)	0.16 (0.37)
Caste SC	Categorical	0.17 (0.37)	0.14 (0.35)	0.18 (0.38)
Caste OBC	Categorical	0.44 (0.49)	0.35 (0.47)	0.48 (0.49)
Caste Others	Categorical	0.18 (0.39)	0.22 (0.41)	0.16 (0.37)
Land Area	Continuous	2.20 (3.57)	2.2 (3.7)	2.1 (3.4)
Wealth index	Continuous	0.18 (1.18)	0.07 (1.2)	0.24 (1.1)
Wealth Q1 (Poorest)	Categorical	0.17 (0.37)	0.20 (0.40)	0.15 (0.36)
Wealth Q2	Categorical	0.29 (0.45)	0.31 (0.46)	0.28 (0.45)
Wealth Q3	Categorical	0.34 (0.47)	0.30 (0.46)	0.36 (0.48)
Wealth Q4	Categorical	0.18 (0.38)	0.17 (0.37)	0.18 (0.39)
Log of MPCE	Continuous	8.27 (0.46)	8.1 (0.48)	8.3 (0.44)
MPCE Q1 (Poorest)	Categorical	0.23 (0.42)	0.32 (0.46)	0.19 (0.39)
MPCE Q2	Categorical	0.25 (0.43)	0.25 (0.43)	0.25 (0.43)
MPCE Q3	Categorical	0.24 (0.42)	0.19 (0.39)	0.26 (0.44)
MPCE Q4	Categorical	0.18 (0.38)	0.14 (0.35)	0.20 (0.40)
MPCE Q5 (Richest)	Categorical	0.08 (0.27)	0.07 (0.25)	0.08 (0.28)
Price Variables				
Wheat price	Continuous	38.80 (11.98)	34.2 (12.0)	41.2 (11.2)
NC price	Continuous	32.96 (12.86)	29.9 (13.7)	34.5 (12.0)
Rice price	Continuous	47.54 (12.77)	47.8 (14.4)	47.3 (11.8)
PDS grains dummy (rice and wheat)	Categorical	0.39 (0.48)	0.78 (0.41)	0.18 (0.39)
Major income activity				
Self-employment	Categorical	0.54 (0.49)	0.54 (0.49)	0.53 (0.49)
Wage labor	Categorical	0.09 (0.29)	0.10 (0.30)	0.09 (0.29)
Casual labor	Categorical	0.31 (0.46)	0.30 (0.45)	0.31 (0.46)
None	Continuous	0.04 (0.21)	0.04 (0.21)	0.04 (0.21)

Source: Author's Estimates from HCES 2022-23
. Note: Standard deviations are in the parenthesis.

Summary statistics for household and demographic characteristics are shown in Table 4 following matching, for the treated and the control households. Each variable's mean value is presented along with the differences among both the groups. It can be observed that important demographic and socioeconomic characteristics have closely aligned as a result of the matching process: the treatment and control groups are balanced on these observable characteristics, as evidenced by the lack of significant differences among these variables. The matching model excludes the price variables. According to the PSM procedure, price variables are not included in the matching model since they are influenced by the treatment and are therefore inappropriate to consider them as pre-treatment covariates (Heckman et al., 1998; Caliendo and Kopeinig, 2008). Incorporating such post-treatment outcomes may cause conditioning on variables along the causal framework, hence biasing the estimated treatment impact.

Table 4: Summary measures of covariate balance

		Unmatched proportions		Matched proportions		
Variable	Variable type	Treated group	Untreated group	Treated group	Untreated group	Difference@
Characteristics of Household head						
Age	Continuous	50.54 (13.7)	51.1 (13.2)	50.5 (13.7)	50.7 (0.28)	-0.2
Gender						
Male	Categorical	0.88 (0.31)	0.83 (0.37)	0.88 (0.32)	0.88 (0.006)	0
Female	Categorical	0.11 (0.31)	0.16 (0.37)	0.11 (0.32)	0.11 (0.006)	0
Education						
No formal education	Categorical	0.40 (0.49)	0.45 (0.49)	0.40 (0.49)	0.4 (0.01)	0
Basic education	Categorical	0.36 (0.48)	0.34 (0.47)	0.36 (0.48)	0.36 (0.01)	0
Secondary education	Categorical	0.17 (0.38)	0.16 (0.37)	0.17 (0.38)	0.17 (0.007)	0
Higher education	Categorical	0.05 (0.22)	0.03 (0.18)	0.05 (0.22)	0.05 (0.005)	0
Marital status						

Table 4 continued...

Never married	Categorical	0.009 (0.09)	0.01 (0.11)	0.009 (0.09)	0.009 (0.001)	0
Currently married	Categorical	0.85 (0.35)	0.81 (0.39)	0.85 (0.35)	0.85 (0.007)	0
Widowed	Categorical	0.13 (0.34)	0.16 (0.37)	0.13 (0.34)	0.13 (0.006)	0
Divorced	Categorical	0.004 (0.06)	0.005 (0.07)	0.004 (0.06)	0.003 (0.001)	0.001
Demographic variables						
Proportion of children (0-14 years)	Continuous	0.21 (0.21)	0.18 (0.20)	0.21 (0.21)	0.20 (0.004)	0.01
Proportion of adults (15-54 years)	Continuous	0.57 (0.27)	0.60 (0.28)	0.57 (0.28)	0.58 (0.005)	-0.01
Proportion of elderly (>54 years)	Continuous	0.20 (0.28)	0.21 (0.28)	0.20 (0.28)	0.21 (0.005)	-0.01
Household size	Continuous	4.9 (2.4)	4.4 (2.1)	4.9 (2.34)	4.8 (0.05)	0.1
Socio-Economic variables						
Caste ST	Categorical	0.26 (0.44)	0.16 (0.37)	0.26 (0.44)	0.25 (0.009)	0.01
Caste SC	Categorical	0.14 (0.35)	0.18 (0.38)	0.15 (0.35)	0.14 (0.007)	0.01
Caste OBC	Categorical	0.35 (0.47)	0.48 (0.49)	0.36 (0.48)	0.37 (0.009)	-0.01
Caste Others	Categorical	0.22 (0.41)	0.16 (0.37)	0.22 (0.41)	0.22 (0.008)	0
Land Area	Continuous	2.2 (3.7)	2.1 (3.4)	2.2 (3.6)	2.3 (0.09)	-0.01
Wealth Q1 (Poorest)	Categorical	0.20 (0.40)	0.15 (0.36)	0.20 (0.40)	0.21 (0.009)	-0.01
Wealth Q2	Categorical	0.31 (0.46)	0.28 (0.45)	0.31 (0.46)	0.31 (0.009)	0
Wealth Q3	Categorical	0.30 (0.46)	0.36 (0.48)	0.30 (0.46)	0.30 (0.009)	0
Wealth Q4	Categorical	0.17 (0.37)	0.18 (0.39)	0.17 (0.37)	0.17 (0.007)	0
Log of MPCE	Continuous	8.1 (0.48)	8.3 (0.44)	8.1 (0.48)	8.1 (0.009)	0
Major income activity (household)						

Table 4 continued...

Self-employment	Categorical	0.54 (0.49)	0.53 (0.49)	0.54 (0.49)	0.55 (0.01)	-0.1
Wage labor	Categorical	0.10 (0.30)	0.09 (0.29)	0.10 (0.30)	0.10 (0.006)	0
Casual labor	Categorical	0.30 (0.45)	0.31 (0.46)	0.30 (0.45)	0.29 (0.009)	0.1
None	Continuous	0.04 (0.21)	0.04 (0.21)	0.04 (0.21)	0.05 (0.004)	-0.01
Observations		4610	8823	4566	8823	

The average per capita intake of rice is lower than that of households that receive free grains, whereas the average per capita consumption of NCs is slightly greater among those that do not. At the same time, the group which is not taking free grains consumes significantly more wheat per capita. The fact that several of the states in the analysis are historically wheat-consuming regions and that there is a discernible trend toward higher wheat consumption even in historically rice-dominated states contributes to explain this pattern. Other plausible factors include shifting dietary preferences toward wheat-based meals and rising income among households is marginally higher in the treatment group while the per capita rice is lower compared to control group. In order to exclude the possibility that the treatment and control group could be differently selected on observables, we use the ATT estimates derived through PSM which helps to understand the significant impact of the intervention. The ATET for per capita NC consumption while controlling for important covariates is estimated using the teffects ipwra command in Stata, which employs robust standard errors and inverse probability weighting in conjunction with regression adjustment.

The ATT estimation in Table 4 shows that the treated group of households who do not consume free grains (in spite of PMGKAY access) consumed 12 percent more NCs than others (control group) clearly indicating NCs are substituted away by access to free grain consumption among households that preferred NC. In a nutrient intake point of view, the control group gains marginally in protein intake and a larger gain in calories from rice and wheat but loses out on the micronutrient consumption from NC, thereby adversely affecting nutritional diversity from cereals.

Table 5: Effect of providing free grains on PC NC consumption (Kgs/month)

Variables	**Coef.**	**Robust Std. Errors**
Treatment (ATT IPWRA)	0.12 ***	0.031
Gender (base: male)	-0.02	0.07
Age	0.003	0.003
Education Category (base: no formal education)		
Basic Education	0.18 ***	0.05
Secondary Education	0.40 ***	0.07
Higher Education	1.04 ***	0.13
Social Group (base: ST)		
SC	-0.34 ***	0.07
OBC	-0.47 ***	0.06
Others	0.11 **	0.07
Demographics		
Household size	0.03	0.01
Proportion of children	0.39 ***	0.14
Proportion of elderly	0.34 ***	0.11
Economic variables		
Log of MPCE	0.45 ***	0.06
Land area	-0.04 ***	0.01
Square of land area	0.001 ***	0.001
Price variables		
Log of Price of wheat	-2.1 ***	0.09
Log of Price of coarse grains	-0.41 ***	0.09
Log of Price of rice	-0.40 ***	0.092
PDS grains dummy (rice+ wheat)	2.7 ***	0.04
Constant	4.5 ***	0.67

Note: *** p<0.01, ** p<0.05, * p<0.1

After accounting for the difference between the treated and control households, it is observed that households with higher education levels or those belonging to the less disadvantaged social groups are more likely to consume greater quantities of NCs. This can be due to greater awareness about the health benefits of diverse and nutrient-rich diets, more access to information, and the ability to afford a variety of food items. Moreover, these households may place greater value on dietary quality and are more responsive to changing nutritional trends and government policies for promoting millets.

The estimated own-price elasticity indicates that a 10 percent increase in the price of NCs leads to a 4.1 percent decline in their per capita per month consumption. The negative cross-price elasticity coefficients for wheat and rice prices shows that an increase in the price of these staples is associated with a decrease in the consumption of NCs. This may be due to the complementary use of these grains in household diets. Additionally, households accessing rice and wheat through PDS are consuming greater quantities of NCs per capita.

CONCLUSION

The PMGKAY, which was implemented in 2020, has given free grains including wheat and rice to around 800 million people. This study used PSM to assess the Average Treatment Effect on the Treated of choosing free grains on per capita NC consumption using data from the NSSO HCES 2022–2023. The findings highlight a clear trade-off between short-term food security and long-term nutritional adequacy and dietary diversity. While current food policies particularly the free distribution of rice and wheat have played a critical role in addressing hunger and caloric intake, they may inadvertently undermine the consumption of nutrient-dense cereals, thereby limiting dietary quality. To ensure more balanced nutritional outcomes, it is imperative to reorient food policy by more systematically integrating NCs into food security programs (Pingali and Puri, 2024). As a single staple diet, millets provide roughly 30% of the daily requirements for fiber and zinc, 40 percent for iron, and 60 percent for calcium (Makkar et al., 2019). An effective framework for promoting NCs is thus exemplified by proactive state-level policies like those that Karnataka has implemented, including the establishment of a Minimum Support Price for NCs and targeted distribution via the PDS could have implications in regions with established cultivation and dietary traditions for these crops (Raju et al., 2018). The NITI Aayog study, "Promoting Millets in Diets: Best Practices across States/UTs of India", highlights successful ways for incorporating millets into the Indian diet. It studies millet production, processing, and consumption patterns, with a focus on state-level initiatives, inclusion in programs such as ICDS, and R&D efforts. Particularly, NITI Aayog and the World Food Programme (WFP) announced the Mapping and Exchange of Good Practices (MEGP) Initiative, which aims to document and enable the exchange of best practices for mainstreaming millets across Asia and Africa. Moreover, promoting the production and consumption of local millet varieties through supportive policy interventions can strengthen agro-nutritional linkages, improve dietary diversity, and contribute to sustainable food systems. These measures are essential to address the emerging challenges of hidden hunger, obesity, and non-communicable diseases in the long term.

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Appendix

Table A1: Probit model used for propensity score

Variables	**Coefficient**	**Std. Error**
Gender (Base = Male)	-0.249***	0.054
Marital status (Never married)		
Currently married	0.266 **	0.110
Widowed	0.394 ***	0.121
Divorced	0.190	0.198
Social Group (Caste ST)		
SC	-0.353 ***	0.038
OBC	-0.416 ***	0.032
Others	-0.042	0.038
Education (No formal education)		
Basic education	0.165 ***	0.028
Secondary education	0.206 ***	0.036
Higher education	0.512 ***	0.061
Age	-0.002 *	0.001
Household size (hhsize1)	0.050 ***	0.006
Land area	-0.015 **	0.006
Square of land area	0.000 **	0.000
Proportion elderly	0.154 ***	0.060
Proportion children	-0.007	0.068
Wealth (quintile 1)		
Wealth quintile (2)	-0.142 ***	0.034
Wealth quintile (3)	-0.312 ***	0.035
Wealth quintile (4)	-0.238 ***	0.042
Log of MPCE	-0.231 ***	0.030
Major income activity		
Self-employment	-0.178 ***	0.061
Wage labor	-0.138 **	0.069
Casual labor	-0.255 ***	0.062
Constant	1.509 ***	0.280
Observations	**13,433**	

Note: *** p<0.01, ** p<0.05, * p<0.1

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