Gendered Time Use: Do Community Food Programs Affect Women's Labour Force Decisions?

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March 26, 2025

Abstract

Women in India face barriers to labor force participation due to entrenched gender norms, with rural women spending 301 minutes daily on unpaid domestic work compared to 98 minutes for men (TUS 2019). Cooking chores are a major constraint, limiting time for paid work. While subsidized food programs like Tamil Nadu's Amma Canteens primarily target food security, their impact on easing domestic burdens and boosting women's employment remains largely underexplored. Using TUS 2019 data, this study analyzes cooking time and employment outcomes across treated and control districts, employing different econometric methods. Findings show that subsidized food schemes reduce women's cooking time by 20–48 minutes daily, correlating with increased labor force participation. Additional factors like urbanisation, education, and access to clean cooking fuels also influence these patterns. This study highlights the role of welfare programs in addressing gendered domestic constraints, emphasizing their potential to enhance women's economic participation and broader economic development (Duflo, 2012).

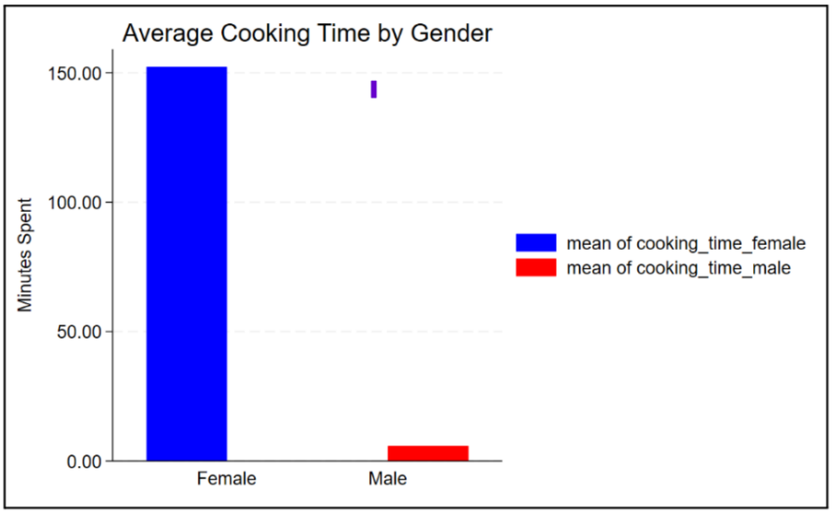
*This paper was written under the guidance and supervision of Professor Ashwini Deshpande. We thank her for her inputs and suggestions throughout the process.

1 Introduction

Gender norms in India have historically characterized women as the primary caregivers. Consequently, women spend a substantial amount of time daily on household activities. According to the Time Use Survey (TUS 2019), rural women spent 301 minutes per day on unpaid domestic services[1], while rural men spent 98 minutes per day on the same tasks. This reflects the participation rate recorded for these tasks: 82.1% for rural women and 27.7% for rural men. Graph 1 highlights the difference in time spent on domestic tasks by men and women throughout the country.

An extensive range of scholarship has noted the correlation between this *traditional* division of work and women's decision-making (Badgett, 1999; Bridges et. al, 2011; Ferrant et. al, 2014). In particular, different employment surveys provide information on the chores performed by women and related economic benefits. Using NSSO data, Mehta and Pratap (2017) study the significance of women's *principal activity status* in their employment. They argue that tasks such as maintaining gardens and poultry, collecting firewood, and preserving meat are incorrectly categorized as *not working.* In this paper, we attempt to examine what opportunities arise when Indian women spend less time cooking.

Figure 1: Graph 1. Average time in minutes spent on cooking by males and females across the country.



Subsidized food programs in India originally emerged to address food security and policy concerns, particularly amongst the urban poor. These schemes aim to provide nutritious meals at extremely affordable prices. The concept gained attention, particularly after the launch of Amma Canteens[2] in Tamil Nadu in 2013. Their success had trickle-down effects – with each canteen employing 12 to 16 women (Mahendran and Indrakant, 2021). Soon, several states replicated this model – the Aahaar scheme was kickstarted in Odisha in 2015, Indira Canteens in Karnataka in 2017 and Annapurna Rasoi in Rajasthan in 2020.

[1]This included cooking, cleaning, pet care, etc.

[2]The scheme, started by then CM Jayalalitha, widely grew in prevalence and popularity

By providing affordable meals, these schemes not only affect food insecurity but also the economic and time burden of household meal preparation. The time spent on these tasks by women, who primarily bear these responsibilities, can be redirected towards other opportunities. These could take the form of income-generating activities or acquiring skills to eventually earn. In this paper, we aim to study this relationship. We argue that subsidized food schemes reduce domestic time constraints for women, freeing up their time towards productive tasks. This will further contribute to women's labour force participation rates (LFPR). Using the TUS 2019 data, we examine the time spent on cooking and paid activities in regions with subsidized food schemes and those without.

2 Overview and Context

Trends in womens Labour Force Participation Rate (LFPR) in India have seen notable fluctuations over the years. The increases in LFPR have been attributed to the generation of self-employment and an increase in service sector jobs. On the other hand, decreases have been thought to be due to barriers to workforce entry. Gendered expectations of responsibilities limit womens time for paid work (Deshpande, 2021). Rising education levels have also led to delays or forgone entries into the labour force, particularly due to a skill mismatch (Andres et. al, 2017). Insufficient childcare facilities and poor logistical factors (such as public transportation) are additional deterrents (Klasen and Pieters, 2015).

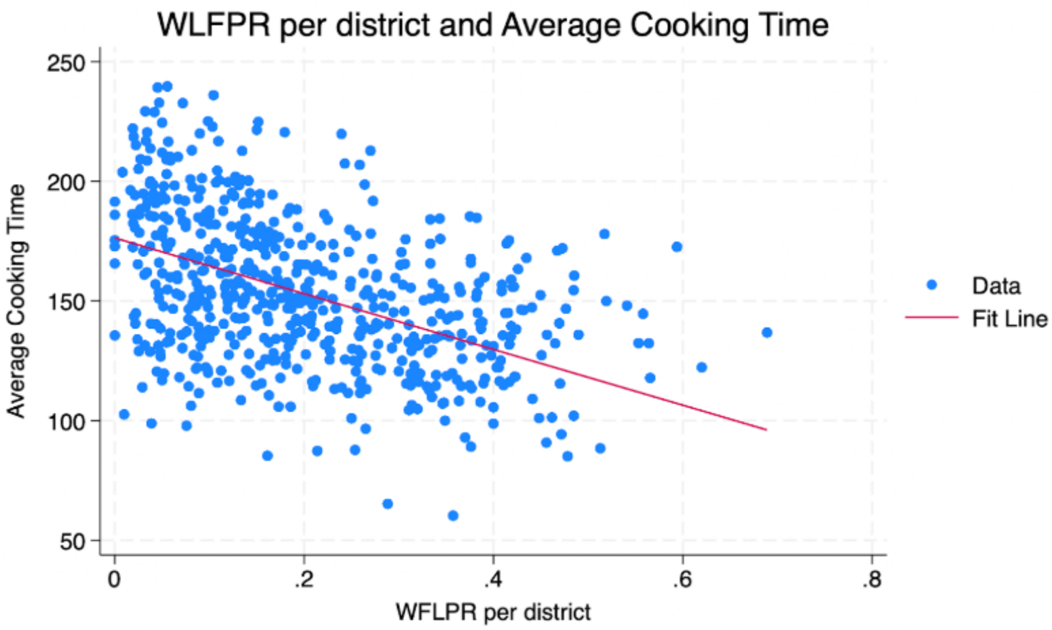
The challenge that domestic responsibilities pose to labour participation has been studied from the perspective of childcare in particular. Outsourcing this work removes hurdles to women's ability to engage in paid employment. Nandi et. al (2020) conduct a randomized trial in rural Rajasthan – assessing how access to affordable daycare helps women's economic outcomes two years later. They find that it increases the probability of women engaging in paid work by 2.6 percentage points. Another study that examines this phenomenon utilizes data from the Integrated Child Development Scheme (ICDS). It records an 8% increase in the probability of mothers finding employment, relative to the mean at baseline (Biswas and Adkins, 2024).

Other work has focused on the undervaluation of care work in India. Even paid care work, through Anganwadi centres and the Integrated Child Development Scheme, is underpaid and given limited recognition (Palriwala and Neetha, 2010). These tasks are characterized as being inherently "feminine." Overall shocks to the economy leave women even worse off: Deshpande (2021) records how the Covid-19 pandemic worsened the burden of domestic chores for women.

Wealth, marital status, caste and religion are all important factors to consider. A study of households in West Bengal finds that women being in charge of domestic chores lowers their probability of "working" (Deshpande and Kabeer, 2019). It documents that social markers such as religion do not significantly impact this figure. Other studies highlight the continued relevance of the caste gap in differential reactions to labour market shocks (Deshpande and Ramachandran, 2023). Intersectionality can play differing, region-specific roles in labour market outcomes.

Domestic burdens can also be reduced by technological advancements. Su and Azam (2023), using the TUS data, examine the impact of Liquified Petroleum Gas (LPG) on cooking time, and subsequently, their employment (2023). They find that employment marginally increases as a result of LPG availability. This is in line with similar findings globally: as households in Sub-Saharan Africa used better more efficient types of fuel[3], female labour participation rates saw improvement (Uchenna and Oluwabunmi, 2020). Their results show that earlier fuels had a high cost in terms of women's productive time.

Figure 2: Graph 2. Preliminary estimation of average time spent on cooking by females vs WLFPR of each district



In this study, we aim to highlight how gender norms pervade women's lives, affecting their choices, decisions and employment status. We specifically look at the time Indian women spend cooking – and how food schemes lead to reductions in the same. This, as established, can lead to increased labour participation. A preliminary visualization of the relationship between the time spent on cooking across states and WLFPR can be seen in Graph 2[4]. Increases in women's LFPR are crucial to India's overall growth picture, in terms of both economic and social welfare targets. The benefits of an increased workforce span different sectors – poverty reduction, gender equality and GDP growth. In developing countries, a 10% increase in women's participation in the labour market leads to a 3 to 5% increase in GDP per capita (Duflo, 2012). Despite this, Indian women contribute only 17% to the country's GDP in the status quo (World Bank, 2022). India's gender gap contributes significantly to the world average – when it is controlled for, the global number decreases by 10 percentage points (World Bank, 2022). The argument we put forth, points to the importance of incorporating norms in policy and labour market

[3]In comparison with solid fuel, which is less efficient

[4]The Women's Labor Force Participation Rate (WLFPR) for each district was estimated by calculating the average of the "paid employment status (women)" variable for each district

decisions. The study itself is restricted to a select sample of regions. We look at certain districts that experience(d) a subsidized food scheme at the time of the TUS survey vis a vis those that did not experience such a scheme.

3 Methodology

3.1 Data and Sample Collection

We examine the time spent by women on cooking using data from the Time Use Survey, 2019. The survey, conducted by the Ministry of Statistics and Programme Implementation, captures time use over a 24-hour period. The dataset records the time spent by men, women and other groups of people on paid and unpaid activities. It specifically has records of time spent on domestic tasks such as cooking, caregiving and cleaning. The dataset captures these patterns across 1,38,799 households and 4,47,250 individuals. This includes 2,73,195 individuals from rural areas and 1,74,055 from urban areas. For the purpose of the survey, each household in the sample was visited once.

Respondents were given a 24-hour recall period, and information was collected about activities they participated in from 4.00 AM the previous day to 4.00 AM on the day of the interview. This reference period was split into 48 time slots, of 30 minutes each. The survey was conducted over four sub-rounds that spanned a year. An equal number of subunits (divisions of regions based on populations) were surveyed in each subround. Hence, the data is cross-sectional, not longitudinal. This limits our analysis somewhat – it cannot have temporal elements. Most variables in the dataset are standard and were used in the original form. Activities in the data are categorised based on the International Classification of Activities for Time Use Statistics (ICATUS 2016), with 3-digit codes.

Treated District	**State**	**Scheme**	**Control District**	**State**
Chandigarh	Chandigarh	Annapurna Akshaya Patra Yojana	Patiala	Punjab
			Sangrur (for placebo comparison)	Punjab
Annupur	Madhya Pradesh	Deen Dayal Yojana	Koriya	Chhattisgarh

Table 1: List of treated, control districts and schemes for Models 1 and 2

As established earlier, subsidized food schemes are prevalent throughout the country. However, there are certain limitations to studying all of these schemes. First, some schemes, like the Indira Canteen in Karnataka, faced logistical hurdles and partially shut down (Goudar, 2024). Typically, these shutdowns are due to infrastructural failures or changes in the state government. Second, data on the spread and locations of food canteens under schemes is not readily accessible for every state. For example, while the existence of the Antyodaya Anna Yojana in Jharkhand is known, records of where the scheme is located within the state are not accessible. Hence, for the purpose of this paper, we worked on an elimination basis. Starting with a list of states and their subsidized food schemes, we shortlisted on two counts. First, we checked for the active status of the scheme's operation in 2019, when the TUS data was collected. Second, we checked for records of districts within the state where the scheme was located. Based on the above, we constructed a sample that comprises three pairs of a 'treated' district and a 'control' district each.

Three models make up our empirical framework: the first is a baseline regression, the second has additional control variables to the same regression framework and the third is based on the method of 'Propensity Score Matching (PSM).' Using three models helps ensure the robustness of our results.

In Models 1 and 2, districts are classified as 'treated' if they experienced a subsidized food scheme conducted by their state government in the year 2019. On the other hand, they are classified as 'control' if they did not experience a scheme at that point in time. The treated districts, the scheme they experienced, and the control district that they are weighed against are listed in Table 1. In the TUS data, we retain female data points from these select districts. The TUS questionnaire records time spent on 'food and meals management and preparation.' This is recorded within a variable called 'cooking time' for all individuals and 'cooking_time_female' for the retained data points. The stratifying of the dataset results in a sample of count observations.

To account for the labour force participation of the individuals in the sample, we set up a variable called 'paid status'. The labour force participation is determined by identifying individuals whose principal activity status, as recorded in the TUS questionnaire, falls under codes below 81. This classification includes all individuals engaged in self-employment, salaried employment, or casual employment, ensuring that all economically active individuals are accounted for in the labour force. The summary statistics of these variables and the other demographic factors involved are listed in Table 2. To account for the effect of various demographic factors on the relationship we are studying, we included covariates. Initially, these are limited to age, education and marital status. While 'age' and 'marital_status' are taken as given in the TUS data, education was a continuous variable. Hence, we condensed it into six categories[5]. We also use controls for 'Urban Residency,' 'Monthly Consumption,' 'Social Group' and 'Religion.' Again, these variables were taken in their standard form as in the dataset. 'Urban Residency' and 'Monthly Consumption' were also aggregated to a district level average for further analysis.

Additionally, for the last section of our analysis, we use the NFHS dataset. This helps us in our PSM framework, explained further in the empirical framework. The NFHS survey offers district-level indicators on population, health, nutrition, etc. across the country. These help in matching comparable districts on the basis of different demographic factors. These are listed further in the framework. In Model 3 (PSM), we consider districts that have experienced a subsidized food scheme in the year 2019 to be 'treated' and all other districts to be 'control.'

3.2 Summary Statistics

Table 2 shows the mean and standard deviation of relevant variables and demographic factors. In treated districts, 36.6% of the sample resides in urban areas, while 39.4% of

[5]Illiterate, primary, middle and sec, higher sec, graduates and above

the control sample is urban. Additionally, 61.75% of the sample is classified as *married*, with the remainder as *not married* or *widowed/divorced/separated*.

As explained above, education is classified into six categories. 26.16% of women in the sample are illiterate, 54.02% have attained primary education and 9.92% have completed middle or secondary school. Meanwhile, 0.65% have completed higher secondary, 9.25% are graduates and above. 77.5% of the sample believed in Hinduism, 12.5% believed in Islam, 5.6% believed in Christianity. 1.83% believed in Sikhism, 0.26% in Jainism and 0.90% in Buddhism. Finally, 0.02% of the sample believed in Zoroastrianism and the rest classified as others. The monthly consumption in the treated areas averaged Rs.6043, while in the untreated areas, it averaged Rs.6683.

Table 2: Summary Statistics

Variable	**Treated (n=12,624)**	**Control (n=189,661)**
	Mean (Std. Dev.)	*Mean (Std. Dev.)*
Cooking Time (min)	145.25 (121.67)	153.60 (124.50)
Paid Status	1.01 (0.25)	1.02 (0.36)
Urban	0.37 (0.48)	0.39 (0.49)
Religion	1.11 (0.46)	1.46 (1.15)
Social Group (n)	2.62 (1.00)	2.86 (0.99)
Monthly Cons. Exp.	6,042.61 (4,005.84)	6,683.07 (4,022.36)
Age	33.57 (17.93)	34.92 (17.77)
Marital Status	1.79 (0.60)	1.84 (0.61)
Education (Index)	0.96 (1.00)	1.14 (1.10)
NFHS Variables	**Obs**	**Mean (Std. Dev.)**
Avg. Employment Rate	202,380	0.20 (0.12)
Urban Proportion	202,380	0.39 (0.25)
Avg. Monthly Cons. Exp.	202,285	6,643.10 (1,512.60)
Female Literacy (%)	202,246	76.08 (11.93)
Household Clean Fuel (%)	202,246	58.13 (23.30)
Population Sanitation (%)	202,246	72.18 (14.05)
Sex Ratio (per 1000)	202,246	1,020.65 (71.63)

Notes: Summary statistics are provided for treated and control groups in the first section. NFHS-specific variables are reported in the second section with corresponding standard deviations and ranges. The count of control observations is larger because more districts, including a placebo, are included in the control group.

The average time spent on cooking in those districts where a food scheme was present, is 145 minutes. On the other hand, in untreated districts, it is 154 minutes. While the difference here seems minute, it is significant in comparing specific pairs (when other factors are more or less similar). 19.12% of the sample classified as employed (had a usual principal activity status ¡ 81). Further, of those that are employed, 9.16% are engaged in self-employment, 4.88% in salaried labour, and 5.08% are engaged in casual labour. The NFHS indicators of the districts in the sample points to average employment being around 19%. Female literacy in these districts averages to 76%, while the measure of extent of sanitation among the population is 72%.

4 Effect of Cooking Time on Labour Participation

We set up an empirical framework to explore the relationship between subsidized food schemes and the differences in time spent on cooking by women. We compare treated districts to control or untreated districts, as defined above. We take on a three-fold approach: (1) a baseline regression focusing on border district comparisons, (2) enhanced regression models with additional control variables, and (3) propensity score matching (PSM) to address selection bias to ensure robust inferences.

4.1 Model 1: Baseline Regression

The first step in our empirical framework involves regressing the binary variable cooking_time on the following dependent variables. This is a baseline regression to compare cooking time across districts with and without subsidized food schemes. The regression model is specified as follows:

$$\begin{aligned}\text{CookingTime}_{ij} = \beta_0 + \beta_1\text{PaidStatus}_{ij} + \beta_2\text{Treated}_{ij} + \beta_3\text{Age}_{ij} + \beta_4\text{Age}_{ij}^2 + \\ \beta_5\text{Education}_{ij} + \beta_6\text{MaritalStatus}_{ij} + \epsilon_{ij}\end{aligned}$$

Here, CookingTime_{ij} represents the time spent on cooking by individual i in district j. PaidStatus_{ij} is a binary variable indicating paid employment. Covariates include age (with its square), education, and marital status.

In this setup, we use the regression model to estimate cooking time for individuals in both treated and untreated districts. The key coefficient of interest is that on the Treated binary variable. By comparing the coefficient for treated districts with that for untreated districts, we can directly assess the impact of the subsidized food scheme on cooking time.

4.2 Model 2: Enhanced Regression

To improve the precision of our estimates, we augment the baseline regression with additional covariates. These account for potential confounding factors. The enhanced regression is specified as:

$$\begin{aligned}\text{CookingTime}_{ij} = \beta_0 &+ \beta_1\text{PaidStatus}_{ij} + \beta_2\text{Treated}_{ij} + \beta_3\text{Age}_{ij} + \beta_4\text{Age}_{ij}^2 + \\ &\beta_5\text{Education}_{ij} + \beta_6\text{MaritalStatus}_{ij} + \beta_7\text{Urban}_{ij} + \beta_8\text{SocialGroup}_{ij} + \\ &\beta_9\text{MonthlyConsumption}_{ij} + \beta_{10}\text{Religion}_{ij} + \epsilon_{ij}\end{aligned}$$

Here, the key additions to the model include urban residency, social group and religion and monthly consumption expenditure. Urban residency accounts for differences in access to subsidized food schemes between urban and rural areas, which can significantly influence cooking patterns.

The social group and religion variables control for caste and religion-based disparities in time use and access to resources. Lastly, monthly consumption expenditure serves as a proxy for household economic status and helps differentiate the reliance on subsidized food schemes across income levels.

4.3 Model 3: Propensity Score Matching (PSM)

Finally, to address any selection bias—where districts with subsidized food schemes might systematically differ from untreated districts—we employ propensity score matching (PSM). This method ensures that treated districts are compared with untreated districts that have similar observable characteristics, thereby supporting the causal validity of our findings.

We estimate propensity scores using a logit model with the following covariates: average employment rate, urban proportion and monthly consumption expenditure, female literacy rate, percentage of households with clean cooking fuel, sanitation access and sex ratio, and percentage of women married below 18. The first covariate reflects economic activity levels that may correlate with scheme implementation and the second captures urbanization's influence on access to subsidized food schemes. The female literacy rate reflects the proportion of educated women, which may influence time use patterns. The cooking fuel variable represents the accessibility of resources that may reduce cooking time. The last few variables also represent broader social development indicators and socio-cultural norms that are relevant to our study.

We employ nearest-neighbor matching with a caliper of 0.1, ensuring that treated and untreated districts are closely matched in terms of their propensity scores. Post-matching, we compare the average cooking time between treated and untreated groups to estimate the average treatment effect.

In using this three-model framework, we attempt to achieve consistency in our results across different specifications. This approach ensures that our findings are not sensitive to the choice of model, providing more robust estimates of the effect of subsidized food schemes on cooking time and consequently, on labour participation.

5 Findings

Tables 3, 4 and 5 shows the results of the three estimations. We discuss the model-wise results below.

5.1 Model 1

Using Model 1, we first perform a pairwise comparison between Chandigarh (treated district) and Patiala (control district). We see that the coefficient on the 'treated' variable is statistically significant, suggesting that women in the treated district (Chandigarh) spend, on average, 20 minutes less on cooking compared to women in Patiala. This suggests that the implementation of the food scheme in Chandigarh has reduced the time spent on cooking activities by women. Next, we compare Anuppur (treated district) and Koriya (control district). The coefficient on the 'treated' variable is again significant. It shows that women in Anuppur spend 30 minutes less on cooking than those in Koriya.

We also use Sangrur and Patiala as placebo districts to test whether the observed difference in cooking time between treated and non-treated districts is due to the scheme itself. Both districts, being non-treated, should not show a significant difference (if the scheme is the true cause of variation in cooking time). The coefficient on the 'treated' variable in the placebo analysis is insignificant, indicating that there is no significant difference in cooking time between Sangrur and Patiala. This suggests that the observed variation in cooking time between treated and non-treated districts in the main analysis is likely the scheme itself, rather than other factors.

5.2 Model 2

In Model 2, we include additional controls such as social group, religion, monthly expenditure, and urbanicity, while testing the same pairwise comparisons as in Model 1. Our results remain largely consistent, with only minor adjustments, confirming the robustness of the initial findings.

For the comparison between Patiala and Chandigarh, the difference in time spent cooking by women in Chandigarh (treated) compared to Patiala (control) increases by 1 minute. In the placebo comparison between Patiala and Sangrur, the difference in cooking time remains insignificant. This indicates that the food scheme's effect is not being incorrectly attributed to non-treated districts, supporting the validity of the treatment effect.

When comparing Anuppur (treated) and Koriya (control), the time difference in cooking between the two districts is now approximately 27 minutes, which is a slight decrease from the 30 minutes observed in Model 1. Despite this adjustment, the result still shows a significant difference. Furthermore, the R^2 for all pairwise comparisons in this model increases, indicating that the additional controls help explain more of the variation in cooking time. This improvement in model fit suggests that the added factors—such as

Table 3: Impact of Food Scheme on Cooking Time

Variables	**Chandigarh vs Patiala** Coefficient (SE)	**Sangrur vs Patiala** Coefficient (SE)	**Anuppur vs Koriya** Coefficient (SE)
Treated District	-20.68^{***}	3.50	-30.96^{***}
	(6.89)	(6.22)	(10.89)
Paid Employment (binary)	-58.19	-39.11	42.42
	(64.13)	(34.99)	(102.26)
Age	7.45^{***}	8.09^{***}	7.12^{***}
	(1.16)	(1.03)	(1.63)
Age Squared	-0.10^{***}	-0.11^{***}	-0.09^{***}
	(0.01)	(0.01)	(0.02)
Marital Status (Reference: Never Married)			
Married	145.49^{***}	153.43^{***}	135.05^{***}
	(12.60)	(12.07)	(20.08)
Divorced	89.82^{***}	73.75^{***}	108.44^{***}
	(18.75)	(17.19)	(28.47)
Widowed	68.90	–	189.90^{**}
	(65.15)	–	(75.40)
Education			
Primary	4.20	18.52^{**}	19.69
	(9.62)	(9.02)	(13.86)
Middle & Secondary	23.83^{*}	28.30^{**}	71.16^{***}
	(12.80)	(12.15)	(22.36)
Higher Secondary	-68.58	-9.04	-93.69
	(45.95)	(53.65)	(103.94)
Graduates & Above	-15.72	24.18^{**}	60.39^{*}
	(11.70)	(11.90)	(33.81)
Constant	-40.48^{**}	-75.83^{***}	-40.64
	(19.07)	(17.54)	(27.99)
Observations	747	882	383
R-squared	0.4692	0.5159	0.4137
Adj. R-squared	0.4613	0.5103	0.3964

Notes: Robust standard errors are in parentheses. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$. Columns represent results for Chandigarh vs Patiala, Sangrur vs Patiala, and Anuppur vs Koriya, respectively. '–' indicates no data.

Table 4: Impact of Additional Covariates on Cooking Time

Variables	Patiala and Chandigarh Coefficient (SE)	Patiala and Sangrur Coefficient (SE)	Annupur and Koriya Coefficient (SE)
Treated (Reference: Untreated)			
Chandigarh	−21.97**		
	(8.54)		
Sangrur		9.24	
		(6.35)	
Annupur			−27.30**
			(12.33)
Age	7.27***	7.97***	6.86***
	(1.17)	(1.03)	(1.62)
Age Squared	−0.10***	−0.10***	−0.09***
	(0.01)	(0.01)	(0.02)
Education			
Primary	7.53	18.85**	14.29
	(9.77)	(9.13)	(13.93)
Middle & Secondary	29.53**	27.94**	61.11***
	(13.17)	(12.44)	(22.64)
Higher Secondary	−72.52	−21.27	−59.48
	(46.20)	(53.55)	(102.43)
Graduates & Above	−6.35	25.39**	38.43
	(12.43)	(12.50)	(35.86)
Marital Status (Reference: Never Married)			
Married	143.93***	153.46***	143.27***
	(12.64)	(12.00)	(20.13)
Divorced	87.54***	74.39***	118.75***
	(18.83)	(17.09)	(28.36)
Widowed	73.22		191.47**
	(65.09)		(74.79)
Urban	−19.40**	−8.76	2.42
	(8.91)	(8.15)	(13.41)
Social Group (Reference: ST)			
SC	−15.83	−94.91	40.28**
	(41.09)	(64.79)	(15.54)
OBC	−10.56	−99.21	24.03*
	(41.66)	(64.94)	(13.58)
Others	−13.00	−100.06	5.47
	(40.93)	(64.82)	(21.60)
Religion (Reference: Hinduism)			
Islam	17.43	−56.63***	44.58
	(20.54)	(19.17)	(33.04)
Christianity	−25.64	−37.75	6.77
	(52.45)	(64.87)	(33.52)
Sikhism	−22.76***	−23.62***	
	(8.44)	(7.66)	
Jainism	−74.56	−86.98	34.20
	(52.91)	(53.21)	(44.55)
Monthly Cons. Exp.	−0.0003	0.0008	0.0036**
	(0.0010)	(0.0009)	(0.0014)
Constant	−8.76	31.75	−76.13***
	(46.79)	(67.95)	(28.98)
Observations	747	882	383
R-squared	0.480	0.531	0.447
Adj. R-squared	0.465	0.520	0.418

Notes: Standard errors in parentheses. *** p< 0.01, ** p< 0.05, * p< 0.1.

social group, religion, and urbanicity—are relevant in explaining the differences in cooking time across districts.

5.3 Model 3

Model 3, which uses Propensity Score Matching, provides further evidence. In the unmatched comparison, women in the treated districts (e.g., Chandigarh, Anuppur) spend, on average, 8.35 minutes less on cooking compared to those in control districts (e.g., Patiala, Koriya). This is statistically significant. This suggests that the implementation of food schemes in treated districts is associated with a reduction in cooking time.

Table 5: Logistic Regression Results and ATT Estimates

Logistic Regression Results

Variable	**Coefficient**	**Std. Err.**	**z**
Cooking Time	-0.0005505***	(0.0000886)	-6.21
Avg. Employment Rate	6.960536***	(0.0975205)	71.38
Middle Male %	0.0041275***	(0.0002354)	17.53
Urban Proportion	3.852368***	(0.0698606)	55.14
Avg. Monthly Cons. Exp.	-0.0003078***	(0.0000081)	-37.80
Women Married Below 18	-0.0554968***	(0.0012964)	-42.81
Female Literacy %	-0.0667095***	(0.0015087)	-44.22
Households with Clean Fuel %	-0.0649049***	(0.0008372)	-77.53
Sanitation Access %	-0.0365542***	(0.0011776)	-31.04
Sex Ratio	-0.0235014***	(0.0002418)	-97.21
Constant	31.36959***	(0.3040781)	103.16

ATT Estimates

Variable	**Sample**	**Treated**	**Controls**	**Difference (S.E.)**	
Cooking Time	Unmatched	145.246	153.595	-8.349 (1.143)	$t = -7.30$
	ATT	145.246	194.218	-48.972 (9.241)	$t = -5.30$

Note: ***p< 0.01, **p< 0.05, *p< 0.1. Standard errors in parentheses. ATT results indicate the Average Treatment Effect on the Treated. Standard errors do not account for the estimation of the propensity score.

After applying propensity score matching (PSM) to control for observable socio-economic characteristics, the average treatment effect on the treated (ATT) reveals a substantial reduction in cooking time: women in treated districts spend 48.97 minutes less on cooking compared to those in control districts. This reduction is larger than the differences observed in Model 1 (30 minutes) and Model 2 (27 minutes), highlighting the improved balance achieved through matching in Model 3.

The logistic regression coefficients used in the propensity score estimation indicate how various factors influence the likelihood of being in a treated district. Specifically, higher employment rates, a greater proportion of urban households, and higher average monthly consumption expenditure are associated with a higher probability of treatment (i.e., being in a district with the intervention). In contrast, higher female literacy rates, a greater proportion of marriages under 18, and better access to clean fuel and sanitation are associated with a lower probability of treatment.

Some of these relationships may seem counterintuitive at first glance. For instance, one might expect higher employment rates and urbanization to correlate with better socio-economic conditions, making treatment less likely. However, this pattern could reflect targeting strategies where programs are implemented in areas with a mix of both need and administrative feasibility.

In conclusion, our results consistently support the hypothesis that food schemes significantly reduce the time women spend cooking in treated districts. Across all three models—Model 1 (pairwise comparison), Model 2 (with additional controls), and Model 3 (Propensity Score Matching)—we observe a clear and statistically significant reduction in cooking time for women in treated districts.

6 Discussion and Concluding Remarks

Subsidized food schemes have been lauded for their success in reducing food insecurity and poverty. These reasons have alone prompted their expansion throughout the country. Our analysis points to another clear benefit that arises from these schemes. By helping women somewhat escape their domestic burden, these schemes have the potential to significantly help labour force participation. As other work has made clear, they also help in directly employing women, by providing them with a paid avenue to perform what is considered domestic work.

A limitation of our analysis, however, is its cross-sectional design. Without access to time-varying data on cooking time, we rely on a single comparison between districts with and without subsidized food schemes. This restricts our ability to establish causality over time. Any observed differences in cooking time could be influenced by other unaccounted temporal factors, such as broader economic fluctuations or policy changes. These might be affecting cooking time independently, outside of the subsidy scheme. It is also challenging to isolate the long-term impacts of the food schemes from the short-term: to examine whether there are prolonged impacts from experiencing a scheme for longer. Additionally, lesser districts qualified for our analysis – they are relevant only if they experienced a scheme in 2019, at the time of the TUS survey.

The TUS data captures self-reported estimates of time spent on different activities, including cooking. This may not fully capture the intricacies of time use at the individual level, leading to potential measurement bias. Finally, our analysis assumes that the relationship between subsidized food schemes and cooking time is uniform across all districts, not accounting for potential heterogeneity in how different regions respond to these policies. Factors such as local cultural norms, access to alternative food sources, or varying levels of government enforcement could lead to differential impacts across districts, which our model does not fully address.

Our sampling has its disadvantages too. The small n-size limits the external validity of the results, making them less generalizable. The diversity of the country – broadly different bureaucracy, government types and infrastructure – means the results derived based on two states (Chandigarh and Madhya Pradesh) cannot be extended to all those that have experienced food schemes. However, our analysis lays the groundwork for future research on the subject. If data on more schemes and their implementation can be mined, the analysis can be extended to more states. Rural women likely face bigger hurdles in terms of the domestic responsibilities. Urban households often distribute the burden by employing domestic helpers (Deshpande, 2020). There is scope to examine micro-differences in rural and urban areas that have experienced a food scheme. While our two pairs are distinct in this sense – Chandigarh and Patiala are "urban" districts compared to Anuppur and Koriya – they do not provide enough basis to derive rural-urban inferences.

Women are, as a demographic, disproportionately harmed by shocks. Their contribution to the labour force, as noted earlier, has marked positive effects on the economy. Given this, the results of our paper are hopeful. They suggest that the empowerment of women can come through schemes that have multifold welfare benefits. As Duflo (2012) notes, pushing the lever of women's empowerment is a virtuous cycle, and sets off a series of developmental benefits. Ferrant (2014) posits what the analysis of this paper has reinforced: time use patterns reflect the attribution of gender roles. These govern activities and labour divisions, separated as "feminine" and "masculine." The argument this paper puts forth could represent a broader shift in undoing such norms through the reduction of cooking time. By providing a mechanism that eases this burden directly, food schemes may, in the long-term, weaken gender norms and women's overall economic participation.

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