Impact of Climate Shocks on Gender Division of Unpaid and Paid Labor: A Case Study from an Indian Coastal Hotspot

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Abstract

This paper examines impact of climate shocks on gender division of unpaid and paid labor in India. Given that over three-fourths of Indian districts are susceptible to extreme climate events, understanding their effects on intrahousehold dynamics is crucial. While the Unitary Household Model suggests that intrahousehold labor allocation does not matter for overall household welfare efficiency, Cooperative Bargaining Model contends that the intrahousehold distribution of welfare outcomes are unequal across individuals. The underlying theoretical framework relies on the Collective Household Model which shows that climate-induced labor supply depends on an individual's bargaining power and earnings. Utilizing 2019 August floods in Kerala, India, as a case study, the research employs difference-in-difference strategy. The objective is to compare gender disparities in time spent on unpaid household labor and paid labor force participation between "treatment" and "control" groups. Key results show that the flood event increases women's and men's unpaid household work by 12-13 hours per week and 6-7 hours per week respectively. However, the gendered effects of climate shock on labor force participation are not the same: women's participation in paid labor increased by 3 hours per week, while men's participation showed an insignificant decline. Marital Status and caregiving responsibilities towards children, elderly and disabled influence the relationship between climate shock and gender division of unpaid and paid labor. Access to time-saving technology or the ability to outsource domestic tasks does not significantly alleviate the impact of climate-induced changes on unpaid and paid labor for either men or women. Robustness checks with alternative definitions of treatment and control districts, accounting for factors such as poverty, migration caste and age, confirm the main findings.

Keywords: Climate Shock, Paid labor, Unpaid labor, Time Use, Gender

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Introduction

Globally, anthropogenic activities have led to rampant destruction and degradation of ecosystems resulting from greed, neglect, and the insatiable appetite of mankind. Human-led actions such as rapid urbanization, agricultural intensification, and industrial pollution have caused overexploitation of natural resources and their functions. According to the Intergovernmental Panel on Climate Change (IPCC), the global average temperature is likely to rise by at least 1.5°C in the next two decades (IPCC 2021). This is expected to exacerbate the frequency of climate extremes such as droughts, heatwaves, and flash floods. According to Global Climate Risk Index report (2020), India is among the top ten most affected countries by long run climate events. More than 3/4th of Indian districts is susceptible to extreme climate events (CEEW 2021).

Despite efforts to improve educational and labor force outcomes among young girls and women, biased attitudes against women such as child marriages, intimate partner violence, lack of asset ownership continue to be an acute social hazard in the global south. In patriarchal societies like India, social norms allocate women to carry out unpaid household chores, particularly, domestic work (e.g., cleaning, cooking, fetching water) and caregiving activities (e.g., childcare) while men are primarily expected to engage in paid activities. For example, there is a gender gap of 48 percent in paid labor force participation in India (World Bank 2021). Although unpaid household activities remain 'invisible' in national accounts and do not produce financial returns, women spend a considerable amount of their time in this type of work. For example, nearly 81.2 percent of Indian women spent about 8 hours per day on domestic and care work related to their own household members (Indian Time Use Survey 2019). Globally, about 40 percent of women opt out of the labor market due to their unpaid household responsibilities (Oxfam 2022).

Studies have found that climate shocks increase discriminatory behavior against women, such as child marriages, intimate partner violence, limited educational attainment, and health issues in South Asian and sub-Saharan African countries (e.g., Corno et al. 2017, Sorensen et al. 2018). Similarly, macroeconomic studies highlight the economic costs of unpaid work done by women (Folbre and Yoon 2007, Hirway 2015, Samman et al. 2016). Few studies have examined gendered effects of climate change events on paid jobs in agricultural sector (Afridi et al. 2022). Specifically, long term climate change events like droughts reduce women's workdays relative to men's in climate sensitive occupations like agriculture (Afridi et al. 2022). Understanding how men and women reallocate their time between unpaid household work and participation in paid labor force

in response to exogenous shocks such as climate events can explain the gender disparity in the labor market in affected regions.

Time use surveys show how much time an individual devotes to paid work, unpaid work and other activities. Unlike other household surveys, time use surveys highlight individual behaviors and preferences in terms of time allocation. This, in turn, has the potential to reflect behavioral resilience in the form of time use against exogenous shocks. Using the 2019 Indian time use survey, this study investigates the relationship between climate shock and gender division of unpaid and paid labor. To do this, I focus on the flash floods of coastal hotspot, Kerala in August of 2019 as case study. The underlying hypothesis is that extreme climate events, such as loss of income opportunities, depletion of natural resources, and health hazards, influence demand for unpaid household labor and supply for the paid labor force. In patriarchal societies like India, these effects are gendered due to social norms. Using a difference-in-difference strategy, key findings show that climate shocks lead to an increase in unpaid work by 12-13 hours per week in case of married women and 6-7 hours per week in case of married men in Kerala. In the context of paid labor force participation, the flood event results in a rise by about 3 hours per week for married women while it is insignificant for married men. In this regard, it is important to see the long run implications of the flood shock on gender division of unpaid and paid labor. However, the dataset only provides information till December 2019. Another limitation of the survey is that it is cross-sectional in nature. Nevertheless, the main findings remain robust after accounting for factors like poverty and migration—both of which are sensitive to climate change conditions. Moreover, caste and age play important roles in quantifying the gendered effects of climate shock on unpaid household labor and paid labor force participation. Besides, household technology and caregiving responsibilities affect gender division of unpaid household labor and paid labor. Additionally, marital status influences the relationship between climate shock and gender division of unpaid household labor for both men and women.

It is noteworthy that some communities in Kerala, such as the Nayars of Cochin and Travancore, the Ezhavas, and the Malabar Muslims of northern Kerala (Sebastian 2016), are predominantly matrilineal, which may influence social norms. However, this aspect is not captured in the current analysis due to the limitations of the time use survey, which only provides broad classifications for social groups—namely Scheduled Caste (SC), Scheduled Tribe, Other Backward Class (OBC), and Unreserved. It is important to distinguish that matriliny does not equate to matriarchy (Jeffery 2004). Additionally, it has been argued that decision-making power within these matrilineal communities was predominantly held by men (Jeffery 2004, Sebastian 2016).

The rest of the paper is organized as follows. Section 2 shows the relationship between climate shock and the gender division of paid and unpaid labor. Section 3 discusses the theoretical framework which showcases welfare distribution based on the type of work an individual does. Section 4 presents the case study utilized in this paper. Section 5 discusses the data sources used. Section 6 gives the empirical strategy. Section 7 shows the key results and heterogeneity effects. Section 8 presents robustness checks. Section 9 draws conclusions and highlights policy implications.

Relationship Between Climate Shock and Gender Division of Labor

Several studies have shown that there exist gender differences in paid and unpaid work: women, on average, spend more time on unpaid household work (e.g., domestic work, childcare), while men spent more time on paid jobs (e.g., Shelton 2006, Boye 2009, Wheatley et al. 2018, Gimenez-Nadal and Molina 2022, Kim 2022, Espino et al. 2024). In patriarchal societies, women primarily bear the bulk of household responsibilities, while men predominantly engage in paid employment. Such gendered social norms influence labor force participation and create gender disparities in income and economic wellbeing.

There are two economic theories used to examine the unequal distribution of labor across unpaid household and paid work. First, Becker's household specialization model (Becker 1981) utilizes unitary household model which assumes altruistic family members. According to this model, the source of household income does not matter for allocation of expenditure because both partners pool their resources irrespective of individual income. Early researchers utilized this unitary framework and maximized household utility function subject to household's budget constraint (Pitt, Rosenzweig, & Hassan, 1990; Alderman et al., 1995). But since unitary household function does not account for distinct individual preferences, it cannot adequately explain the distribution of welfare outcomes due to gender division of labor in a household. Higher burden of unpaid household work is related to lower levels of utility of individuals (Gimenez-Nadal and Molina 2014). The second explanation draws from bargaining theories, which emphasize the role of resources and power in determining the division of housework. The argument here is that since household chores are generally viewed as undesirable, the partner with more resources will negotiate to avoid them, while the one with fewer resources will take on more domestic responsibilities. This dynamic can occur in a cooperative framework (McElroy and Horney, 1981) or through collective decision-making models where decisions are made based on Pareto efficiency (Chiappori 1992, Browning

and Chiappori 1998). Despite different reasons, both these theories argue that the partner with higher market wages will spend less time in unpaid household work: In Becker's specialization model, this is due to economic rationality and comparative advantage while the bargaining theories argue that this is solely due to stronger bargaining positions.

While it can be argued that employment status influences the amount of unpaid household work done (Amarante et al. 2023), unemployed women carry out more unpaid household work than unemployed men (van der Lippe et al. 2018). Moreover, women spend more time on household work when their husbands are unemployed (van der Lippe et al. 2018). Gender gap in unpaid domestic work and childcare are caused by social norms (Gimenez-Nadal and Molina 2022). But it is the gender disparity in unpaid household work which makes it more difficult to increase women's labor force participation (Gimenez-Nadal and Molina 2022). Thus, social norms play a pivotal role in allocating unpaid and paid labor among household members.

Exogenous shocks can influence these norms and either expand pre-existing gender division of labor or contract them, with people of both genders spending more time on unpaid labor to cope with emergencies. Based on the recent global COVID-19 shock, Charmes (2022) reveal that women in developing regions, especially in Asia and the Pacific, have disproportionately borne the increased burden of unpaid domestic and care work during lockdowns, risking setbacks in gender equality. Conversely, in developed countries like the UK, there has been a slight rebalancing, with men increasing their participation in childcare and household duties during lockdowns. In Netherlands, Huls et al. (2021) find that people with partner and children, particularly, women spend more time on unpaid work compared to leisure.

Wilma Dunaway (2001) links women's labor to ecological crises: women are heavily involved in food production, water collection, and care work. Both gradual climate change and sudden climate extremes put significant stress on natural resources like land and water (Connolly-Boutin & Smit 2016; Navone 2021). This stress increases the time required for environmental resource-related domestic activities, such as collecting fuelwood and water, and food production for household members. Additionally, it reduces labor demand and income in climate-sensitive sectors like agricultural labor (Afridi et al. 2022; McKinsey 2020), leaving both men and women with more time out of the work force. While it is most likely for women to spend additional time in fulfilling unpaid household labor demands (Gimenez-Nadal and Molina 2014, van der Lippe 2018), it is less straightforward in case of men: they could either spend time in helping women by sharing unpaid household burden or utilizing the time in searching for paid jobs, that is, in labor force

participation. Thus, climate shocks can influence gender division of labor (and hence leisure). This is summarized in **figure 1**.

The Theoretical Framework

The cooperative approach recognizes that the allocation of resources within the household will depend on the respective 'weights' of household members[2]. Following Chiappori (1992, 1998), the conceptual framework relies on collective model. This approach is based on two fundamental assumptions: (i) there exists a decision process in the household and is stable; (ii) this process leads to Pareto efficient outcomes.

Assume that there are two types of agents only (i)—male (m) and female (f). A representative agent is endowed with a unit of time that can be allocated to (a) paid work (L_i), (b) unpaid household work, (c_i) leisure activities $(1 - L_i - d_i)$. Each agent derives positive utility from private consumption (c_i), household production (H_i) and leisure activities $(1 - L_i - d_i)$. But labor (both paid and unpaid) generates disutility $v(.)$ for paid labor[3] and $g(.)$ for unpaid labor[4]. Wages (w_i) are taken as given and assume for simplicity that the price of privately produced goods is unity. Then, the utility function of each agent is

$$U_m = u_m(c_m, H_m, 1 - L_m, -d_m) - v(L_m) \text{ ----- } (1.1)$$

$$U_f = u_f(c_f, H_f, 1 - L_f, -d_f) - v(L_f) - g(d_f) \text{ -----} (1.2)$$

Here, the utility is assumed to be well-behaved, i.e., increasing at a decreasing rate in all arguments. Furthermore, I assume that the disutility generated from unpaid labor is greater than that of paid labor. Here, I present an extreme case whereby only female agent derives disutility from unpaid household work while male agent does not. The rationale behind this stems from social norms by virtue of which male agent spends considerable amount of their labor time in paid work while women in unpaid household work.

Let θ be the Pareto weight for female agent and $(1 - \theta)$ be that of male agent within a household. Then, the utility maximization problem is:

$$Max_{c_i, H_i, d_i, L_i} (1 - \theta)U_m + \theta U_f \text{ -----} (2)$$

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[2] However, it assumes that all resources are allocated, and none are left on the table.

[3] $v' > 0; v'' < 0$

[4] $g' > 0; g'' < 0$

subject to

$$c_m + c_f \leq w_m L_m + w_f L_f \text{ ------(3)}$$

$$H_m + H_f \leq f(d_m, d_f), f' > 0, f'' < 0\text{------(4)}$$

On the production side, the production function of aggregate output produced using 'visible' labor is given by Cobb Douglas function:

$$Y = \eta(L_m + L_f)^{\alpha} K^{1-\alpha}\text{------(5)}$$

Where η is productivity parameter; $L = L_m + L_f$ is total labor employed and K is the (fixed) capital input; α being share parameter for labor.

The producer's profit maximization is:

$$Max_{L_m, L_f} \pi = \eta(L_m + L_f)^{\alpha} K^{1-\alpha} - (w_m L_m + w_f L_f)\text{-------(6)}$$

Profit maximization condition requires wage rate of male agent and female agent to be equal: $w_m = w_f = w^*$ (say).

An exogenous climate shock, denoted by C, reduces profit maximizing aggregate labor demand ($L^* = K\left(\frac{\alpha\eta}{w}\right)^{\frac{1}{1-\alpha}}$ and hence depresses profit-maximizing wage rate (i.e., $\frac{dw^*}{dC} < 0$).

The solution to the utility maximization problem gives unpaid household labor and paid labor supply functions for male and female agent, each of which is function of parameters (w_i, θ). Since I am interested in observing how the climate shock influences gender division of labor, I look into the difference in unpaid and paid labor supply functions between male and female agents. These are expressed as following:

Case I: Paid Labor Supply

$$\frac{dL_f}{dC} = \left(\frac{dL_f}{dw_f} \times \frac{dw_f}{dC}\right) + \left(\frac{dL_f}{d\theta} \times \frac{d\theta}{dC}\right) \text{ ----(7a)}$$

$$\frac{dL_m}{dC} = \left(\frac{dL_m}{dw_m} \times \frac{dw_f}{dC}\right) + \left(\frac{dL_m}{d\theta} \times \frac{d\theta}{dC}\right) \text{ ----(7b)}$$

Each of $\frac{dL_i}{dw_i}$ and $\frac{dL_i}{d\theta}$ can be obtained from solving system of linear equations using the double derivatives of utility function[5]. Let $\frac{dL_i}{dw_i} = \frac{A_i}{B_i}$ and $\frac{dL_i}{d\theta} = \frac{C_i}{D_i}$

Then, both 7a and 7b can be written as

$$\frac{dL_f}{dC} = (\frac{A_f}{B_f})(\frac{dw_f}{dC}) + (\frac{C_f}{D_f})(\frac{d\theta}{dC})\text{----(7c)}$$

$$\frac{dL_m}{dC} = (\frac{A_m}{B_m})(\frac{dw_m}{dC}) + (\frac{C_m}{D_m})(\frac{d\theta}{dC})\text{ ----(7d)}$$

(7c) and (7d) show how climate shock influences paid labor supply depends not only on the impact on wages but also on the bargaining power. Under well-behaved circumstances, labor supply as function of wage is positively sloped. That is, $\frac{A_i}{B_i} > 0$. But it has been shown in the above production sector that climate shock contracts wage rate. So, $\frac{dw_i}{dC} < 0$. Thus, $\left(\frac{A_i}{B_i}\right)\left(\frac{dw_i}{dC}\right) < 0$.

In the preceding section, I discussed how climate shock increases unpaid household labor of women which may leave them with lesser time for self-care/productivity enhancing activities or switching jobs from one sector (e.g., agriculture) to another (e.g., non-agricultural sector). With lesser economic empowerment, women become more vulnerable to climate change scenario (cite some literature) and their bargaining power declines. By this argument, $\frac{d\theta}{dC} < 0$. Studies on bargaining power and labor force participation show varying results, especially in case of women (Moeeni 2019, Miller and Bairoliya 2021). For instance, Miller and Bairoliya (2021) show that bargaining power and labor supply function has inverse relationship: as the bargaining power of a woman rises, her formal labor supply declines. On the contrary, Moeeni (2019) show that female labor force participation has an inverse U-shaped relationship with their own bargaining power. Hence, if I assume that the female agent, here, has bargaining power below the threshold level, $\frac{C_f}{D_f} > 0$. But if I follow Miller and Bairoliya (2021), then $\frac{C_f}{D_f} < 0$. Hence, if $\frac{C_f}{D_f} > 0$, $\frac{dL_f}{dC} < 0$ and if $\frac{C_f}{D_f} < 0$, the net sign of $\frac{dL_f}{dC}$ is ambiguous and depends on the relative strength of $(\frac{C_f}{D_f})(\frac{d\theta}{dC})$ and $(\frac{A_f}{B_f})(\frac{dw_f}{dC})$.

According to different studies, women's bargaining power is often positively related to their men's labor force participation. Following the two-person household model in Miller and Bairoliya (2021), $\frac{C_m}{D_m} > 0$. That is, increase in female agent's bargaining power increases male agent's paid labor supply. While Moeeni (2019) did not explicitly look into the relationship between women's bargaining power and men's labor force participation, the study does show that women's

[5] The entire solution is based on 10 x10 matrix which comprises of 10 linear equations and 10 variables. The general solutions are quite large and hence used simple representations like A, B, C, D.

bargaining power is often associated with husband's higher education and wealth---both of which are strong indicator of men's positive labor supply. Thus, $\frac{C_m}{D_m} > 0$. Hence, $\frac{dL_m}{dC} < 0$.

Combining all the above arguments, the sign of $(\frac{dL_f}{dC} - \frac{dL_m}{dC})$ depends on (i) the sign of $\frac{C_f}{D_f}$ and (ii)magnitude of $\frac{dL_f}{dC}$ and $\frac{dL_m}{dC}$. If $\frac{dL_f}{dC} < 0$, the gender division of paid labor is favorable towards female only if the magnitude of $\frac{dL_f}{dC}$ is less than that of $\frac{dL_m}{dC}$.

Case II: Unpaid Household Labor Supply

$$\frac{dd_f}{dC} = (\frac{dd_f}{dw_f} \times \frac{dw_f}{dC}) + (\frac{dd_f}{d\theta} \times \frac{d\theta}{dC}) \text{ ----(8a)}$$

$$\frac{dd_m}{dC} = (\frac{dd_m}{dw_m} \times \frac{dw_f}{dC}) + (\frac{dd_m}{d\theta} \times \frac{d\theta}{dC}) \text{ ----(8b)}$$

Each of $\frac{dd_i}{dw_i}$ and $\frac{dd_i}{d\theta}$ can be obtained from solving system of linear equations using the double derivatives of utility function[6]. Let $\frac{dd_i}{dw_i} = \frac{E_i}{F_i}$ and $\frac{dd_i}{d\theta} = \frac{G_i}{H_i}$. Then (8a) and (8b) can be written as:

$$\frac{dd_f}{dC} = (\frac{E_f}{F_f} \times \frac{dw_f}{dC}) + (\frac{G_f}{H_f} \times \frac{d\theta}{dC}) \text{ ----(8c)}$$

$$\frac{dd_m}{dC} = (\frac{E_m}{F_m} \times \frac{dw_m}{dC}) + (\frac{G_m}{H_m} \times \frac{d\theta}{dC}) \text{ ----(8d)}$$

(8c) and (8d) show how climate shock influences unpaid household labor demand is not independent of market wage earnings of each agent. The effect depends on both the bargaining power and wage earnings from paid work. From the production side, it has been observed that $\frac{dw_i}{dC} < 0$. By similar arguments from the case of paid labor supply (Case I), $\frac{d\theta}{dC} < 0$. How a climate shock affects unpaid household labor of female and male agents, therefore, depends on $\frac{E_i}{F_i}$ and $\frac{G_i}{H_i}$. Most studies have shown that a woman's earnings have strong inverse relationship with her unpaid household work which means $\frac{E_f}{F_f} < 0$ (Bittman et al. 2003, Carlson and Lynch 2017). Similarly, for men, increase in housework is associated with decline in their earnings (Carlson and Lynch 2017), that is, $\frac{E_m}{F_m} < 0$.

Studies have shown mixed results when it comes to understanding the relationship between bargaining power and unpaid household work. Apparently, reduction in bargaining power of a woman relative to her husband can increase her unpaid work burdens such as caregiving responsibilities (Miller and Bairoliya 2021). But Fengdan (2016) shows that bargaining power has

[6] The entire solution is based on 10 x10 matrix which comprises of 10 linear equations and 10 variables. The general solutions are quite large and hence used simple representations like E,F,G,H.

no significant effect on women's unpaid household work while it has inverse relationship with men's unpaid household work. Cárdenas-Retamal (2023) show that increase in women's bargaining power can reduce her unpaid household work but "women continue to spend more time on domestic activities than men" even when they have the ability to bridge the gap between paid and unpaid labor. These arguments highlight that Thus, $\frac{G_f}{H_f} \leq 0,\ \frac{G_m}{H_m} < 0$.

Combining all the above discussions, both $\frac{dd_m}{dC}$ and $\frac{dd_f}{dC}$ are positive. If $\frac{G_f}{H_f} = 0$, $(\frac{dd_f}{dC} - \frac{dd_m}{dC}) < 0$. This implies that the gender division of unpaid labor is unfavorable to men compared to women in the aftermath of climate shock. However, if $\frac{G_f}{H_f} < 0$, the sign of $(\frac{dd_f}{dC} - \frac{dd_m}{dC})$ depends on the magnitudes of $\frac{dd_f}{dC}$ and $\frac{dd_m}{dC}$.

The Case Study: 2019 Kerala Flood

Located on the southwestern coast of India, Kerala is highly vulnerable to climate vulnerability. More than 70 per cent of Kerala's population resides in coastal districts which creates immense pressure on its shoreline (Census 2011, Estimated Census 2024). In fact, a study by National Centre for Coastal Research shows that almost one-third of Indian coastline, including Kerala's, has eroded in the past two decades (NCCR 2022). The state has faced recurring extreme climate events, such as the catastrophic floods in 2018 and 2019. The 2018 flood, occurring from June to August, claimed 500 lives (NDMA 2018), while the 2019 flash floods and landslides further devastated the region.

Between August 8 and 31, 2019, Kerala experienced a deluge, affecting 1038 villages across 14 districts (Kerala State Disaster Management 2019). This extreme climate event claimed 125 lives and severely affected sectors like housing, power, and agriculture (Kerala State Disaster Management 2019). The onset of the monsoon was initially weak and delayed, but the situation escalated in August due to a low-pressure area and depression over the Bay of Bengal, resulting in 123 per cent excess rainfall compared to the average (Kerala State Disaster Management 2019). Over 200,000 people were affected (Kerala State Disaster Management 2019).

Using district-level data on various factors, including excess rainfall, crop land loss, and affected fish farms, among others, I computed Principal Component Analysis (PCA) scores and rescaled the index to keep the values between 0 and 1. The higher the value, the higher the extent of

damage. A detailed description of these variables is provided in the **Appendix**. Districts with PCA score exceeding 20 percent were categorized as treated districts, while those with scores below 20 percent were classified as control districts. Details on the PCA scores are also included in the **Appendix**. **Figure 2** illustrates the affected districts on the state map, marked in blue.

The agriculture sector, crucial to Kerala's economy, suffered significant damage. Small and marginal farmers were particularly affected, leading to substantial losses in crop production. Over 33 per cent of agricultural areas were damaged, resulting in estimated losses of INR 358.667 million (Kerala State Disaster Management 2019). Approximately 6244.37 hectares of agricultural land were affected with districts like Palakkad and Malappuram bearing most of the losses (Kerala State Disaster Management 2019).

The floods also severely impacted Kerala's fishery sector. A total of 54 boats were fully damaged, and 696 nets were fully destroyed, resulting in a total financial loss of INR 1.8 million (Kerala State Disaster Management 2019). Additionally, fish farms across the state incurred significant losses, with approximately 7081.85 hectares affected, particularly in districts like Thrissur (Kerala State Disaster Management 2019).

Public infrastructure, especially roads and bridges, suffered extensive damage, hampering transportation and connectivity. For example, around 3900.17 kilometers of roads were damaged (Kerala State Disaster Management 2019). The estimated cost for immediate restoration of roads stands at nearly INR 390 million (Kerala State Disaster Management 2019). Additionally, 95 bridges were damaged, with Palakkad district reporting the highest number of damaged bridges (21) (Kerala State Disaster Management 2019). This caused an approximate INR 164.5 million in funding for repairs (Kerala State Disaster Management 2019).

Data

Time use surveys are an important tool to understand how individuals allocate their time to various activities which broadly include paid work, unpaid work, leisure and personal care. By tracking how time use changes in response to external shocks like economic crises, climate events, these surveys can gauge behavioral resilience. For example, these data can show how individuals can reallocate their time between various activities, broadly between unpaid household responsibilities and paid labor force to cope up with climate shocks. The detailed features of time use surveys such as temporal and spatial resolution, robustness and representation are particularly

valuable for developing models in various domains (Osman and Ouf 2021). Time use data collected on various activities, locations, age, sample, survey period, multi-member households and simultaneous activities can improve accuracy and applicability of various household models (Osman and Ouf 2021). Standard micro surveys like labor force surveys, often under-represent or exclude unpaid household activities, leisure and self-care which are significant parameters of well-being. By shedding light on various unpaid household activities, time use surveys can explain gender disparities in labor market participation.

2019 Indian Time Use Survey

This analysis relies on the most recent Indian time use survey from 2019 which comprises information from 138,799 households and a total of 447,250 individuals aged 6 years and above. This dataset spans four sub-rounds across the year 2019:

(i) January-March
(ii) April-June
(iii) July-September
(iv) October-December

Since the flood shock happened during August in Kerala, I utilize data on Kerala households, with the first two sub-rounds as pre-event periods and the fourth sub-round as post-event period. In this study, I am particularly interested in the time allocation to (a) unpaid household work; (b) paid labor force participation for married individuals. Here, unpaid household work includes both domestic work and care work for other household members. That is, the time spent on unpaid household work is the sum total of time spent on domestic and care work. Participation in paid labor force includes working in paid jobs, seeking employment, and/or setting up business. The rationale behind focusing on married individuals is to be in line with the theoretical framework which discusses the distribution of welfare change among married individuals due to exogenous shock. Table 1 gives the list of activities under both unpaid household work and paid labor force participation.

Descriptive Statistics

The Indian Time Use Survey categorizes reported activities into major and minor activities. According to the survey, an activity is classified as a major activity if it was deemed the most important by the informant during a given time slot. If only one activity was performed during a time slot, it was always classified as major. Conversely, if multiple activities were performed, one

activity was designated as major, while the remaining activities were categorized as minor. **Table 2** presents the proportions of married men and married women who identify unpaid and paid work as major or minor activities in Kerala. This classification provides insight into the prevailing norms related to these two broad types of work. Additionally, the survey records whether individuals engaged in multiple activities within a single time slot and whether these activities were simultaneous. Given that people often perform several tasks throughout the day or simultaneously, it is insightful to examine the distribution of multiple activities between paid and unpaid work for both men and women. This information is also presented in Table 2 for the case of Kerala.

Table 3 reports summary statistics of (i) overall unpaid household work and (ii) paid labor force participation by gender of married individuals. On an average, married women dedicate about 56 hours to unpaid household work which is approximately 8 hours per day. On the contrary, married men spend about 9.4 hours per week on an average, that is roughly 1.3 hours per day. In case of participation in paid labor force, married men work on average of 31.5 hours per week which is equivalent to nearly 5 hours per day, while married women spend on an average 7 hours per week which is equal to 1 hour per day. These descriptive statistics show that women bear a much larger share of unpaid household work, and men are more extensively engaged in paid work. Here, I did not classify the unpaid and paid activities into major/minor or account for whether these are performed simultaneously or multiple times. This is because my objective is to capture the aggregate time spent on unpaid and paid work performed by men and women.

Additionally, the frequency of social group, religion and main household occupation of the sample individuals are shown in Table 4. It exhibits that nearly 70 per cent of total population belonged to socially minor group, that is, an aggregate of Scheduled Caste (SCs), Scheduled Tribes (STs) and Other Backward Classes (OBCs). Table 3 shows that more than half of the rural households worked as self-employed to sustain their livelihood. Though the absolute numbers as displayed in Table 4, the proportion of population with regular income was higher in the urban areas (52 per cent) compared to rural areas (37.8 per cent).

Empirical Strategy

Shocks have implications on individuals' time use, and how they use their time broadly between unpaid household work and paid work is an indicator of their coping strategy to a certain shock. I utilize difference-in-difference strategy to see the effects of climate shock on unpaid labor and paid labor force participation. The regression specification is as following:

$$y_{ihdt}^{g} = \beta_0^g + \beta_1^g Shock_{ihdt} + \beta_2^g Treatment_{ihd} + \beta_3^g Time_t + \beta_4^g Z_{ihdt} + \beta_5^g X_{hdt} + \beta_6^g \tau_d + \varepsilon_{ihdt}^g \quad (*)$$

where y_{ihdt} measures the outcome of interest--- (i) total amount of time (minutes per day) spent on unpaid household work by married individual i from household h located in district d during sub-round t; (ii) total amount of time (minutes per day) spent on labor force participation by married individual i from household h located in district d during sub-round t.

The above specification is estimated separately for each gender $g \epsilon \{female, male\}$. $Shock_{ihdt}$ is the interaction of "treatment" dummy ($Treatment_{ihd}$) and "time" dummy ($Time_t$). The corresponding coefficient, β_1^g compares the impact of climate shock on outcomes of interest---unpaid household work and paid work of "treatment" and "control" groups. Because the climate shock is exogenously determined, β_1^g captures the causal relationship between the flood event and outcome variables. The first difference compares the unpaid household work and paid labor force participation of married women (men) between affected districts and unaffected districts. Since households are likely to adapt better over time, this difference is likely to be compounded by time-varying changes taking place in Kerala. To account for this, I utilize sub rounds as "time" dummy---since the event took place in August, there are two pre-event period of data (January-March, April-June) which takes value 0 for "time" dummy and there is one post-event period data (October-December) which takes value 1 for the "time" dummy. The second difference, therefore, compares the outcomes before and after the flood has occurred.

To control for individual level and household level characteristics, I include vector Z_{ihdt} of individual level controls (age, education, occupation) and vector X_{hdt} of household level controls (religion, caste, monthly consumption expenditure, presence of time-saving assets, dependency ratio, sex ratio) during sub round t. ε_{ihdt}^g is the error term. τ_d captures district fixed effects. The errors are clustered at the household level.

Key Results

A. Parallel Trend Test

The difference-in-difference strategy relies on the assumption of parallel trends. This assumption posits that, in the absence of treatment, the trends in outcomes for the treatment and control groups would have followed parallel paths over time. This means that any divergence between the two groups observed after the intervention can be attributed to the treatment effect itself. In the

context of this paper, this assumption suggests that, without the climate shock, the difference in unpaid household work between the "treatment" group (those affected by the shock) and the "control" group (those not affected) would have remained constant over time. I test for parallel trends in the double difference strategy for both unpaid household labor and paid labor force participation in the two sub-rounds: January-March and April-June. The results are respectively shown in **Table 6a** and **Table 6b**. In both cases, I find that the coefficients on the double interaction term "Shock" for both cases are statistically insignificant. This implies that I do not reject the null hypothesis of parallel trends.

B. Main Findings

The double difference estimates of the impact of flood shock, based on equation (*) are presented in **Table 7a** and **Table 7b**. **Table 7a** focuses on unpaid household work. Columns (1) and (2) provide estimates without and with individual-level controls, respectively. Columns (3) and (4) further include household-level controls and district fixed effects. Panel A reports results for married women, while the panel B reports for married men. In each panel, the first row reports the difference-in-difference coefficient on 'Shock'.

In panel A, the estimates with no control and with individual level control suggest that the climate shock raises unpaid household work for married women by about 12-14 hours per week (column (1)-(2), **Table 7a**), while including household level controls reduces the coefficient to nearly 13 hours per week (column (3), **Table 7a**). Accounting for district fixed effects further decreases the coefficient to about 11.5 hours per week (column (4), **Table 7a**). However, the coefficient on "treatment" dummy is negative (column (1)-(3), **Table 7a**) in absence of district fixed effects. This implies that women affected districts spend less time on unpaid work compared to their counterparts in non-affected districts. But the coefficient becomes negligible but insignificant when including district fixed effects (column (4), **Table 7a**). Besides, the effect of "time" dummy alone is negative but not statistically significant. This means that women might actually spend less time on unpaid household work after the flood than before.

In panel B, the double difference estimates show that the climate shock raises unpaid household work for married men by about 6 hours per week in absence of controls and in presence of individual level control (column (1)-(2), **Table 7a**). By accounting for household level controls, the coefficient rises to 7 hours per week and falls back to 6 hours per week (column (3), **Table 7a**) when controlled for district fixed effects (column (4), **Table 7a**). The coefficient on "treatment" dummy shows mixed results. In column (2)-(3) of **Table 7a**, the treatment effect is negative which

indicates that men in affected districts initially reduce their unpaid work compared to those in unaffected districts. However, in column (4), the effect turns insignificant when accounted for district level unobserved factors. On the contrary, the time dummy consistently shows a negative significant effect throughout all columns (1)-(4). This indicates that men are spending less time on unpaid household work after the flood.

Table 7b examines the impact of flood shock on paid labor force participation. Like Table 7a, columns (1)-(2) show estimates in absence of controls and in presence of individual-level controls while columns (3)-(4) include additional household level controls and district fixed effects. Panel A focuses on married women and panel B on married men.

In panel A, the estimates with no control and with individual level control suggest that the climate shock raises married women's paid labor force participation by about 2 hours per week (column (1)-(2), Table 7b). Further controlling for household level control and district fixed effects, the estimate declines to about 2.83-3.02 hours per week (column (3)-(4), Table 7b). Overall, married women experience climate-induced rise in paid labor force participation by nearly 3 hours per week. But the coefficient on both "treatment" and "time" dummy are negative. In case of "treatment" dummy, the coefficients are not statistically insignificant. In case of "time" dummy, the coefficient remains statistically significant throughout column (3)-(4) and it suggests that women experiences decline in their paid labor force participation by 2.08-4 hours per week after the climate shock has happened.

In panel B, the effect of climate shock on married men's paid labor force participation is negative (column (3)-(4), Table 7b) but statistically insignificant. This implies that there is no significant difference in men's labor force participation between the "treatment" group and "control" group after the flood occurred.

C. Heterogeneity Effects

The above results show that married women bear disproportionately higher burden of unpaid household work than that of married men. In the case of paid labor force participation, the climate shock leads to an increase in women's time spent on participating in paid labor force while has no significant effect on men's labor force participation. It is important to further decompose the gendered effects of flood shock on unpaid household labor and paid labor force participation by factors which could potentially influence the double difference estimate 'shock'. Following

Muralidharan and Prakash (2017), I address this by using triple difference strategy as shown in the following specification:

$$y_{ihdt}^{g} = \gamma_0^g + \gamma_1^g(Time_t \times Treatment_{ihd} \times Factor) + \sum_{i=2}^{4}\gamma_i^g(Double\ Interactions) + \sum_{i=5}^{8}\gamma_i^g(Linear\ Dummies) + \gamma_9^g Z_{ihdt} + \gamma_{10}^g X_{hdt} + \gamma_{11}^g \tau_d + \epsilon_{ihdt}^g \quad ---(**)$$

Here, "Factor" can be household-level or individual-level variable which can influence the relationship between climate shock and gendered paid and unpaid labor. Each of these factors are examined below.

Role of Household Technology and Outsourcing

In the 2019 Indian Time Use Survey, there are information on type of washing clothes (manual, mechanical, outsourcing), type of sweeping floor (manual, mechanical, outsourcing), primary source of energy for cooking (e.g., firewood and chips, LPG, other natural gas, electricity). Each of these variables influences the extent of time spent on unpaid household work and may influence availability for paid labor force participation. I define the dummy variable "Absent Time-Saving Assets" which takes 1 if the response is mechanical and/or outsourcing for washing and sweeping floor and for cooking, if it is the source of energy in which cooking gets faster. I estimate the effect of double difference estimate of climate shock as function of time saving assets.

In both **Table 12a** and **Table 12b**, columns (1) and (2) provide triple difference estimates without and with individual-level controls, respectively. Columns (3) and (4) further include household-level controls and district fixed effects. Panel A reports results for married women, while the panel B reports for married men. In each panel, the first row reports the heterogeneous effect which is the triple difference estimate between "time" dummy, "treatment" dummy and presence of time-saving assets/outsourcing.

Panel A shows that the presence of household technology/outsourcing reduces married women's climate-induced unpaid household work by 4.5-5.8 hours per week, but this effect is statistically insignificant (column (3)-(4), **Table 12a**). This suggests that time-saving assets, such as mechanical washing or improved cooking facilities, do not significantly reduce the additional unpaid labor required post-shock. One possible explanation for this insignificance is that the nature of unpaid household work encompasses substantial caregiving tasks, including looking after children, the elderly, and disabled family members. After a climate event, the increased need for caregiving can overshadow the benefits provided by time-saving technology, which may not effectively address the heightened demands of care work.

Panel B shows that climate shock leads to a decrease in married men's unpaid household work by 3.37-4.67 hours per week, but these results are not statistically significant (column (3)-(4), **Table 12b**). This suggests that time-saving assets do not significantly mitigate the rise in unpaid work for men post-shock. Several factors could contribute to this result: firstly, while time-saving devices may reduce the time spent on certain household tasks, the overall increase in caregiving responsibilities and other related tasks after a climate shock can diminish their impact; secondly, men's roles in unpaid household work may not fully align with the types of tasks that benefit from time-saving technology. For example, if men are primarily involved in tasks that are less amenable to technological improvements (e.g., going outside to get medical supplies or food items for the household) or if their increased workload is more related to the disruption of economic activities rather than household chores, time-saving assets may have a limited effect.

While existing literature highlights how household technology boosts female labor force participation (Tewari and Wang 2021; Bose et al. 2022), **Table 12b** shows that time-saving assets do not significantly mediate the impact of climate shocks on women's or men's paid labor participation. This is obvious because while household technology can alleviate domestic work, demand for care giving activities towards children, sick, elderly and disabled may increase after climate shock. This, in turn, can influence an individual's availability for paid labor force participation. Besides, the flood event can curtail labor demand by directly damaging climate-sensitive occupation, namely, agriculture and fishery. Consequently, presence of time saving assets may not influence time spent in labor force participation in absence of adequate jobs.

Social Cost

Gender norms often result in social costs which can influence the women's paid and unpaid work. For example, married women with children are more likely to be responsible for unpaid household work than their husbands and other women (Barnes 2015, Afridi et al. 2022, Gonalons-Pons 2023). This, in turn, results in gender-differentiated labor outcomes (Bertrand et al. 2016, Afridi et al. 2022, Righetto 2023). The gender norms around 'invisible' household production is likely to reduce women's paid labor force participation. But it has been observed in the above that the presence of time saving assets does not improve the female paid labor force participation in the aftermath of climate shock. One possible reason could be that time-saving assets does not mitigate rising demand for care work especially for children, sick, disabled and elderly after the flood occurred (as explained in the section 2). This is especially the case for married women. In the following, I estimate the heterogeneous effects of caregiving responsibilities and marital status.

Care Work

Studies have found that care work reduces women's labor force participation but has no effect on men's in India (e.g., Sinha et al. 2024, Janiso et al. 2023). To verify whether demand for care work can influence the relationship between climate shock and paid and unpaid labor, I decompose the double difference estimates of flood shock by whether an individual care for children, sick, elderly, and disabled persons in own households.

Table 9a and **Table 9b** shows the triple difference results based on equation (**) where I include a dummy which takes value 1 for caring about children, sick, elderly and disabled person within same household. Panel A and panel B respectively show the results for married women and married men. I define a dummy "caregiving" which takes 1 if an individual takes care of children, sick, elderly, differently abled persons in own households.

In **Table 9a**, panel A shows that caregiving responsibilities exacerbate climate-induced unpaid household work by 9.97-10.341 hours per week (Column (3)-(4), **Table 9a**). This indicates that as caregiving responsibilities increase, the amount of unpaid household work performed by women also increases significantly in response to the climate shock. Thus, women with higher caregiving responsibilities are likely to take on more unpaid household tasks when faced with a climate shock. In case of married men, caregiving responsibilities increases climate-induced unpaid household work by nearly 6 hours per week, but this is not statistically significant (Column (3)-(4), **Table 9a**). This could be due to men's lesser involvement in caregiving work compared to women's by virtue of gender norms.

In **Table 9b,** panel A shows that married women's paid labor force participation decreases by more than 3 hours per week if they engage in caregiving for children, the elderly, the sick, or disabled individuals (first row, columns (1)-(4), **Table 9b**). This indicates that as caregiving responsibilities increase, the negative impact of the climate shock on women's paid labor force participation becomes more pronounced. Besides, this finding suggests that the insignificant triple difference estimate for married women's labor force participation in presence of time-saving assets (Panel A**,** **Table 9a**) could be explained by caregiving responsibilities. Conversely, the results for married men's labor force participation are not statistically significant as shown in Panel B (first row, column (1)-(4), Panel B, **Table 9b**). This implies that any change in men's labor force participation after the flood is not associated with caregiving responsibilities.

Hence, caregiving responsibilities play a crucial role in creating gender disparities, especially for paid labor force participation. Even in case of unpaid household work, women spend more time than men to take care of elderly, children and disabled, compared to that of men from the same "treatment" group.

Marital Status

Marital status influences a woman's unpaid and paid labor force participation (Connelly and Kimmel 2003, Baxter 2005, Ahituv and Lerman 2007, Pepin et al. 2018, Righetto 2023). This, in turn, can influence gender disparities in unpaid and paid labor. So far in this study, I examine the effects of flood shock on married men and women. Now, I compare whether marital status impacts the relationship between climate shock and gender division of unpaid and paid labor. To do this, I define a dummy variable "married" that takes value 1 if an individual is married and 0 if unmarried. **Table 10a** and **10b** show the heterogenous effect using equation (**) and by including the "married" dummy.

Table 10a shows that climate shocks significantly increase unpaid household work for both married women and men. Married women see their unpaid work rise by approximately 12-14 hours per week (Column (3)-(4), Panel A, **Table 10a**), while married men experience an increase of about 5 hours per week (Column (3)-(4), Panel B, **Table 10b**). The substantial increase in unpaid work for married women suggests that they bear a greater burden of unpaid household responsibilities which include both domestic and care work during climate shocks. This can also imply that the insignificant benefits of time-saving technology/outsourcing for married women's unpaid household work (Panel A**,** **Table 8a**) could be due to social norms attached to their marital status.

Table 10b reveals that marital status does not significantly explain any change in paid labor force participation due to the flood shock. Both Panel A and Panel B show that marital status have negative effect on the relationship between climate shock and paid labor force participation for both men and women, but the results are not statistically significant. This implies that marital status alone does not matter for impacting labor force participation but those who are married and have caregiving responsibilities experience larger negative effect of the climate shock, as shown in **Table 9b** (Barnes 2015, Afridi et al. 2022).

Robustness Check

Alternative Treatment and Control Groups

There are three limitations of the data used in this study: first, the data consists of cross-sectional time use survey because of which it is difficult to observe the trend in unpaid and paid labor by gender over time. Second, the data is available only four months after the event occurred. Besides, the nature of the data is not monthly, but rather by three-month period which leaves me with only one post-event period data. Consequently, I am unable to see whether the change in the time allocation towards unpaid household labor and paid labor force due to climate shock persists longer than four months. Moreover, the difference in the results for paid labor force participation between men and women may be attributable to that men migrate away from their households in affected districts while women did not (as highlighted in most of climate change and migration literature, e.g., Afridi et al. 2022, Sultana et al. 2024). Socioeconomic status can also influence an individual's time allocation between unpaid work and paid labor force participation in response to shock. It may be more plausible that an economically marginalized woman may spend more time in both unpaid and paid work unlike a woman coming from relatively richer household. Furthermore, the estimates may vary by age group. Typically, younger women are more likely to face the double burden of paid and unpaid work than older women. In this section, I check the robustness of my analysis by accounting for migration, economic condition, caste and age.

(a) ***Migration:*** Existing literature on climate shock and migration suggests that affected individuals often migrate to unaffected regions within or outside their own country to mitigate the economic effects of climate events (Sultana et al. 2024, Almulhim et al. 2024). However, the Indian time use survey does not give information about migration status of household members. Out-migration of individuals could potentially result in biased estimates. Floods with the treated district could potentially lead to migration to "control" districts which share common border. Thus, the second way to address the migration concern is to drop the border districts. The new set of treatment and control districts are shown in the map (**figure 3**). **Tables 11a** and **11b** show the results which remain similar to key findings.

(b) ***Extreme Poverty:*** The World Bank defines extreme poverty as living on less than $2.15 per person per day, adjusted for the 2017 purchasing power parity index. The 2019-21 National Family and Health Survey (NFHS) indicates that Kerala has the lowest multidimensional poverty index among Indian states. Despite this, there are still severely deprived areas within the state. To refine the analysis, I used data from the Extreme Poverty Eradication Program, which tracks the number of extremely poor families by district and aligns with the poverty rankings from the NFHS 2019-2021. Districts with the highest shares of poor families are now dropped to circumvent any bias in the double

difference estimate. In **Figure 4**, red districts are classified as "treatment" areas, while yellow districts are "control" areas. The results are shown in **Tables 12a** and **12b** and remain similar to the main findings.

(c) ***Caste:*** Societal norms play a crucial role in gendering paid and unpaid work which is further mediated by caste (Das 2006, Eswaran et al. 2013, Singh and Pattanaik 2020). Women from lower castes, who generally have less access to education and economic resources, face compounded disadvantages—they are more likely to be confined to unpaid domestic work and encounter greater obstacles to securing paid employment. Singh and Pattanaik (2020) show that caste-based societal norms dictate the extent to which women are expected to engage in unpaid domestic work. Specifically, lower-caste women often bear a disproportionate share of unpaid housework burden (Eswaran et al. 2013, Singh and Pattanaik 2020). These norms, deeply intertwined with patriarchal values, restrict women's access to paid work.

Table 13a and 13b respectively show the case of unpaid household work and paid labor force participation by married women and men across low caste and high caste. Following the official classification, I include only those in the categories of Scheduled Caste, Scheduled Tribe and Other Backward Class as marginalized caste group while the population sub-group belonging to unreserved category as upper caste group. Overall, the results show findings similar to the key results. Some notable observations include (i) Among married women, unpaid work burden in response to climate shock is more acute in case of those belonging to marginalized caste than those in the upper caste category; (ii) women coming from minority caste group increase their paid labor force participation in response to climate shock while those from higher caste group experiences an insignificant change in the same. This implies that minority women face double burden of paid and unpaid labor as a result of climate shock.

(d) ***Age Group:*** According to the 2019 Indian Time Use Survey, young women aged 15-29 years dedicate nearly 90 percent of their time to unpaid domestic work, while older women aged 60 years and above spend 79 percent of their time on the same. When it comes to caregiving responsibilities, young women allocate over 40 percent of their time, compared to about 17 percent for older women. Among men, younger individuals spend 25 percent of their time on unpaid domestic work, whereas older men dedicate 36 percent of their time to these tasks. Unlike young women, young men spend only 13 percent of their time on caregiving, and this figure drops slightly to nearly 11 percent for older men aged 60 and above. Regarding paid employment and related activities, young men devote 54 percent of their time, while young women spend just 14 percent of theirs.

Tables 14a and 14b present the detailed results for unpaid household work and paid labor force participation, respectively, for men and women across three age groups: 15-29 years (column (1)), 30-59 years (column (2)), and 60 years and above (column (3)). Overall, the results are similar to those of the main findings. Noteworthy are three things: (i) younger women (aged 15-29 years) experience a rise by more than 20 hours per week due to climate shock while the rise in their labor force participation due to climate shock is not significant for them; (ii) younger men (aged 15-29 years) does not significantly increase their unpaid household labor in response to climate shock while they witness a rise in their paid labor force participation by more than 40 hours per week. However, for men aged 30 years and above, the change in paid labor force participation due to climate shock is statistically significant; (iii) The sample size for the younger generation aged 15-29 years is much smaller (<3000) than the relatively older two groups (>60,000). So, the key findings (Table 7a and 7b) show findings similar to those of the older two groups.

Conclusion

In this study, I utilize 2019 Indian Time Use Survey to examine the relationship between climate shock and gender division of labor in both unpaid household work and paid labor force participation. I find that climate shock increases gender division of labor in the aftermath of climate shock among individuals located in affected districts. Following the August 2019 flood in Kerala, married women experience rise in time spent in both unpaid household work and paid labor force participation. On the contrary, men only witness rise in unpaid work while there is no significant effect on their paid labor force participation. Hence, the aggregate labor increases for women compared to men after a climate shock occurs. The effect also varies depending upon socioeconomic characteristics like marital status and caregiving responsibilities. The analysis remains robust under alternative treatment and control groups.

This paper underscores the importance of Time Use Surveys (TUS) in understanding resilience against climate disasters. However, conducting time use surveys can be resource-intensive which requires significant time and financial investment for data collection and processing. Characteristics of time use surveys like resolution of data collection and representation, can impact their robustness and accuracy of various economic and social models developed using this type of data.

Policymakers must develop targeted interventions to address the increased burden of unpaid labor on women during climate shocks. Effective strategies should include enhancing access to affordable childcare services, establishing gender-responsive disaster management frameworks, and ensuring women's active involvement in climate resilience and disaster response decision-making. Recent research highlights the need for gender-smart climate investments that go beyond providing agricultural technologies to include measures that empower women and address the underlying causes of gender inequality (Huyer and Chanana, 2021; Quisumbing et al., 2023). Such approaches support women in coping with climate shocks while fostering transformative changes in gender dynamics.

Addressing and redistributing unpaid labor is macro-critical, as an uneven distribution of unpaid work can constrain female labor force participation and lead to resource misallocation. When women are allocated to low-productivity household tasks, economic growth potential is diminished, and the benefits of complementarity between male and female workforces are reduced (Ostry et al., 2019). Additionally, even for women who participate in paid work, occupational downgrading is common as they often accept lower-skill or part-time jobs to balance paid and care work, perpetuating gender wage gaps (Connolly and Gregory, 2007; Garnero et al., 2013; Blau and Kahn, 2017). Recognizing and addressing these disparities in unpaid work is essential for boosting female labor force participation and aligns with the Sustainable Development Goals (SDGs) (Blau and Kahn, 2017).

Promoting flexible work arrangements, such as remote work options and flexible hours, can help reduce the dual burden of paid and unpaid work on women, allowing them more time for leisure. Enhancing access to affordable childcare and elder care can significantly alleviate the burden of unpaid care work, freeing up valuable time for self-care activities. Gender-responsive social protection programs, including cash transfers and insurance schemes that support caregiving responsibilities, are essential for addressing gender-specific needs and ensuring equitable distribution of unpaid work. Community-based support systems, such as local support networks and community centers, can help distribute domestic and caregiving tasks more evenly and facilitate shared responsibilities.

References

Ahituv, A., & Lerman, R. I. (2007). How do marital status, work effort, and wage rates interact? *Demography, 44*(4), 623–647. https://doi.org/10.1353/dem.2007.0021

Alderman, H., Chiappori, P.-A., Haddad, L., Hoddinott, J., & Kanbur, R. (1995). Unitary versus collective models of the household: Is it time to shift the burden of proof? *The World Bank Research Observer, 10*(1), 1–19. https://doi.org/10.1093/wbro/10.1.1

Almulhim, A.I., Alverio, G.N., Sharifi, A. *et al.* (2024). Climate-induced migration in the Global South: an in depth analysis. *npj Clim. Action* 3 (47). https://doi.org/10.1038/s44168-024-00133-1

Amarante, V., Rossel, C., & Scalese, F. (2023). Housework and earnings: Intrahousehold evidence from Latin America. *Journal of Family Studies, 30*(3), 440–460. https://doi.org/10.1080/13229400.2023.2241440

Afridi, F., Mahajan, K., & Sangwan, N. (2022). The gendered effects of droughts: Production shocks and labor response in agriculture. *Labour Economics, 78*, 102227. https://doi.org/10.1016/j.labeco.2022.102227

Baker, M. J., & Jacobsen, J. P. (2007). Marriage, specialization, and the gender division of labor. *Journal of Labor Economics, 25*(4), 763–793. https://doi.org/10.1086/522907

Barnes, M. W. (2015). Gender differentiation in paid and unpaid work during the transition to parenthood. *Sociology Compass*. https://doi.org/10.1111/soc4.12263

Becker, G. S. (1991). *A treatise on the family* (Enlarged ed.). Harvard University Press. (Original work published 1981)

Bittman, M., England, P., Sayer, L., Folbre, N., & Matheson, G. (2003). When does gender trump money? Bargaining and time in household work. *American Journal of Sociology, 109*(1), 186–214.

Boye, K. (2009). Relatively different? How do gender differences in well-being depend on paid and unpaid work in Europe? *Social Indicators Research, 93*, 509–525. https://doi.org/10.1007/s11205-008-9434-1

Browning, M., & Chiappori, P. A. (1998). Efficient intra-household allocations: A general characterization and empirical tests. *Econometrica*, *66*(6), 1241–1278. https://doi.org/10.2307/2999616

Carlson, D. L., & Lynch, J. L. (2017). Purchases, Penalties, and Power: The Relationship Between Earnings and Housework. *Journal of Marriage and Family*, *79*(1), 199–224. http://www.jstor.org/stable/26646153

Cárdenas-Retamal, R., Barrientos Cifuentes, M., Vásquez Lavín, F., & Ponce Oliva, R. (2023). Intrahousehold bargaining power and time allocation for multiple activities. *Latin American Economic Review, 32*, 1–22. https://doi.org/10.60758/laer.v32.149

Charmes, J. (2022). Variety and change of patterns in the gender balance between unpaid care-work, paid work, and free time across the world and over time: A measure of well-being? *Wellbeing, Space and Society, 3*, 100081. https://doi.org/10.1016/j.wss.2022.100081

Chiappori, P.-A. (1992). Collective labor supply and welfare. *Journal of Political Economy, 100*(3), 437–467. http://www.jstor.org/stable/2138727

Connelly, R., & Kimmel, J. (2003). Marital status and full-time/part-time work status in child care choices. *Applied Economics, 35* (7), 761–777. https://doi.org/10.1080/0003684022000020841

Connolly-Boutin, L., & Smit, B. (2016). Climate change, food security, and livelihoods in sub-Saharan Africa. *Regional Environmental Change, 16* (2), 385–399. https://doi.org/10.1007/s10113-015-0761-x

Corno, L., Hildebrandt, N., & Voena, A. (2020). Age of marriage, weather shocks, and the direction of marriage payments. *Econometrica, 88* (3), 879–915. https://www.jstor.org/stable/48584105

Das, M. B. (2006). *Do traditional axes of exclusion affect labor market outcomes in India?* (Social Development Papers No. 97, South Asia Series). World Bank.

Delbiso, T. D., Chiappori, P.-A., Rodriguez-Llanes, J. M., Doocy, S., & Guha-Sapir, D. (2017). Drought and child mortality: A meta-analysis of small-scale surveys from Ethiopia. *Scientific Reports, 7* (1), 2212. https://doi.org/10.1038/s41598-017-02271-5

Eckstein, D., Künzel, V., Schäfer, L., Winges, M., & Brönstrup, A. (2021). *Global climate risk index 2021.* Germanwatch e.V.

Eswaran, M., Ramaswami, B., & Wadhwa, W. (2013). Status, caste, and the time allocation of women in rural India. *Economic Development and Cultural Change, 61*(2), 311–333. https://doi.org/10.1086/668276

Fengdan, S., Pan, X., Bruyere, C., & Floro, M. S. (2016). Bargaining power and the household division of labour: Evidence from the 2008 China time-use survey. *Asia-Pacific Population Journal, 31*(1), 63–85. https://doi.org/10.18356/bb63671b-en

Folbre, N., & Yoon, J. (2007). What is child care? Lessons from time use surveys of major English-speaking countries. *Review of Economics of the Household, 5* (3), 275–288. https://doi.org/10.1007/s11150-007-9012-3

Gimenez-Nadal, J. I., & Molina, J. A. (2022). The gender gap in time allocation. *IZA World of Labor, 2022*, 497. https://doi.org/10.15185/izawol.497

Gimenez-Nadal, J. I., & Molina, J. A. (2014). Regional unemployment, gender, and time allocation of the unemployed. *Review of Economics of the Household, 12*, 105–127. https://doi.org/10.1007/s11150-013-9186-9

Görges, L. (2021). Of housewives and feminists: Gender norms and intra-household division of labor. *Labor Economics, 72*, 102044. https://doi.org/10.1016/j.labeco.2021.102044

Gonalons-Pons, P. (2023). Differentiated egalitarianism: The impact of paid family leave policy on women's and men's paid and unpaid work. *Social Forces, 101* (4), 1744–1771. https://doi.org/10.1093/sf/soac081

Huls, S. P. I., Sajjad, A., Kanters, T. A., Hakkaart van Roijen, L., Brouwer, W. B. F., & van Exel, J. (2021). Productivity of working at home and time allocation between paid work, unpaid work, and leisure activities during a pandemic. *PharmacoEconomics, 40*, 77–90. https://doi.org/10.1007/s40273-021-01078-7

Hirway, I. (2015). Unpaid work and the economy: Linkages and their implications. *Working Paper No. 838*. Levy Economics Institute of Bard College.

Intergovernmental Panel on Climate Change (IPCC). (2021). *Climate change 2021: The physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Janiso, A., Shukla, P. K., & Reddy, B. A. (2023). What explains the gender gap in unpaid housework and care work in India? *Development Policy Review, 41* (2), e12730. https://doi.org/10.1111/dpr.12730

Kim, Y. (2023). A study on the effects of gendered social norms on the tradeoff between paid and unpaid work in Korea. *Journal of Family and Economic Issues, 44*, 870–882. https://doi.org/10.1007/s10834-022-09878-5

Lundberg, S., & Pollak, R. A. (2008). Family decision making. In *The new Palgrave dictionary of economics*. Palgrave Macmillan. https://doi.org/10.1057/978-1-349-95121-5_2551-1

Marcén, M., & Morales, M. (2019). Gender division of household labor: How does culture operate? /7*Discussion Paper No. 373*. Global Labor Organization (GLO).

McElroy, M. B., & Horney, M. J. (1981). Nash-bargained household decisions: Toward a generalization of the theory of demand. *International Economic Review, 22* (2), 333–349. https://doi.org/10.2307/2526280

McKinsey Global Institute. (2020). *Climate risk and response: Physical hazards and socioeconomic impacts*. McKinsey.

Miller, R., & Bairoliya, N. (2021). Parental Caregivers and Household Power Dynamics. *Feminist Economics, 28*(3), 114–144. https://doi.org/10.1080/13545701.2021.1975793

Moeeni, S. (2021). Married women's labor force participation and intra-household bargaining power. *Empirical Economics, 60*(3), 1411–1448. https://doi.org/10.1007/s00181-019-01800-7

Muralidharan, K., & Prakash, N. (2017). Cycling to school: Increasing secondary school enrollment for girls in India. *American Economic Journal: Applied Economics, 9*(3), 321–350. https://doi.org/10.1257/app.20160004

Muttarak, R., & Dimitrova, A. (2019). Climate change and seasonal floods: Potential long-term nutritional consequences for children in Kerala, India. *BMJ Global Health, 4* (1), e001215. http://dx.doi.org/10.1136/bmjgh-2018-001215

Navone, A. (2021). The intertwined futures of climate action, fragility and peacebuilding. *United States Institute of Peace*. https://www.usip.org/publications/2021/04/intertwined-futures-climate-action-fragility-and-peacebuilding

Noy, I., & Vu, Q. (2020). The economic impact of climate change in developing countries: An update. *Briefing Paper*. Climate and Development.

Rausch, S., & Ruhl, J. (2018). Gender and time use: The impact of household income and economic stress on women's and men's allocation of time. *The Journal of Economic Perspectives, 32* (4), 183–208. https://doi.org/10.1257/jep.32.4.183

Roberts, K. (2022). Gender differences in the impact of climate change on unpaid household work in Sub-Saharan Africa. *Climate and Development, 14* (2), 245–258. https://doi.org/10.1080/17565529.2021.2013865

Singh, P., & Pattanaik, F. (2020). Unfolding unpaid domestic work in India: Women's constraints, choices, and career. *Palgrave Communications, 6*(111). https://doi.org/10.1057/s41599-020-0488-2

Smith, P. J., & Caines, K. (2021). Gender inequality and climate change: How women are disproportionately affected. *Environmental Research Letters, 16* (9), 094015. https://doi.org/10.1088/1748-9326/ac1f15

Sultana, N., Sarkar, J., & Meurs, M. (2024). Climate Change Induced Migration: A Gendered Conceptual Framework. *Migration and Diversity*.

Van der Zanden, E., & Van der Horst, D. (2023). Paid and unpaid work during the pandemic: Evidence from time use surveys in Europe. *European Journal of Population, 39* (4), 543–568. https://doi.org/10.1007/s10680-023-09728-5

Weller, S. (2022). Gendered impacts of climate extremes: Evidence from the time use surveys. *Climate Risk Management, 35*, 100443. https://doi.org/10.1016/j.crm.2022.100443

West, A., & Dimitrova, G. (2023). Gender, climate change, and unpaid care work: An analysis of policy and practice. *Gender, Place & Culture, 30* (1), 14–33. https://doi.org/10.1080/0966369X.2022.2076749

Figures

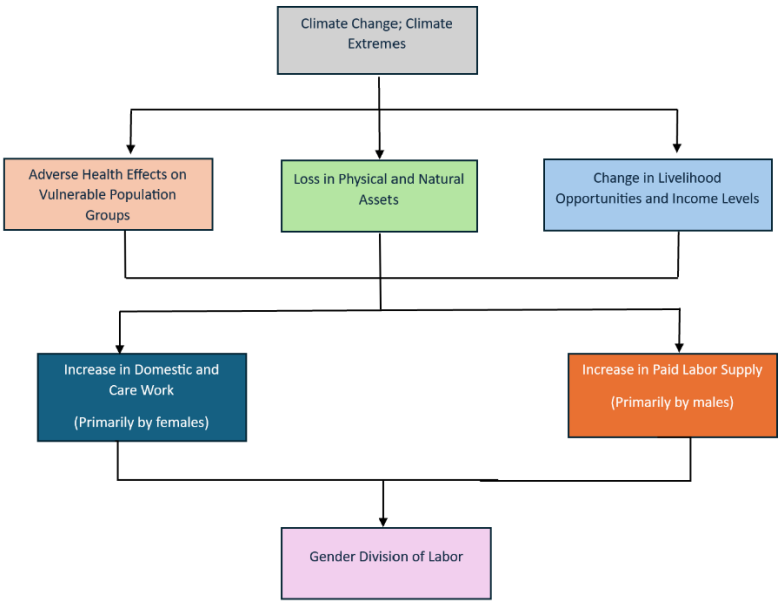


Figure 1. Climate Shock and Gender Division of Labor

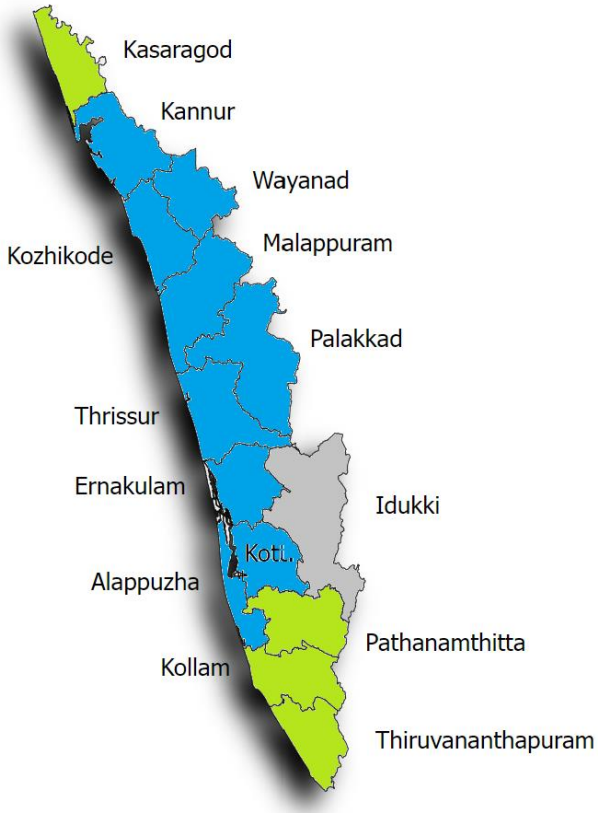


Figure 2. Map of 2019 Flood Affected Districts. Source: PaintMaps.com; customized using data from the State Disaster Management Handbook 2019 (Note that Idukki has been excluded from the analysis due to the absence of data for the first sub-round, colored grey)

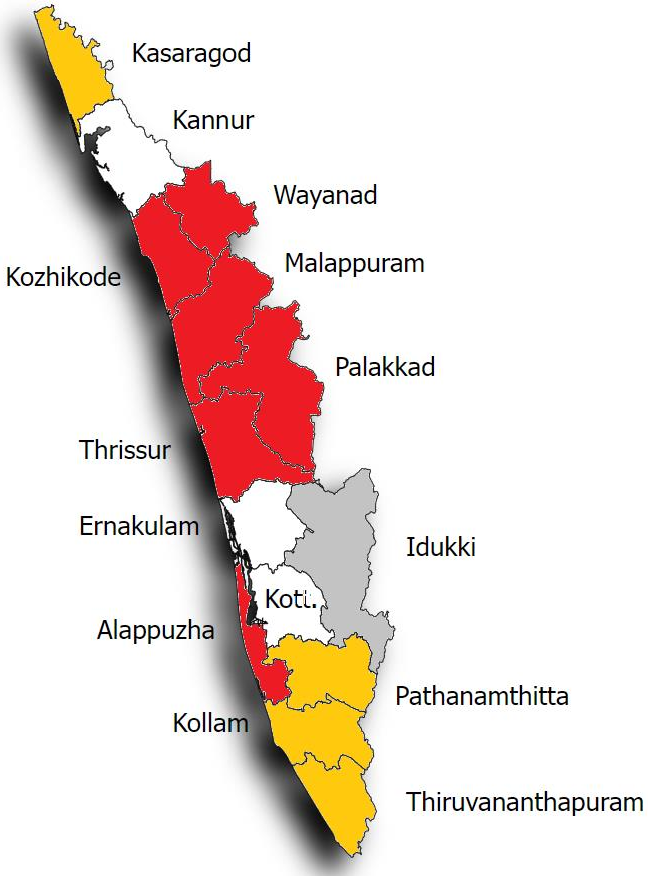


Figure 3. Map of 2019 Flood Affected Districts by excluding border treatment districts (Kannur, Ernakulam, Kottayam---each colored white). Affected districts are colored red and unaffected by yellow. (Using State Disaster Management Handbook 2019.)

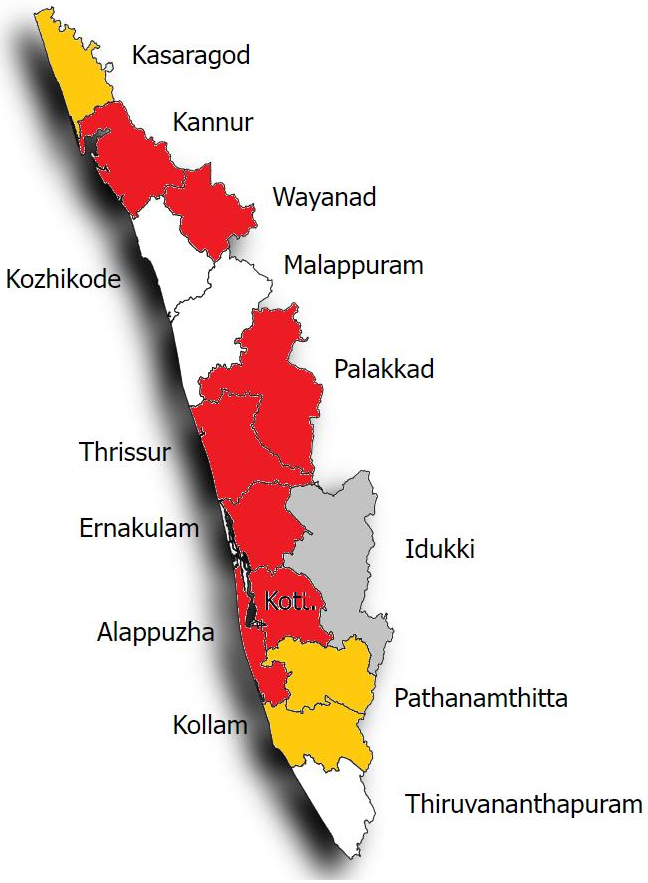


Figure 4. Map of 2019 Flood Affected Districts by excluding treatment districts, with extremely poor families (Kozhikode, Malappuram, Thiruvananthapuram ---each colored white). Affected districts are colored red and unaffected by yellow. (Using State Disaster Management Handbook 2019.)

Tables

Unpaid Household Work
Domestic work
Food and meals management and preparation
Cleaning and maintaining of own dwelling and surroundings
Do-it-yourself decoration, maintenance and repair
Care and maintenance of textiles and footwear
Household management for own final use
Pet care
Shopping for own household members
Travelling, moving, transporting or accompanying goods or persons related to unpaid domestic services for household members
Other unpaid domestic services for household members
Care work
Childcare and instruction
Care for dependent adults
Help to non-dependent adult household members
Travelling and accompanying goods or persons related to unpaid caregiving services for household members
Other activities related to unpaid caregiving services for household members
Paid Labor Force Participation
Self-employment for production of goods
Self-employment for production of services
Regular wage/ salary for production of goods
Regular wage/ salary for production of services
Casual labor for production of goods
Casual labor: for production of services

Table 1. List of Unpaid and Paid Labor. Source: 2019 Indian Time Use Survey

	Unpaid Household Work		Paid Labor Force	
	Men (%)	Women (%)	Men	Women
Major Activity	4,484 (6.38%)	33,811 (36.34%)	12,665 (73.8%)	3,914 (10.41%)
Minor Activity	1,079 (5.08%)	7,209 (26.48%)	1009 (48.54%)	306 (4.13%)
Whether Performed Simultaneously	500 (4.96%)	3,100 (28.19%)	872 (61.72%)	281 (8.24%)
Whether Performed Multiple times	1,309 (6.67%)	9,718 (38.79%)	1,860 (57.73%)	567 (5.51%)

Table 2. Gender Distribution of Major and Minor Activities in Unpaid Household Work and Paid Labor, including whether performed simultaneously and multiple times.

Variable	No. of Observations	Mean	Std. Deviation	Minimum	Maximum
Married Women					
Unpaid Household Work (hours/week)	117,578	55.94	23.88	0	115.5
Overall Labor force (hours/week)	119,858	7.09	17.10	0	98
Age (years)	119,874	43	13.36	18	92
Married Men					
Unpaid Household Work (hours/week)	91,906	9.39	13.37	0	98
Overall Labor force (hours/week)	91,891	31.48	28.19	0	115
Age (years)	92,060	51	13.72	17	94

Table 3. Summary Statistics of Time Use in Unpaid and Paid Labor. Note that the observations include major/minor activities, multiple activities and simultaneous activities.

Region	Religion		Caste	
	Major	Minor	Major	Minor
Rural	83,063	24,651	35,101	72,612
Urban	92,785	17,367	78,655	31,498
Total	175,848	42,018	113,756	104,110

Table 4. Number of Individuals of Religion and Caste by Region

Region	Self-Employed	Regular	Casual
Rural	16,870	13,525	5,356
Urban	14,314	19,294	3,413
Total	31,184	32,819	8,769

Table 5. Number of Households Based on Main Sources of Earning by Region

A. Unpaid Household Work by Married Women (Hours/Week)	
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**-3.559** **(3.171)**
$Time_t$	1.071 (2.921)
$Treatment_{ihd}$	-1.254 (2.087)
No. of Observations	57,147
R-Squared	0.005
B. Unpaid Household Work by Married Men (Hours/Week)	
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**2.581** **(2.039)**
$Time_t$	-2.094 (1.896)
$Treatment_{ihd}$	-4.297*** (1.526)
No. of Observations	44,434
R-Squared	0.0090

*Table 6a. Testing for Parallel Trend Assumption in case of unpaid household work by gender. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).*

A. Paid Labor force Participation by Married Women (Hours/Week)	
$\mathbf{Shock_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd})}$	**2.162** **(2.169)**
$\mathbf{Time_t}$	-2.855 (1.967)
$\mathbf{Treatment_{ihd}}$	-2.203 (1.229)
No. of Observations	88,916
R-Squared	0.002
B. Paid Labor force Participation by Married Men (Hours/Week)	
$\mathbf{Shock_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd})}$	**0.213** **(3.466)**
$\mathbf{Time_t}$	3.433 (3.057)
$\mathbf{Treatment_{ihd}}$	0.527 (2.057)
No. of Observations	68,226
R-Squared	0.003

Table 6b. Testing for Parallel Trend Assumption in case of *paid labor force participation by gender. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).*

Unpaid Household Work by Married Women (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**14.501*** (2.498)**	**12.123*** (2.228)**	**12.59*** (2.282)**	**11.515*** (2.189)**
$Time_t$	-7.911*** (2.233)	-7.316*** (1.982)	-7.472*** (2.038)	-5.947*** (1.946)
$Treatment_{ihd}$	-3.119** (1.584)	-3.677** (1.445)	-4.523** (1.514)	0.657 (2.458)
No. of Observations	87,399	87,399	81,068	81,068
R-Squared	0.02	0.25	0.26	0.28
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓
Unpaid Household Work by Married Men (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**6.6*** (1.415)**	**6.254*** (1.418)**	**7.213*** (1.428)**	**5.99*** (1.375)**
$Time_t$	-6.22** (1.229)	-5.878*** (1.244)	-6.886*** (1.252)	-5.756*** (1.209)
$Treatment_{ihd}$	-3.021*** (1.025)	-3.279** (1.011)	-3.582*** (1.035)	-1.162 (1.653)
No. of Observations	69,004	69,004	66,520	66,520
R-Squared	0.012	0.06	0.081	0.098
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓

*Table 7a. Double Difference Estimates of Climate Shock on Unpaid Household Labor. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

Paid Labor Force Participation by Married Women (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**2.161 (2.169)**	**2.561** (1.316)**	**2.836** (1.44)**	**3.017** (1.368)**
$Time_t$	-2.855 (1.967)	-2.875*** (1.176)	-3.086** (1.302)	-3.23*** (1.225)
$Treatment_{ihd}$	-2.203 (1.229)	-0.768 (0.844)	-1.045 (0.901)	-3.191 (2.02)
No. of Observations	88,916	88,916	82,468	82,468
R-Squared	0.002	0.58	0.588	0.592
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓
Paid Labor Force Participation by Married Men	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**0.213 (3.466)**	**0.878 (3.000)**	**-1.081 (3.109)**	**-0.225 (2.940)**
$Time_t$	3.443 (3.057)	2.114 (2.674)	4.34 (2.78)	3.229 (2.612)
$Treatment_{ihd}$	0.527 (2.056)	-0.035 (1.736)	0.853 (1.812)	-3.544** (3.37)
No. of Observations	68,226	68,226	65,744	65,744
R-Squared	0.003	0.355	0.348	0.353
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓

*Table 7b. Double Difference Estimates of Climate Shock on Paid Labor Force Participation. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

Unpaid Household Work by Married Women (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt} \times TimeSavingAssets_{hd}$ ($Time_t \times Treatment_{ihd} \times TimeSavingAssets_{hdt}$)	**- 1.430 (5.039)**	**-2.104 (4.507)**	**-5.809 (4.605)**	**-4.464 (4.546)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	15.614*** (3.789)	13.865*** (3.469)	16.207*** (3.387)	14.337*** (3.39)
$Time_t \times TimeSavingAssets_{hdt}$	-4.019 (4.52)	-0.595 (4.023)	2.73 (4.105)	1.873 (4.065)
$Treatment_{ihd} \times TimeSavingAssets_{hdt}$	-0.334 (3.306)	3.492 (3.049)	4.349 (3.096)	6.841** (3.1)
$Time_t$	-5.859* (3.416)	-7.419** (3.11)	-9.388*** (3.02)	-7.625*** (3.043)
$Treatment_{ihd}$	-2.908** (2.649)	-5.934** (2.472)	-4.771*** (1.541)	-3.311 (2.90)
$TimeSavingAssets_{hdt}$	0.842 (3.057)	-2.594 (2.858)	-7.553*** (2.485)	-4.547 (2.875)
No. of Observations	87,399	87,399	81,068	81,068
R-Squared	0.022	0.25	0.25	0.28
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓
Unpaid Household Work by Married Men (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt} \times TimeSavingAssets_{hd}$ ($Time_t \times Treatment_{ihd} \times TimeSavingAssets_{hdt}$)	**-2.244 (2.875)**	**-3.216 (2.870)**	**-4.668 (2.835)**	**-3.369 (2.917)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	7.759*** (2.074)	8.029*** (2.066)	9.625*** (2.020)	7.911*** (2.018)
$Time_t \times TimeSavingAssets_{hdt}$	1.216 (2.495)	2.178 (2.518)	3.797 (2.478)	2.383 (2.56)
$Treatment_{ihd} \times TimeSavingAssets_{hdt}$	0.761 (2.084)	1.381 (2.025)	-0.766 (5.774)	2.424 (2.031)
$Time_t$	-6.708*** (1.76)	-7.013*** (1.77)	-8.649*** (1.704)	-6.939*** (1.702)
$Treatment_{ihd}$	-3.524** (1.599)	-4.141*** (1.544)	-4.476*** (1.564)	-2.552 (1.909)
$TimeSavingAssets_{hdt}$	0.515 (1.928)	-0.825 (1.915)	-1.368 (1.898)	-1.278 (1.898)
No. of Observations	69,004	69,004	66,520	66,520
R-Squared	0.012	0.058	0.076	0.09

Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	*X*	*X*	*X*	✓

*Table 8a. Heterogeneous Effects on Double Difference Estimates of Climate Shock on Unpaid Labor by Household Technology. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

Paid Labor Force Participation by Married Women (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$\mathbf{Shock_{ihdt} \times TimeSavingAssets_{hd}}$ $\mathbf{(Time_t \times Treatment_{ihd} \times TimeSavingAssets_{hdt})}$	**-3.178** **(4.471)**	**-2.021** **(2.747)**	**-1.599** **(2.898)**	**-1.039** **(2.853)**
$\mathbf{Shock_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd})}$	4.738 (3.235)	2.479* (1.183)	3.746 (2.377)	3.604 (2.264)
$\mathbf{Time_t \times TimeSavingAssets_{hdt}}$	7.168 (4.097)	2.74 (2.499)	2.613 (2.644)	1.993 (2.583)
$\mathbf{Treatment_{ihd} \times TimeSavingAssets_{hdt}}$	9.084 (2.675)	1.981 (1.908)	1.419 (1.971)	0.649 (1.994)
$\mathbf{Time_t}$	-7.745*** (2.975)	-4.606** (2.087)	-4.543*** (2.21)	-4.338** (2.084)
$\mathbf{Treatment_{ihd}}$	-7.972** (2.309)	-2.078 (1.713)	-1.892 (1.766)	-3.471 (2.359)
$\mathbf{TimeSavingAssets_{hdt}}$	-9.308*** (2.462)	-2.854 (1.789)	-2.601 (1.848)	-1.998 (1.862)
No. of Observations	88,916	88,916	82,468	82,468
R-Squared	0.011	0.579	0.587	0.591
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓
Paid Labor Force Participation by Married Men (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$\mathbf{Shock_{ihdt} \times TimeSavingAssets_{hd}}$ $\mathbf{(Time_t \times Treatment_{ihd} \times TimeSavingAssets_{hdt})}$	**-7.597** **(6.969)**	**0.879** **(5.996)**	**0.869** **(6.211)**	**0.598** **(6.087)**
$\mathbf{Shock_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd})}$	4.836 (5.426)	0.511 (4.861)	-1.129 (5.008)	-0.406 (4.833)

$\mathbf{Time_t \times TimeSavingAssets_{hdt}}$	6.609 (6.128)	0.808 (5.335)	1.022 (5.59)	1.324 (5.427)
$\mathbf{Treatment_{ihd} \times TimeSavingAssets_{hdt}}$	6.171 (4.246)	2.727 (3.64)	2.141 (3.763)	0.444 (3.819)
$\mathbf{Time_t}$	-0.617 (4.79)	1.55 (4.315)	3.296 (4.488)	2.271 (4.282)
$\mathbf{Treatment_{ihd}}$	-3.27 (3.368)	-1.767 (2.924)	-0.691 (3.049)	-3.933 (3.967)
$\mathbf{TimeSavingAssets_{hdt}}$	-6.502 (3.818)	-1.171 (3.322)	-0.816 (3.45)	-0.192 (3.481)
No. of Observations	68,226	68,226	65,744	65,744
R-Squared	0.004	0.355	0.344	0.348
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓

*Table 8b. Heterogeneous Effects on Double Difference Estimates of Climate Shock on Paid Labor Force Participation by Household Technology. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

A. Unpaid Household Work by Married Women (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$\mathbf{Shock_{ihdt} \times caregiving_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd} \times caregiving_{ihdt})}$	**7.247** **(3.563)**	**8.904*** **(3.248)**	**10.341*** **(3.281)**	**9.972*** **(3.086)**
$\mathbf{Shock_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd})}$	13.748*** (2.462)	11.532*** (2.204)	11.895*** (2.248)	10.566*** (2.163)
$\mathbf{Time_t \times caregiving_{ihdt}}$	-7.4** (3.180)	-9.313*** (2.897)	-10.949*** (2.923)	-10.46*** (2.716)
$\mathbf{Treatment_{ihd} \times caregiving_{ihdt}}$	1.638 (2.299)	1.501 (2.211)	0.416 (2.285)	0.235 (2.196)
$\mathbf{Time_t}$	-7.404*** (2.201)	-6.281*** (1.964)	-6.964*** (2.005)	-5.544** (1.924)
$\mathbf{Treatment_{ihd}}$	-3.147**	-3.714***	-4.744***	0.439

	(1.526)	(1.414)	(1.485)	(2.387)
$\mathbf{caregiving_{ihdt}}$	16.365*** (2.079)	11.317*** (2.019)	12.425*** (2.082)	12.482*** (1.991)
No. of Observations	87,399	87,399	81,068	81,068
R-Squared	0.047	0.263	0.27	0.29
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓
B. Unpaid Household Work by Married Men (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$\mathbf{Shock_{ihdt} \times caregiving_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd} \times caregiving_{ihdt})}$	**8.0157*** **(4.493)**	**7.75*** **(4.391)**	**6.209** **(4.349)**	**5.941** **(4.249)**
$\mathbf{Shock_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd})}$	6.341*** (1.365)	6.04** (1.371)	6.928*** (1.371)	5.727*** (1.322)
$\mathbf{Time_t \times caregiving_{ihdt}}$	-9.707*** (3.589)	-9.387*** (3.593)	-7.074** (3.565)	-6.763** (2.582)
$\mathbf{Treatment_{ihd} \times caregiving_{ihdt}}$	-2.067 (3.304)	-2.466 (3.275)	-2.592 (3.198)	-2.796 (3.083)
$\mathbf{Time_t}$	-5.998*** (1.192)	-5.679*** (1.206)	-6.509*** (1.194)	-5.414*** (1.158)
$\mathbf{Treatment_{ihd}}$	-2.947*** (0.986)	-3.181*** (0.972)	-3.322*** (0.996)	-0.928 (1.591)
$\mathbf{caregiving_{ihdt}}$	18.754*** (2.942)	18.155*** (2.941)	17.442*** (2.871)	17.545*** (2.767)
No. of Observations	69,004	69,004	66,520	66,520
R-Squared	0.037	0.081	0.098	0.115
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓

*Table 9a. Heterogeneous Effects on Double Difference Estimates of Climate Shock on Unpaid Household work by caregiving responsibilities. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).*

A. Paid Labor Force Participation by Married Women (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt} \times caregiving_{ihdt}$ ($Time_t \times Treatment_{ihd} \times caregiving_{ihdt}$)	**-3.163 (2.184)**	**-4.121** (1.495)**	**-3.723** (1.559)**	**-3.450** (1.663)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	2.475** (2.207)	2.804** (1.359)	3.000** (1.489)	3.166** (1.406)
$Time_t \times caregiving_{ihdt}$	2.363** (1.978)	3.309** (1.275)	3.286** (1.348)	2.988** (1.469)
$Treatment_{ihd} \times caregiving_{ihdt}$	1.977 (1.321)	1.136 (0.924)	1.073 (0.909)	1.299 (0.943)
$Time_t$	-3.046 (1.993)	-3.051** (1.218)	-3.123** (1.344)	-3.264** (1.258)
$Treatment_{ihd}$	-3.294 (2.042)	-0.838 (0.867)	-1.028 (0.927)	-3.294 (2.042)
$caregiving_{ihdt}$	-2.336* (1.265)	-1.979** (0.813)	-2.050** (0.796)	-2.163*** (0.826)
No. of Observations	88,916	88,916	82,468	82,468
R-Squared	0.006	0.579	0.586	0.59
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓
B. Paid Labor Force Participation by Married Men (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt} \times caregiving_{ihdt}$ ($Time_t \times Treatment_{ihd} \times caregiving_{ihdt}$)	**-8.576 (7.004)**	**-7.211 (6.68)**	**-6.919 (6.58)**	**-6.377 (6.308)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	0.444 (3.465)	1.081 (2.981)	-0.494 (3.11)	0.277 (2.956)
$Time_t \times caregiving_{ihdt}$	10.686* (6.182)	9.037 (5.986)	9.515 (5.868)	9.142 (5.574)
$Treatment_{ihd} \times caregiving_{ihdt}$	3.789 (4.021)	5.355 (3.998)	4.929 (3.984)	5.346 (3.898)
$Time_t$	3.21 (3.056)	1.081 (2.981)	3.673 (2.791)	2.695 (2.632)
$Treatment_{ihd}$	0.419 (2.057)	-0.191 (1.722)	0.505 (1.816)	-3.715 (3.357)
$caregiving_{ihdt}$	-13.222 (3.588)	-15.868** (3.584)	-15.955** (3.573)	-16.38** (3.477)
No. of Observations	68,226	68,226	65,744	65,744
R-Squared	0.004	0.357	0.346	0.351

Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓

*Table 9b. Heterogeneous Effects on Double Difference Estimates of Climate Shock on Paid Labor Force Participation by caregiving responsibilities. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).*

A. Unpaid Household Work by Married Women (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$\mathbf{Shock_{ihdt} \times married_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd} \times married_{ihdt})}$	**12.705*** (3.674)**	**11.781*** (3.000)**	**12.427*** (3.414)**	**13.624*** (3.429)**
$\mathbf{Shock_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd})}$	1.850 (2.699)	0.539 (2.026)	0.620 (2.544)	-1.631 (2.567)
$\mathbf{Time_t \times married_{ihdt}}$	-4.967 (3.233)	-6.219** (1.882)	-6.565** (3.055)	-7.011** (3.081)
$\mathbf{Treatment_{ihd} \times married_{ihdt}}$	-2.083 (2.278)	-2.154 (1.988)	-2.015 (2.194)	-2.157 (2.19)
$\mathbf{Time_t}$	-3.067 (2.354)	-1.309 (1.763)	-1.315 (2.291)	0.352 (1.319)
$\mathbf{Treatment_{ihd}}$	-1.009 (1.623)	-1.754 (1.332)	-2.785* (1.332)	1.149 (2.282)
$\mathbf{married_{ihdt}}$	38.253*** (1.465)	16.479*** (1.992)	17.436*** (2.262)	17.232*** (2.261)

No. of Observations	137,715	137,238	122,462	122,462
R-Squared	0.394	0.564	0.563	0.574
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓
B. Unpaid Household Work by Married Men (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$\mathbf{Shock_{ihdt} \times married_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd} \times married_{ihdt})}$	**3.678*** **(1.985)**	**3.526*** **(1.939)**	**4.879**** **(1.932)**	**4.648**** **(1.946)**
$\mathbf{Shock_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd})}$	3.596*** (1.366)	3.788*** (1.267)	3.739*** (1.284)	3.143** (1.378)
$\mathbf{Time_t \times married_{ihdt}}$	-3.575*** (1.682)	-2.995* (1.637)	-4.361** (1.628)	-4.141** (1.246)
$\mathbf{Treatment_{ihd} \times married_{ihdt}}$	-1.881 (1.452)	-1.084 (1.036)	-2.475* (1.061)	-2.418* (1.438)
$\mathbf{Time_t}$	-3.156*** (1.126)	-2.218 (1.404)	-3.619*** (1.042)	-3.156*** (1.159)
$\mathbf{Treatment_{ihd}}$	-1.728* (0.980)	-1.457 (0.700)	-1.696* (0.937)	-1.965 (1.691)
$\mathbf{married_{ihdt}}$	7.132*** (1.352)	4.561*** (1.541)	6.325*** (1.577)	6.352*** (1.591)
No. of Observations	109,606	109,181	106,375	106,375
R-Squared	0.051	0.117	0.127	0.141
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	*X*	*X*	*X*	✓

*Table 10a. Heterogeneous Effects on Double Difference Estimates of Climate Shock on Unpaid Household work by marital status. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).*

A. Paid Labor Force Participation by Married Women (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt} \times married_{ihdt}$ $(Time_t \times Treatment_{ihd} \times married_{ihdt})$	**0.476 (2.997)**	**-0.0704 (1.793)**	**-0.453 (1.967)**	**-1.136 (1.949)**
$Shock_{ihdt}$ $(Time_t \times Treatment_{ihd})$	1.4003 (2.021)	2.343* (1.237)	2.914** (1.429)	3.627** (1.455)
$Time_t \times married_{ihdt}$	-0.111 (2.713)	-0.204 (1.608)	0.194 (1.796)	0.855** (1.771)
$Treatment_{ihd} \times married_{ihdt}$	0.214 (1.839)	0.101 (1.159)	0.288 (1.199)	0.204 (1.188)
$Time_t$	-2.549 (1.822)	-2.391** (1.121)	-2.975** (1.334)	-3.594*** (1.354)
$Treatment_{ihd}$	-2.254* (1.345)	-0.787 (0.809)	-1.273 (0.884)	-2.986** (1.494)
$married_{ihdt}$	3.582 (1.669)	-0.778 (1.209)	-1.265 (1.283)	-1.163 (1.268)
No. of Observations	139,508	139,031	124,216	124,216
R-Squared	0.012	0.599	0.602	0.606
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓
B. Paid Labor Force Participation by Married Men (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt} \times married_{ihdt}$ $(Time_t \times Treatment_{ihd} \times married_{ihdt})$	**6.359 (7.758)**	**-0.266 (6.918)**	**0.591 (6.682)**	**0.714 (6.616)**
$Shock_{ihdt}$ $(Time_t \times Treatment_{ihd})$	-2.423 (7.081)	2.928 (6.095)	0.862 (5.839)	0.555 (5.774)
$Time_t \times married_{ihdt}$	-2.109 (6.744)	3.785 (6.002)	3.449 (5.772)	3.445 (5.701)
$Treatment_{ihd} \times married_{ihdt}$	-3.152 (5.266)	2.541 (4.3005)	2.134 (4.275)	1.876 (4.321)
$Time_t$	2.163 (6.126)	-2.701 (5.24)	-1.036 (4.974)	-0.901 (4.921)
$Treatment_{ihd}$	0.696 (4.721)	-4.463 (3.618)	-4.158 (3.611)	-2.834 (4.723)
$married_{ihdt}$	6.427 (4.758)	0.774 (4.003)	-1.353 (4.053)	-1.09 (4.098)
No. of Observations	121,224	121,224	106,409	106,409
R-Squared	0.007	0.118	0.135	0.139

Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓

*Table 10b. Heterogeneous Effects on Double Difference Estimates of Climate Shock on Paid Labor force by marital status. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).*

Unpaid Household Work by Married Women (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**8.890*** (2.885)**	**7.872*** (2.48)**	**8.798** (2.485)**	**9.444*** (2.367)**
$Time_t$	-4.484** (2.564)	-4.319** (2.187)	-5.066** (2.196)	-5.299** (2.063)
$Treatment_{ihd}$	0.122 (1.767)	-0.526** (1.617)	-1.072 (1.683)	1.971 (2.428)
No. of Observations	61,845	61,845	57,759	57,759
R-Squared	0.01	0.258	0.281	0.297
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓
Unpaid Household Work by Married Men (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**4.473*** (1.516)**	**3.888** (1.51)**	**4.736*** (1.472)**	**4.259*** (1.409)**
$Time_t$	-4.894*** (1.316)	-4.313*** (1.332)	-5.181*** (1.313)	-4.711*** (1.244)
$Treatment_{ihd}$	-1.155 (1.106)	-1.483** (1.072)	-1.692*** (1.118)	-0.622 (1.624)
No. of Observations	50,536	50,536	48,724	48,724
R-Squared	0.008	0.069	0.102	0.118
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓

*Table 11a. Double Difference Estimates of Climate Shock on Unpaid Household Labor by excluding districts with highest number of poorest families. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05).*

Paid Labor Force Participation by Married Women (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**1.918 (2.795)**	**2.988* (1.631)**	**2.995* (1.775)**	**2.413 (1.708)**
$Time_t$	-2.554 (2.548)	-3.85** (1.469)	-4.027** (1.624)	-3.515** (1.539)
$Treatment_{ihd}$	-2.515 (1.617)	-1.551 (1.02)	-2.022** (1.078)	-3.794* (2.051)
No. of Observations	62,780	62,780	58,574	58,574
R-Squared	0.002	0.598	0.611	0.612
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓
Paid Labor Force Participation by Married Men	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**-1.531 (4.033)**	**0.095 (3.364)**	**-1.54 (3.458)**	**-2.281 (3.283)**
$Time_t$	3.443 (3.057)	2.974 (3.009)	4.593 (3.096)	4.979* (2.907)
$Treatment_{ihd}$	1.223 (2.11)	-0.916 (1.989)	-0.625 (2.062)	-2.229 (3.431)
No. of Observations	49,917	49,917	48,107	48,107
R-Squared	0.004	0.367	0.359	0.363
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓

*Table 11b. Double Difference Estimates of Climate Shock on Paid Labor force Participation by excluding districts with highest number of poorest families. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05).*

Unpaid Household Work by Married Women (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**16.55*** (2.596)**	**13.55*** (2.335)**	**13.738*** (2.386)**	**12.548*** (2.296)**
$Time_t$	-7.911*** (2.233)	-7.039*** (1.991)	-7.204*** (2.047)	-5.877*** (1.956)
$Treatment_{ihd}$	-2.483*** (1.641)	-3.580** (1.482)	-4.348** (1.548)	0.0321*** (2.511)
No. of Observations	65,510	65,510	60,882	60,882
R-Squared	0.033	0.263	0.274	0.287
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓
Unpaid Household Work by Married Men (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**7.310*** (1.5)**	**6.857*** (1.503)**	**7.446*** (1.531)**	**6.374*** (1.478)**
$Time_t$	-6.221*** (1.229)	-5.899*** (1.234)	-6.946*** (1.263)	-5.949*** (1.218)
$Treatment_{ihd}$	-3.285*** (1.073)	-3.423*** (1.049)	-3.568*** (1.079)	-1.475 (1.669)
No. of Observations	50,848	50,848	49,214	49,214
R-Squared	0.015	0.056	0.083	0.09
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓

*Table 12a. Double Difference Estimates of Climate Shock on Unpaid Household Labor by excluding border treatment districts. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05*, *p<0.1).*

Paid Labor Force Participation by Married Women (Hours/Week)	*(1)*	*(2)*	*(3)*	*(4)*
$Shock_{ihdt}$ $(Time_t \times Treatment_{ihd})$	*2.211* *(2.241)*	*2.537** *(1.385)*	*2.878** *(1.519)*	*3.141*** *(1.441)*
$Time_t$	*-2.855* *(1.967)*	*-2.928*** *(1.190)*	*-3.143*** *(1.325)*	*-3.253*** *(1.245)*
$Treatment_{ihd}$	*-3.281*** *(1.266)*	*-0.895* *(0.871)*	*-1.069* *(0.931)*	*-2.825* *(2.072)*
No. of Observations	*66,699*	*66,699*	*61,978*	*61,978*
R-Squared	*0.005*	*0.559*	*0.571*	*0.575*
Individual Level Controls	*X*	✓	✓	✓
Household Level Controls	*X*	*X*	✓	✓
District Fixed Effects	*X*	*X*	*X*	✓
Paid Labor Force Participation by Married Men	**(1)**	**(2)**	**(3)**	**(4)**
$\mathbf{Shock_{ihdt}}$ $\mathbf{(Time_t \times Treatment_{ihd})}$	**1.133** **(3.64)**	**1.644** **(3.149)**	**-0.578** **(3.264)**	**0.318** **(3.088)**
$\mathbf{Time_t}$	3.443 (3.06)	2.242 (2.699)	4.514 (2.80)	3.486 (2.627)
$\mathbf{Treatment_{ihd}}$	1.402 (2.161)	-0.384 (1.838)	0.787 (1.928)	-3.016 (3.427)
No. of Observations	50,288	50,288	48,656	48,656
R-Squared	0.005	0.35	0.347	0.352
Individual Level Controls	X	✓	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	X	X	X	✓

*Table 12b. Double Difference Estimates of Climate Shock on Paid Labor force Participation by excluding border districts. Individual level controls include occupation, education, age. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

Unpaid Household Work by Married Women (Hours/Week)	**(1)** (Only marginalized Caste)	**(2)** (Only marginalized Caste)	**(3)** (Only Upper Caste)	**(4)** (Only Upper Caste)
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**17.102*** (3.077)**	**14.19*** (2.335)**	**8.383** (4.197)**	**8.803** (2.296)**
$Time_t$	-9.309*** (2.787)	-8.26*** (2.448)	-5.113 (3.587)	-3.377 (3.398)
$Treatment_{ihd}$	-2.969 (1.929)	-4.320** (1.837)	-3.474 (2.767)	-4.028 (2.488)
No. of Observations	61,460	57,472	25,939	23,596
R-Squared	0.028	0.259	0.006	0.303
Individual Level Controls	X	✓	X	✓
Household Level Controls	X	✓	X	✓
District Fixed Effects	X	✓	X	✓
Unpaid Household Work by Married Men (Hours/Week)	**(1)**	**(2)**	**(3)**	**(4)**
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**8.277*** (1.624)**	**6.857*** (1.503)**	**3.041 (2.666)**	**8.854*** (1.677)**
$Time_t$	-7.325*** (1.401)	-5.899*** (1.234)	-3.991* (2.309)	-7.955*** (1.461)
$Treatment_{ihd}$	-4.329*** (1.237)	-3.423*** (1.049)	-0.2144*** (1.799)	-4.303 (1.192)
No. of Observations	48,059	50,848	20,945	46,891
R-Squared	0.016	0.056	0.006	0.098
Individual Level Controls	X	✓	X	✓
Household Level Controls	X	✓	X	✓
District Fixed Effects	X	✓	X	✓

*Table 13a. Double Difference Estimates of Climate Shock on Unpaid Household Labor by different population subgroups based on caste. Individual level controls include occupation, education, age. Household level controls include religion, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05*, *p<0.1).*

Paid Labor Force Participation by Married Women (Hours/Week)	**(1)** (Only marginalized Caste)	**(2)** (Only marginalized Caste)	**(3)** (Only Upper Caste)	**(4)** (Only Upper Caste)
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**2.474** **(2.851)**	**3.184*** **(1.737)**	**1.340** **(3.005)**	**3.241** **(2.603)**
$Time_t$	-3.191 (2.667)	-2.661* (1.564)	-1.689 (2.297)	-5.121** (2.277)
$Treatment_{ihd}$	-4.963*** (1.548)	-2.221** (1.081)	4.196 (1.86)	1.810 (1.577)
No. of Observations	62,497	58,386	26,419	24,082
R-Squared	0.008	0.592	0.010	0.598
Individual Level Controls	X	✓	X	✓
Household Level Controls	X	✓	X	✓
District Fixed Effects	X	✓	X	✓
Paid Labor Force Participation by Married Men (Hours/Week)	(1) (Only marginalized Caste)	(2) (Only marginalized Caste)	(3) (Only Upper Caste)	(4) (Only Upper Caste)
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**0.659** **(4.151)**	**-2.763** **(3.59)**	**-1.405** **(6.228)**	**-1.265** **(5.968)**
$Time_t$	3.035*** (3.665)	5.073 (3.149)	4.961 (5.459)	6.705 (5.482)
$Treatment_{ihd}$	-0.616*** (2.418)	1.725 (2.081)	3.034 (3.861)	0.677 (3.469)
No. of Observations	47,516	46,350	20,710	19,394
R-Squared	0.003	0.337	0.004	0.402
Individual Level Controls	X	✓	X	✓
Household Level Controls	X	✓	X	✓
District Fixed Effects	X	✓	X	✓

*Table 13b. Double Difference Estimates of Climate Shock on Paid Labor Force Participation by different population subgroups based on caste. Individual level controls include occupation, education, age. Household level controls include religion, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05*, *p<0.1).*

Unpaid Household Work by Married Women (Hours/Week)	**(1)** (15-29 years)	**(2)** (30-59 years)	**(3)** (60 years & above)
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**23.518*** (6.006)**	**12.633** (2.403)**	**7.66 (6.249)**
$Time_t$	-14.965*** (5.286)	-7.859*** (2.119)	-1.329 (4.052)
$Treatment_{ihd}$	-3.543*** (3.965)	-5.123** (1.678)	0.988 (3.428)
No. of Observations	14,417	57,908	8,743
R-Squared	0.322	0.243	0.269
Individual Level Controls	✓	✓	✓
Household Level Controls	✓	✓	✓
District Fixed Effects	✓	✓	✓
Unpaid Household Work by Married Men (Hours/Week)	(1) (15-29 years)	(2) (30-59 years)	(3) (60 years & above)
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**8.636 (5.719)**	**6.927*** (1.591)**	**7.906*** (2.983)**
$Time_t$	-4.667*** (5.799)	-6.271*** (1.363)	-9.362*** (2.722)
$Treatment_{ihd}$	-9.678* (5.418)	-2.873** (1.254)	-5.266*** (1.848)
No. of Observations	2,723	45,577	18,220
R-Squared	0.655	0.072	0.131
Individual Level Controls	✓	✓	✓
Household Level Controls	✓	✓	✓
District Fixed Effects	✓	✓	✓

*Table 14a. Double Difference Estimates of Climate Shock on Unpaid Household Labor by age group. Individual level controls include occupation and education. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05*, *p<0.1).*

Paid Labor force Participation by Married Women (Hours/Week)	**(1)** (15-29 years)	**(2)** (30-59 years)	**(3)** (60 years & above)
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**1.288** **(2.063)**	**2.961*** **(1.789)**	**3.43** **(3.131)**
$Time_t$	-1.403 (1.591)	-2.957** (1.632)	-1.329** (4.052)
$Treatment_{ihd}$	-1.125 (1.039)	-1.269** (1.146)	2.481 (1.685)
No. of Observations	14,982	58,658	8,828
R-Squared	0.56	0.601	0.476
Individual Level Controls	✓	✓	✓
Household Level Controls	✓	✓	✓
District Fixed Effects	✓	✓	✓
Paid Labor force Participation by Married Men (Hours/Week)	(1) (15-29 years)	(2) (30-59 years)	(3) (60 years & above)
$Shock_{ihdt}$ ($Time_t \times Treatment_{ihd}$)	**44.129*** **(20.155)**	**0.519** **(3.895)**	**-6.429** **(4.263)**
$Time_t$	-40.748** (17.269)	3.593 (3.495)	6.026 (3.850)
$Treatment_{ihd}$	-0.789 (12.183)	0.368 (2.568)	1.272 (2.101)
No. of Observations	2,637	45,011	18,096
R-Squared	0.469	0.165	0.519
Individual Level Controls	✓	✓	✓
Household Level Controls	✓	✓	✓
District Fixed Effects	✓	✓	✓

*Table 14b. Double Difference Estimates of Climate Shock on Paid Labor Force Participation by age group. Individual level controls include occupation and education. Household level controls include religion, caste, main source of income, monthly consumption expenditure, dependency ratio, sex ratio, type of washing clothes and housing (both serve as proxy for household assets which reflect adaptation capacity of households), primary sources of cooking. District level fixed effects include unobserved district level characteristics. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05*, *p<0.1).*

Appendix

District Names	Excess rainfall (in%)	Fatalities & Injuries	Loss in Cropped Areas (Hectares)	No. of fully damaged & severely damaged	No. of houses flood hit and cleaned
Thiruvananthapuram	126	0	209.57	205	2
Kollam	113	0	90.065	431	484
Pathanamthitta	115	0	1268.82	127	3929
Alapuzha	99	6	114	452	15758
Kottyam	103	6	1002.52	226	26496
Ernakulam	140	1	420.276	377	14064
Thrissur	127	17	1021.17	769	23144
Palakkad	217	12	3811.57	2229	7179
Malappuram	176	64	525.3838	4204	48012
Kozhikode	176	17	102.89	1168	47534
Wayanad	110	23	1262.0862	7702	9079
Kannur	100	9	544.42	2159	15185
Kasaragod	81	2	148.78	506	5146

Table A.1.a. District wise Damages by Kerala Flood 2019. Source: State Disaster Management Handbook 2019.

District Names	Affected Fish Farms (Hectares)	Total losses in dairy farm (in '00,000 (INR))	Damaged roads (in Km)	Affected wells	Affected families (based on relief data)
Thiruvananthapuram	0	0	275.71	0	177
Kollam	3.2184	59.26845	108.876	97	312
Pathanamthitta	96.2	50.73605	110.32	971	2097
Alapuzha	196.438	239.8431	56.75	1499	6264
Kottyam	1374.72	90.58325	323.02	10936	6146
Ernakulam	83.034	160.79	320.525	4458	11184
Thrissur	4356	158.183	458.96	17650	65718
Palakkad	38.94	638.20997	379.48	4516	4765
Malappuram	588	608.0219	414.762	41748	17768
Kozhikode	39.038	806.57565	202.5	43085	47342
Wayanad	40.919	378.85624	401.28	3945	24563

Kannur	257	334.53645	132.029	15011	27534
Kasaragod	2.33	105.3362	226.21	4768	1098

Table A.1.b. District wise Damages by Kerala Flood 2019. Source: State Disaster Management Handbook 2019.

District Names	**pc1**	**pc2**	**pc3**	**pc4**	**pc5**	**pc6**	**pc7**	**Shock Index**
Thiruvananthapuram	-1.039442	-0.4509	-0.7715	-1.0799	-0.0898	-0.5970	-0.6315	0
Kollam	-1.009287	-0.4482	-0.76501	-0.85077	-0.4271	-0.7160	-0.5278	2.973
Pathanamthitta	-0.7937	-0.3712	-0.70605	-0.8837	-0.3752	0.4573	-0.66735	6.5003
Alapuzha	-0.0536	-0.2881	-0.6704	-0.1525	-0.7903	-0.6922	-0.5182	24.105
Kottyam	0.61810	0.6879	-0.0338	-0.7296	-0.6865	0.1923	-0.6219	43.0108
Ernakulam	-0.15968	-0.3821	-0.47082	-0.4582	0.2734	-0.3873	-0.5526	20.7168
Thrissur	0.40839	3.15779	0.41911	-0.4683	-0.0638	0.2101	-0.373	75.945
Palakkad	-0.59043	-0.41865	-0.4669	1.3878	2.2711	2.988	0.2973	36.0259
Malappuram	1.96421	0.0362076	2.045	1.271005	1.2074	-0.283	1.204	95.8675
Kozhikode	1.93431	-0.4185	2.135	2.03872	1.2074	-0.7032	-0.1896	100
Wayanad	-0.47156	-0.41702	-0.5054	0.3849	-0.5049	0.4507	2.809	25.8300
Kannur	-0.08955	-0.23801	0.2410	0.21359	-0.7644	-0.2637	0.2652	38.4104
Kasaragod	-0.7176	-0.44898	-0.4499	-0.672	-1.25732	-0.6576	-0.4934	11.6561

Table A.2. District wise First Seven Principal Components (pcs) and overall shock index. *Author's own calculations. The overall shock index is derived through a two-step process: first, by averaging the seven principal components; and second, by rescaling this average to a range of 0 to 100%. This rescaling is done by subtracting the minimum average from each average and then dividing it by the range (i.e., the difference between the maximum and minimum averages).*