Impact of Flood on Labor Market through Gender Lens: A Case from India

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Abstract

In less developed economies, frequent climate events continue to threaten both gender equality and stability of local labor markets. This study examines how climate shocks affect gender gap in paid labor outcomes. Using the catastrophic 2018 floods in Indian coastal state, Kerala, this paper employs a difference-in-difference design using a population weighted flood exposure to define treatment districts. Key findings indicate that the flood shock significantly reduces paid labor hours of both men and women, with a disproportionately larger impact on women. These effects are especially pronounced in rural areas. Casual labor is most vulnerable to the flood while self-employment emerged as a key coping mechanism, particularly, among men. Moreover, marital status and dependency burden further shape the extent to which the flood affects paid labor outcomes differently between men and women.

Keywords: Climate Shock, Flood, Gender, Paid Labor, India

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1. Introduction

Climate change has increasingly become a global phenomenon with far-reaching consequences beyond changing weather conditions. 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 and intensity of extreme climate events such as floods, cyclones, droughts, heatwaves. The resulting shocks from these events impact various economic systems (McKinsey 2020). This is especially the case in less developed countries where majority of the population rely on agricultural activities and casual labor for their living. For example, agriculture is the biggest absorber of workers in India which accounts for 46.5% of total workers (PLFS 2020-21). More than half of the Indian workers are self-employed or casual workers who lack formal work arrangements (PLFS 2020-21).

In low-and middle-income countries, gender disparities are widespread which could be attributed to social norms and are often exacerbated by various factors, including climate change and related shocks. Existing studies have shown that climate shocks increase discriminatory behavior against women such as early marriages (Corno et al. 2020), intimate partner violence (Aguilar-Gómez & Sallazar- Díaz 2025), food insecurity (Hadley et al. 2023, Asfaw & Maggio 2017), and migration (Afridi et al. 2020). However, less attention has been paid to how climate shocks impact men's and women's participation in the labor market.

Climate extremes disrupt both labor demand and labor supply. On the demand side, climate change affects sectors which are heavily dependent on environmental conditions such as agriculture, construction and tourism. Floods and droughts can lead to crop failures which affect agricultural productivity and result in reduced job opportunities for farm laborers. Similarly, extreme weather events like cyclones or floods adversely affect construction sites and make tourist destinations unsafe---both providing examples of climate-induced fall in labor demand in non-agricultural sectors. On the supply side, climate change affects workers' ability and desire to participate in labor market. Extreme temperatures and weather shocks increase risk of heat stress, illness or injury especially for outdoor workers which reduce workers' productivity and supply (Dasgupta et al. 2021, Somanthan et al. 2021). At the same time, financial pressure caused by climate shocks influence an individual's time allocation towards paid labor in affected areas (Dasgupta et al. 2021). While this may indicate increase in labor supply for both men and women, social norms and an individual's capacity to migrate could influence labor supply both in affected and unaffected areas (Afridi et al. 2020).

This study examines whether and to what extent extreme climate shocks impact gender disparities in the paid labor market, specifically, men's and women's participation in paid labor. Specifically, this study seeks to assess the impact of a catastrophic flood that occurred in Kerala, an Indian coastal state, in 2018 on gender differences in paid employment outcomes.

Key findings show that the 2018 Kerala flood was more pronounced on the intensive margin than the extensive margin. Women's weekly paid labor declined by 1.42 hours after the flood, which represents nearly 23.5% drop relative to pre-flood levels while men's working hours declined by 1.16 hours per week but not significant. The latter is 7.3% of the pre-flood levels. Thus, women were more adversely affected in the post-flood labor market. While the effect of the flood was statistically insignificant on employment participation, it is noteworthy that women's employment participation declined by 1.6 percentage points (pp) but men's employment participation did increase by 1.7 pp. This implies that those who remained employed reduced their working hours, particularly men. When I focus on districts that are less affected by the flood, I find that men's employment participation recovered by 3.2 percentage points (pp) and their paid labor hours declined only marginally. However, women's weekly paid labor declined by 1.55 hours in less affected districts after the flood. This implies that women's employment is more vulnerable after floods irrespective of whether they are in more affected or less affected districts. The results remain robust under all alternative definitions of treatment groups—(a) districts closer to mismanaged dams (b) districts affected by flood-induced landslides.

Moreover, the results show interesting heterogeneous effects shaped by location of dwelling, sector of employment, and gender norms. Urban labor markets appeared relatively more resilient than rural labor markets for both men and women. Casual labor is found to be most vulnerable to floods and self-employment emerged as fallback position. The latter implies a shift toward more home-based work after the flood. Gender norms reflected in marital status and dependency burden, explain these divergent outcomes. Married women were more likely to reduce their paid labor supply compared to unmarried women. Similarly, women in households with higher share of dependent family members were more likely to cut back on paid work, while men increased their labor supply in response. On the contrary, women were more likely to increase their paid labor hours in low-dependency households, while men's labor supply was relatively muted. These findings are consistent with social expectations around gender, especially in less developed countries.

My findings contribute to the emerging studies that examine the relationship between climate extremes and labor dynamics in developing countries. Afridi et al. (2022) found that droughts reduced women's agricultural workdays relative to men's. Maitri & Tagat (2024) reported that negative rainfall shocks increased men's participation in regular wage work by nearly 0.6 days per week while having insignificant effect on women's involvement in paid work. Conversely, studies on flooding present differing results: probability of non-employed women entering employment increased by 13 percentage points in the aftermath of the 2014 floods in Bangladesh (Canessa & Giannelli 2021). The 2017 Bangladesh floods increased women's participation in market activities, while men took on more domestic responsibilities (Vitellozzi & Giannelli 2024). However, it is important to note that the term "market activities" is not restricted to participation in jobs where an individual directly get paid but also includes unpaid contributions to family establishments. (Vitellozzi & Giannelli 2024). In low-and middle-income countries, most women engage in unpaid work within the family business which even though categorized as market activities, does not generate any income in the hands of laborer. According to ILO definition, such individuals are "contributing family workers" who cannot be considered as similar levels as the self-employed in family enterprises because "their degree of commitment to the operation of the establishment is not at a level comparable to that of the head of the establishment".

My research contributes to this recent strand of literature in two possible ways:

First, most publicly available labor force surveys and household survey data in developing countries provide district-level data without georeferenced information. This poses challenges for impact assessment by using more granular level for treatment. To address this, I demonstrate a method to construct district-level population exposure estimates using satellite-based flood data from Google Earth Engine (GEE). By combining proportion of flooded area and population at sub-district level and averaging this for each district, I produce a weighted exposure measure. This approach offers a method to define treatment at the district level when georeferenced survey data is unavailable.

Second, there exists lack of empirical studies on the effects of flood on labor market outcomes in South Asia, particularly in India. Existing studies have focused on droughts or rainfall variability when examining the nexus between climate shocks and gender differences in labor market participation (Afridi et al. 2020, Maitri and Tagat 2024). Among a few studies that look at floods, the focus has been limited. For example, Canessa and Giannelli (2021) study the impact of flood on women's paid employment in subsistence activities in Bangladesh but do not consider men's outcomes. In contrast, my study examines the impact of floods on both men's and women's paid labor outcomes beyond subsistence work. Furthermore, I include both extensive margin (i.e., binary outcome—whether an individual is employed or not) and intensive margin (i.e., weekly working hours). While Vitellozzi and Giannelli (2024) include both men and women in their analysis, they only focus on unpaid work in family businesses which does not capture the full picture of paid labor markets. This study fills this gap by including all activities under paid labor across self-employment, regular wage work, and informal or casual labor.

Section 2 outlines the conceptual framework explaining the relationship between climate shocks and the gender division of labor. Section 3 provides the case study context for this analysis. Section 4 details the data and research methodology used for empirical analysis. Section 5 presents the results, followed by the conclusion in Section 6.

2. Conceptual Framework

This study examines the effects of climate shock, specifically flood, on gender division of labor. I utilize the conceptual framework depicted in figure 1 to explain how climate events affect gender division in paid labor which I later present in empirical analysis.

When a climate event like a flood occurs, it affects human lives through three key pathways: household wealth/assets, natural resources, and health. Floods can lead to significant losses in household wealth and income, particularly for those dependent on climate-sensitive activities such as agriculture and daily wage labor. These economic disruptions create financial strain, often compelling household members to spend more hours in paid labor. At the same time, disruptions in water supply, food availability, and energy access increase domestic work burdens. Climate extremes also exacerbate health risks, particularly for children, the elderly, and individuals with pre-existing conditions. The increased demand for caregiving and domestic chores can reduce the time available for paid labor, while rising healthcare expenses may push household members—regardless of gender—to enter the labor market to cover increased expenditure.

In many developing and less developed countries, social norms dictate that women are primarily responsible for household maintenance and caregiving, while men are expected to seek income outside the home. These norms shape how men and women adjust their labor allocation in response to climate shocks. This is reflected by the factor 'gender norms' in figure 1.

Men, who generally have greater mobility, may migrate to unaffected areas in search of work, while women are more likely to remain in disaster-affected regions, and take on increased domestic and caregiving responsibilities (Afridi et al., 2020). Higher dependency burdens tend to reduce women's time to engage in paid employment.

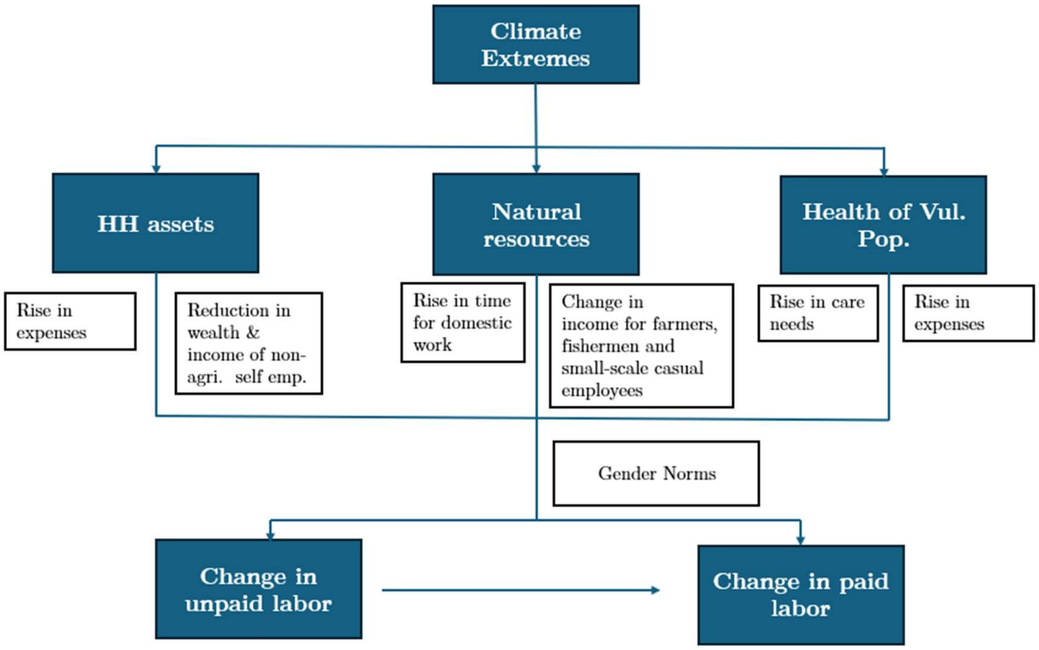

Figure 1. Conceptual Framework

3. Case Study

Kerala, a southwestern coastal state of India, is bordered by the Arabian Sea on the west and the Western Ghats on the east. The state spans a coastline of 580 km and features three distinct geographical regions: hills and valleys, midlands, and coastal areas. The state's river system consists of 44 rivers, primarily originating in the Western Ghats. Due to its geographical positioning, Kerala is highly vulnerable to multiple natural disasters, including floods, landslides, cyclones, and coastal erosion (World Bank, Asian Development Bank, & Government of Kerala, 2018). Approximately 14.8% of the state is flood-prone, and the monsoon season frequently triggers landslides in the hilly regions (World Bank, Asian Development Bank, & Government of Kerala, 2018). The map of Kerala is shown in figure 2.

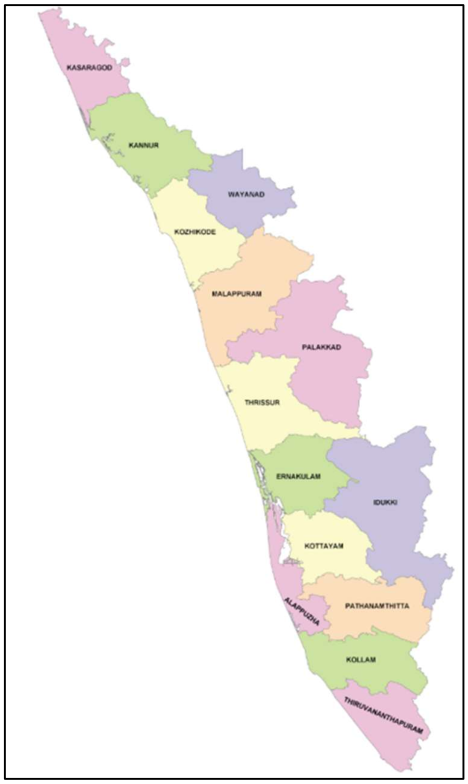

Figure 2. District Boundaries of Kerala.

Kerala has 57 large dams, four of which are operated by the Tamil Nadu government. The total live storage capacity of these dams is 5.806 BCM, accounting for 7.4% of the state's annual average runoff of 78 BCM (Central Water Commission 2018). Seven major reservoirs hold 74% of this capacity (Central Water Commission 2018). Despite these water management infrastructures, the state remains prone to flooding due to heavy monsoons and inadequate dam management and draining capacities (World Bank, Asian Development Bank, & Government of Kerala, 2018).

Kerala received the heaviest downpours between August 8-10, 2018, and August 14-19, 2018. While excessive rainfall is a necessary condition for flooding, the severity of the flood also depends on additional factors such as dam management. In this case, poor reservoir management worsened the flood-induced damage across the state. By early August, most dams were already filled to 90% of their capacity (State Disaster Management of Kerala 2018). Consequently, the heavy downpours led to the opening of 35 dams across the state, including all five gates of the Idukki Dam for the first time in 26 years (Central Water Commission 2018). The intense rainfall and dam releases led to devastating floods, landslides, and widespread destruction across 13 of Kerala's 14 districts (Central Water Commission 2018). The floods resulted in 498 confirmed casualties and displaced over 1.4 million people, who sought refuge in relief camps (World Bank, Asian Development Bank, & Government of Kerala, 2018). The floods caused extensive damage to water supply infrastructure, disrupting urban water supply and contaminating drinking water sources. The siltation of intake wells and damage to treatment plants significantly reduced water quality (World Bank, Asian Development Bank, & Government of Kerala, 2018). About 83,506 household toilets were damaged, leading to sanitation challenges and potential public health hazards (World Bank, Asian Development Bank, & Government of Kerala, 2018).

Figure 3. Pre- and Post-2018 Kerala Floods. The left panel shows Kerala on February 6, 2018, before the floods, while the right panel depicts the region on August 22, 2018, after the floods. Based on false-color imagery, here, bright green indicates vegetation; dark blue represents floodwaters visible in the post-flood image; darker hues in the pre-flood image denote permanent water bodies such as rivers and lakes; white color indicates cloud cover. NASA Earth Observatory images.

The estimated damage was initially valued at INR 19,512 crore (USD 2.8 billion) but was later revised to INR 24,308.35 crore (USD 3.5 billion) as per the Government of Kerala's memorandum to the Government of India. According to satellite imagery, approximately 65,188 hectares of land were submerged (World Bank, Asian Development Bank, & Government of Kerala, 2018).

Sector	Damage (in USD Million)	Worst impacted Districts
Agriculture (Crops and farmland)	2,159	Idukki, Wayanad, Alappuzha, Pathanamthitta
Livestock	24.6	Ernakulam, Malappuram
Fisheries	20.16	Alappuzha, Thrissur, Kottayam
Small Enterprises & Industry	91.7	Statewide
Tourism	72.7 (Infrastructure) + 243 (Revenue Loss)	Alappuzha, Idukki, Ernakulam

Table 1. Summary of Infrastructure Damages and Worst-Affected Districts Due to the 2018 Kerala Floods (Self-Compilation from joint report on 2018 Kerala Floods by Government of Kerala, Asian Development Bank and World Bank).

4. Data and Empirical Strategy

4.1. Data

Information at Individual and Household Level

This paper utilizes data from two rounds of Periodic Labor Force Surveys (PLFS) conducted during four quarters of July 2017-June 2018 and July 2018-June 2019. PLFS is a nationally representative survey conducted by the National Statistical Office (NSO) of India to assess key labor market indicators, including employment, unemployment, and labor force participation. Introduced in July 2017, PLFS is collected on quarterly basis in each round. These surveys include demographic and socioeconomic information for all household members. My main variable as outcome of interest is hours worked for pay by men and women per week. PLFS provides data on hours worked based on activity status—both primary and subsidiary activities for each day of the reference week (Day 1 to Day 7). To obtain a comprehensive measure of paid labor, I aggregate hours worked across both types of activities. Relevant variables at individual level also include weekly occupation status (broad classification includes total labor force, employment, unemployment, unpaid labor), years of education, highest education level, age, and marital status. At the household level, the surveys collect data on religion, social group, relationships to the household head, household size. Using the demographic information, I created (i) sex ratio which is defined as the number of females per male in a household, (ii) dependency ratio which is defined as number of dependent family members per working age population in a household.

Despite the richness of the data, there are three notable limitations. First, the PLFS data is available as repeated cross-sections for combined rural and urban areas but panel data for only urban households. Since both rural and urban areas are affected by floods, this analysis focuses on the repeated cross-sectional data. Second, while individuals often divide their time between paid and unpaid work, the PLFS framework classifies individuals engaged in unpaid work as exclusively outside the paid labor force. Thus, when data on how much time an individual has worked per day is collected, it only includes paid work. Third, PLFS did not start collecting information on migration until July 2020-June 2021.

Information on Climate Shock: Determining Treatment and Control Group

Data on the 2018 Kerala flood damages are obtained from two sources: (a) Memorandum: Kerala Floods—2018, prepared by State Disaster Management Authority, Government of Kerala; (b) Google Earth Engine Maps.

Because out of 14 districts in Kerala, 13 experienced flood-related damage (Kerala State Disaster Management Authority, 2018), I utilize flood extent estimates derive from Google Earth Engine (GEE). These estimates provide taluk-wise inundation data for Kerala in 2018, based on satellite imagery from European Space Agency's Sentinel-1[2]. However, total inundation alone may not fully capture the flood exposure because with larger inundated areas may simply have a greater total land area. To better account for inhabited regions, I incorporate the total area and population of each subdivision from 2011 Census to estimate the affected population in each district:

$$Exposure_d = \sum_{i=0}^{d} \left(\frac{Inundation_i}{Total\ Area_i} \times Population_i \right)$$

This measure accounts for human exposure to flooding rather than just physical extent of inundation. It is evident from table A.1. that Kozhikode, Malappuram, Palakkad, Thrissur, Kottayam and Alappuzha are highly exposed to floods and remaining districts are relatively less exposed to floods. This is shown in figure

[2] Unlike conventional optical satellites, Sentinel-1 uses radar-based imaging and enable flood detection under all weather conditions both during day and night. This particularly makes it reliable to assess flood extent in regions affected by monsoon cloud cover.

A.2. For the main results, I use highly flood-exposed districts as the treatment group. Since lesser affected districts may have had little prior exposure, flood impact could be substantial in less affected districts. Hence, I include all districts of the neighboring state, Tamil Nadu as control. In the early December 2017, however, a cyclone named 'Ockhi' passed by Kerala and Tamil Nadu while heading towards Lakshadweep. This cyclonic storm heavily impacted two districts (out of 14) in Kerala-Ernakulam and Thiruvananthapuram and four (out of 32 districts) districts in Tamil Nadu-Kanyakumari, Thoothukudi, Tirunelveli and Ramnathapuram. To ensure a cleaner comparison, I exclude these districts.

Table 2 presents summary statistics for key continuous and binary variables for treatment and control groups. Men's employment participation is high across both groups—58.4% in the treatment group and 61.7% in the control group. In contrast, women's participation is much lower, at 15.6% in the treatment group and 24.8% in the control group—which reflects the well-documented gender disparities in Indian labor market (PLFS 2018-19). In terms of intensive margin, men in treatment group report an average of 25.02 hours of weekly work while those in control group works 30.31 hours per week. Among women, the average is 11.24 hours of weekly work in the control group while in treatment group it is 6.41 hours of weekly work in the treatment group. Demographic characteristics are similar across the treatment and control groups. Average age of men and women are around 32-33 years and mean years of education vary approximately between 7—8 years, that is, completion of secondary education. On average, overall household size is 4 in control group and nearly 5 in treatment group. Households in the treatment group also report a higher average number of dependent members (1.5 vs 1.11) and also a higher sex-ratio.

	Treatment			***Control***		
Variable	**No. of Obs.**	**Mean**	**SD**	**No. of Obs.**	**Mean**	**SD**
		Individual Level				
Employment Participation (men)	11,848	0.584	0.493	28,432	0.617	0.486
Employment Participation (women)	13,302	0.156	0.363	28,824	0.248	0.432
Weekly working hours (men)	10,958	25.02	26.11	26,562	30.31	27.78
Weekly working hours (women)	12,386	6.41	16.269	27,093	11.24	20.38
Age of men (years)	11,848	31.980	19.696	28,432	31.286	18.19
Age of women (years)	13,302	33.196	19.275	28,824	31.996	17.905
Years of formal education of men	11,848	8.209	4.641	28,432	8.126	5.135
Years of formal education of women	13,302	8.313	4.865	28,824	7.212	5.395
		Household Level				
Overall Household Size	26,877	4.632	1.943	59,908	4.140	1.557
No. of Working Age Household members	26,877	2.831	2.216	59,908	2.796	2.114
No. of Dependent Household members	26,877	1.495	1.746	59,908	1.108	1.434
Sex Ratio	19,375	1.042	0.930	45,154	0.937	0.842

Table 2. Summary Statistics for Binary and Continuous Variables.

4.2. Empirical Strategy

To estimate the effects of the 2018 August flood, I use difference-in-difference (DID) strategy, separately for men and women:

$$y^s_{ihdt} = \beta^s_0 + \beta^s_1 Treat_{ihd} + \beta^s_2 Post_t + \beta^s_3 (Treat_{ihd} \times Post_t) + \beta^s_4 X'_{ihdt} + \beta^s_5 Z'_{hdt} + \tau^s_d + \varepsilon^s_{ihdt} \quad (1)$$

where y^s_{ihdt} represents paid labor outcome for individual i from household h in district d at quarter t. This paid labor outcome is measured in two ways: (a) extensive margin: it is a binary variable which takes value 1 if an individual i from household h in district d at quarter t participates in paid labor force and 0 otherwise; (b) intensive margin: it is a continuous variable that captures hours spent on paid labor by an individual i from household h in district d at quarter t.

$Treat_d$ is a treatment dummy that takes value 1 if individual i from household h is located in affected district and 0 otherwise. $Post_t$ is a time dummy which takes value 1 for all quarters after the flood has occurred and 0 before the flood. X'_{ihdt} is the vector of individual level characteristics which include age, education, and marital status. Z'_{hdt} is vector of household level characteristics which include religion, social group, household size, monthly consumption spending. τ^s_d is district fixed effect that controls for unobserved district level factors which may impact outcome variable. ε^s_{ihdt} is error term which is clustered at household level. Eq. (1) is estimated separately for $s\epsilon\{female, male\}$.

5. Results

5.1. Parallel Trend Test: Event Study Results

To validate the difference-in-differences identification strategy, it is important to test the presence of pre-event trends between treatment and control groups. If there exist no statistically significant differences in pre-event trends, it supports the validity of attributing the post-event differences in outcomes to the 2018 August flood and we can infer the regression estimates as causal results.

I assess this assumption using an event study analysis where I present the effect of the 2018 August flood on paid labor outcomes for each quarter during July 2017-June 2019 with the base period as April 2018-June 2018 (t=-1). The estimations from this event study analysis are given in Panels (A)—(D) of Figure 3. Panels (A)—(B) report the effects on extensive margin (employment participation) while Panels (C)—(D) report results for the intensive margin (weekly working hours).

For employment participation (Panels (A)—(B), Figure 3), there are no statistically significant differences in paid labor trends for men (Panel (A), Figure 3) prior to the flood. However, I cannot rule out the possibility of pre-flood differences in employment participation trends for women (Panel B, Figure 3). In case of weekly working hours (Panels (C)—(D), Figure 3), there are no statistically significant difference in trends for both men and women before the 2018 August flood. After the flood, both employment participation and weekly working hours decline significantly for both men and women (Panels (A)—(D), Figure 3). However, the timing and extent of these effects differ by gender. For men, the reduction in paid labor outcomes occurs in the same quarter as the flood event but it eventually recovers (Panels (A) and (C), Figure 3). In contrast, for women, the negative effect emerges with a lag one quarter following the flood (Panels (B) and (D), Figure 3). This suggests that while men experience immediate labor market disruptions, women's paid labor outcomes are affected more gradually in the aftermath of the flood. This gradual effect for women likely reflects increased domestic and caregiving responsibilities after the disaster (Mathew 2014). Moreover, women in Kerala are concentrated in service (formal and informal) sectors (Beyer, Narayan and Thakur 2022) which require stable conditions, restoration of public services and reopening of workplaces and hence recovery takes time.

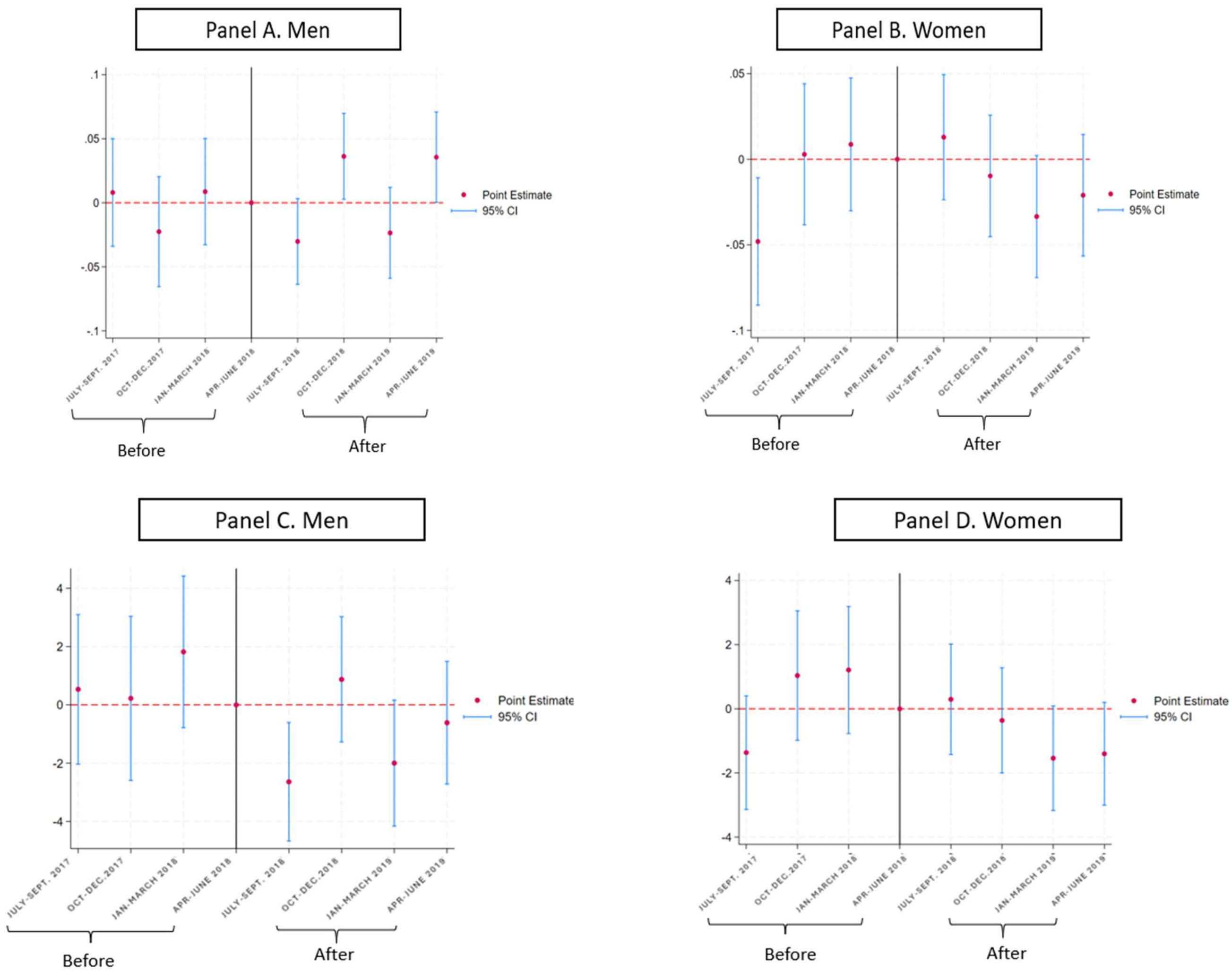

Figure 3. Event Study results for paid labor outcomes whereby treatment group consists of all districts highly exposed in Kerala while control group consists of all districts in Tamil Nadu. Panels (A)-(B) show results for extensive margin and Panels (C)-(D) show results for intensive margin.

5.2. Main Regression Results

I report the estimated effect of the 2018 August flood on labor market outcomes using eq. (1) in Table 3. Columns (1)—(2) report the results for employment participation, while the columns (3)—(4) include individual-level and household-level controls. Panel A shows the estimates on the extensive margin (employment participation), while Panel B presents the estimates on the intensive margin (hours worked per week). In each panel, the first row reports the coefficient on the interaction term $(\boldsymbol{Treat_d} \times \boldsymbol{Post_t})$ while the second and third row respectively report the effects of $\boldsymbol{Post_t}$ and $\boldsymbol{Treat_d}$, respectively. Mean of dependent variable for control group is reported at the bottom of each panel.

Panel A shows that the 2018 floods had no statistically significant impact on employment participation for either women or men. Women's employment participation declined by 1.5 percentage points (pp) (column (1), Panel A, Table 3) and men's participation increased by 2.6 pp (column (2), Panel B, Table 3) in treated areas after the flood but neither effect is statistically significant. These findings remain consistent after controlling individual-and household-level characteristics: women's participation fell by 1.6 pp and men's employment participation rose by 1.7 pp (Columns (3)—(4), Panel A, Table 3). The small positive effect on men's employment participation may reflect marginal entry into the labor force as households sought to cope with income losses after the flood (e.g., Baez et al. 2019, Deryugina 2017).

Panel B presents results for the intensive margin of labor market outcomes. After controlling for individual and household level characteristics, hours worked per week fell significantly for both women and men following the floods. Specifically, women reduced their weekly paid labor by 1.42 hours (Column (3), Panel A, Table 3). Compared to the mean working hours of 6.38 hours per week of control group, this reduction corresponds to a decline in labor hours by nearly 23.5%. For men, the results show a reduction of 1.40 hours per week (Column (4), Panel B, Table 3). Relative to mean of 26.06 working hours per week of control group, the estimated decrease for men represents about a 7.3% fall in hours worked per week.

Thus, the results suggest that the adverse effects of the 2018 floods on paid labor outcomes were primarily concentrated along the intensive margin rather than the extensive margin. While individuals did not significantly enter or exit employment following the floods, those who remained employed substantially reduced their labor supply, as measured by hours worked per week. This is consistent with literature on negative effects of disasters on local labor markets (e.g., Skoufias et al. 2011, Groeger and Zylberberg 2022). The proportionate decline in hours worked was larger for women which indicate that female workers may have been more vulnerable to disruptions in labor market engagement following the extreme climate events. One possible explanation is that women often bear a disproportionate burden of increased household and caregiving responsibilities in the aftermath of environmental disasters which can limit their ability to sustain pre-flood levels of paid work (Afridi et al. 2022). Moreover, substantial disruptions in local infrastructure—including damage to roads, bridges, and public transport—likely restrict access to workplaces and hence working hours for both men and women.

Panel A: Employment Participation				
Employment Participation	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
$(\boldsymbol{Treat_d \times Post_t})$	**-0.015**	**0.026**	**-0.016**	**0.017**
	(0.014)	**(0.018)**	**(0.014)**	**(0.015)**
$\boldsymbol{Post_t}$	0.001	-0.018	0.008	-0.019
	(0.019)	(0.020)	(0.019)	(0.017)
$\mathbf{Treat_d}$	-0.136***	-0.123***	-0.082***	-0.065**
	(0.029)	(0.031)	(0.030)	(0.025)
Control Group	0.145	0.583	0.145	0.583
No. of Observations	33,632	32,064	33,632	32,064
R-Squared	0.039	0.009	0.150	0.291
Individual Level Controls	X	X	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	✓	✓	✓	✓
Panel B: Hours worked per week				
Hours worked per week	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
$(\boldsymbol{Treat_d \times Post_t})$	**-1.427****	**-1.169**	**-1.425****	**-1.409**
	(0.659)	**(1.029)**	**(0.641)**	**(0.900)**
$\boldsymbol{Post_t}$	0.356	0.635	0.103	0.356
	(0.919)	(1.221)	(0.902)	(1.056)
$\mathbf{Treat_d}$	-7.105***	-13.869***	-5.121***	-11.994***
	(1.378)	(1.867)	(1.461)	(1.680)
Control Group	6.38	26.06	6.38	26.06
No. of Observations	30,483	29,502	30,483	29,502
R-Squared	0.032	0.028	0.096	0.381
Individual Level Controls	X	X	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	✓	✓	✓	✓

*Table 3. Regression results for paid labor outcomes whereby treatment group consists of all districts in Kerala with high exposure to flood while control group consists of all districts in Tamil Nadu. Panel (A) and Panel (B) respectively show results for extensive margin and intensive margin. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

5.3. Labor Market Outcomes in Less Affected Districts

While the previous section focused on districts that were severely affected by the 2018 August flood, it is equally important to examine labor market responses in relatively less exposed areas. These areas are often overlooked in disaster recovery efforts since they are presumed to be relatively more resilient. However, many of such areas were affected for the first time which could disrupt local labor markets despite lower levels of destruction. To explore this, I re-estimate eq. (1) using less affected districts by 2018 August flood in Kerala—Kasargod, Kannur, Wayanad, Palakkad, Idukki, Pathanamthitta and Kollam—as the treatment group. These are represented by white colored areas in figure A.2. The control group continues to be the same.

In table 4, panel A reports the estimates for extensive margin (employment participation) while panel B shows the results for intensive margin (weekly working hours). Accounting for both household and individual level controls, the flood reduced women's employment participation by 0.1 pp, though not statistically significant (Column (3), Panel A, Table 4). However, men experienced increase in employment participation by 3.2 pp after the flood (Column (4), Panel A, Table 4). This suggests that men may have been more successful with post-flood recovery in less-affected districts compared to those in more affected districts. It could possibly be due to higher employment in recovery-related jobs such as reconstruction of damaged buildings.

In case of intensive margin, I observe the decline in women's paid labor hours even in less affected districts. After the flood, women reduced their paid labor by 1.55 hours per week which is consistent with my main findings. This underscores the vulnerability of female labor supply to environmental shocks even at moderate levels. Men also experienced reduction in their paid labor hours but it is marginal and statistically insignificant. Though the magnitude of men's paid labor hours is much lower in less affected districts compared to those in highly affected districts as in previous section, the direction of the effect remains similar to the main regression results in the previous section.

Panel A: Employment Participation				
Employment Participation	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
$(\boldsymbol{Treat_d \times Post_t})$	**0.007**	**0.031**	**-0.001**	**0.029***
	(0.016)	**(0.019)**	**(0.015)**	**(0.016)**
$\boldsymbol{Post_t}$	0.008	-0.009	0.034	-0.019
	(0.020)	(0.021)	(0.015)	(0.017)
$\mathbf{Treat_d}$	-0.172***	-0.199***	-0.109***	-0.129***
	(0.032)	(0.036)	(0.032)	(0.035)
Control Group	0.154	0.558	0.154	0.558
No. of Observations	32,031	30,468	36,713	30,468
R-Squared	0.037	0.009	0.147	0.477
Individual Level Controls	X	X	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	✓	✓	✓	✓
Panel B: Hours worked per week				
Hours worked per week	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
$(\boldsymbol{Treat_d \times Post_t})$	**-0.837**	**-0.449**	**-1.099**	**-0.416**
	(0.723)	**(1.085)**	**(0.709)**	**(0.936)**
$\boldsymbol{Post_t}$	-0.106	0.264	0.092	0.131
	(0.945)	(1.252)	(0.929)	(1.081)
$\mathbf{Treat_d}$	-7.264***	-18.821***	-5.158***	-16.42***
	(1.486)	(2.099)	(1.555)	(1.954)
Control Group	7.43	24.86	7.43	24.86
No. of Observations	29,109	28,010	29,109	28,010
R-Squared	0.028	0.028	0.095	0.388
Individual Level Controls	X	X	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	✓	✓	✓	✓

*Table 4. Regression results for paid labor outcomes whereby treatment group consists of all districts in Kerala with low exposure to flood while control group consists of all districts in Tamil Nadu. Panel (A) and Panel (B) show results for extensive margin and intensive margin. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

5.4. Robustness Check

To test the robustness of the main findings, I estimate eq. (1) using alternative treatment definitions while the control group remains unchanged. These alternative specifications help assess whether the observed labor market effects of 2018 flood were concentrated in the most affected areas or present across other aspects of flood exposure. Across all three robustness checks, similar results are found: While employment participation of men does not seem to be impacted by flood, their working hours declined significantly after flood. In case of women, both their participation and working hours reduced after flood.

5.4.1. Districts Most Affected by Flood-Induced Landslides

Here, I restrict the treatment group to districts in Kerala that experienced the most severe flood-induced landslide—a secondary disaster linked to floods. Wayanad and Idukki accounted for 42% of all landslides during the 2018 August floods. Wayanad experienced heavy rainfall which triggered soil slippage and landslides (RGIDS 2018, Kerala State Disaster Management 2018). Pathanamthitta experienced massive landslides in hilly areas such as Chittar, Seethathode and Sabarimala (RGIDS 2018, Kerala State Disaster Management 2018). Thus, the treated districts include Wayanad, Kozhikode, Idukki, Kottayam and Pathanamthitta. This is shown in figure A.3. The results are shown in table 5 which remain consistent with the main findings.

After the flood, panel A shows that women's employment participation fell by 3.3 pp (Column (3), Panel A, Table 5) while men experienced an insignificant increase (Columns (2) and (4), Panel A, Table 5). This suggests that men may have post-flood recovery while women did not.

In case of intensive margin, I find that the flood reduced women's paid labor hours by nearly 2.5 hours per week (Columns (1) and (3), Panel B, Table 5). Men also experienced decline in their employment by 1.8 hours per week (Column (4), Panel B, Table 5). These results show that the flood-induced landslides further worsen paid labor outcomes whereby women are disproportionately worse off.

Panel A: Employment Participation				
Employment Participation	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
$(\boldsymbol{Treat_d \times Post_t})$	**-0.033***	**0.047****	**-0.033***	**0.029**
	(0.019)	**(0.021)**	**(0.018)**	**(0.018)**
$\boldsymbol{Post_t}$	0.003	-0.005	0.008	-0.014
	(0.021)	(0.021)	(0.021)	(0.017)
$\mathbf{Treat_d}$	-0.089**	-0.061	-0.041	-0.033
	(0.040)	(0.036)	(0.042)	(0.036)
Control Group	0.187	0.598	0.187	0.598
No. of Observations	29,683	28,759	29,683	28,759
R-Squared	0.034	0.008	0.148	0.475
Individual Level Controls	X	X	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	✓	✓	✓	✓
Panel B: Hours worked per week				
Hours worked per week	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
$(\boldsymbol{Treat_d \times Post_t})$	**-2.543*****	**-1.101**	**-2.449*****	**-1.888***
	(0.865)	**(1.221)**	**(0.852)**	**(1.092)**
$\boldsymbol{Post_t}$	-0.479	0.666	-0.304	0.359
	(0.987)	(1.287)	(0.971)	(1.113)
$\mathbf{Treat_d}$	-4.411**	-12.502***	-2.700	-11.489***
	(1.897)	(2.529)	(2.007)	(2.346)
Control Group	7.88	27.91	7.88	27.91
No. of Observations	26,903	26,490	26,903	26,490
R-Squared	0.027	0.024	0.092	0.383
Individual Level Controls	X	X	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	✓	✓	✓	✓

*Table 5. Regression results for paid labor outcomes whereby treatment group consists of all districts in Kerala which are affected by flood-induced landslides while control group consists of all districts in Tamil Nadu. Panel (A) and Panel (B) respectively show results for extensive margin and intensive margin. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

5.4.2. Districts Closest to Mismanaged Dams

Here, I define the treatment group as districts closest to dams which were most mismanaged during the 2018 flood. Particularly, Idukki district is home to the large Idukki dam and Cheruthoni dam— saw poor reservoir management such as use of flood cushion capacity and delayed water releases (Kerala State Disaster Management 2018). Similarly, dam discharges from Idamalayar, Mullaperiyar, Upper Sholayar, Peringalkuthu and Bhoothathankettu attributed to flooding in districts of Kottayam, Pathanamthitta and Thrissur (RGIDS 2018). Thus, the treated districts include Palakkad, Thrissur, Idukki, Kottayam and Pathanamthitta. This is shown in figure A.4. Poor governance and operational decisions of dams are likely to amplify the flood damage

(Kerala State Disaster Management 2018). The results are shown in table 6, which align with the main findings.

After the flood, panel A shows that women's employment participation fell by 1.8 pp (Column (3), Panel A, Table 6) while men experienced increase by 3.2 pp (Column (4), Panel A, Table 6). This shows that men are likely to have post-flood recovery while women did not.

Panel B shows the results for intensive margin. Here, I find that the flood reduced women's paid labor hours by nearly 1.55 hours per week (Columns (3), Panel B, Table 5). Men also experienced decline in their employment by 0.3 hours per week after accounting for controls (Column (4), Panel B, Table 5). These estimates suggest that the proximity to mismanaged dams worsened the negative effects of floods on paid labor which is especially skewed against women.

Panel A: Employment Participation				
Employment Participation	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
$(\boldsymbol{Treat_d \times Post_t})$	**-0.014**	**0.015**	**-0.018**	**0.032***
	(0.018)	**(0.021)**	**(0.017)**	**(0.018)**
$\boldsymbol{Post_t}$	0.008	-0.009	0.035	0.005
	(0.021)	(0.021)	(0.015)	(0.017)
$\mathbf{Treat_d}$	-0.109***	-0.199***	-0.109***	-0.125***
	(0.031)	(0.033)	(0.032)	(0.035)
Control Group	0.183	0.577	0.183	0.577
No. of Observations	30,075	29,143	34,437	33,439
R-Squared	0.032	0.008	0.147	0.290
Individual Level Controls	X	X	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	✓	✓	✓	✓
Panel B: Hours worked per week				
Hours worked per week	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
$(\boldsymbol{Treat_d \times Post_t})$	**-2.216****	**-3.178****	**-1.551****	**-0.338**
	(0.865)	**(1.202)**	**(0.714)**	**(0.930)**
$\boldsymbol{Post_t}$	-0.352	0.538	0.649	1.317
	(0.982)	(1.278)	(0.702)	(0.905)
$\mathbf{Treat_d}$	-4.926***	-13.915***	-6.079***	-17.207***
	(1.481)	(2.034)	(1.521)	(1.858)
Control Group	9.1	27.94	9.1	27.94
No. of Observations	34,467	26,810	34,467	32,614
R-Squared	0.033	0.025	0.104	0.372
Individual Level Controls	X	X	✓	✓
Household Level Controls	X	X	✓	✓
District Fixed Effects	✓	✓	✓	✓

*Table 6. Regression results for paid labor outcomes whereby treatment group consists of all districts in Kerala which are closest to mismanaged dams while control group consists of all districts in Tamil Nadu. Panel (A) and Panel (B) respectively show results for extensive margin and intensive margin. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

5.5. Heterogeneous Effects

5.5.1. Location of Dwelling (Rural/Urban)

Rural and urban labor markets differ in terms of composition and access to opportunities. In India, rural areas are predominantly agricultural and heavily reliant on informal and casual labor. As a result, individuals and households dwelling in rural areas are especially vulnerable to climate shocks like floods which can destroy crops, livestock, local enterprises. In contrast, urban areas offer more diversified employment in manufacturing, construction and service sectors. Moreover, gender norms and expectations regarding paid labor participation also vary across rural and urban areas: rural women typically face more mobility and employment restrictions than their urban counterparts.

I explore whether the 2018 Kerala floods had differential effects on paid labor market outcomes across rural and urban areas by estimating eq. (1) separately by location of dwelling. In table 7, panel A presents results for employment participation (extensive margin), while panel B shows results for hours worked per week (intensive margin).

In case of extensive margin, rural women experienced a reduction of 3.2 percentage points (pp) in employment participation (Column 1, Panel A, Table 7) while urban women witnessed smaller decline of 0.7 pp after the flood (Column 3, Panel A, Table 7). Rural men faced a decline in employment by 0.9 pp (Column 2, Panel A, Table 7), whereas urban men show a positive though insignificant increase of 1.5 pp (Column 4, Panel A, Table 7). This reflects that the urban men experienced a relatively faster employment recovery compared to rural men due to more diversified access to non-agricultural employment. In terms of intensive margin, the flood had statistically significant effect on rural labor hours for both men and women. Rural women faced a statistically significant reduction in paid labor by 1.63 hours per week after the flood which is about 13.9% decline relative to the average workload of control group (Column 1, Panel B, Table 7). Rural men also experienced a decline of 2.94 working hours per week which is 10.7% drop from their control group's average paid labor hours (Column 2, Panel B, Table 7). The effects were negligible and statistically insignificant for both urban men and women (Columns (3)—(4), Panel B, Table 7). Thus, the flood had more adverse impact on rural labor markets, particularly on women's paid labor.

Panel A: Employment Participation				
	Rural		Urban	
Employment Participation	Women (1)	Men (2)	Women (3)	Men (4)
$(\boldsymbol{Treat_d} \times \boldsymbol{Post_t})$	**-0.032** **(0.021)**	**0.009** **(0.026)**	**-0.007** **(0.016)**	**0.015** **(0.020)**
$\boldsymbol{Post_t}$	0.050** (0.022)	0.009 (0.023)	-0.009 (0.017)	0.009 (0.022)
$\mathbf{Treat_d}$	0.009 (0.050)	-0.026 (0.053)	-0.111*** (0.039)	-0.096*** (0.035)
Control Group	0.287	0.601	0.210	0.624
No. of Observations	17,980	16,948	20,270	19,666
R-Squared	0.204	0.328	0.094	0.260
Individual Level Controls	✓	✓	✓	✓
Household Level Controls	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓
Panel B: Hours worked per week				
	Rural		Urban	
Hours worked per week	Women (1)	Men (2)	Women (3)	Men (4)
$(\boldsymbol{Treat_d} \times \boldsymbol{Post_t})$	**-1.630**** **(0.912)**	**-2.94**** **(1.298)**	**-0.619** **(0.831)**	**0.239** **(1.103)**
$\boldsymbol{Post_t}$	1.436 (0.972)	0.840 (1.198)	0.634 (0.986)	3.097** (1.266)
$\mathbf{Treat_d}$	-3.061 (2.107)	-9.487*** (2.565)	-8.324*** (2.072)	-16.573*** (2.115)
Control Group	11.72	27.58	10.78	32.88
No. of Observations	16,849	15,783	19,000	18,369
R-Squared	0.155	0.394	0.075	0.350
Individual Level Controls	✓	✓	✓	✓
Household Level Controls	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓

*Table 7. Heterogeneous effects of 2018 Kerala flood on gender division of paid labor outcomes by location of dwelling. Panel (A) and Panel (B) respectively show results for extensive margin and intensive margin. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

5.5.2. Employment by Sector[3]

The type of employment, whether self-employed, regular wage work or casual labor shapes the extent to which individuals experience and respond to shocks including climate events. Casual labor which includes informal, and daily-wage based work, is particularly sensitive to economic shocks, Regular wage work tends to offer relatively more stability while self-employment depends heavily on personal assets and local resources which

[3] There were lots of missing values in terms of individuals' detailed occupations—primarily agriculture, manufacturing and service sectors.

are likely to be compromised by disasters. After flood, people are likely to lose jobs and may shift to self-employment as alternative means to support themselves.

To explore how the 2018 Kerala floods affect paid labor outcomes by different sectors of employment, I estimate eq. (1) separately for self-employment, regular wage labor and casual labor. Table 8 shows these results where panel A and panel B show the estimates for employment participation (extensive margin) and weekly working hours (intensive margin).

On the extensive margin, the flood did not have a statistically significant effect on women's employment participation in any sector. However, the estimates suggest some modest sectoral shifts: participation in self-employment increased by 0.5 pp (Column 1, Panel A, Table 8), while participation in regular and casual labor reduced by 1.1 pp (Column 3, Panel A, Table 8) and 2.2 pp respectively (Column 5, Panel A, Table 8). For men, the flood led to a statistically significant increase of 1.5 pp in self-employment participation (Column 2, Panel A, Table 8). This may reflect a shift toward more home-based work after the flood. After the flood, however, participation in regular and casual labor declined by 1.2 pp and 2.6 pp respectively, though not statistically significant (Columns (4) and (6), Panel A, Table 8).

Similar trends are observed in the case of intensive margin. After flood, women experienced reduction in regular wage labor by 1.42 hours per week (Column (3), Panel B, Table 8) and an even larger drop in casual labor by 2.26 hours per week (Column (5), Panel B, Table 8). In the case of self-employment, however, the change in women's weekly working hours remained minimal and statistically insignificant (Column (1), Panel B, Table 8). On the contrary, men faced significant drop in case of casual labor by 3.09 hours per week (Column (6), Panel B, Table 8). Hours worked in self-employment also declined by 1.89 hours per week (Column (2), Panel B, Table 8). The effect is negligible for regular wage work in case of men (Column (4), Panel B, Table 8).

These results highlight two key insights: firstly, casual labor appears to be most vulnerable to floods. The reduction in casual labor hours for both men and women highlight how fragile daily-wage work is to external shocks like floods. Second, self-employment may serve as a fallback option for men as reflected in their increased participation. But this did not translate into a rise in their hours worked which suggests reduced business activity—possibly due to flood-related damage to capital, decline in demand for output or destruction of supply chain. Thus, while self-employment may be a coping mechanism of men, it does not fully insure them against income loss after the flood.

Panel A: Employment Participation						
	Self-Employment		Regular Labor		Casual Labor	
Employment Participation	Women (1)	Men (2)	Women (3)	Men (4)	Women (5)	Men (6)
$(\boldsymbol{Treat_d \times Post_t})$	**0.005** **(0.010)**	**0.015**** **(0.006)**	**-0.011** **(0.015)**	**-0.012** **(0.011)**	**-0.022** **(0.049)**	**0.026** **(0.016)**
$\boldsymbol{Post_t}$	0.015 (0.020)	-0.009 (0.009)	-0.005 (0.013)	-0.006 (0.016)	0.017 (0.022)	-0.029** (0.011)
$\mathbf{Treat_d}$	-0.007 (0.009)	-0.006 (0.007)	-0.005 (0.021)	-0.0007 (0.008)	-0.0001 (0.028)	-0.031 (0.021)
No. of Observations	2,918	6,939	3,247	7,376	2,146	5,079
R-Squared	0.13	0.092	0.069	0.035	0.091	0.035
Individual Level Controls	✓	✓	✓	✓	✓	✓
Household Level Controls	✓	✓	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓	✓	✓
Panel B: Hours worked per week						
	Self-Employment		Regular Labor		Casual Labor	
Hours worked per week	Women (1)	Men (2)	Women (3)	Men (4)	Women (5)	Men (6)
$(\boldsymbol{Treat_d \times Post_t})$	**-0.651** **(2.609)**	**-1.886** **(1.460)**	**-1.420** **(1.608)**	**0.028** **(1.126)**	**-2.261** **(2.831)**	**-3.087**** **(1.292)**
$\boldsymbol{Post_t}$	-4.091** (2.135)	2.325 (1.387)	-0.644 (1.442)	0.353 (0.938)	-1.047 (1.739)	1.533 (1.454)
$\mathbf{Treat_d}$	-26.525*** (4.113)	-7.776 (1.798)	-3.464 (2.315)	-6.673*** (1.836)	-6.874 (3.674)	-11.119*** (2.386)
No. of Observations	2,918	6,939	3,247	7,376	2,408	5,805
R-Squared	0.264	0.131	0.118	0.144	0.225	0.161
Individual Level Controls	✓	✓	✓	✓	✓	✓
Household Level Controls	✓	✓	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓	✓	✓

*Table 8. Heterogeneous effects of the 2018 Kerala flood on gender division of paid labor outcomes by sector of employment. Panel (A) and Panel (B) respectively show results for extensive margin and intensive margin. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

5.5.3. Gender Norms

Gender norms assign primary responsibility for home production and caregiving to women. This, in turn, influence women's participation in paid labor, especially during environmental crises. Such effects can vary by marital status and household dependency burden. Married women often face greater time constraints due to expectations around domestic responsibilities and caregiving for children or elderly. Similarly, working-age individuals in households with higher share of dependents are more likely to engage in unpaid domestic and care work compared to those in low-dependent households. Because gender norms expect women to shoulder these responsibilities, the effect of exogenous shocks such as floods disproportionately worsen women's paid labor compared to men.

To explore this, Tables 9 and 10 examine the heterogeneity in the paid labor responses to the 2018 Kerala flood by marital status and dependency burden respectively. In each of these tables, panel A show the results for extensive margin, that is, employment participation and panel B presents the estimates for intensive margin, that is, weekly working hours, separately for men and women.

(a) Marital Status[4]:

In case of extensive margin, unmarried women faced a statistically significant increase in employment participation by 3.6 pp (Column (1), Panel A, Table 9), whereas unmarried men experienced negligible and insignificant change in employment (Column (2), Panel A, Table 9). In contrast, married women experienced a decline of 3.3 pp in employment participation (Column (3), Panel A, Table 9), while married men saw an increase of 2.7 pp (Column (3), Panel A, Table 9).

The effect of 2018 Kerala flood revealed sharper gender differences in case of intensive margin (hours worked per week). Among unmarried individuals, women increased their paid labor by 1.86 hours per week (Column (1), Panel B, Table 9), while men saw a negligible change in paid labor hours per week (Columns (2), Panel B, Table 9). Married women, on the contrary, experienced statistically significant drop of 1.93 hours per week but married men faced relatively smaller and insignificant decline of 1.37 hours per week (Columns (1)—(2), Panel B, Table 9).

These results suggest contrasting pattern in paid labor outcomes among men and women based on their marital status. Unmarried women may have more flexibility to respond to paid labor market opportunities after the flood mainly due to fewer domestic responsibilities. Married women, on the contrary, face substantial time constraints because of social expectations around domestic work and caregiving. Moreover, time spent on domestic chores like collecting water, cooking increases and similarly more time is required for caregiving responsibilities in response to flood shocks. As a result, married women are more likely to reduce their paid labor outcomes.

[4] Note that I only show the case of unmarried and married and did not show the case of widow/divorced because the sample size for widow/divorced men is very small (less than 600).

Panel A: Employment Participation				
	Unmarried		Married	
Employment Participation	Women (1)	Men (2)	Women (3)	Men (4)
$(\boldsymbol{Treat_d} \times \boldsymbol{Post_t})$	**0.036***** **(0.014)**	**0.009** **(0.027)**	**-0.033** **(0.021)**	**0.027** **(0.018)**
$\boldsymbol{Post_t}$	-0.019 (0.014)	-0.003 (0.027)	0.058 (0.023)	0.015 (0.017)
$\mathbf{Treat_d}$	-0.076*** (0.026)	-0.119 (0.057)	-0.064 (0.047)	-0.031 (0.026)
No. of Observations	13,438	17,607	20,957	18,388
R-Squared	0.155	0.077	0.091	0.156
Individual Level Controls	✓	✓	✓	✓
Household Level Controls	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓
Panel B: Hours worked per week				
	Unmarried		**Married**	
Hours worked per week	Women (1)	Men (2)	Women (3)	Men (4)
$(\boldsymbol{Treat_d} \times \boldsymbol{Post_t})$	**1.864**** **(0.681)**	**0.446** **(1.109)**	**-1.931**** **(0.908)**	**-1.371** **(1.141)**
$\boldsymbol{Post_t}$	-1.582 (0.839)	-0.165 (1.194)	2.389 (0.979)	2.581 (1.094)
$\mathbf{Treat_d}$	-5.406** (1.681)	-12.494*** (2.635)	-6.174 (2.130)	-12.55*** (1.989)
No. of Observations	11,037	15,145	20,957	18,388
R-Squared	0.151	0.336	0.068	0.163
Individual Level Controls	✓	✓	✓	✓
Household Level Controls	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓

*Table 9. Heterogeneous effects of 2018 Kerala flood on gender division of paid labor outcomes by Marital Status. Panel (A) and Panel (B) respectively show results for extensive margin and intensive margin. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

(b) Dependency Burden:

High dependency is defined based on the number of children (less than 11 years) and elderly (above 70 years) in a household compared to working family members. If a household has more than 50% dependent family members, it is a highly dependent household. On the other hand, if a household has less than or equal to 50% dependent family members, it is low dependent household. In both panels A and B of table 10, columns (1)—(2) show results for paid labor outcomes of women and men in households characterized by high dependency while columns (3)—(4) present estimates for paid labor outcomes of women and men in households characterized by low dependency.

In high dependency households, women experienced decline in employment participation by 2.5 pp (Column (1), Panel A, Table 10) while men faced increase in employment participation by 3.0 pp (Column

(2), Panel A, Table 10). On the contrary, in low dependency households, men coming from witnessed drop in employment participation by 0.4 pp (Column (4), Panel A, Table 10) while women saw decline in their employment by 0.6 pp after flood (Column (3), Panel A, Table 10). Though the results are not statistically significant, these indicate that men may be more responsive to paid labor under dependency pressure, while women's paid labor participation is further deterred due to caregiving responsibilities.

Panel B also shows similar results for intensive margin. In high dependency households, women reduced their paid labor by 1.5 hours per week (Column (1), Panel B, Table 10) while men faced insignificant drop in their paid labor hours (Column (2), Panel B, Table 10). In low-dependency households, women experienced decline in their paid labor hours by nearly 1.1 hours per week (Column (3), Panel B, Table 10) which is less than 1.9-hour decline for men (Column (4), Panel B, Table 10).

Panel A: Employment Participation				
	High Dependency		**Low Dependency**	
Employment Participation	Women (1)	Men (2)	Women (3)	Men (4)
$(\boldsymbol{Treat_d} \times \boldsymbol{Post_t})$	**-0.025**	**0.030**	**-0.006**	**-0.004**
	(0.017)	**(0.024)**	**(0.019)**	**(0.021)**
$\boldsymbol{Post_t}$	0.017	-0.023	-0.003	-0.019
	(0.026)	(0.029)	(0.026)	(0.024)
$\mathbf{Treat_d}$	-0.058	0.053	-0.087**	0.046
	(0.045)	(0.052)	(0.042)	(0.036)
No. of Observations	12,745	11,195	19,848	19,818
R-Squared	0.202	0.387	0.121	0.269
Individual Level Controls	✓	✓	✓	✓
Household Level Controls	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓
Panel B: Hours worked per week				
	High Dependency		**Low Dependency**	
Hours worked per week	Women (1)	Men (2)	Women (3)	Men (4)
$(\boldsymbol{Treat_d} \times \boldsymbol{Post_t})$	**-1.537***	**-1.468**	**-1.121**	**-1.966***
	(0.834)	**(1.165)**	**(0.872)**	**(1.173)**
$\boldsymbol{Post_t}$	0.053	0.402	-0.820	0.404
	(1.28)	(1.390)	(1.215)	(1.413)
$\mathbf{Treat_d}$	-3.787	-8.699	-7.176	-13.674**
	(2.246)	(2.397)	(2.054)	(2.378)
No. of Observations	11,121	9,571	19,465	19,443
R-Squared	0.154	0.581	0.089	0.253
Individual Level Controls	✓	✓	✓	✓
Household Level Controls	✓	✓	✓	✓
District Fixed Effects	✓	✓	✓	✓

*Table 10. Heterogeneous effects of 2018 Kerala flood on gender division of paid labor outcomes by dependency burden. Panel (A) and Panel (B) respectively show results for extensive margin and intensive margin. Standard errors clustered at household level are reported in parentheses (*** p<0.01, ** p<0.05, *p<0.1).*

6. Conclusion

Floods can affect livelihoods both directly by damaging physical infrastructure and assets and indirectly by (a) disrupting markets, mobility, and (b) exacerbating domestic and care work. In less developed countries like India, traditional gender norms shape participation in paid work and hence, environmental disasters like flash floods can have unequal consequences for men and women. This paper examines the gendered labor market effects of the 2018 Kerala floods which is one of the most catastrophic flood events in the recent Indian history. I find that both men and women faced decline in their paid labor hours per week after the flood, but the effect is more pronounced among women.

I also show that the extent to which flood impact gendered paid labor market also vary by location of dwelling, sectors of employment, marital status and dependency burden. Both men and women are worse-off if they are dwelling in rural areas. Labor markets are more resilient for both men and women in urban areas. Casual laborers are most vulnerable to the flood shocks. Besides, men are found to be shifting towards self-employment work after flood, though their increased participation is not automatically translated into more working hours. This is plausible because lack of jobs may induce the primary earners to become self-employed but inadequate infrastructure, assets and capital might not allow them to work enough. Moreover, the findings suggest that women's work is more vulnerable to their marital status and greater burden of unpaid care work. Married women were less likely to work after flood unlike their unmarried counterparts. Similarly, women coming from households with higher share of children and elderly faced reduction in their paid labor compared to those from low-dependency households.

This study highlights how exogenous shocks like extreme weather events can reinforce gender disparities in employment outcomes. This is concerning since greater gender disparities in labor market impede economic development. As extreme weather events become more frequent and severe, policymakers must adopt gender-sensitive approaches in disaster response and economic recovery strategies.

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Appendix

District	District Code	Weighted Exposure
Thiruvananthapuram	14	7061.041307
Kollam	13	5193.163371
Pathanamthitta	12	5966.460576
Alappuzha	11	30114.46937
Kottayam	10	31980.33178
Idukki	9	1266.632302
Ernakulam	8	10152.94701
Thrissur	7	29619.24674
Palakkad	6	7181.99244
Malappuram	5	11167.33218
Kozhikode	4	12309.48623
Wayanad	3	3615.535054
Kannur	2	3451.859686
Kasaragod	1	711.2990982

Table A.1. Population Weighted Exposure to 2018 Flood by Districts in Kerala. Red colored rows indicate districts with high exposure to flood. Grey colored rows refer to those districts which were dropped from the analysis.

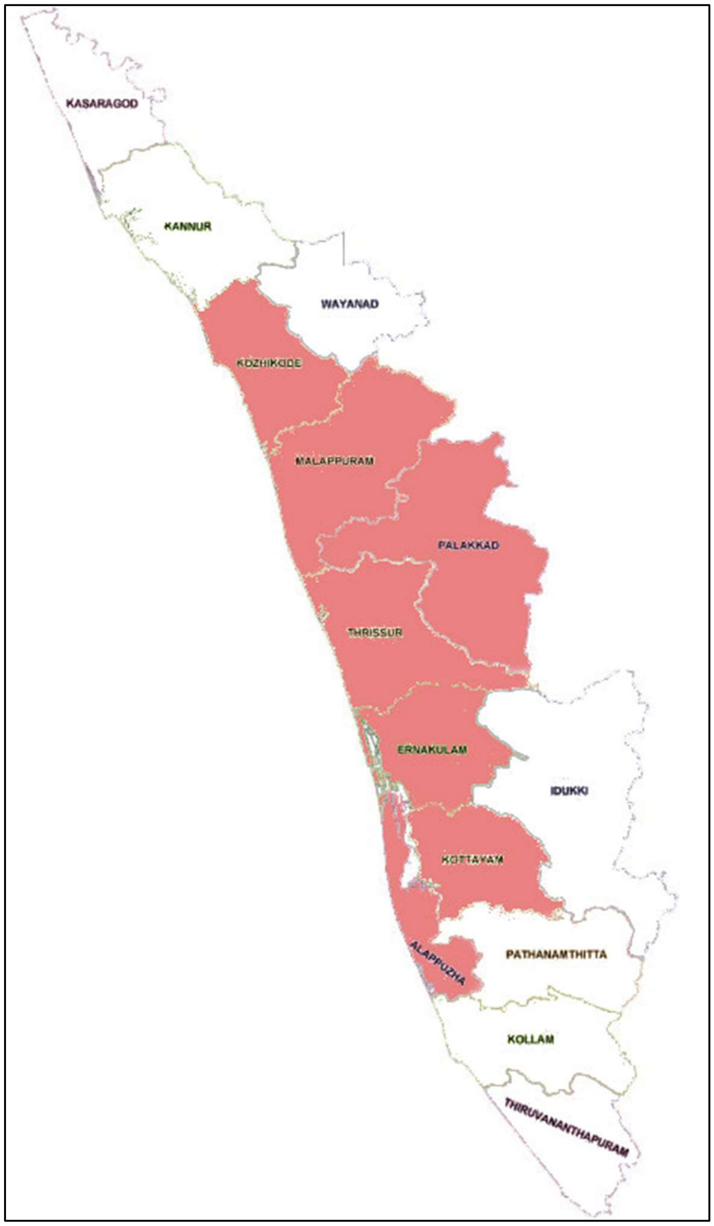

Figure A.2. Districts which are highly exposed and less exposed to the 2018 August Flood. Red colored districts are most exposed to the flood and white colored districts are relatively less exposed to the flood. Note that Ernakulam and Thiruvananthapuram are dropped from the analysis.

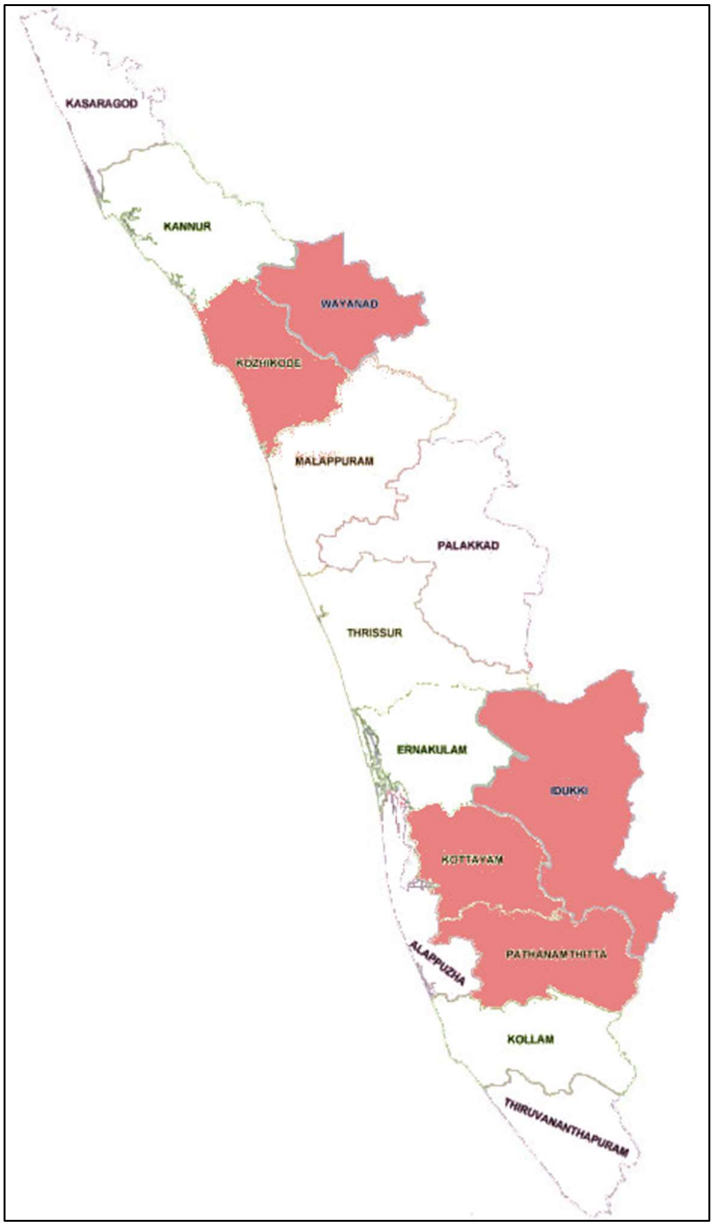

Figure A.3. Districts which are most affected by flood-induced landslides. Red colored districts are most impacted by flood-induced landslides and white colored districts are relatively less affected by the flood-induced landslides. Note that Ernakulam and Thiruvananthapuram are dropped from the analysis.

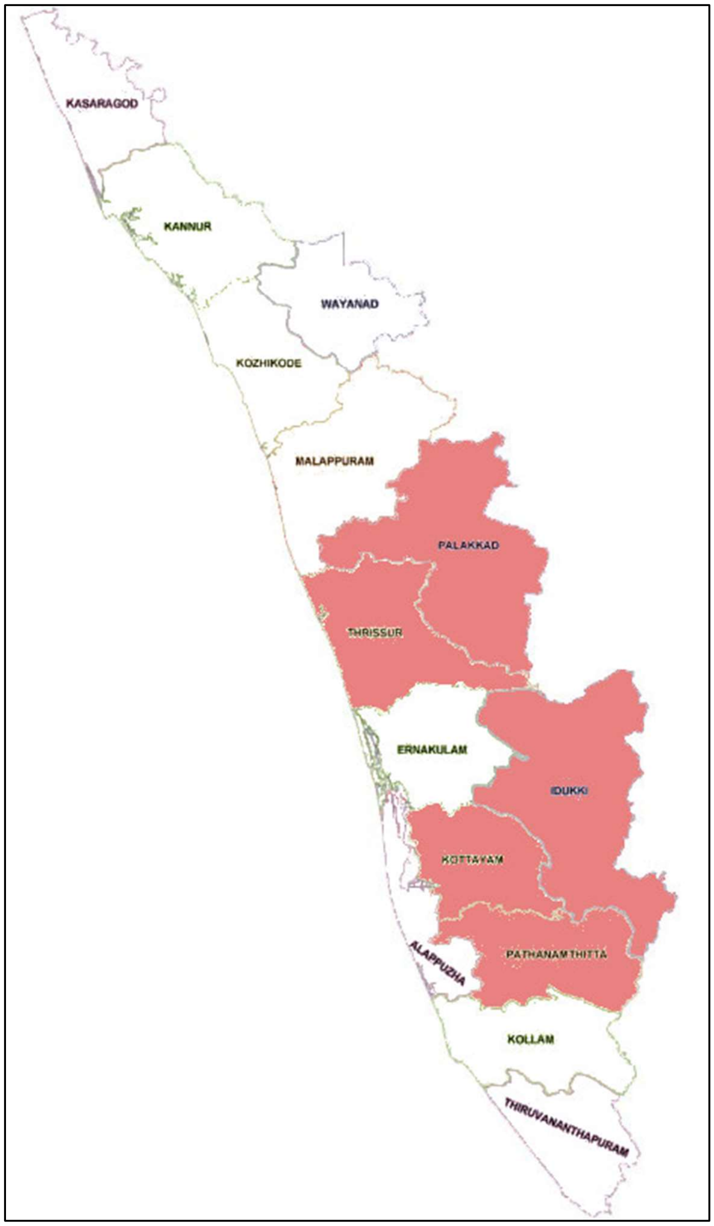

Figure A.4. Districts which are nearest to mismanaged dams. Red colored districts are closest to mis-managed dams and white colored districts are located relatively farther from dams (but might be impacted from being downstream or other spillover effects). Note that Ernakulam and Thiruvananthapuram are dropped from the analysis.