Droughts and Deluges: Non-Linear Effects of Climate Extremes on the Gender Gap in Labor Supply

Jheelum Sarkar[†]

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Abstract

Over the past three decades, extreme climate events have caused losses of worth USD 4.5 trillion. Using collective bargaining model, I find that the gendered labor supply response to adverse shocks is not straightforward since it depends on relative strength of income and substitution effects of men's and women's participation. Using a panel of 151 countries (1995-2019), I examine how extreme climate conditions shape gender gap in labor force participation. Key results show that the gender gap in paid labor exhibits a U-shaped relationship with droughts and an inverted U-shaped relationship with extreme wet conditions. The drought pattern is primarily driven by gender gap in employment while wetness affects gender gap in participation through unemployment. These relationships vary with country characteristics. Countries with high disaster-displacement risk exhibit declining gender gaps in participation during excess wetness while moderate-risk economies experience expanded gaps during droughts. Furthermore, the drought U-shape is most pronounced in countries with low to moderate empowerment while the nonlinear wet responses is concentrated only in moderately empowered countries. Lastly, both droughts and excess wetness expands gender gap in countries with weak net resilience to climate shocks.

[†]PhD Candidate, Department of Economics, American University. Email: js8622a@american.edu.

1 Introduction

According to World Meteorological Organization (2024), global average temperature is likely to exceed the 1.5°C threshold in the next five years. This implies that extreme climate events such as floods, droughts and storms are more frequent and intense (WMO, n.d.). By 2025, droughts have adversely affected 1.5 billion lives worldwide (UNDRR, 2025a). Floods account for nearly 50% of all extreme weather events over four decades (UNDRR, 2025b). Eastern and Southern Africa are major hotspots for prolonged droughts where more than 90 million people suffer from drought-induced acute hunger (NDMC, 2025). 23% of the global population are exposed to floods and majority of them are located in East and South Asian countries (Rentschler et al., 2022). Even advanced economies like U.S. and U.K. are exposed to floods and droughts (Chu et al., 2025; Wahl et al., 2022).

Extreme weather shocks affect labor supply by altering productivity, sectoral composition, migration and time reallocation (Chen and Yang, 2019; Graff Zivin and Neidell, 2014; Groen and Polivka, 2008; Parsons et al., 2021). In India, for instance, extreme temperature increased absenteeism in manufacturing sector (Somanathan et al., 2021). During 1988-2019, flood risks reduced labor supply by 0.33% in United States (Jia et al., 2022). However, evidence is mixed when it comes to gender disparities in paid labor. Droughts reduced women's agricultural working days by 19% relative to men's in rural India (Afridi et al., 2022). On the contrary, both negative and positive rainfall shocks have no significant effect on gender gap in paid labor in India (Maitra and Tagat, 2024). After a flood, women spent more time in paid labor than men in Bangladesh (Vitellozzi and Giannelli, 2024). Despite rising trend in women's participation after flood in Pakistan, it remains much lower than men (Akter, 2021).

These mixed findings could be attributable to a non-linear relationship between extreme events and gender differences in paid labor. Mild droughts can incentivize both men and women to increase paid work for coping with financial hardships while acute droughts may raise demand for home production (Afridi et al., 2022; Elmallakh et al., 2025; Maitra and Tagat, 2024). Moderate wet conditions increases demand for unpaid care work due to disease burdens and can expand gender inequality in paid labor (Boyd, 2023; Dimitrova et al., 2022, 2023). But extreme wet conditions trigger floods and storms which could induce both men and women to temporarily work more for smoothing household consumption and distress-driven labor supply (Gröger and Zylberberg, 2016; Pecha Garzón, 2017; Vitellozzi and Giannelli, 2024). Using a panel of 151 countries over 1995-2019, this paper, therefore, examines whether drought and extreme wet conditions share non-linear relationship with gender gap in labor force participation (LFP). To focus on extreme climate conditions, I construct extreme dry and wet intensities using 12-month Standardized Precipitation Evapotranspiration Index (SPEI).

Using a two way fixed effects (TWFE) model, three interesting results emerge. Firstly, gender

gap in LFP shares a non-linear relationship with extreme climate conditions: drought intensity has a U-shaped relation with gender gap in LFP while wet intensity exhibits inverted U-shaped relationship. Secondly, excess wetness mainly affects gender gap in unemployment while drought conditions shifts gender gap in LFP through employment. Lastly, the key patterns differ by country characteristics, namely, natural disaster-related displacement risk, women empowerment and net resilience. Countries with high displacement risk are more sensitive to excess wetness while drought responses are pronounced in countries with moderate displacement risk. Droughts and excess wet conditions influence gender gap in LFP in countries with low and moderate empowerment. Least resilient countries exhibit U-shaped relationship between droughts and gender gap in paid labor. Main findings remain robust under alternative specifications.

Rest of the paper is organized as follows. I set up a theoretical framework in section 2. Section 3 describes the data and estimation strategy. Section 4 presents the main results, robustness checks and heterogeneous effects. This is followed by concluding remarks in section 5.

2 Theoretical Framework

I develop a simple theoretical model to discuss why the effect of climate extremes on the gendered paid labor is not straight forward. Because labor supply decisions and time allocation often depend on household wealth, spouse's education and income, I am setting up a collective bargaining household model. Apart from changing household resources, a climate shock alters the relative returns and costs of market work. This is reflected in the income and substitution effects. The net balance between these two effects determine the direction of the gendered labor supply response to a climate shock.

Setup. Let us consider a representative household with husband (m) and wife (f). Each spends one unit of time across paid work (L_j), home production (h_j), and leisure (l_j), for $j \in \{f, m\}$. That is,

$$L_i + \ell_i + h_i = 1 \tag{1}$$

Let U_m and U_f denote husband's and wife's utility functions respectively which depend on consumption (C_i), leisure (ℓ_i) and home production (H):

$$U_m = U_m(C_m, \ell_m, H), \tag{2}$$

$$U_f = U_f(C_f, \ell_f, H) - \kappa(L_f; \theta) \tag{3}$$

where $U_i'(\cdot) > 0,\ U_i''(\cdot) < 0$. $\kappa(.)$ is social cost of the woman's paid labor due to social norms (e.g., mobility, domestic work and care burdens). κ is also sensitive with climate shock, given by

parameter θ. Higher the value of θ, more adverse is the shock. I parameterize $\kappa(L_f;\theta)$ as:

$$\kappa(L_f;\theta) = s(\theta)\,\tilde{\kappa} L_f, \qquad s(\theta) > 0, \quad s'(\theta) \geq 0, \quad \kappa'(L_f) > 0 \quad \kappa''(L_f) \geq 0 \tag{4}$$

Consumptions (C_f, C_m) are financed by the labor income and non-labor earnings from asset ownership. Thus, the usual household budget constraint is:

$$C_f + C_m = w_f L_f + w_m L_m + Y \tag{5}$$

where w_j denotes the wages and Y captures non-labor income (e.g., farm profits, transfers, asset income). In presence of negative shock such as floods and droughts, physical assets ($Y'(\theta) < 0$) are destroyed and wages can fall ($w_i'(\theta) < 0$).

Home production function produces good H (e.g., domestic and care work) which depends on contributions by both family members and shock parameter. An extreme climate event (θ) can increase the amount of time required to complete household responsibilities (e.g., water collection, caregiving), or can reduce the productivity of time spent on household work. It is given by

$$H = H(h_m, h_f; \theta), \qquad H_{h_j} > 0, \;\; H_{h_j h_j} < 0. \tag{6}$$

Using collective bargaining model approach, the utility maximization of the representative household is given by:

$$U = \alpha U_f + (1-\alpha) U_m \tag{7}$$

subject to equations (1), (5) and (6). Solving this maximization problem gives:

Opportunity costs of home production. Let λ denote the Lagrange multiplier. Define the shadow value of an hour spent in home production by spouse j as

$$q_j(\theta) \;\equiv\; \frac{u_H}{\lambda} H_{h_j}(h_m, h_f; \theta), \qquad j \in \{f, m\}. \tag{8}$$

where u_H is marginal utility from household production. From the F.O.Cs,

$$\begin{aligned} u_H H_{h_f} &= \lambda w_f - \alpha\kappa, \\ \implies \quad q_f(\theta) &= w_f - \frac{\alpha\kappa}{\lambda}. \end{aligned} \tag{9}$$

and

$$q_m(\theta) = w_m. \tag{10}$$

Thus, women's value of household work her wage net of the social cost from working outside. On the contrary, men's opportunity cost of home labor is simply their wages.

Reduced-form labor supply and decomposition. Solving the household problem yields Marshallian labor-supply functions:

$$L_f^* = \mathcal{L}_f\big(Y(\theta), w_f(\theta), w_m(\theta), \tilde{\kappa}, s(\theta), \theta, \alpha\big) \tag{11}$$

$$L_m^* = \mathcal{L}_m\big(Y(\theta), w_f(\theta), w_m(\theta), \theta, \alpha\big) \tag{12}$$

Total differentiation of (11) and (12) with respect to θ gives:

$$\frac{dL_f^*}{d\theta} = \underbrace{\frac{\partial \mathcal{L}_f}{\partial Y}\, Y'(\theta)}_{\text{Income effect}} + \underbrace{\left[\overbrace{\frac{\partial \mathcal{L}_f}{\partial w_f}\, w_f'(\theta) + \frac{\partial \mathcal{L}_f}{\partial w_m}\, w_m'(\theta)}^{\text{Market-return}} + \overbrace{\frac{\partial \mathcal{L}_f}{\partial s}\, s'(\theta)}^{\text{Social cost}} + \overbrace{\frac{\partial \mathcal{L}_f}{\partial \theta}}^{\text{Home prod.}}\right]}_{\text{Substitution effects}}, \tag{13}$$

$$\frac{dL_m^*}{d\theta} = \underbrace{\frac{\partial \mathcal{L}_m}{\partial Y}\, Y'(\theta)}_{\text{Income effect}} + \underbrace{\left[\overbrace{\frac{\partial \mathcal{L}_m}{\partial w_f}\, w_f'(\theta) + \frac{\partial \mathcal{L}_m}{\partial w_m}\, w_m'(\theta)}^{\text{Market-return}} + \overbrace{\frac{\partial \mathcal{L}_m}{\partial \theta}}^{\text{Home prod.}}\right]}_{\text{Substitution effects}}. \tag{14}$$

In each of the above equation,

- *Income Effect:* This is captured by the non-labor income channel. Higher household wealth reduces women's labor supply, i.e., $\frac{\partial \mathcal{L}_f}{\partial Y} < 0$ (AlAzzawi and Hlasny, 2019; Fu et al., 2016; Klasen and Pieters, 2015). While there isn't adequate research on how men's labor supply is linked to household wealth, Cesarini et al. (2015) shows that higher non-labor income reduces labor of both men and women, i.e., $\frac{\partial \mathcal{L}_m}{\partial Y} < 0$. If adverse shock depletes non-labor wealth and physical assets, $Y'(\theta) < 0$. Thus, the income effect is positive for both men and women.

$$\frac{\partial \mathcal{L}_i}{\partial Y}\, Y'(\theta) \;>\; 0$$

- *Substitution Effect:* This is measured by market-return, home production and social cost channels.
  - *Market-return Channel:* It is captured by changes in wages. In case of both men and women, an increase in own wage raises their own paid labor ($\frac{\partial \mathcal{L}_i}{\partial w_i} > 0$). But the cross-wage effects differ by gender. For women, higher husband's income reduces their labor supply, i.e., $\frac{\partial \mathcal{L}_f}{\partial w_m} < 0$ (Albanesi & Prados, 2022; Cheng & Sheng, 2023; Zhu et al., 2023). On the contrary, some studies suggest that higher wife's income can induce husbands to work more, i.e., $\frac{\partial \mathcal{L}_m}{\partial w_f} > 0$ (Chang et al., 2025; Cheng & Sheng, 2023). If negative

shock may dampen wages ($w_i'(\theta) < 0$), the market-return effect is negative for men but ambiguous in case of women since the latter depends on the net strength of own wage and cross-wage effects.

– *Home Production Channel:* Climate shocks can also alter home productivity ($\frac{\partial \mathcal{L}_i}{\partial \theta}$) by changing time spent on unpaid domestic and care work (h_i). Studies have shown that climate extremes increase unpaid household responsibilities including repairing damaged assets (Escalante & Maisonnave, 2022; Ouédraogo et al., 2025). This raises time poverty and reduces paid labor of both men and women by reducing the productivity of household work done by them:

$$\frac{\partial \mathcal{L}_i}{\partial \theta} < 0$$

– *Social Cost Channel.* Adverse shock such as climate extremes increase social cost of women's paid labor ($s'(\theta) > 0$) by raising mobility constraints, household burden and reducing economic opportunities in affected regions(Afridi et al., 2022; Escalante & Maisonnave, 2022; Flatø & Kotsadam, 2014; Rao et al., 2019). Conservative social constraints, as indicated by higher $s(\theta)$, raises marginal cost of women's paid work, i.e., $\frac{\partial \mathcal{L}_f}{\partial s} < 0$. This generates an additional substitution for paid labor in case of women through $s(\theta)$. Hence, the climate shock reduces women's paid labor through social cost channel:

$$\frac{\partial \mathcal{L}_f}{\partial s} s'(\theta) < 0$$

The effect of climate shock on gender gap in paid labor supply is given by:

$$\frac{d\,\text{Gap}}{d\theta} = \frac{dL_m^*}{d\theta} - \frac{dL_f^*}{d\theta} \tag{15}$$

The direction of the climate shock's effect on the gender gap in paid labor depends on the net effect of income and substitution effect in case of men and women. The income effect is positive for both genders when adverse shocks reduce non-labor income. Substitution effect is negative for men since both market returns and home production channels generate adverse effects on their paid labor. In case of women, the substitution effect depends on two factors: (a) relative strength of market-returns to home production and social cost channels; (b) sign of market-returns channel since it depends on whether the effect of own wage or cross wage is stronger.

3 Data and Research Method

This study uses a panel of 151 countries (1995-2019) on paid labor, economic and climate conditions.

Labor Data. Annual gender-disaggregated data on labor force participation, employment rate and unemployment rate are drawn from ILOSTAT modeled estimates in each year. ILO-modeled estimates are useful for making cross-country comparisons since these use harmonized methods across countries over years. The modeled series include imputed values where underlying national estimates are missing. Because imputation is done only using observations that are sufficiently comparable across countries, these estimates are reliable.

SPEI data. The Standardized Precipitation Evapotranspiration Index (SPEI) is a multi-scalar metric for drought and excess wetness. It standardizes anomalies in climate water balance that allow comparisons across regions over time. Monthly gridded SPEI values are obtained from the `SPEIbase v2.10` and aggregated to the country levels over 1980–2019. `SPEIbase v2.10` is a global dataset which is provided at (0.25 x 0.25) resolution. SPEI-12 is used in this analysis to derive drought and extreme wet intensities which are main independent variables. The rationale behind focusing on 12-month SPEI instead of 3-month and 6-month SPEI values is that it captures climatic shifts as reflected in the long-term changes in moisture contents while the shorter SPEI scales (3 or 6-month SPEI) capture seasonal and agricultural shocks respectively (Beguería et al., 2010; Vicente-Serrano et al., 2010). Negative and positive SPEI-12 values indicate drier and wet conditions respectively.

Let $SPEI_{ct}$ denote SPEI-12 value for country c and year t. Figure 1 shows the distribution of $SPEI_{ct}$.

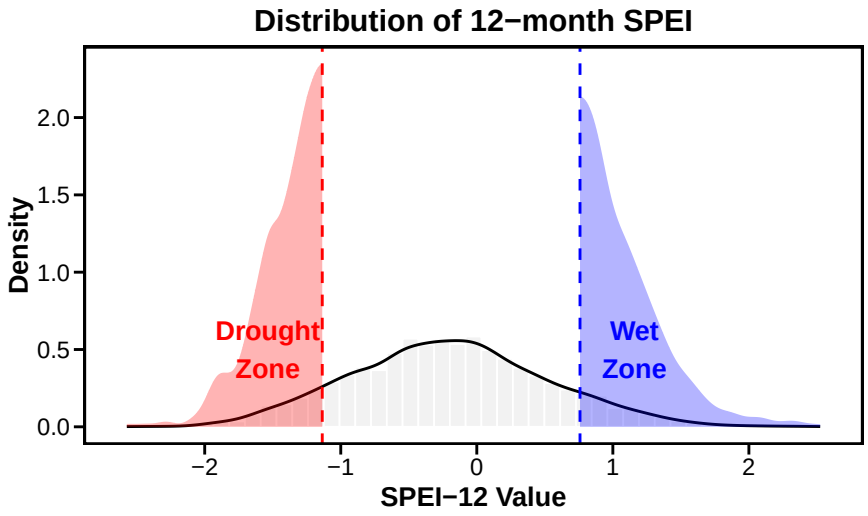


Figure 1: *Distribution of 12-month SPEI during 1995-2019. 10th percentile and 90th percentile values are considered as thresholds for extreme drought and wet intensities.*

To capture extreme drought and wet conditions, I define:
(i) **Drought intensity:** the extent to which the distance falls behind the 10th percentile and zero otherwise.

$$\text{Drought}_{ct} = \max\{0, -SPEI_{ct} - t_D\}, \tag{16}$$

where t_D is the 10th percentile value in the sample $SPEI_{ct}$ distribution; max(,) function captures extreme droughts since Drought_{ct} takes positive values only when $SPEI_{ct} < t_D$.
(ii) **Wet intensity:** the extent to which actual magnitude of 12-month SPEI exceeds its 90th percentile value and zero otherwise.

$$\text{Wet}_{ct} = \max\{0,\, SPEI_{ct} - t_W\}, \tag{17}$$

where t_W is the 90th percentile value in the sample $SPEI_{ct}$ distribution; max(,) function captures extreme wet conditions since Wet_{ct} takes positive values only when $SPEI_{ct} > t_W$.

Demographic and Economic Indicators. Data on demographic and economic controls are drawn from World Bank's World Development Indicators. These include GDP growth, foreign direct investment (FDI) inflows, gender-disaggregated population, land area, fertility, share of dependent population and urbanization. Using these data, I construct sex ratio and population density for each country in every year. Economic growth, urbanization and FDI also influence labor force participation but the same year values are likely to cause reverse causality. Hence, I use lagged values of economic growth, urbanization and FDI inflows as controls.

Data on disaster displacement risk is obtained from the Internal Displacement Monitoring Centre. As the term suggests, it measures vulnerability to displacement due to natural disasters. Women empowerment data comes from the World Bank's Women, Business and the Law database. It measures legal and institutional constraints that shape women's agency and access to work. I measure a country's net resilience by the Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index. It highlights net capacity to withstand and adapt to climate shocks.

Table 1 shows the summary statistics.

3.1 Empirical Methodology

Using a TWFE model, I explore the relationship between climate extremes and gender gap in paid labor using the following specification:

$$\text{GenderGap}_{ct} = \beta_0 + \beta_1 \text{Drought}_{ct} + \beta_2 \text{Drought}_{ct}^2 + \beta_3 \text{Wet}_{ct} + \beta_4 \text{Wet}_{ct}^2 + \mathbf{X'}_{ct}\beta_5 + \mathbf{Z'}_{ct-1}\beta_6 + \tau_c + \tau_t + u_{ct}, \tag{18}$$

where GenderGap_{ct} is the difference between men's and women's LFP. Drought_{ct} and Wet_{ct} are respectively drought and wet intensities. If the coefficients of squared terms Drought_{ct}^2 and Wet_{ct}^2 are showing opposite sign to their linear counterparts and are statistically significant, that captures the non-linear relationship between climate extremes and gender gap in paid labor outcomes. $\mathbf{X'}_{ct}$ are vectors of time-varying controls which include fertility, share of dependent population and gender gap in secondary education enrollment in country c and year t. $\mathbf{Z'}_{ct-1}$ are vectors of lagged

Table 1: Summary Statistics

Variable	N	Mean	Std. dev.
Gender gap in LFP (pp)	4,000	21.620	14.424
Gender gap in employment (pp)	4,000	20.691	13.796
Gender gap in unemployment (pp)	4,000	-1.847	3.558
Drought intensity (SPEI-12 tail)	5,400	0.021	0.098
Wet intensity (SPEI-12 tail)	5,400	0.024	0.120
Economic growth (lag)	4,865	3.776	6.080
Urbanization (lag)	5,160	57.339	24.529
FDI inflows (lag, % of GDP)	4,596	0.064	0.453
Age dependency ratio	5,375	62.221	18.981
Fertility rate	5,375	2.989	1.591
Sex ratio (female/male)	5,375	1.012	0.083
Population density	5,236	400.541	1869.108

Notes: Table reports means and standard deviations for the main variables used in the analysis. Gender gap in labor outcomes is the difference between men's and women's outcomes. Gender gaps are expressed in percentage points. Lagged variables are denoted by t–1.

controls including economic growth, urbanization and FDI. τ_c and τ_t are country and year fixed effects. u_{ct} are standard errors which are clustered at the country level.

4 Results

4.1 Main Results

Table 2 presents the main estimates from equation (18). Column (1) reports results for the main dependent variable, gender gap in labor force participation (LFP). Based on these estimates, Figure 2 visualizes the fitted relationship between gender gap in LFP with drought intensity (left panel) and wet intensity (right panel). Columns (2) and (3) report estimates for gender gap of LFP's constituents, namely, employment rate and unemployment rate.

Droughts. Column (1) shows non-linear relationship between gender gap in LFP and drought intensity (since $\beta_1 = -2.977$ and $\beta_2 = 5.354$). As drought intensity increases from zero to its turning point ($D^* = 0.278$), gender gap in LFP shrinks by nearly 3 percentage points (Column (1), Table 2). Beyond this threshold, the gap expands (Column (1), Table 2; Figure 2). Thus, gender gap in LFP has a U-shaped relationship with drought intensity (Figure 2). Drought conditions primarily affect gender gap in LFP through increasing gender gap in employment (Column (2), Table 2). This pattern explains mixed findings in the literature: moderate dry spells increases women's paid labor while large scale drought tend to the widen gender gap (Afridi et al., 2022; Maitra and Tagat, 2024).

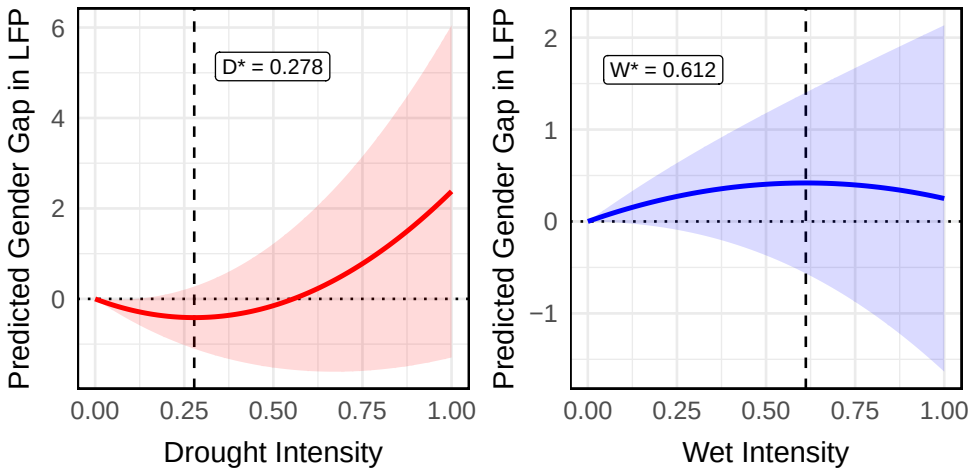


Figure 2: *Non-linear Relationship Between Climate Extremes and Gender Gap in LFP. Plots are based on the predicted gender gap in LFP using eq 18. Left panel captures the relationship with extreme drought and right panel shows the relationship with extreme wet conditions. Dashed vertical lines mark the estimated turning points:* $D^* = 0.278$ *and* $W^* = 0.612$*. Shaded areas indicate 95% confidence intervals and the horizontal dotted line denotes zero.*

Excess Wetness. Wet intensity also depicts non-linear effects. At low wetness, gender gap initially expands by 1.37 percentage points but it is not statistically significant (Column (1), Table 2). As wet intensity exceeds $W^* = 0.612$, gender gap starts to decline (Column (1), Table 2; Figure 2). This implies that there exists inverted U-shaped relationship between gender gap in LFP and wet intensity (Figure 2). It is noteworthy that the post-threshold fall in gender gap is attributable to declining gender gap in unemployment (Column (3), Table 2). This pattern is consistent with recent findings that women increases their paid labor supply after floods (Akter, 2021; Vitellozzi and Giannelli, 2024).

4.2 Robustness Checks

One concern with the baseline specification is that the non-linear relationship between climate extremes and gender gap in paid labor could be attributable to quadratic form of droughts and excess wetness in equation (18). Imposing squared terms may generate non-linear curvature and mask the true nature of the relationship. Hence, I introduce two alternative specifications by relaxing quadratic assumptions while keeping everything else unchanged in equation (18).

Cubic Spline Specification. First, I model drought intensities and wetness intensities using spline bases instead of quadratic form of climate extreme measures in equation (18). This approach model non-linear trends by altering both the number and position of knots which join different polynomial segments. By doing this, splines provide more continuous and accurate approximations

to the true functional form. Using the distribution of drought and wet intensities separately, I use 25th, 50th and 75th percentiles as three interior knots. This generates two spline terms which are now main independent variables: $\text{DroughtSpline}_{ct,1}$ and $\text{DroughtSpline}_{ct,2}$ for drought, and $\text{WetSpline}_{ct,1}$ and $\text{WetSpline}_{ct,2}$ for wetness. Results are reported in table 3 and I summarize the resultant relationship using predicted response plots in figure 3. These yield similar pattern as the main results which implies that the non-linear relationship in figure 2 is not merely because of quadratic specification.

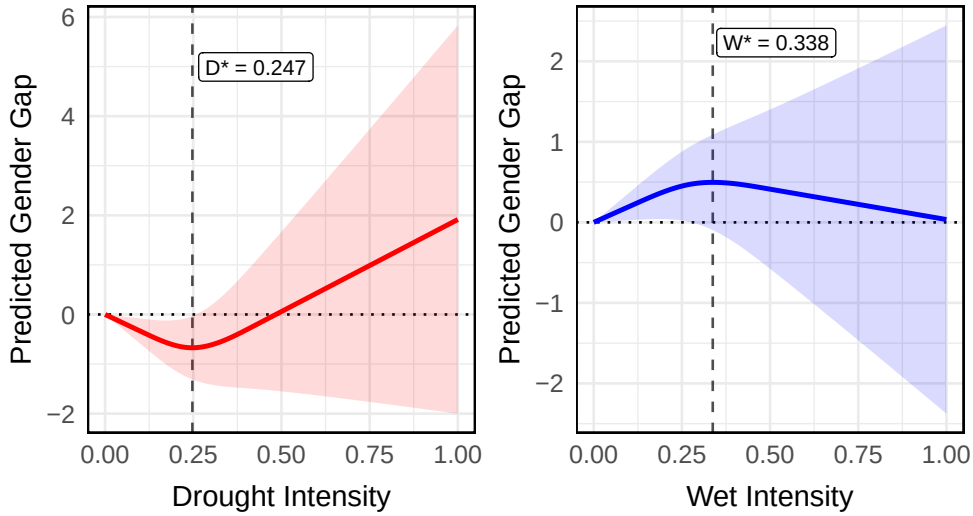


Figure 3: *Non-linear Relationship Between Climate Extremes and Gender Gap in LFP. Plots are based on the predicted gender gap in LFP using cubic spline specification. Left panel captures the relationship with extreme drought and right panel shows the relationship with extreme wet conditions. Dashed vertical lines mark the estimated turning points:* $D^* = 0.247$ *and* $W^* = 0.338$. *Shaded areas indicate 95% confidence intervals and the horizontal dotted line denotes zero.*

Piecewise Linear Specification. Next, I replace the quadratic forms of droughts and excess wetness in equation (18) with piecewise linear specification. The objective is to test whether the non-linearity exists, that is, the slope changes sign around the baseline turning points. Using $D^* = 0.278$ and $W^* = 0.612$, I construct $D_{ct}^{\text{below}} = \min\{\text{Drought}_{ct}, D^*\}$ and $D_{ct}^{\text{above}} = \max\{0, \text{Drought}_{ct} - D^*\}$, and analogously for wetness.

The results are reported in table 4 and figure 4 which remain consistent with the trends observed in figure 2. In case of droughts, gender gap initially declines below the turning point while it goes up if drought exceeds the turning point (Column (1), Table 4 and Figure 4). This drought-led U-shaped relationship is explained by gender gap in employment which is similar to baseline results (Column (2), Table 2 and Column (2), Table 4). In case of excess wetness, gender gap first rises if wetness falls short of the turning point but it declines once wetness goes beyond the cutoff (Column (1), Table 4 and Figure 4). while this wetness-gender gap nexus is not statistically

significant, the wetness-driven gender gap in paid labor is explained by gender gap in unemployment which remains significant as in the baseline results (Column (3), Table 2 and Column (3), Table 4).

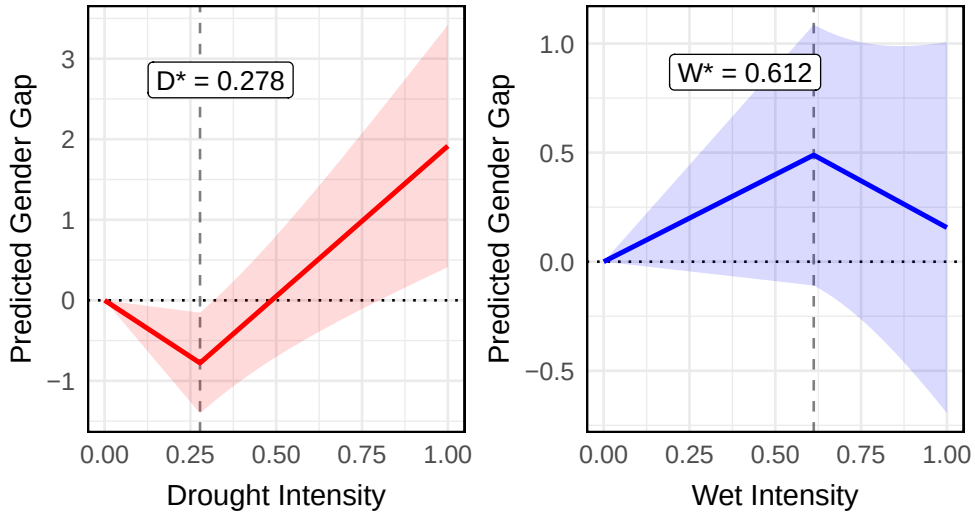


Figure 4: *Non-linear Relationship Between Climate Extremes and Gender Gap in LFP. Plots are based on the predicted gender gap in LFP using linear piecewise specification. Left panel captures the relationship with extreme drought and right panel shows the relationship with extreme wet conditions. Dashed vertical lines mark the estimated turning points:* $D^* = 0.278$ *and* $W^* = 0.612$*. Shaded areas indicate 95% confidence intervals and the horizontal dotted line denotes zero.*

4.3 Heterogeneous Effects

The above results indicate that gender gap in paid labor are sensitive to droughts and excess wetness. What factors explain this in non-linear relationship between climate extremes and gender gap in paid labor? I analyze equation 18 to examine whether the non-linear effects differ by country characteristics, namely, disaster related displacement risk, women's empowerment and net resilience. Tables 5–7 report the corresponding coefficients and figure 5 gives the visualization.

Disaster-related displacement risk. Disaster displacement risk refers to the probability that displacement at a certain scale will occur during a specific period of time due to the onset of a hazardous event (UNISDR, 2018). In countries with high displacement risk, the non-linear relationship is most pronounced for excess wetness (Column (3), Table 5; Panel A, Figure 5). This implies that excess wetness is significant in countries where wet shocks are most likely to trigger displacements. With sudden onset of wet shocks, gender gap can increase due to rise in household work, childcare burdens and safety constraints (Fruttero et al., 2023; Kreutzer et al., 2023). But as wetness become severe, men may also lose employment and the gender gap shrinks (Chowdhury

et al., 2022; Jia et al., 2022; Vitellozzi and Giannelli, 2024). Table 2 shows that the wet-labor nexus is driven by drop in gender gap of unemployment.

On the other hand, the effect of droughts is prominent in countries with moderate displacement risk (Column (2), Table 5; Panel A, Figure 5). This is expected because droughts are slow-onset disasters. Women are over-represented in agricultural sectors, especially in developing and less developed countries where droughts are more frequent (Chatterjee, 2021). Studies have shown that migration is gendered and women are less likely to migrate than men after droughts (Afridi et al., 2022; Sultana et al., 2024). However, both linear and non-linear effects of drought and excess wetness are muted in countries with low-displacement risk (Column (1), Table 5; Panel A, Figure 5).

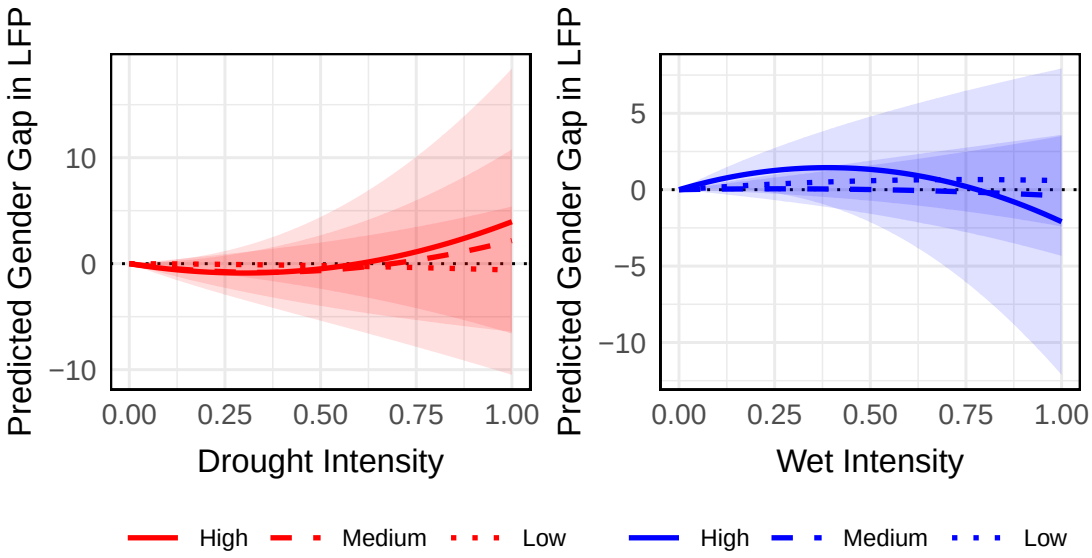


Figure 5: *Heterogeneous Effects of Drought and Excess Wet Intensities on Gender Gap in LFP by Disaster Displacement Risk. Predicted gender gap in LFP are plotted for different drought intensity (left-side panel) and excess wet intensity (right-side panel). Shaded areas indicate 95% Confidence Intervals.*

Women empowerment. Women empowerment is captured by Women, Business and Law (WBL) index which measures how laws and regulations affect women's economic opportunity. This index reflects both constraints and protections which influence women's economic agency such as right to work, asset ownership, free mobility. By measuring institutional environment rather than labor market outcomes, WBL rules out concerns about reverse causality that could arise if better female labor market outcomes improve legal protections for women. Higher WBL value indicates more gender equal legal rights and fewer constraints to women's work. Using WBL distribution, I classify

countries into low, medium and high empowerment terciles.

The U-shaped drought-gender-gap relationship is concentrated in countries with low and moderate levels of women empowerment (Columns (1)–(2), Table 6; Figure 6). This indicates that extreme weather conditions amplify gender gap in paid work where women face more legal and institutional constraints. Low drought intensities absorb more women in paid labor when households face financial loss due to dry spells (e.g., Moshoeshoe et al., 2025). But as droughts become severe, gender norms dominate in countries with low and medium empowerment. During severe droughts, time required for unpaid domestic (e.g., water collection, fuel wood) and care work (caring for malnourished children and/or diseased elderly) increases. This, in turn, pulls women out of paid labor to cater household responsibilities (Afridi et al., 2022; Musungu et al., 2024)

In case of excess wet conditions, the inverted U-shaped relationship is pronounced in countries with moderate empowerment (Columns (2), Table 6; Figure 6). At low levels of excess wetness, gender gap rises as women face increased mobility constraints and care burdens (Kreutzer et al., 2023). As excess wetness goes beyond the turning point, widespread economic disruption reduces male employment and induces women to spend more time in income-generating activities (Akter, 2021; Canessa & Giannelli, 2021; Vitellozzi & Giannelli, 2024). As a result, gender inequality in paid labor declines after extreme wetness. However, gender gap is more resilient to climate extremes in countries with high empowerment (Column (3), Table 6).

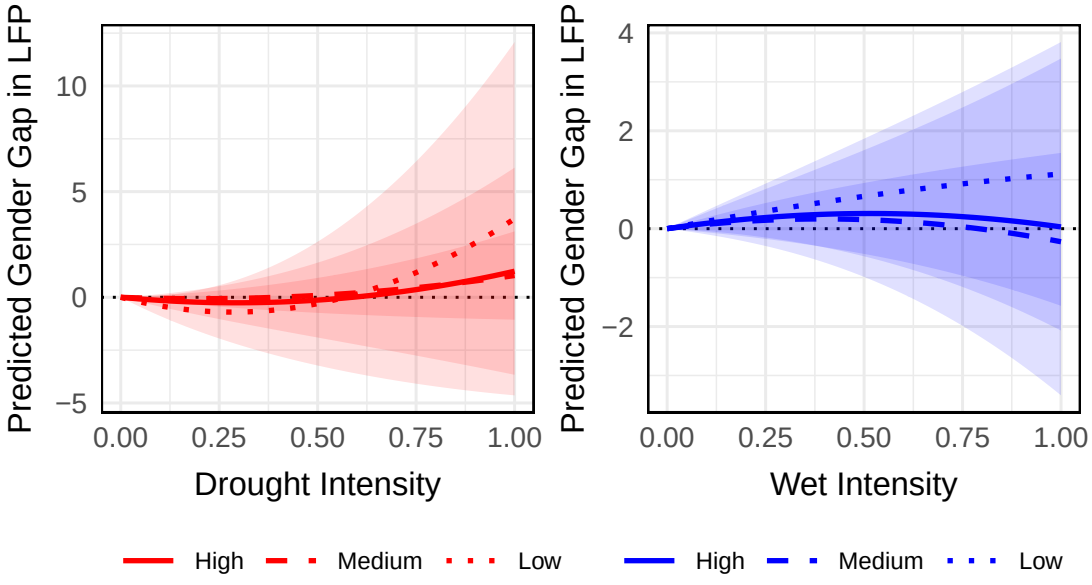


Figure 6: *Heterogeneous Effects of Drought and Excess Wet Intensities on Gender Gap in LFP by Women Empowerment. Predicted gender gap in LFP are plotted for different drought intensity (left-side panel) and excess wet intensity (right-side panel). Shaded areas indicate 95% Confidence Intervals.*

Net resilience. I measure each country's net resilience using ND-GAIN index which is composed of vulnerability and readiness (Notre Dame Global Adaptation Initiative, 2026)[1]. Vulnerability is defined as a country's sensitivity, exposure and adaptive capacity to adverse effects of climate change. Readiness evaluates a country's capacity to capitalize investments for adaptation actions. It includes three components, namely, governance, economic and social readiness. Using terciles, countries are classified into low, medium and high net resilient groups.

In countries with low resilience, extreme climate conditions matter more for gender gap in paid labor. Drought conditions share U-shaped relationship with gender gap in paid labor in low resilient countries (Column (1), Table 7 and Figure 7). At low to moderate drought intensities, gender gap shrinks as women enter in paid labor to smooth household consumption and alleviate income loss (Kochar, 1999; Moshoeshoe et al., 2025). But as drought intensity exceeds its turning point ($D^* = 0.34$), gender gap expands in low resilient countries. Furthermore, wet intensity has linear but again positive influence on gender gap in LFP in countries with least resilience against climate change (Column (1), Table 7 and Figure 7).

The positive relationship between climate extremes and gender gap in countries with low resilience could be attributable to lack of readiness and limited adaptation capabilities of such countries. Agricultural sector tend to be predominant in less resilient economies where women are overrepresented (Food and Agriculture Organization of the United Nations, 2011; Palacios-Lopez et al., 2017; Sellers & Gray, 2024). As droughts or excess wetness worsen, time required for unpaid domestic chores (e.g., collection of fuelwood and water) and care work increases (Sellers & Gray, 2024; UN Women, 2023). These pull out women from participating in paid labor (Afridi et al., 2022; Fruttero et al., 2024). Moreover, structural and social norms also deter women to migrate away from affected regions and look for alternative income opportunities (Afridi et al., 2022; Sellers & Gray, 2024; Sultana et al., 2024).

[1] $\text{GAIN} = (\text{Readiness}_{0 \leq \text{Readiness} \leq 100} - \text{Vulnerability}_{0 \leq \text{Vulnerability} \leq 1} + 1) \times 50;\ 0 \leq \text{GAIN} \leq 100$

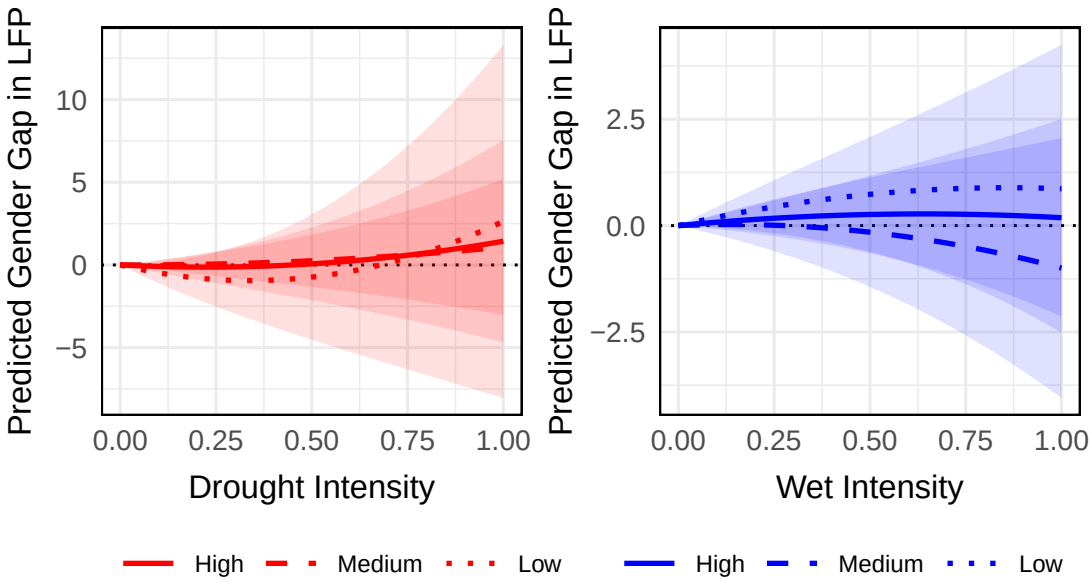


Figure 7: *Heterogeneous Effects of Drought and Excess Wet Intensities on Gender Gap in LFP by Net Resilience. Predicted gender gap in LFP are plotted for different drought intensity (left-side panel) and excess wet intensity (right-side panel). Shaded areas indicate 95% Confidence Intervals.*

5 Conclusion

This paper examines how extreme climate conditions shape gender disparity in labor force participation across 151 countries during past 24 years. The theoretical model shows that the balance between income and substitution effects determine whether adverse shock such as climate extremes expand or contract the gender gap in paid labor force participation. Key findings highlight non-linearities: first, gender gap in LFP exhibits U-shaped relationship with drought intensity. That is, gender gap narrows at low to moderate drought intensities but it starts to widen during extreme droughts. On the contrary, gender differences in paid labor shares an inverted U-shaped relationship with wet intensity. Thus, gender gap initially expands but declines once wet conditions become severe. Furthermore, drought-induced gender inequalities is mainly driven by gender gap in employment while wetness led gender gaps is attributable to gender gap in unemployment (ie., those seeking jobs).

Country characteristics and institutional context play important role in shaping these relationships. Non-linear effects of excess wetness is most pronounced in countries with high disaster-related displacement risk. This is plausible because extreme wet shocks such as floods are sudden and cause widespread destruction which are likely to trigger displacement and influence gendered labor market outcomes. But droughts have non-linear impact on gender gap in countries with

moderate disaster-related displacement risk where slow onset of droughts and gendered migration constraints gradually worsen gender gap in paid labor. Moreover, drought-driven non-linear effects are also concentrated in countries with least and moderate regulatory and legal support for women empowerment. The inverted U-shaped relationship Limited agency and conservative institutional context often constrain women's mobility, asset ownership and participation in paid labor. Lastly, a country's resilience against climate shocks matters. The U-shaped nexus between gender gap in LFP and drought intensity is prominent in countries with least net resilience. Excess wetness also has positive effect on gender gap in paid labor in countries with weak resilience against climate extremes.

These results have significant implications for climate adaptation policies. First, climate adaptation cannot assume uniform effects of climate extremes: same climate event such as droughts could narrow gender gaps at low intensity while expand the gender differences at high levels. Policies should adhere to the intensity of the shocks. Nature of climate event also matters for designing adaptation policies. Excess wetness and droughts have different types of relationship with gender inequality in paid labor. Second, strengthening institutional regulation towards women economic empowerment is important to reshape the extent to which climate extremes impact gender gap in paid labor. Countries with stronger women-friendly laws and regulations depict insignificant effect of droughts and wetness on gender gap in paid labor. Third, ecologically fragile countries should boost up their investments in infrastructure for climate actions: gender gap in LFP is not influenced by droughts and excess wetness in countries with moderate and high net resilience against climate events. To sum up, social insurance (e.g., unemployment benefits), social assistance (e.g., cash transfers) and care services (e.g., child care) should be provided to affected households in climate hotspots. This could help households to alleviate financial loss without forcing women to exit from labor market or enter distress-driven paid labor.

Some limitations remain. Because this study utilizes country-year panel data, I measure climatic moisture conditions by annual mean of SPEI-12 values. This approach could smooth within-year climate variations and weaken effects of short-lived extreme weather events in a country. Besides, the ILO modeled labor market series harmonize national estimates from labor force surveys of various countries. But the series may still have measurement error from differences in various national labor force surveys.

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Appendix

A Theoretical Framework (Proof)

Setup. Consider a representative household with husband (m) and wife (f). Each allocates one unit of time across paid work L_j, leisure ℓ_j, and home production h_j:

$$L_j + \ell_j + h_j = 1, \qquad j \in \{f, m\}. \tag{A.1}$$

Preferences are

$$U_m = U_m(C_m, \ell_m, H), \tag{A.2}$$
$$U_f = U_f(C_f, \ell_f, H) - \kappa(L_f; \theta), \tag{A.3}$$

where U_i is increasing and concave in its arguments. The term $\kappa(L_f; \theta)$ captures the social cost of women's paid work, which varies with climate conditions θ. A higher θ denotes a more adverse climate shock.

Social cost. I parameterize the social cost as

$$\kappa(L_f; \theta) = s(\theta)\, \tilde{\kappa}\, L_f, \qquad s(\theta) > 0, \quad s'(\theta) \geq 0, \quad \tilde{\kappa} > 0, \tag{A.4}$$

so the marginal social cost of women's market work is

$$\kappa_L(L_f; \theta) \equiv \frac{\partial \kappa(L_f; \theta)}{\partial L_f} = s(\theta)\, \tilde{\kappa}. \tag{A.5}$$

Budget constraint. Household consumption is financed by labor income and non-labor income:

$$C_f + C_m = w_f L_f + w_m L_m + Y(\theta), \tag{A.6}$$

where $Y'(\theta) < 0$ and wages may also decline under adverse climate conditions, $w_j'(\theta) < 0$.

Home production. The home good H is produced using spouses' home time:

$$H = H(h_m, h_f; \theta), \qquad H_{h_j} > 0, \;\; H_{h_j h_j} < 0. \tag{A.7}$$

Collective Bargaining Model. The household maximizes a weighted sum of individual utilities:

$$U = \alpha U_f + (1-\alpha)U_m, \qquad \alpha \in (0,1), \tag{A.8}$$

subject to (A.1), (A.6), and (A.7).

Rewriting the budget constraint Using $L_j = 1 - \ell_j - h_j$ from (A.1), rewrite (A.6) as

$$C_f + C_m + w_f(\ell_f + h_f) + w_m(\ell_m + h_m) = w_f + w_m + Y(\theta). \tag{A.9}$$

Lagrangian Function Let λ denote the multiplier on (A.9). The Lagrangian is

$$\begin{aligned}\mathcal{L} = \alpha\Big[U_f(C_f, \ell_f, H) - \kappa(1 - \ell_f - h_f; \theta)\Big] + (1-\alpha)U_m(C_m, \ell_m, H) \\ + \lambda\Big[w_f + w_m + Y(\theta) - C_f - C_m - w_f(\ell_f + h_f) - w_m(\ell_m + h_m)\Big].\end{aligned} \tag{A.10}$$

First-order conditions Denote by u_H the *marginal utility of household production* in the weighted objective:

$$u_H \;\equiv\; \alpha\, U_{f,H}(C_f, \ell_f, H) + (1-\alpha)\, U_{m,H}(C_m, \ell_m, H). \tag{A.11}$$

Consumption.

$$\frac{\partial \mathcal{L}}{\partial C_f} = 0 \Rightarrow \alpha\, U_{f,C} = \lambda, \tag{A.12}$$

$$\frac{\partial \mathcal{L}}{\partial C_m} = 0 \Rightarrow (1-\alpha)\, U_{m,C} = \lambda. \tag{A.13}$$

Home production time. Using $H_{h_j} \equiv \partial H / \partial h_j$ and $u_H = [\alpha \frac{\partial U_f}{\partial H} + (1-\alpha)\frac{\partial U_m}{\partial H}]$:

$$\frac{\partial \mathcal{L}}{\partial h_f} = 0 \Rightarrow u_H\, H_{h_f} = \lambda w_f - \alpha\, \tilde{\kappa}, \tag{A.14}$$

$$\frac{\partial \mathcal{L}}{\partial h_m} = 0 \Rightarrow u_H\, H_{h_m} = \lambda w_m. \tag{A.15}$$

Opportunity costs of home production Define the shadow value of an hour in home production by spouse j:

$$q_j(\theta) \equiv \frac{u_H}{\lambda}\, H_{h_j}(h_m, h_f; \theta), \qquad j \in \{f, m\}. \tag{A.16}$$

Using (A.14)–(A.15), we obtain

$$q_f(\theta) = w_f - \frac{\alpha}{\lambda}\,\kappa_L(L_f;\theta) = w_f - \frac{\alpha}{\lambda}\,s(\theta)\tilde{\kappa}, \tag{A.17}$$

$$q_m(\theta) = w_m. \tag{A.18}$$

Thus, women's shadow value of home time equals their market wage net of the marginal social cost from working outside their home, whereas men's shadow value of home time equals their wage. The ratio of their opportunity cost is:

$$\frac{q_f(\theta)}{q_m(\theta)} = \frac{w_f - \frac{\alpha}{\lambda}s(\theta)\tilde{\kappa}}{w_m}. \tag{A.19}$$

Reduced-form labor supply and income–substitution decomposition Solving the household problem yields Marshallian (uncompensated) labor supplies:

$$L_f^* = \mathcal{L}_f\big(Y(\theta), w_f(\theta), w_m(\theta), \tilde{\kappa}s(\theta), \theta, \alpha\big), \tag{A.20}$$

$$L_m^* = \mathcal{L}_m\big(Y(\theta), w_f(\theta), w_m(\theta), \theta, \alpha\big). \tag{A.21}$$

Taking total derivatives with respect to θ gives the decomposition into an income and substitution effects:

$$\frac{dL_f^*}{d\theta} = \frac{\partial \mathcal{L}_f}{\partial Y}\,Y'(\theta) + \left[\frac{\partial \mathcal{L}_f}{\partial w_f}\,w_f'(\theta) + \frac{\partial \mathcal{L}_f}{\partial w_m}\,w_m'(\theta) + \frac{\partial \mathcal{L}_f}{\partial s}\,s'(\theta) + \frac{\partial \mathcal{L}_f}{\partial \theta}\right], \tag{A.22}$$

$$\frac{dL_m^*}{d\theta} = \frac{\partial \mathcal{L}_m}{\partial Y}\,Y'(\theta) + \left[\frac{\partial \mathcal{L}_m}{\partial w_f}\,w_f'(\theta) + \frac{\partial \mathcal{L}_m}{\partial w_m}\,w_m'(\theta) + \frac{\partial \mathcal{L}_m}{\partial \theta}\right]. \tag{A.23}$$

Gender gap response. Effect of the shock on gender gap in paid labor is given by Gap $\equiv L_m^* - L_f^*$, then ,

$$\begin{aligned}
&\frac{d\,\mathrm{Gap}}{d\theta} = \frac{dL_m^*}{d\theta} - \frac{dL_f^*}{d\theta} \\
\implies &\frac{d\,\mathrm{Gap}}{d\theta} = \left[\frac{\partial \mathcal{L}_m}{\partial Y} - \frac{\partial \mathcal{L}_f}{\partial Y}\right] Y'(\theta) \\
&\qquad + \left[\frac{\partial(\mathcal{L}_m - \mathcal{L}_f)}{\partial w_f} w_f'(\theta) + \frac{\partial(\mathcal{L}_m - \mathcal{L}_f)}{\partial w_m} w_m'(\theta)\right] \\
&\qquad - \frac{\partial \mathcal{L}_f}{\partial s} s'(\theta) + \left[\frac{\partial \mathcal{L}_m}{\partial \theta} - \frac{\partial \mathcal{L}_f}{\partial \theta}\right] \\
\implies &\frac{d\,\mathrm{Gap}}{d\theta} = AY'(\theta) + Bw_f'(\theta) + Cw_m'(\theta) - \frac{\partial \mathcal{L}_f}{\partial s} s'(\theta) + D
\end{aligned} \tag{A.24}$$

where $Y'(\theta) < 0, w'_f(\theta) < 0, w'_m(\theta) < 0, s'(\theta) > 0$; $[\frac{\partial \mathcal{L}_m}{\partial Y} - \frac{\partial \mathcal{L}_f}{\partial Y}] = A$, $[\frac{\partial(\mathcal{L}_m - \mathcal{L}_f)}{\partial w_f} = B$, $\frac{\partial(\mathcal{L}_m - \mathcal{L}_f)}{\partial w_m} = C$, $\left[\frac{\partial \mathcal{L}_m}{\partial \theta} - \frac{\partial \mathcal{L}_f}{\partial \theta}\right] = D$.

If higher non-labor income reduces women's labor supply more than that of men's paid labor, $A > 0$. Rise in own wage income (w_m, w_f) raises incentives to work and increases labor supply $\frac{\partial \mathcal{L}_i}{\partial w_i} > 0, i \in [m, f]$.. But studies have shown that women reduce their participation if their husbands earn more. That is, $\frac{\partial \mathcal{L}_f}{\partial w_m} < 0$. This implies that $C > 0$. However, whether men reduce or raise their labor if wives earn more is debatable. Assuming husbands reduce their paid labor if women earn more $(\frac{\partial \mathcal{L}_m}{\partial w_f} < 0)$, rise in women's paid labor due to rising wage would be more than decline in men's labor. Thus, $B > 0$. In case, husbands don't alter or increase their paid labor in response to wives' higher wage , it will keep $B > 0$. Besides, $s'(\theta) > 0$ and $(\frac{\partial \mathcal{L}_f}{\partial s} < 0)$. So, $[AY'(\theta) + Bw'_f(\theta) + Cw'_m(\theta) - \frac{\partial \mathcal{L}_f}{\partial s} s'(\theta)] > 0$. Hence, the sign of $\frac{\partial \text{Gap}}{\partial \theta}$ depends on D.

B Main Regression Results

Table 2: Climate Extremes and Gender Gap in Paid Labor Outcomes

Gender gap	LFP (1)	Employment (2)	Unemployment (3)
Drought_{ct}^2	5.354***	4.088***	1.037
	(1.431)	(1.417)	(1.096)
Drought_{ct}	-2.977**	-2.447**	-0.230
	(1.187)	(1.187)	(0.768)
Wet_{ct}^2	-1.119*	-0.617	-0.938**
	(0.628)	(0.653)	(0.465)
Wet_{ct}	1.369*	0.903	0.628
	(0.718)	(0.720)	(0.398)
Economic growth (lag)	✓	✓	✓
Urbanization (lag)	✓	✓	✓
FDI inflows (lag, % of GDP)	✓	✓	✓
Age dependency	✓	✓	✓
Fertility	✓	✓	✓
Sex ratio	✓	✓	✓
Population density	✓	✓	✓
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,646	3,646	3,646
Countries (clusters)	156	156	156
R^2	0.967	0.964	0.789
Within R^2	0.045	0.039	0.036

Notes: Dependent variables are gender gaps in labor force participation, employment rate, and unemployment rate. Drought_{ct} and Wet_{ct} are climate extreme measures constructed from 12-month SPEI tail-ends on both sides (see text); squared terms allow for non-linear effects. Robust standard errors clustered at the country level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

C Regression Results for Robustness Checks

Table 3: Robustness: Spline Specification

	LFP (1)	Employment (2)	Unemployment (3)
$\text{DroughtSpline}_{ct,1}$ (dcs1)	-3.361**	-2.898**	0.063
	(1.306)	(1.259)	(0.871)
$\text{DroughtSpline}_{ct,2}$ (dcs2)	5.501***	4.426***	0.534
	(1.577)	(1.520)	(1.212)
$\text{WetSpline}_{ct,1}$ (wcs1)	1.957**	1.143	1.098*
	(0.870)	(0.913)	(0.577)
$\text{WetSpline}_{ct,2}$ (wcs2)	-2.154**	-1.075	-1.764**
	(0.976)	(1.048)	(0.781)
Economic growth (lag)	✓	✓	✓
Urbanization (lag)	✓	✓	✓
FDI inflows (lag, % of GDP)	✓	✓	✓
Age dependency	✓	✓	✓
Fertility	✓	✓	✓
Sex ratio	✓	✓	✓
Population density	✓	✓	✓
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,646	3,646	3,646
Countries (clusters)	156	156	156
R^2	0.967	0.964	0.789
Within R^2	0.046	0.040	0.036

Notes: Dependent variables are gender gaps (male minus female, in percentage points) in labor force participation (LFP), employment rate, and unemployment rate. Drought and wetness tail-intensity measures derived from SPEI-12 are modeled flexibly using restricted cubic spline bases. Knots are set at the 25th, 50th, and 75th percentiles of the positive tail intensity distributions: drought knots (0.106, 0.239, 0.416) and wet knots (0.114, 0.271, 0.488). All specifications include country and year fixed effects and the full set of controls shown. Robust standard errors clustered at the country level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 4: Robustness: Piecewise Linear Specification

	LFP	Employment	Unemployment
	(1)	(2)	(3)
DroughtBelow_{ct} ($\min\{\text{Drought}_{ct}, D^*\}$)	-2.800**	-2.380**	0.056
	(1.147)	(1.119)	(0.745)
DroughtAbove_{ct} ($\max\{0, \text{Drought}_{ct} - D^*\}$)	3.732***	2.748***	0.801
	(0.967)	(0.974)	(0.786)
WetBelow_{ct} ($\min\{\text{Wet}_{ct}, W^*\}$)	0.799	0.567	0.233
	(0.498)	(0.479)	(0.228)
WetAbove_{ct} ($\max\{0, \text{Wet}_{ct} - W^*\}$)	-0.857	-0.263	-1.464**
	(0.796)	(0.829)	(0.682)
Economic growth (lag)	✓	✓	✓
Urbanization (lag)	✓	✓	✓
FDI inflows (lag, % of GDP)	✓	✓	✓
Age dependency	✓	✓	✓
Fertility	✓	✓	✓
Sex ratio	✓	✓	✓
Population density	✓	✓	✓
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,646	3,646	3,646
Countries (clusters)	156	156	156
R^2	0.967	0.964	0.789
Within R^2	0.045	0.039	0.036

Notes: Dependent variables are gender gaps (male minus female, in percentage points) in labor force participation (LFP), employment rate, and unemployment rate. Drought_{ct} and Wet_{ct} are tail-intensity measures derived from SPEI-12 using the 10th and 90th percentile thresholds. The piecewise linear specification allows different slopes below and above knots $D^* = 0.278$ and $W^* = 0.612$. All specifications include country and year fixed effects and the full set of controls shown. Robust standard errors clustered at the country level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

D Regression Results for Heterogeneous Effects

Table 5: Climate Extremes and Gender Gap in Labor Force Participation by Natural Disaster related Displacement Risk

Displacement Risk	Low (1)	Medium (2)	High (3)
Drought_{ct}^2	-0.446	6.952**	9.862
	(2.352)	(3.107)	(6.099)
Drought_{ct}	-0.156	-4.772	-5.903
	(1.814)	(2.911)	(3.793)
Wet_{ct}^2	-1.171	-0.856	-9.500**
	(0.827)	(1.321)	(4.166)
Wet_{ct}	1.761	0.447	7.405***
	(1.232)	(1.424)	(2.732)
Economic growth (lag)	✓	✓	✓
Urbanization (lag)	✓	✓	✓
FDI inflows (lag, % of GDP)	✓	✓	✓
Age dependency	✓	✓	✓
Fertility	✓	✓	✓
Sex ratio	✓	✓	✓
Population density	✓	✓	✓
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	999	1,008	1,111
Countries (clusters)	43	42	48
R^2	0.948	0.957	0.981
Within R^2	0.068	0.125	0.121

Notes: Dependent variable is the gender gap in labor force participation (percentage points). Using the natural disaster displacement risks, countries are classified into terciles based on the sample distribution: low risk (`displacement`$\leq$ 1,131), medium risk (1,407 $\leq$ `displacement` $\leq$ 29,542), and high risk (`displacement` $\geq$ 31,164). Robust standard errors clustered at the country level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 6: Climate Extremes and Gender Gap in Labor Force Participation by Women's Empowerment

Empowerment group	Low	Medium	High
	(1)	(2)	(3)
Drought_{ct}^2	8.634**	1.698**	2.997
	(3.454)	(0.742)	(1.965)
Drought_{ct}	-4.914**	-0.667	-1.763
	(2.378)	(0.747)	(1.486)
Wet_{ct}^2	-0.407	-1.272**	-1.167
	(0.760)	(0.596)	(1.316)
Wet_{ct}	1.526	1.005	1.202
	(1.119)	(0.695)	(1.124)
Economic growth (lag)	✓	✓	✓
Urbanization (lag)	✓	✓	✓
FDI inflows (lag, % of GDP)	✓	✓	✓
Age dependency	✓	✓	✓
Fertility	✓	✓	✓
Sex ratio	✓	✓	✓
Population density	✓	✓	✓
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,141	1,187	1,254
Countries (clusters)	73	99	84
R^2	0.985	0.982	0.965
Within R^2	0.192	0.054	0.191

Notes: Dependent variable is the gender gap in labor force participation (percentage points). Using the Women, Business and the Law (WBL) index, countries are classified into terciles of women's empowerment based on the sample distribution: low empowerment (WBL $\leq$ 58.75), medium empowerment (59.375 $\leq$ WBL $\leq$ 75.0), and high empowerment (WBL $\geq$ 75.625). Robust standard errors clustered at the country level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 7: Climate Extremes and Gender Gap in Labor Force Participation by Net Resilience

Net Resilience	Low	Medium	High
	(1)	(2)	(3)
Drought_{ct}^2	8.215*	1.156	2.612
	(4.354)	(1.514)	(2.450)
Drought_{ct}	-5.580*	-0.071	-1.178
	(3.105)	(1.396)	(1.835)
Wet_{ct}^2	-1.207	-1.376	-0.676
	(1.181)	(0.956)	(0.831)
Wet_{ct}	2.073*	0.378	0.861
	(1.215)	(1.198)	(0.811)
Economic growth (lag)	✓	✓	✓
Urbanization (lag)	✓	✓	✓
FDI inflows (lag, % of GDP)	✓	✓	✓
Age dependency	✓	✓	✓
Fertility	✓	✓	✓
Sex ratio	✓	✓	✓
Population density	✓	✓	✓
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,174	1,110	1,179
Countries (clusters)	64	73	64
R^2	0.977	0.976	0.972
Within R^2	0.151	0.042	0.190

Notes: Dependent variable is the gender gap in labor force participation (percentage points). Using the ND-GAIN's *GAIN* index, countries are classified into terciles of net resilience based on the sample distribution: low resilience (GAIN $\leq$ 39.741), middle resilience (39.746 $\leq$ GAIN $\leq$ 49.026), and high resilience (GAIN $\geq$ 49.033). Robust standard errors clustered at the country level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.