Crime and Constrained Mobility: Examining the Impact of Crime on Women's Outdoor Time in India

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Professor Bharat Ramaswami

1 Introduction

In India, the intersection of crime and gender inequality poses significant challenges to women's participation in public life. Despite increasing attention to issues of women's safety, the country continues to report alarmingly high levels of gender-targeted crimes. Anecdotal evidence and survey data suggest that these safety concerns profoundly influence women's daily activities, from their willingness to work outside the home to their overall mobility. A 2009 survey of non-working women in Delhi revealed that safety concerns were the second most important reason behind their decision not to work (Sudarshan, Bhattacharya, 2009). Such barriers not only restrict women's access to economic opportunities but also limit their ability to engage in social and recreational activities.

The well-established U-shaped model of female labor force participation (Goldin, 1994) posits that as economies develop, women's participation initially declines during structural shifts before increasing at advanced stages. However, this framework often overlooks barriers like crime and safety concerns, which disproportionately affect women in transitional economies. Studies, such as Saha (2014), using NFHS data, show that unsafe environments significantly decrease women's likelihood of employment, highlighting the interplay between crime and gendered labor dynamics.

Despite the well-documented link between crime and women's employment outcomes, there is limited research on how crime impacts broader aspects of women's lives, such as mobility and social engagement. These dimensions are crucial for understanding the full scope of constraints women face, as restricted mobility and reduced participation in outdoor activities can limit opportunities for personal development, social interaction which in turn facilitate effective economic contribution.

2 Problem Statement

This study aims to examine how crime rates affect women's lives beyond just employment outcomes. Specifically, we aim to understand how crime influences women's social lives and more importantly, their mobility, by analyzing its impact on their time allocation towards outdoor activities.

We do so by proposing a simple theoretical model that characterizes women's time allocation as a constrained optimization problem with an external cost imposed on outdoor time by crime rates and other factors. Herein, we define factors that amplify the negative effects of crime as *deterrents* and factors that moderate the effect of crime as $buffers$. It is essential to study the factors that moderate or amplify the effect of crime, with perhaps, more targeted efforts to reduce the negative effects of crime on a *deterrent* rich populace. Therefore, we put forth four hypotheses following from the model and test them using our empirical framework.

3 Motivation

Although the relationship between female labor force participation (LFPR) and crime rates has been explored—showing that perceived increases in crimes against women can significantly discourage labor force participation (Saha, 2014)—the broader impacts of crime on other aspects of women's lives remain underexplored. While research establishes strong links between crime and adverse health outcomes (Heise et al., 2002, Lancet 2002) for women as well as lowered learning outcomes (Bowen and Bowen, 1999; Schwartz and Gorman, 2003; Ceballo et al., 2004), the effect of crime on women's social life and mobility has received little to no attention in economic literature, despite firm evidence linking aspects of social life such as leisure leading to higher economic productivity (Cui et al., 2019).

Qualitative psychological studies of the effect of crime on women's social life show that many people suffer from anxiety in anticipation of victimization and modify their lives to avoid crime in ways that cost them lost social and work opportunities. The self-imposed outdoor time restriction of people seeking to prevent victimization also reduces their quality of life in terms of participation in social, leisure, and other recreational activities (Riger and Gordon, 1983).

The aim of our study is to investigate the impact of crimes against women on their outdoor behavior in India, using a quantitative approach. India presents a compelling case for such analysis, given its stark gender disparities and rising crime rates against women. According to the National Crime Records Bureau (NCRB), crimes against women in India have steadily increased over the past decade, with 4,45,256 cases reported in 2022 alone—a 4% rise from the previous year. While domestic violence under the category of 'Cruelty by Husband or His Relatives' accounts for the largest proportion of these crimes (31.4%), significant fractions involve public spaces, such as 'Kidnapping and Abduction of Women' (19.2%) and 'Assault on Women with Intent to Outrage Her Modesty' (18.7%). Despite the alarming frequency and public impact of these crimes, there is a lack of empirical research exploring how they influence women's daily lives, particularly in terms of outdoor mobility and time use.

While this relationship may be prone to the issue of reverse causality—where increased time outdoors could lead to higher susceptibility to crime—preliminary findings suggest that this may not entirely be the case. Specifically, they indicate a weak negative correlation between crime rates and time spent outdoors by women.

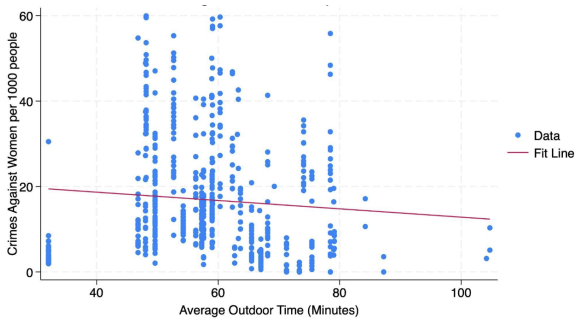

Figure 1: graph showing outdoor time vs. crime rates.

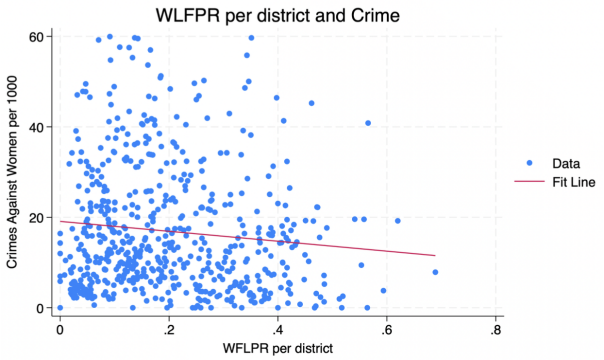

Figure 2: graph showing WLFPR vs. crime rates.

Figure 1. reveals significant variability, suggesting that other factors heavily influence outdoor time. Similar crime rates also correspond to varying outdoor times, highlighting district-level heterogeneity. This makes the need for a more nuanced and detailed analysis on the topic even more apparent, which we aim to address through our paper.

4 Analytical Framework

4.1 Theoretical Framework

To conceptualize how crime affects women's outdoor time, we develop a simple theoretical framework. This model provides some guidance and theoretical backing to the controls and specifications in our empirical framework. It also serves to somewhat generalize our results to other contexts including different countries.

We consider time allocation as a constrained optimization problem, where women balance outdoor activities with competing demands like household activities, caregiving responsibilities, and leisure. We hypothesize that crime imposes an external cost that disproportionately impacts outdoor time, as it directly relates to activities conducted in public spaces.

Let the total time available to a woman be denoted by T, which is allocated across various activities:

$$T = O + H + C + L + R$$

where:

- O: Outdoor time, the variable of interest.
- H: Household activities (e.g., paid work).
- C: Care work (e.g., caregiving, cooking, cleaning).
- L: Leisure and socializing.

- R: Residual time (e.g., self-care, unallocated time).

Outdoor time (O) is determined by maximizing a utility function:

$$\max \quad u(O, H, C, L, R) - C_o \quad \text{subject to} \quad T = O + H + C + L + R \tag{1}$$

where C_o represents the cost of time spent outdoors. The cost is defined as:

$$C_o = f(C_p, C_c)$$

Here:

- C_c includes Crime-related costs of spending time outdoors. Higher crime rates lead to increased vulnerability, discouraging outdoor activities.
- C_p includes other factors that could affect the cost of spending time outdoors, including:
  - $Deterrents$ such as competing responsibilities, socio-economic limitations, and infrastructural disparities, which add to the total cost.
  - $Buffers$ such as marital status, better education, social support, and improved infrastructure, which reduce costs and enhance mobility.

We propose that *deterrents* and $buffers$ may interact with crime rates, amplifying or moderating the effects of C_c, thereby influencing outdoor time allocation.

4.2 Empirical Framework

Since the total cost of spending time outdoors is influenced by both C_p and C_c, it is crucial to isolate the specific impact of C_c on outdoor time. To achieve this, we propose an empirical model of the following form:

$$O_{ihd} = \beta_0 + \beta_1 \text{Crime}_d + X_{ih}\beta_2 + Z_d\beta_3 + T_{ih}\beta_4 + \epsilon_{ihd}$$

where:

- O_{ihd}: Outdoor time for individual i in household h and district d, the dependent variable.
- Crime_d: District-level crime rates against women, the primary independent variable.
- X_{ih}: Individual-level controls, such as age, education, employment status, and monthly consumption expenditure.
- Z_d: District-level controls, such as income levels, infrastructure quality, and sex ratio.
- T_{ih}: Time spent on other activities, capturing competing demands on women's time.
- ϵ_{ihd}: Clustered error term at the district level to account for intra-district correlation.

4.3 Hypotheses

Based on the theoretical framework, we put forth four **hypotheses:**

Hypothesis 1: Higher district-level crime rates against women reduce women's outdoor time, all else constant ($\beta_1 < 0$).

Hypothesis 2: The negative effect of crime on women's outdoor time may be mitigated by buffers such as marital status, employment, and education. ($\beta_2 > 0, \beta_3 > 0$ for buffers).

Married women often adopt cautionary behaviors to address safety concern in public spaces (Jalalkamali, Doratli 2022) and higher education, we believe allows women to become more informed about safety, leading them to more efficiently navigate the negative effects of crime on outdoor time. Employment may act as a buffer by necessitating outdoor mobility for work-related tasks, reducing the perceived cost of being outdoors.

Hypothesis 3: Deterrents such as socio-economic limitations and infrastructural disparities amplify the negative effect of crime on women's outdoor time, all else constant.($\beta_2 < 0, \beta_3 < 0$ for deterrents)

For example, time spent oudoors by OBCs and SCs may be more negatively affected by crime rates than for STs. It is well known that WLFPR and consequently outdoor time is usually higher among the ST group (Eswaran, Ramaswami and Wadhwa, 2013). Infrastructural disparities or uneven access to safe public spaces may magnify the effect of crime.

Hypothesis 4: The negative effect of crime on outdoor time is amplified in urban areas ($\beta_3 < 0$ for urban dummy) .

We include this hypothesis as one that is separate from hypothesis 3, which refers to deterrents, because we believe geographic status plays rather counterintuitive role and interesting when interacted with crime. One would expect urban areas to offer more protection to women than rural areas, moderating the effect of crime. However, we believe that due to higher visibility of crimes, as a consequence of increased media coverage may in fact amplify the cost imposed by crime (Romer, Hall 2003). Moreover, rural women tend to engage in outdoor activities as groups which may moderate the effect of crime.

4.4 Controls

To test these hypotheses, we include the following control variables:

- **Individual-level controls:** Age, education, employment status, and monthly consumption expenditure. Employment reflects work-related mobility, while monthly consumption expenditure measures household wealth and access to safer housing and transportation.
- **Demographic factors:** Religion, social group, and urban-rural residency, which

account for cultural norms and geographic disparities.

- **Time-use variables:** Household, caregiving, leisure, and socializing activities to ensure that observed effects of crime on outdoor time are not confounded by competing demands.
- **District-level controls:** Income, education, employment levels, sex ratio, and access to drinking water, electricity, and sanitation to reflect broader economic and infrastructural environments.
- **Crime-specific factors:** Proportion of crimes against women in total crimes to capture gendered safety risks, along with interaction terms to explore moderating or amplifying effects of buffers and deterrents.

4.5 Limitations

Our analysis is subject to certain limitations. Crime rates are measured at the district level, while outdoor time is observed at the individual or household level. To address this mismatch, we used both a linear regression and a mixed-effects model, treating districts and crime rates as random effects in the latter to account for district-specific variability. We compare the results from both approaches to ensure that our findings are not sensitive to model specifications.

Additionally, direct measures of infrastructure quality, such as access to safe public spaces or law enforcement data, are unavailable. To partially address this, we use district-level variability in outdoor time as a proxy and interact it with crime rates. Moreover, official crime data may underestimate true crime levels due to underreporting. Therefore, our empirical model assumes that the relative proportions of crimes across districts remain consistent. Lastly, the model does not account for unobservable factors, such as individual attitudes toward safety or hyper-local crime dynamics, due to data limitations.

5 Data Sources

5.1 Time Use Survey (TUS) 2019

The TUS 2019 dataset captures time allocation patterns across activities for 4,47,250 individuals from 1,38,799 households (82,897 rural and 55,902 urban). It measures time spent on activities such as employment, household tasks, commuting, and leisure, providing granular insights into outdoor time.

Variables from TUS dataset	Mean	Std. dev.
Monthly Consumption expenditure	6297.96	3889.81
Time spent on Outdoor Activities (In minutes)	64.78	106.31
Time spent on Caregiving Activities (In minutes)	33.49	70.14
Time spent on Leisure Activities (In minutes)	148.93	122.22
Time spent on Household Activities (In minutes)	241. 75	177.07
Proportion living in Urban Areas	0.27	0.45
Proportion currently employed	0.199	0.37

Figure 3: Descriptive Statistics: TUS 2019

From the variables used, the activities taking up the largest proportions of women's time in a day are household tasks and leisure. On average, women allocate over 4 hours daily to household tasks and over 2 hours to leisure, with significant variability, as indicated by standard deviations of 177 and 122 minutes, respectively.

TUS - Categorical Variables	Mean	Std. dev.
Social Groups		
Proportion of Scheduled Tribes	0.151	0.243
Proportion of Scheduled Castes	0.152	0.129
Proportion of OBC	0.327	0.250
Religious Groups		
Proportion of Hinduism	0.650	0.358
Proportion of Islam	0.106	0.157
Proportion of Christianity	0.060	0.185
Proportion of Others	0.184	0.097
Education Group		
Proportion of only primary education	0.341	0.185
Proportion of only secondary dducation	0.362	0.165
Proportion of above secondary education	0.273	0.279
Marital Status		
Proportion of Never Married	0.275	0.448
Proportion of currently married	0.617	0.485
Proportion of Widowed	0.101	0.297
Proportion of divorced	0.005	0.057

Figure 4: Descriptive Statistics: TUS 2019

5.2 National Crime Records Bureau (NCRB) 2019 Report - *Crimes in India*

The NCRB 2019 report provides comprehensive crime statistics across 763 districts in India. The dataset includes 5,156,172 cognizable crimes reported during the year, offering detailed breakdowns of crimes by type, gender, and location. For this study, we focus on crimes specifically targeting women.

Variables from NCRB Dataset	Mean	Std. dev.
Crimes against women (per 1000 people)	19.68	20.65
Ratio of crimes against women to total crimes	8.76	5.69

Figure 5: Descriptive Statistics: NCRB 2019

5.3 National Family Health Survey (NFHS) 2019-21

The NFHS dataset offers detailed information on population, health, and nutrition across 707 districts, reflecting India's socio-economic composition. It includes variables such as urban-rural residency, household composition, and demographic factors, which serve as key controls in our analysis. None of the NFHS variables depict major or unexpected deviations from levels reported in the 2011 Census and other recent reports that estimate them individually.

Variables from NFHS Dataset	Mean	Std. dev.
Proportion of young males (<15 years)	9.16	28.86
Proportion of middle aged male (>15, <50 years)	31.17	46.35
% population with access to drinking water	93.97	8.25
% population with access to electricity	97.05	4.32
% population with access to sanitation	71.69	14.41
% population with health insurance	40.18	23.10
Sex Ratio (Females to Male)	1021.57	73.89
Female Literacy Rate	74.33	12.32
% of male that consume alcohol	22.86	13.09

Figure 6: Descriptive Statistics: NFHS 2019-2021

5.4 Key Derived Variables

- **Crimes Against Women:** Within this derived variable, we include crimes like rape, abduction, public harassment, and dowry deaths, generally categorizing them as crimes that occur outside the household. Data has been normalized to reflect per 1,000 people across districts.
- **Outdoor Time:** We added the time spent on activities such as employment, household-related outdoor tasks (e.g., shopping, healthcare visits), commuting, social events, and recreational activities to derive this variable.

These datasets provide a robust foundation for examining how crime affects women's outdoor mobility, reflecting both the spatial and temporal dimensions of their time use and safety concerns.

6 Findings

	Linear Regression Model			Mixed Effects Regression Model		
Time spent on Outdoor Activities	**Coefficient**	**Robust std. err.**	**P>|t|**	**Coefficient**	**Robust std. err.**	**P>|t|**
% Crimes against women	-0.8490078	0.0469682	0.000	-1.257649	0.131345	0.000
Proportion of young males (<15 years)	-0.0402611	0.0064273	0.000	-0.061717	0.024802	0.013
Proportion of middle aged male (>15, <50 years)	-0.0041907	0.0044413	0.345	-0.026455	0.015771	0.093
Ratio of crimes against women to total crimes	0.2550237	0.0603682	0.000	0.644223	0.177388	0.000
% of total crimes (population)	-4.603316	1.583095	0.004	-4.703416	1.582920	0.004
Relation to Head		Yes				
Age	-0.0490278	0.0110371	0.000	-0.012101	0.010798	0.262
Monthly Consumption expenditure	0.0015754	0.0001222	0.000	0.000858	0.000117	0.000
Female Literacy Rate	0.1243194	0.0249138	0.000	0.083795	0.086536	0.333
% of male that consume alcohol	0.0715757	0.0223044	0.001	0.172769	0.065385	0.008
Sex Ratio	0.0002057	0.0033351	0.951	-0.014518	0.010178	0.154
% population with access to drinking water	0.0222074	0.0278305	0.425	0.030652	0.094359	0.745
% population with access to electricity	-0.7019756	0.0515172	0.000	-0.548415	0.194381	0.005
% population with access to sanitation	0.1534821	0.0216308	0.000	0.054726	0.072795	0.452
% population with health insurance	-0.0232859	0.0099003	0.019	-0.003895	0.035424	0.912
Time spent on household activities	-0.1616369	0.0017321	0.000	-0.163488	0.001514	0.000
Time spent on caregiving activies	-0.1518565	0.0028059	0.000	-0.155169	0.002809	0.000
Time spent on leisure activities	-0.1749082	0.0018899	0.000	-0.178371	0.001846	0.000
Urban Dummy	5.375074	0.6665264	0.000	2.011516	0.709926	0.005
Employement Dummy	53.63023	1.094597	0.000	54.673870	0.771609	0.000
Education dummies		Yes				
Religion Dummies		Yes				
Marital Status Dummies		Yes				
Social Group Dummies		Yes				
Constant	132.9941	6.988957	0.000			

Variables mentioned as '**Highly Significant**' are significant at a 1% level, while those mentioned as '**Significant**' are signifcant at 5% level.

Figure 7: Enter Caption

Our findings are presented in two sections: the first column in the table displays results from the simple linear regression model, while the second column represents results from the mixed-effects regression model. The mixed-effects framework introduces district-level and crime rate variability as random effects, allowing us to capture unobserved heterogeneity across districts.

6.1 Linear Regression Model

The coefficient on **crimes against women** (-0.849) is negative ($\beta_1 < 0$) and highly significant, offering robust support for **Hypothesis 1**. Interestingly, the coefficient on the **ratio of crimes against women to total crimes** (0.25) is positive and significant. This suggests that districts with higher proportions of gender-targeted crimes may exhibit heightened public vigilance or institutional responses, potentially buffering some of the deterrent effects of crime. This specific result may also be a product of reverse causality where increased outdoor time may lead to women becoming more susceptible to crimes.

Time-Use Controls reveal significant competition between **outdoor time** and **household**, **caregiving**, and **leisure activities**, with negative and significant associations. In contrast, **urban residency**(5.37) and **employment** (53.63) positively influence **outdoor time**. Urban women appear to engage more outdoors due to greater opportunities, while employed women's outdoor time reflects occupational mobility requirements despite crime risks.

	Linear Regression Model			Mixed Effects Regression Model		
Time Spent on Outdoor Activities	**Coefficient**	**Robust std. err.**	**P>|t|**	**Coefficient**	**Robust std. err.**	**P>|t|**
Marital Status x Crimes against women (Never Married)						
Currently Married x Crimes against women	0.1496912	0.02558	0.000	0.095984	0.025328	0.000000
Widowed x Crimes against women	0.1944571	0.0453676	0.000	0.124112	0.041122	0.003000
Divorced x Crimes against women	0.1237155	0.2033034	0.543	0.052388	0.149821	0.727000
Age x Crimes against women	-0.0024151	0.0002398	0.000	-0.000959	0.000255	0.000000
Education group x Crimes against women (Primary)						
Secondary x Crimes against women	0.086417	0.022834	0.000	0.056640	0.024485	0.021000
Tertiary x Crimes against women	-0.0324276	0.0341199	0.342	-0.000043	0.030806	0.999000
Std Deviation in Outdoor time x Crimes against women	0.0105029	0.0003522	0.000	0.011655	0.001091	0.000000
Social group x Crimes against women (Scheduled Tribe)						
Scheduled Caste x Crimes against women	-0.1477562	0.0399771	0.000	-0.092300	0.041299	0.025000
OBC x Crimes against women	-0.1199718	0.0353634	0.001	-0.053091	0.037928	0.162000
Others x Crimes against women	0.0142933	0.0354158	0.687	-0.040785	0.038005	0.283000
Urban x Crimes against women	-0.1558173	0.0240879	0.000	0.058411	0.026171	0.026000
Employement x Crimes against women	0.0912776	0.0427643	0.033	0.188237	0.027574	0.000000

Figure 8: Enter Caption

The interaction between **crimes against women** and **marital status** is positive and significant for **married** (0.149), **widowed** (0.194), and **divorced women** (0.123) compared to never married women. This supports **Hypothesis 2**, indicating that marital roles may temper the deterrent effects of crime. The interaction with **age** produces a small negative coefficient (-0.0024), reflecting marginally higher impacts on older women due to compounded vulnerabilities. Social group interactions show that compared to Scheduled Tribes (**STs**), Other Backward Classes (**OBCs**) (-0.119) and Scheduled Castes (**SCs**) (-0.147) are more negatively affected, aligning with **Hypothesis 3**.

Educational attainment, particularly **secondary education**, shows a small positive coefficient (0.086), suggesting that education modestly buffers the effects of crime, supporting **Hypothesis 2**. The interaction between **crime** and **urban residency** yields a negative and significant coefficient (-0.155), amplifying the deterrent effects of crime, consistent with **Hypothesis 4**. As hypothesized, this may be attributed to greater visibility and reporting of crime in urban areas. Conversely, the interaction between **crime** and **employment status** produces a positive and significant coefficient (0.0912), indicating that employment buffers the negative effects of crime by necessitating outdoor mobility. The interaction between **crime** and **variability in outdoor time**, used as a proxy for uneven access to safe public spaces, shows a small positive coefficient (0.0105). This suggests localized improvements in safety may marginally enhance mobility.

6.2 Mixed Effects Model

The mixed-effects model refines these findings by accounting for district-level heterogeneity. The highly significant likelihood ratio (LR) statistic confirms its better fit compared to the linear regression model. Coefficients in the mixed-effects model are generally smaller, indicating that variation attributed to fixed effects in the linear model is linked to unobserved district-level characteristics, such as crime reporting practices, law enforcement quality, and cultural attitudes.

Remarkably, the coefficient on **crimes against women** (-1.25) increases by 67%, suggesting that the linear model underestimates the direct impact of crime by failing to capture unobserved district-level variability. Similarly, the coefficient on the **ratio of crimes against women to total crimes** (0.644) more than doubles, highlighting stronger localized responses in districts with higher proportions of gender-targeted crimes.

A striking result is the reversal in the sign of the interaction between **crime** and **urban residency** in the mixed-effects model, where the coefficient becomes positive (0.0584) and significant. We interpret this as evidence that urban areas, after accounting for district-level heterogeneity, may, in fact, offer protective factors such as improved policing and infrastructure compared to rural areas. This result in the mixed effects model provides evidence against **Hypothesis 3**. The interaction between **crime** and **employment status** more than doubles in magnitude (0.188), potentially reflecting the compounded effects of employment-related mobility and district-specific safety measures.

Hypothsesis 1	**Strongly supported**	Both models confirm significant negative coefficients for district-level crime rates.
Hypothsesis 2	**Partially supported**	Positive interaction terms for education, employment, and marital status, but small effects.
Hypothsesis 3	**Partially supported**	Significant negative interactions for socio-economic factors like age and social group; weaker evidence for infrastructure.
Hypothsesis 4	**Supported in the linear model**	Negative interaction in linear model aligns with increased visibility; mixed model shows moderation due to district-level factors.

Figure 9: Results

7 Conclusion

This study confirms that higher district-level reported rates of crime against women significantly reduce women's outdoor time and underscore the need for targeted interventions to address the structural and systemic barriers limiting women's mobility. Importantly, these findings rustle up a deeper issue, one that seems to hide in plain sight: the perception of crime and the factors that influence it may have an even greater impact on women's outdoor time than reported crime rates. Perceptions often influence behavior

more strongly than objective measures, potentially magnifying the deterrent effect of crime manifold. However, due to data limitations and the localized nature of studies on crime perception, this remains a challenging area to analyze.

The negative effect of crime may also increase with the frequency of occurrence and more importantly, its perception. This implies that an area which experiences a consistently high frequency of crimes may exercise more safety measures leading to reduced time spent outdoors. Moreover, shocks in crime rates in particular time frames may not alter, with as much impact (as consistently high crime rates), the behavior with respect to time spent outdoors. To account for this, a time series analysis may provide a more nuanced understanding of the effect of crime on women's time spent outdoors. Therefore, while our findings are significant, further analysis is required to understand the intricacies of the relationship between crime and women's time spent outdoors. Future research should prioritize understanding the role of crime perception and use time series analysis to better assess its multifaceted impact on women's mobility.

Appendix: Steps to Solve the Theoretical Model

Defining the Utility Function

The utility function is defined as:

$$U = O^{\alpha} H^{\beta} C^{\gamma} L^{\delta} R^{\zeta} - C_O$$

where:

- O, H, C, L, R are time allocations to outdoor activities, household activities, caregiving, leisure, and residual time, respectively.
- $\alpha, \beta, \gamma, \delta, \zeta > 0$ are preference parameters.
- C_O is the cost associated with outdoor time.

Defining the Constraint

The total available time (T) is distributed across all activities:

$$T = O + H + C + L + R$$

Taking the log of the utility function simplifies the analysis:

$$U = \alpha \log(O) + \beta \log(H) + \gamma \log(C) + \delta \log(L) + \zeta \log(R) - C_O$$

The Lagrangian function is:

$$\mathcal{L} = \alpha \log(O) + \beta \log(H) + \gamma \log(C) + \delta \log(L) + \zeta \log(R) - C_O + \lambda(T - O - H - C - L - R)$$

The first-order conditions are:

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial O} &= \frac{\alpha}{O} - \frac{\partial C_O}{\partial O} - \lambda = 0 \\
\frac{\partial \mathcal{L}}{\partial H} &= \frac{\beta}{H} - \lambda = 0 \\
\frac{\partial \mathcal{L}}{\partial C} &= \frac{\gamma}{C} - \lambda = 0 \\
\frac{\partial \mathcal{L}}{\partial L} &= \frac{\delta}{L} - \lambda = 0 \\
\frac{\partial \mathcal{L}}{\partial R} &= \frac{\zeta}{R} - \lambda = 0 \\
\frac{\partial \mathcal{L}}{\partial \lambda} &= T - O - H - C - L - R = 0
\end{aligned}$$

From the second equation:

$$\lambda = \frac{\beta}{H}$$

Equating this with the first equation:

$$\frac{\alpha}{O} - \frac{\partial C_O}{\partial O} = \frac{\beta}{H}$$

Solving for Optimal O^*

Rearranging for O:

$$O^* = \frac{\alpha}{\beta/H \cdot \frac{\partial C_O}{\partial O}}$$

General Form of the Cost Function

The total cost associated with outdoor time, denoted by C_O, is modeled as a function of two primary components: crime-related costs (C_c) and other external costs (C_p). These components can interact, further modifying the total cost. Mathematically, the general form of C_O can be expressed as:

$$C_O = \alpha C_c + \beta C_p + \rho C_c C_p$$

Where:

- α: Weight assigned to crime-related costs.
- β: Weight assigned to other external costs.
- ρ: Interaction coefficient between C_c and C_p.

The crime-related cost (C_c) is proportional to the crime rate and outdoor time:

$$C_c = k \cdot \text{crime rate} \cdot O$$

The other external cost (C_p) depends on deterrents (e.g., caste) and buffers (e.g., education). These factors are modeled as:

$$C_p = w_1 \cdot \text{Caste} \cdot O - w_2 \cdot \text{Education} \cdot O$$

Taking the simplest case: Cost function with One Buffer and One Deterrent

Substituting C_c and C_p into the general cost function, we obtain the specific cost function:

$$C_O = \alpha\,(k \cdot \text{crime rate} \cdot O) + \beta\,(w_1 \cdot \text{Caste} \cdot O - w_2 \cdot \text{Education} \cdot O) + \rho\,(k \cdot \text{crime rate} \cdot O)$$

$$(w_1 \cdot \text{Caste} \cdot O - w_2 \cdot \text{Education} \cdot O)$$

Where:

- w_1: Weight of caste (a deterrent).
- w_2: Weight of education (a buffer).
- k: Coefficient capturing the sensitivity of crime-related costs to outdoor time.

Differentiation of the Cost Function

To determine the effect of outdoor time on the total cost C_O, we differentiate C_O with respect to O. The total cost function is:

$$C_O = \alpha\,(k \cdot \text{crime rate} \cdot O) + \beta\,(w_1 \cdot \text{Caste} \cdot O - w_2 \cdot \text{Education} \cdot O) + \rho\,(k \cdot \text{crime rate} \cdot O)$$

$$(w_1 \cdot \text{Caste} \cdot O - w_2 \cdot \text{Education} \cdot O)$$

Differentiating C_O with respect to O:

$$\frac{\partial C_O}{\partial O} = \frac{\partial}{\partial O}\left[\alpha\,(k \cdot \text{crime rate} \cdot O)\right] + \frac{\partial}{\partial O}\left[\beta\,(w_1 \cdot \text{Caste} \cdot O - w_2 \cdot \text{Education} \cdot O)\right]$$

$$+\frac{\partial}{\partial O}\left[\rho\,(k \cdot \text{crime rate} \cdot O)\,(w_1 \cdot \text{Caste} \cdot O - w_2 \cdot \text{Education} \cdot O)\right]$$

$=$

$$\alpha k \cdot \text{crime rate} + \beta\,(w_1 \cdot \text{Caste} - w_2 \cdot \text{Education}) + \rho[(k \cdot \text{crime rate})\,(w_1 \cdot \text{Caste} \cdot O - w_2 \cdot \text{Education} \cdot O)$$

$$+(k \cdot \text{crime rate} \cdot O)\,(w_1 \cdot \text{Caste} - w_2 \cdot \text{Education})]$$

Substituting into the Optimal O^*

The optimal O^*:

$$O^* = \frac{\alpha}{\frac{b}{H} + \frac{\partial C_O}{\partial O}}$$

Substituting $\frac{\partial C_O}{\partial O}$ into this expression, we obtain:

$$O^* = \frac{\alpha}{\frac{b}{H} + \alpha \cdot k \cdot \text{crime rate} + \beta\left(w_1 \cdot \text{Caste} - w_2 \cdot \text{Education}\right) + \rho\left[(k \cdot \text{crime rate})\right.}$$

$$\left.(w_1 \cdot \text{Caste} \cdot O - w_2 \cdot \text{Education} \cdot O) + (k \cdot \text{crime rate} \cdot O)\left(w_1 \cdot \text{Caste} - w_2 \cdot \text{Education}\right)\right.$$

Differentiation of O^* with Respect to Education and Caste

To examine how O^* changes with Education and Caste, we differentiate O^* with respect to each variable.

With Respect to Education:

$$\frac{\partial O^*}{\partial \text{Education}} = \frac{\beta w_2 + \rho k \cdot \text{crime rate} \cdot O}{\left(b/H + \frac{\partial C_O}{\partial O}\right)^2}$$

Since $\beta w_2 + \rho k \cdot \text{crime rate} \cdot O > 0$, this implies:

$$\frac{\partial O^*}{\partial \text{Education}} > 0$$

Thus, outdoor time increases with Education.

With Respect to Caste:

$$\frac{\partial O^*}{\partial \text{Caste}} = -\frac{\beta w_1 + \rho k \cdot \text{crime rate} \cdot O}{\left(b/H + \frac{\partial C_O}{\partial O}\right)^2}$$

Since $\beta w_1 + \rho k \cdot \text{crime rate} \cdot O > 0$, this implies:

$$\frac{\partial O^*}{\partial \text{Caste}} < 0$$

Thus, outdoor time decreases with Caste (i.e. from ST to OBC)

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