The Effects of Partial Liquor Ban on Intimate Partner Violence

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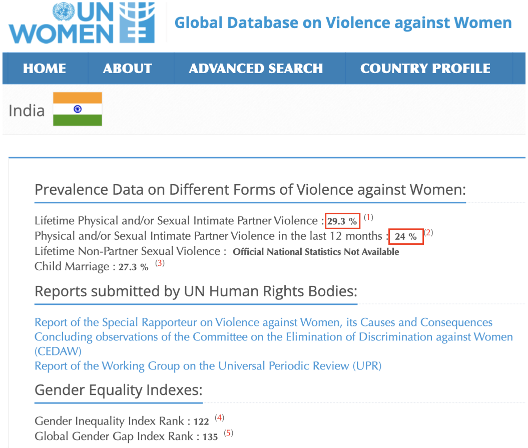

UN WOMEN Global Database on Violence against Women

HOME ABOUT ADVANCED SEARCH COUNTRY PROFILE

India

Prevalence Data on Different Forms of Violence against Women:

Lifetime Physical and/or Sexual Intimate Partner Violence : 29.3 % (1)
Physical and/or Sexual Intimate Partner Violence in the last 12 months : 24 % (2)
Lifetime Non-Partner Sexual Violence : **Official National Statistics Not Available**
Child Marriage : **27.3 %** (3)

Reports submitted by UN Human Rights Bodies:

Report of the Special Rapporteur on Violence against Women, its Causes and Consequences
Concluding observations of the Committee on the Elimination of Discrimination against Women (CEDAW)
Report of the Working Group on the Universal Periodic Review (UPR)

Gender Equality Indexes:

Gender Inequality Index Rank : **122** (4)
Global Gender Gap Index Rank : **135** (5)

Notes: Accessed from UN Women website on July 28, 2023. https://evaw-global-database.unwomen.org/en/countries/asia/india#2

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  - Tax on alcoholic drinks (Markowitz and Grossman 2000; Cook and Durrance 2013)
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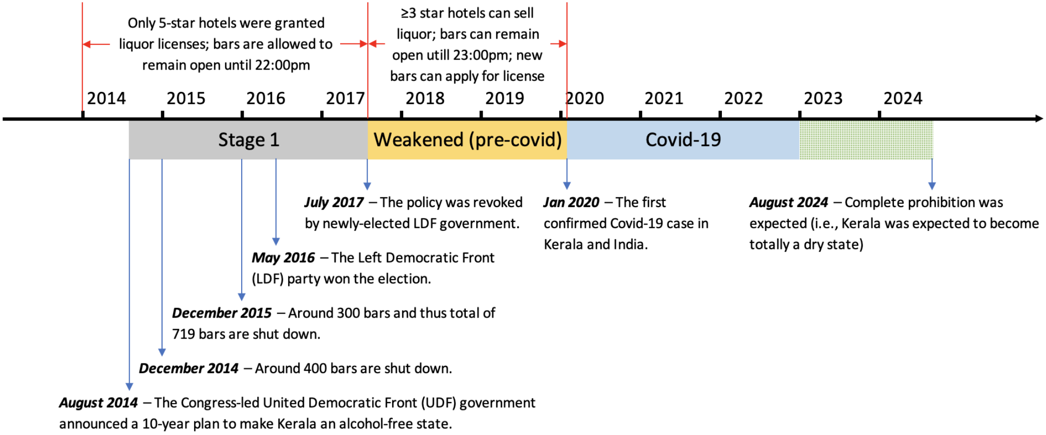
  - Motor vehicle accidents
  - Mortality or health
- This paper
  - Examine a partial liquor ban that shuts down "hard liquor" selling bars in Kerala (India) between 2014 and 2017
  - Draw policy lessons for other developing countries
  - Learn about consumers' behavioral response to alcohol controls

Policy Context: Kerala Partial Liquor Ban (2014-2017)



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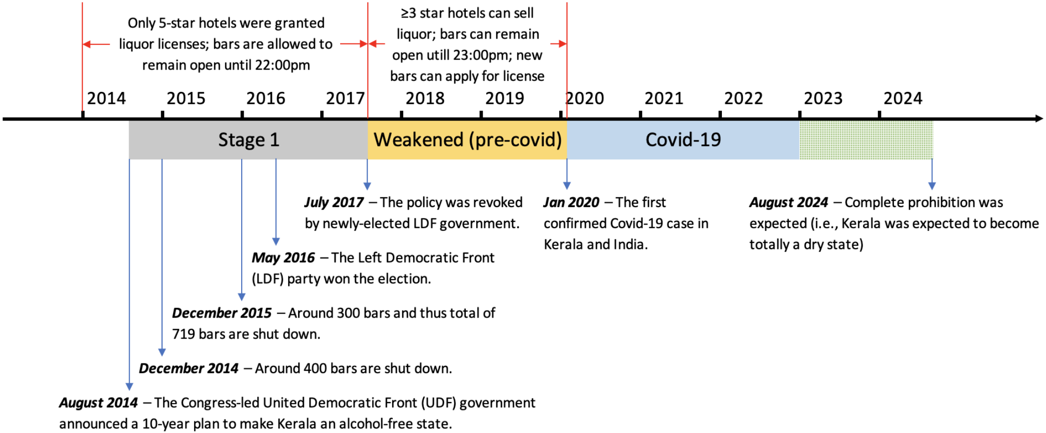

- Define
  - Short-term: During Stage 1 (2014-2017)
  - Long-term: Post Stage 1 (2017-2019)

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  - Quantify the impact of shutting down hard liquor-selling bars on physical IPV against women during the policy period
  - Estimate the impact of (i) policy removal and (ii) the long-run impact of the intervention over the period when the policy was lifted

Preview of Results

- **Short-Run Effects** (during-policy period, 2014-2017, compared to pre-policy period):
  - A decrease in physical IPV ever experienced by women and less frequent physical IPV in the past 12 months within high-income households
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- **Mechanism** (direct effect on liquor consumption):
  - Intoxication effect via changes in alcohol consumption seem to be dominating and mainly explaining the changes in IPV over different episodes of the policy

Data

- DHS-2 (1998-2000), DHS-4 (2015-2016), and DHS-5 (2019-2021):
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  - Household's liquor expenditure in bars and restaurants and total alcohol expenditure
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- NSS (2001-2002 through 2011-2012)
  - District-level treatment intensity based on district-specific hard liquor consumption just before the treatment, i.e., 2011-2012 level
  - <u>Baseline measure</u>: Share of district d's hard liquor consumption in Kerala's total hard liquor consumption
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- Excise Department of Kerala
  - Alternative measure 2: Number of hard liquor serving bars closed down Baseline vs. Alternative Measure 2

Data Pattern: Correlation between Alcohol Use and Physical IPV

	Wife herself drinks	Husband drinks
Physical violence ever experienced	0.0304***	0.2848***
	22772	22767
Physical violence experienced before the past 12 months	0.0204***	0.1511***
	22771	22766
Physical violence experienced in the last 12 months	0.0247***	0.2308***
	22770	22765
Physical violence experienced sometimes in the last 12 months	0.0167**	0.2113***
	22770	22765
Physical violence experienced often in the last 12 months	0.0365***	0.1357***
	22769	22764
Frequency of physical violence experienced in the last 12 months	0.0334***	0.2337***
	22772	22767

Notes: Based on India's DHS datasets 2005-2006, 2015-2016, and 2019-2021. The sample includes three states included in our analysis: Kerala, Karnataka, and Tamil Nadu. Level of analysis is woman. The number of observations is also provided. Significance: *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

Empirical Framework: Short-Run Effects

To estimate the short-run treatment impact on physical IPV during the policy period, we estimate:

$$y_{idst} = \beta(\text{Treatment}_d \times \mathbb{1}_{\{2015 \leq t < 2016\}}) + \boldsymbol{X}'_{idst}\gamma + \boldsymbol{Z}'_{hdst}\boldsymbol{\delta} + \alpha_d + \pi_{st} + \mu_t + \varepsilon_{idst} \quad (1)$$

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- SEs are clustered by districts (75 clusters) (Bertrand et al. 2004, Angrist and Pischke 2009)

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To analyze the impact of policy removal, we estimate:

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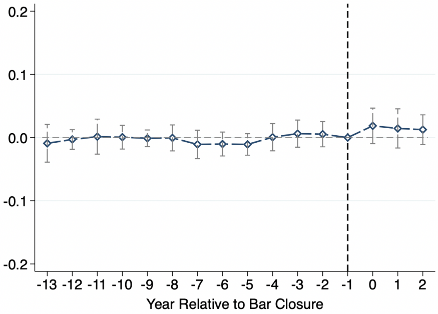
Event study estimation:

$$y_{dst} = \sum_{n \neq 0} \delta_n P_t(n) \times \text{Treated}_d + \alpha_d + \pi_{st} + \mu_t + \varepsilon_{dst},$$



Notes: Based on district-level data on crime records from the National Crime Record Bureau (NCRB) for the thirteen years prior to the 2014 Kerala liquor ban (2001 through 2013) with base year of 2013. Each observation corresponds to log of number of domestic violence incidents (number of cruelty by husband or his relatives) per 1000 population by district and year. The data includes all 14 districts in Kerala and 29 and 32 districts in Karnataka and Tamil Nadu, respectively, bordering Kerala. All specifications control for district and year fixed effects, state-by-year FEs, and a constant term. Standard errors are clustered by districts, and 95% confidence intervals are shown.

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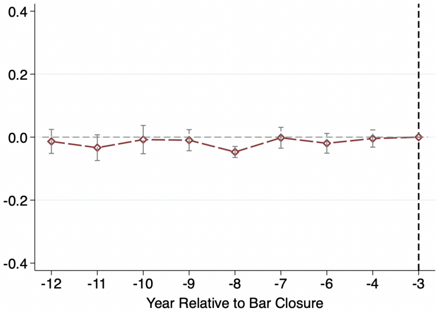
$$y_{hdst} = \sum_{n \neq -1} \delta_n P_t(n) \times \text{Treated}_d + \boldsymbol{X}'_{hdst}\gamma + \alpha_d + \pi_{st} + \mu_t + \varepsilon_{ht},$$



Notes: Based on pooled cross-sectional data of household budget survey from the NSS for the nine years prior to the 2014 Kerala liquor ban (2001-2002 through 2011-2012 with gaps of 2008-2009 and 2010-2011) with base year of 2011-2012. Each observation in a given panel corresponds to consumption of hard liquor by household and year. The data includes all 14 districts in Kerala and the 26 and 28 districts in Karnataka and Tamil Nadu, respectively, bordering Kerala. All specifications control for unreported household covariates, district and year fixed effects, state-by-year FEs, and a constant term. Household covariates include age, gender, education, and marital status of household head, household size, scheduled caste or tribe, urban/rural residence, religion of the household, and monthly per capita expenditure quintile. Standard errors are clustered by districts, and 95% confidence intervals are shown.

II. "Strong" Parallel Pre-Trends Assumption

- Callaway, Goodman-Bacon, and Sant'Anna (2021)
- Event study estimation: District-level domestic violence

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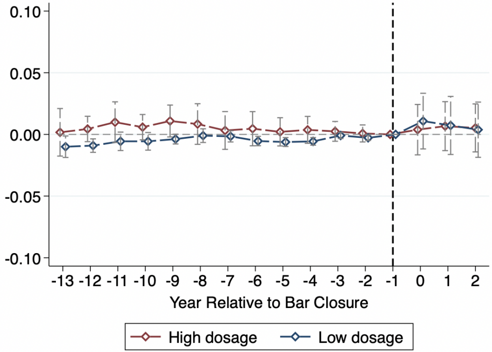

Notes: Parallel pre-trends in domestic violence at the district level for treated districts with treatment "dose" above and below the median treatment intensity over thirteen years before the 2014 Kerala liquor ban. We used district d's per capita consumption of hard liquor in 2012 as a treatment intensity variable in these event study regressions.

Event study estimation: Household consumption of hard liquor

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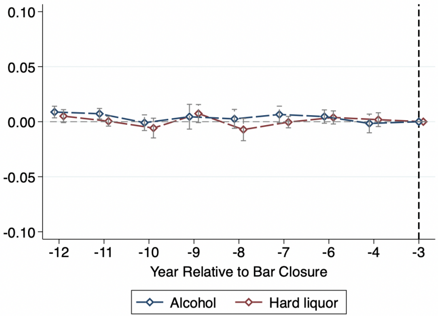
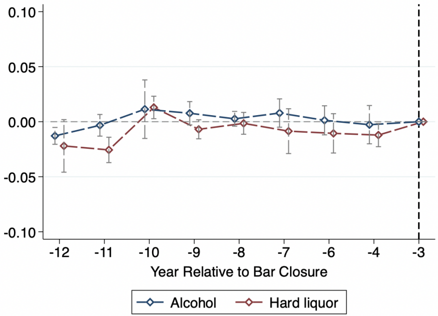
(a) Above median per-capita consumption



(b) Below median per-capita consumption



Notes: Parallel pre-trends in household alcohol consumption for treated districts with treatment “dose” above (left panel) and below (right panel) the median treatment intensity over nine years before the 2014 Kerala liquor ban. We used district d's per capita consumption of hard liquor in 2012 as a treatment intensity variable in these event study regressions.

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    $\Longrightarrow$ Compliance is likely to be high under sufficient state police capacity

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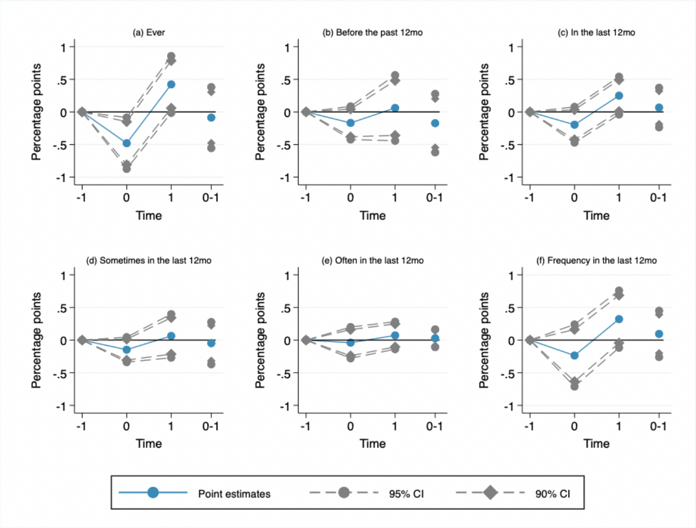
  - Kerala is one of the most equipped states with good institutional capacity to implement an alcohol ban (Dar and Sahay 2018)
    $\implies$ Compliance is likely to be high under sufficient state police capacity
- We show this assumption is plausible in our setting using alternative treatment and control groups.

Spoiler Alert: Things to Focus

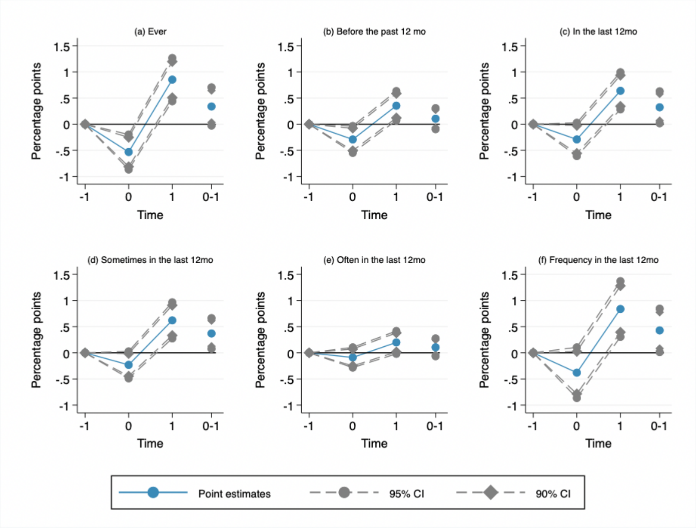
- Baseline vs. Heterogeneity
- Treatment impact in the short-run and long-run
- Responses of physical IPV with different frequencies to the policy changes

Short- and Long-Run Impacts on Physical IPV: Baseline Results



- **Main takeaway:** No impact on the full sample households both in the short and long run

Short- and Long-Run Impacts on Physical IPV: Heterogeneous by Income



- **Main takeaway:** Most of the actions happens within high-income households over the different episodes of this policy.

Short- and Long-Run Impacts on Physical IPV: Other Heterogeneity

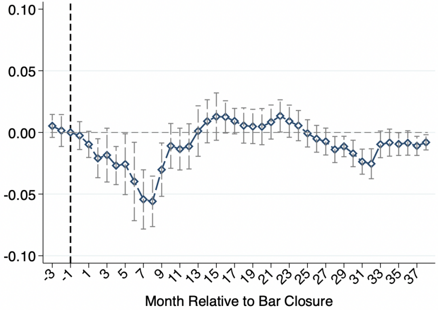
- Additional heterogeneity analysis
  - Education ▶▶ Result
  - Place of residence ▶▶ Result
  - Scheduled caste or tribe ▶▶ Result
  - Whether has a male child ▶▶ Result
  - Age difference between the respondent and her partner ▶▶ Result
- **Main takeaway:** No significant changes in physical IPV under any of these heterogeneity

Robustness Checks

- Use alternative treatment intensity variables
  - District's average per capita consumption of hard liquor [Policy Impact]
  - Number of bars closed down [Baseline] [Income Heterogeneity] [Income + HH Size Heterogeneity]
- Use only the State of Karnataka as the control group [Policy Impact]
- Use interior/border districts in the treatment and control groups in several different ways [Control = Interior/Border Districts] [Treatment = Border Districts] [Treatment = Interior Districts]
- Employ logit and probit regressions [Policy Impact]
- Use sample splitting instead of interacting terms to conduct the heterogeneity [Policy Impact]
- Use district-level crime data on domestic violence to check the robustness of non-heterogeneous baseline results [Policy Impact]

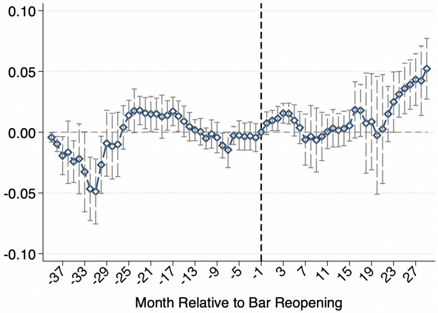
Event study estimation:

$$\log(\text{Consumption}_{ht}) = \alpha + \sum_{\tau \neq -1; \tau = -3}^{\tau = 38} \beta_\tau \times I_\tau \times \text{Treated}_d + \mathbf{X}'_{ht}\boldsymbol{\delta} + \mu_h$$
$$+ \text{Year}_t + \text{Month}_t + \pi_s \times \text{Year}_t + \pi_s \times \text{Month}_t + \xi_{ht}$$



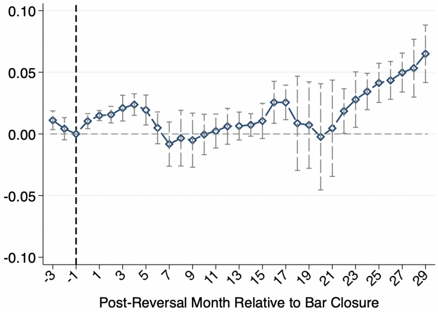
- **Main takeaway:** Household liquor expenditure in bars and restaurants sharply declined right after the shutting down hard liquor-selling bars

$$\log(\text{Consumption}_{ht}) = \alpha + \sum_{\tau \neq -1; \tau = -39}^{\tau = 29} \beta_\tau \times I_\tau \times \text{Treated}_d + \mathbf{X}'_{ht}\boldsymbol{\delta} + \mu_h$$
$$+ \text{Year}_t + \text{Month}_t + \pi_s \times \text{Year}_t + \pi_s \times \text{Month}_t + \xi_{ht}$$



- **Main takeaway:** Household liquor expenditure in bars and restaurants slightly increased right after policy removal and strongly increased in about 2 years

$$\log(\text{Consumption}_{ht}) = \alpha + \sum_{\tau \neq -1; \tau=-3}^{\tau=29} \beta_\tau \times I_\tau \times \text{Treated}_d + \mathbf{X}'_{ht}\boldsymbol{\delta} + \mu_h$$
$$+ \text{Year}_t + \text{Month}_t + \pi_s \times \text{Year}_t + \pi_s \times \text{Month}_t + \xi_{ht}$$

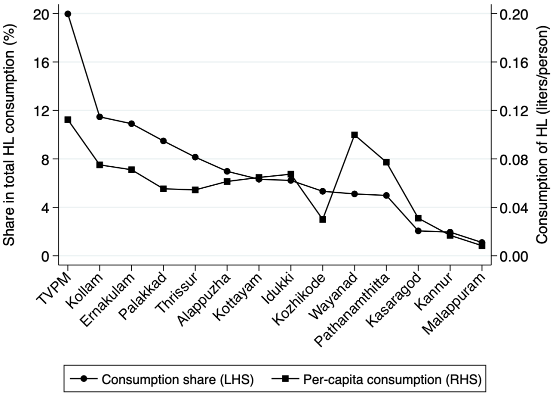


- **Main takeaway:** Compared to the pre-policy level, household liquor expenditure in bars and restaurants increased over the post-removal period

- Our findings suggest that:
    - Partial liquor bans might be effective in reducing physical IPV, although the estimated effects seem weakly significant
    - Alcohol control efforts should focus on reducing heavy drinking and extremely violent behaviors because the Kerala policy did not have any impact on physical IPV often experienced in the past 12 months
    - An overshooting impact of the policy reversal should be taken into account in alcohol control policies

Thank you!
Email: tb497@cornell.edu

Baseline and Alternative Measures of Treatment Intensity



Notes: The figure compares our baseline measure of district-level treatment intensity (districts' share in state's total hard liquor consumption) with an alternative measure based on hard liquor consumption per capita. TVPM stands for Thiruvananthapuram district.

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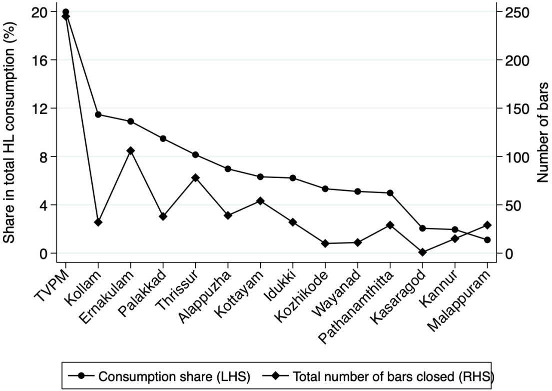
Baseline and Alternative Measures of Treatment Intensity



Notes: The figure compares the baseline treatment intensity measure with another alternative measure based on number of bars closed. TVPM stands for Thiruvananthapuram district.

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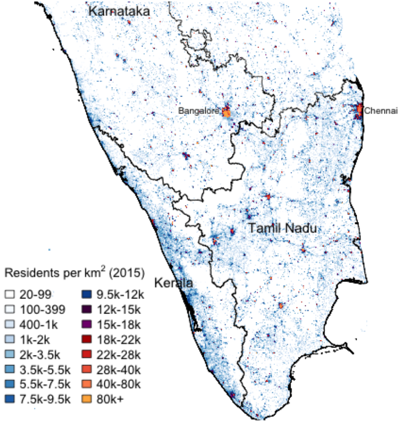
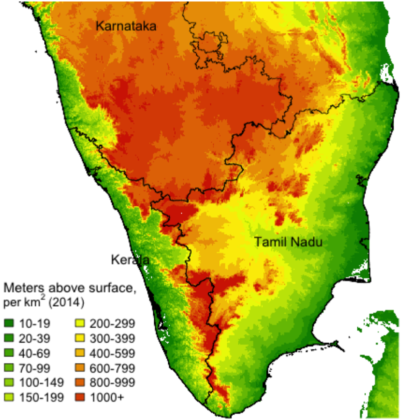
III. Stable Assignment Assumption (SUTVA)

(a) Population Density



(b) Land Elevation



Source: Authors' illustration. Population data comes from the Global Human Settlement Layer (GHSL), and elevation data is obtained from Pacific Islands Ocean Observing System (PacIOOS).

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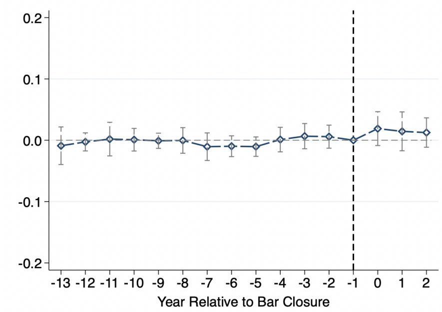
Parallel Pre-Trend Assumption: District-Level Domestic Violence

Event study estimation:

$$y_{dst} = \sum_{n \neq 0} \delta_n P_t(n) \times \text{Treated}_d + \alpha_d + \pi_{st} + \mu_t + \varepsilon_{dst},$$



Notes: Based on district-level data on crime records from the National Crime Record Bureau (NCRB) for the thirteen years prior to the 2014 Kerala liquor ban (2001 through 2013) with base year of 2013. Each observation corresponds to log of number of domestic violence incidents (number of cruelty by husband or his relatives) per 1000 population by district and year. The data includes all 14 districts in Kerala and 29 districts in Karnataka. All specifications control for district and year fixed effects, state-by-year FEs, and a constant term. Standard errors are clustered by districts, and 95% confidence intervals are shown.

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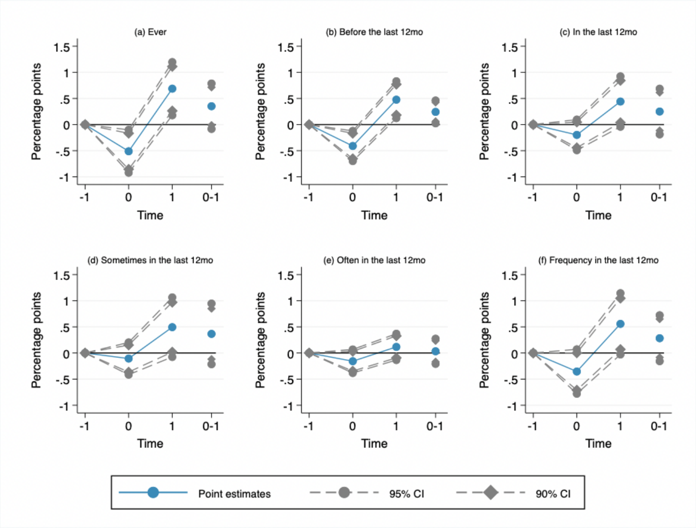
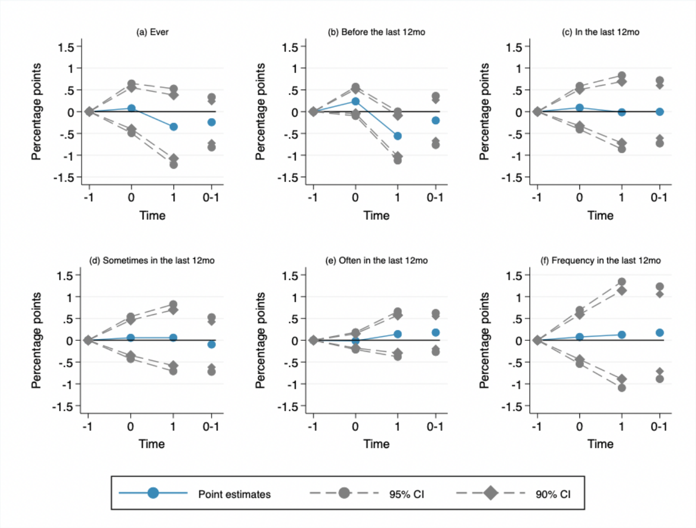


- **Main takeaway:** There is some responses to policy changes among educated individuals, although it is not as much as those within high-income households. Back


(a) Ever
(b) Before the last 12mo
(c) In the last 12mo
(d) Sometimes in the last 12mo
(e) Often in the last 12mo
(f) Frequency in the last 12mo
Percentage points
Time
1.5
1
.5
0
-.5
-1
-1.5
-1
0
1
0-1
Point estimates
95% CI
90% CI

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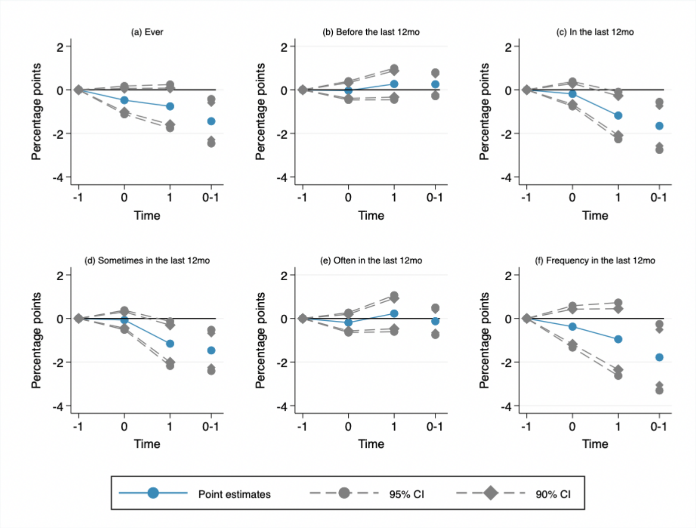
Short- and Long-Run Impacts on Physical IPV: Heterogeneous by Caste



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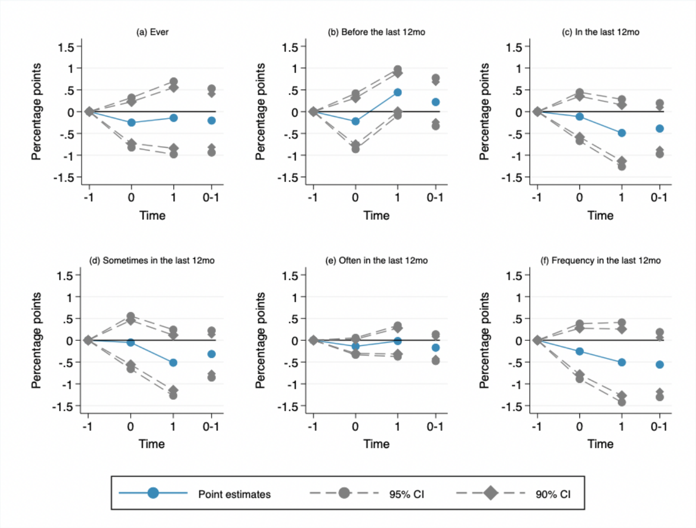
Short- and Long-Run Impacts on Physical IPV: Heterogeneous by Child's Sex



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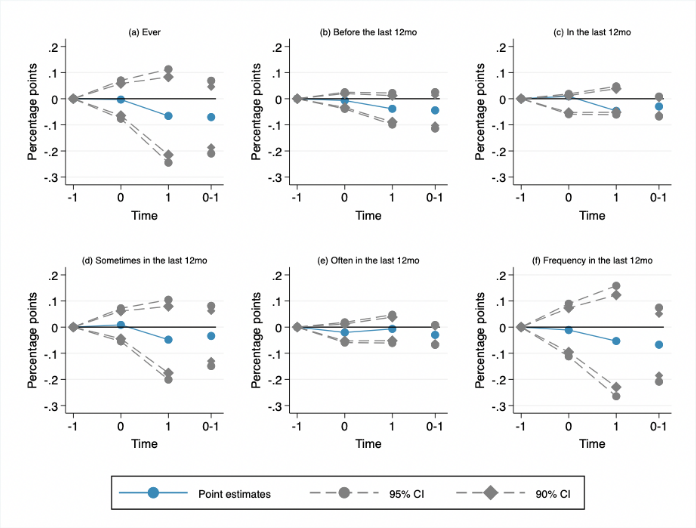
Short- and Long-Run Impacts on Physical IPV: Heterogeneous by Age Diff.



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Mechanisms: Additional Heterogeneity by Household Size

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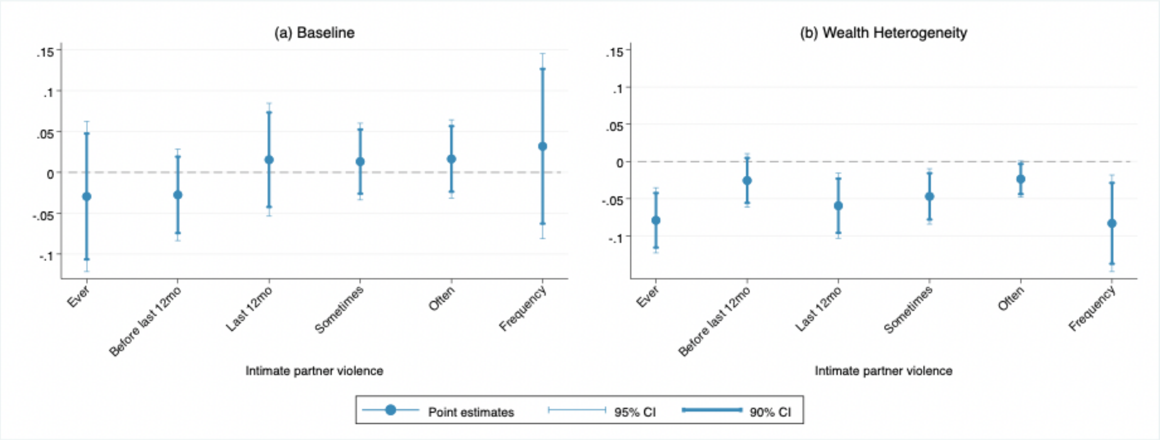
- Why changes in physical IPV within high-income households are concentrated within small households in the first two quintiles?
  - Husbands are more likely to drink in smaller households ($\rho = -0.060$, $SE = 0.007$)
  - Alcohol-induced IPV might be less prevalent in large households due to family monitoring
  - So changes in violence associated with changes in alcohol consumption are concentrated in small families
- Why physical IPV increases within high-income households in the long run?
  - IPV-reducing impact of the policy is similar for households in the first two quintiles of household size distribution
  - But IPV-increasing impact of policy reversal is larger among relatively larger households in the second quintile than that among households in the first quintile
  - More judgment from other family members in relatively larger households when the husband returns to drinking, causing increase in conflict between partners and violence against women

Robustness Checks: District's Per Capita Consumption of Hard Liquor



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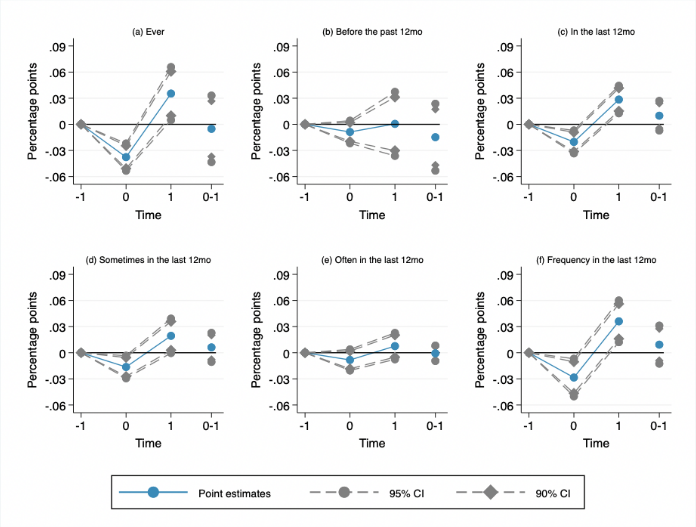
Robustness Checks: Number of Bars Closed Down (Baseline)



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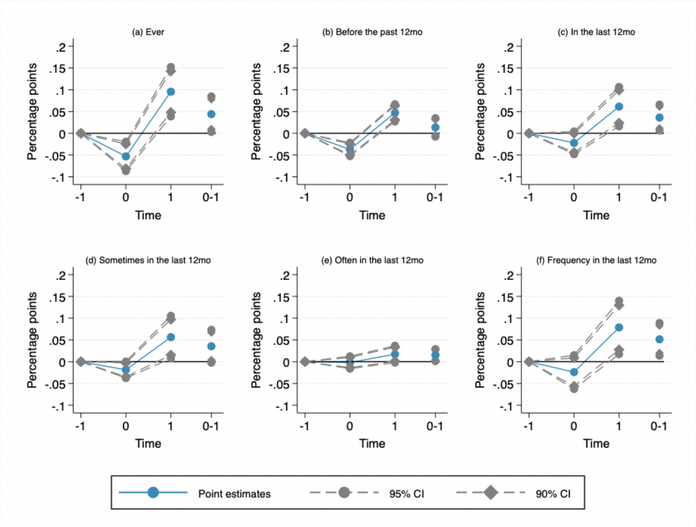
Robustness Checks: Number of Bars Closed Down (Income Heterogeneity)



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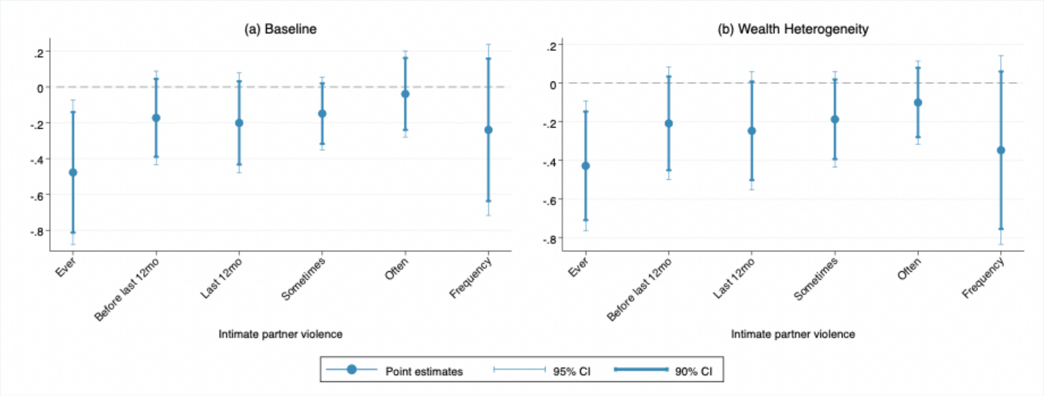
Robustness Checks: Control Group = Karnataka



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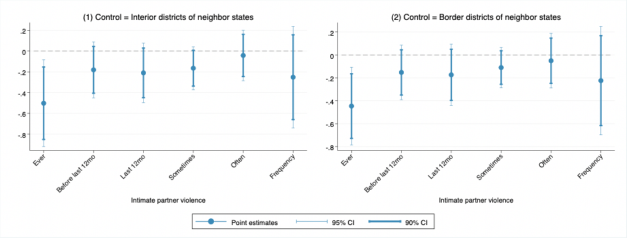
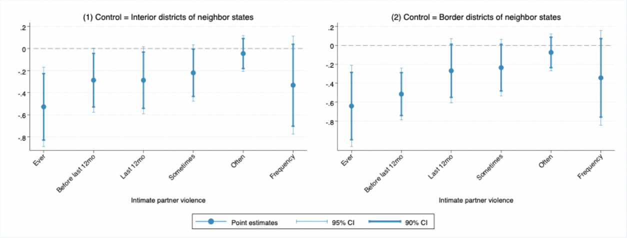
(a) Baseline



(b) Income Heterogeneity



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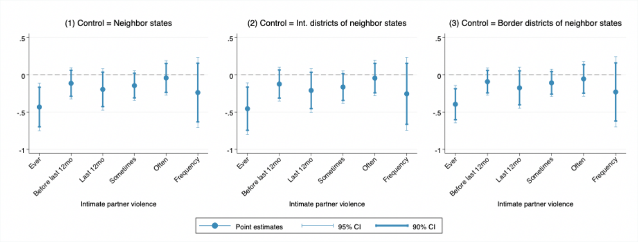
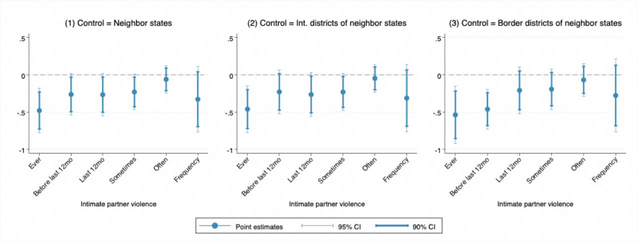
Robustness Checks: Treatment Group = Border Districts

(a) Baseline



(b) Income Heterogeneity



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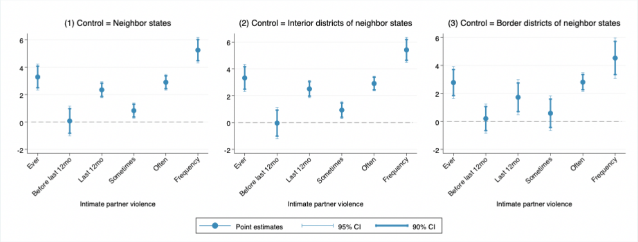
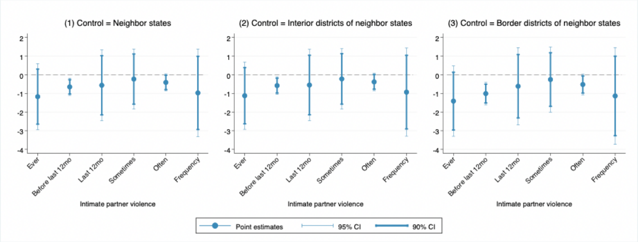
Robustness Checks: Treatment Group = Interior Districts

(a) Baseline



(b) Income Heterogeneity



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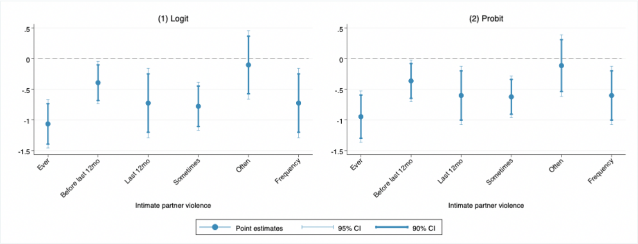
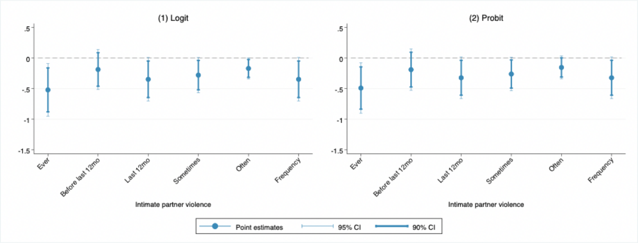
Robustness Checks: Logit and Probit Regressions

(a) Baseline



(b) Income Heterogeneity



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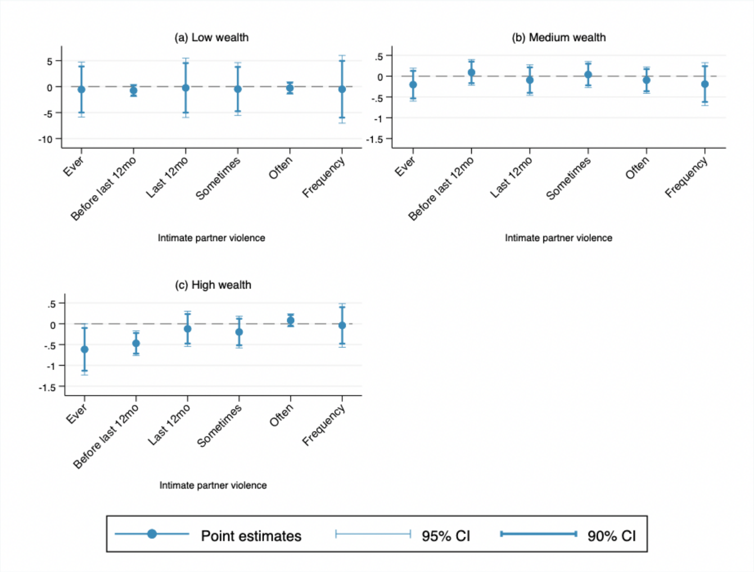
Robustness Checks: Sample Splitting



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Robustness Checks: Impact on District-Level Domestic Violence

	Dependent variable: log(domestic violence per 1000 population)		
	(1) Short-term policy impact	(2) Impact of policy reversal	(3) Long-term policy impact
Treatment intensity × Post	0.004	0.003	-0.001
	(0.007)	(0.016)	(0.024)
Treatment intensity	-10.726	-85.992*	2.901
	(32.495)	(46.899)	(6.841)
Post	-4.465***	0.349	-0.924***
	(0.931)	(0.569)	(0.170)
Observations	520	258	298
R-squared	0.94	0.95	0.94

Notes: The table presents the OLS results from estimating the short-term impact of Kerala's partial liquor ban (Column (1)), the impact of policy reversal (Column (2)), and the long-term impact of the ban (Column (3)) on district-level domestic violence using crime data from the National Crime Record Bureau (NCRB) for the years 2010-2019. The dependent variable in each column is the log of number of domestic violence incidents (number of cruelty by husband or his relatives) per 1000 population. The treatment intensity variable is similar across columns. An indicator variable for post period ("Post") equals one if $2014 \leq t \leq 2016$ and zero if $t < 2014$ in Column (1), one if $t > 2016$ and zero if $2014 \leq t \leq 2016$ in Column (2), and one if $t > 2016$ and zero if $t < 2014$ in Column (3). The control group in Column (1) consists of Karnataka and Tamil Nadu, while the control group in Columns (2)-(3) consists of Karnataka only. All specifications control for district and year fixed effects, state-by-year FEs, district-specific time trends, and a constant term. Standard errors, clustered by districts, are in parentheses. Significance: *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

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