Alcohol Ban and Crime: The ABC's of the Bihar Prohibition

Running Title: Alcohol ban and crime in Bihar

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Abstract

We study the relationship between alcohol consumption and crime, following an alcohol prohibition in Bihar in 2016. Using a difference-in-differences approach, we explore the differential effects of alcohol on different crime types. We find that the prohibition led to a 0.22 standard deviation point reduction in reported violent crimes without significantly impacting nonviolent crimes. Heterogeneity tests reveal stronger effects in interior districts and those with higher baseline alcohol consumption or fewer religious restrictions on alcohol consumption.

Thus, we conclude that the ban affected crime by reducing alcohol availability and consumption, rather than through institutional changes.

1. Introduction

Alcohol consumption imposes significant costs on society in the form of increased mortality, crime, and risky health behavior (Carpenter and Dobkin 2009; Waddell 2012; Carpenter and Dobkin 2015). Previous studies exploited variations in legal access to alcohol to analyze impacts on social costs in high-income countries. However, relatively little is known about the impacts of alcohol consumption in low-income countries that have a higher burden of alcohol-attributable diseases and scarce national alcohol policies (WHO 2018).[1] Poor institutional features within health care and law enforcement sectors further exacerbate outcomes in low-income countries for the same patterns of drinking as in high-income countries (Grittner et al. 2012). Additionally, price elasticity of alcohol is lower in developing countries (Tian and Liu 2011), which has implications for price-based alcohol regulation policies. These observations provided an impetus to study responses to alcohol regulation policies and the impacts of alcohol consumption on social costs, specifically in low-income countries.

Within India, alcohol has been found to be the most prevalent psychoactive substance with 14.6 percent of the population, or 160 million individuals, consuming alcohol (Ambekar et al. 2017). Drinking episodes are frequent, and more than half of all drinkers engage in hazardous drinking (Prasad 2009).[2] Eighty-three percent of heavy drinkers report experiencing alcohol-related harm in the form of physical, sexual, or emotional harm and neglect (Esser et al. 2016). Within this backdrop, our paper revisits the relationship between alcohol consumption and a specific social cost, that is crime in the context of a developing country. We employ a DiD framework to examine the effect of a complete alcohol prohibition on crime in Bihar, India.

Alcohol consumption may be related to crime through multiple pathways (Murdoch and Ross 1990). First, the direct pharmacological effects of alcohol, such as increased aggression and hostility (Zhang, Wieczorek, and Welte 1997; Carpenter and Dobkin 2010) may lead to crime and subsequently, higher chances of violent crime compared to nonviolent crime (Murdoch and Ross 1990; Cook and Moore 1993). Second, alcohol is known to reduce cognitive abilities by impairing perception and inducing a present bias (Steele and Josephs 1990), which could impede individuals' decision-making abilities. Moreover, large doses of alcohol also lead to sedation, which further increases the risk of being victimized (Carpenter and Dobkin 2010).

At the same time, alcohol regulation policies may interact with crime through various channels. For instance, reduced expenditures on alcohol lead to positive income effects, which could decrease crime (Miguel 2005), whereas restrictions on alcohol production may result in unemployment and loss of income, thereby increasing crime. Additionally, prohibition as a policy may contribute to organized crime through bootlegging and smuggling (Thornton 1991). In addition to affecting alcohol availability, alcohol regulation policies (especially, a prohibition) are often accompanied by major changes in police activity. This could potentially increase crime reporting through stricter policing, or reduce criminal behavior through stronger police presence. Alternatively, greater deployment of forces for prohibition enforcement could divert resources away from non-prohibition crimes, which could increase overall crime (Yang 2008; Dar and Sahay 2018). Therefore, *a priori*, the impact of an alcohol prohibition policy on crime is uncertain.

The literature on alcohol regulation policies, such as price and age-based policy restrictions, documents a reduction in violent crimes, as well as nuisance crimes like drunkenness and disorderly conduct (Cook and Moore 1993; Carpenter 2007). Total alcohol prohibition, however, is used less often as a policy tool, perhaps, because of its extreme nature. The empirical evidence on prohibition is concentrated on the prohibition in the United States (1920–33) (Miron and Zwiebel 1991; Miron 1999; Dills, Jacobson, and Miron 2005). The evidence is scarce in the context of developing countries, where the prohibition literature has largely focused on crimes against women and domestic violence. For example, Luca, Owens, and Sharma (2019) found that alcohol prohibition policies in India were associated with lower levels of domestic violence. Khurana and Mahajan (2018) studied the role of a liquor sales restriction policy on reducing reported incidence of sexual assault and harassment. Roy (2020) examined the impact of various alcohol bans on a range of violent and nonviolent crimes and found significant reductions in criminal activities, especially violent crimes.[3]

Our paper fills this gap by studying the effect of alcohol prohibition on a wide portfolio of crimes in Bihar, India. We find that the reported incidence of violent crimes in Bihar declined by 0.22 standard deviation (SD) points as a result of the ban, while that of nonviolent crimes remained largely unchanged. We observe that these effects were largely driven by declines in the incidence of murder (–0.17 SD points, $p < 0.1$) and robbery (–0.36 SD points, $p < 0.05$). Moreover, our results indicate that, on average, the decline in crime persisted over the period of study. Additionally, our paper isolates alcohol availability as the underlying mechanism, thereby contributing to the literature on alcohol consumption and crime (Hansen and Waddell 2018; Lindo, Siminski, and Swensen 2018). Using differences in alcohol consumption patterns at baseline, we document greater reductions in violent crimes in districts with higher pre-ban consumption. We also leverage religious norms pertaining to taboos around alcohol consumption, finding that our effects are amplified in districts with lower shares of such religious groups. Furthermore, we use institutional knowledge on the porous nature of Indian state borders to argue for lower availability of alcohol in interior districts of the state. Our results comparing crime between interior and border districts show that there were larger reductions in violent crimes in the interior districts. Lastly, we bring together novel data and evidence on the state of policing in Bihar to find that there was no differential policing across these districts, implying that police or other institutional factors may not be responsible in mediating the effects of the ban. Together, these results indicate that alcohol availability may be the potential mechanism behind the reduction in violent crimes, thereby contributing to the literature on mechanisms of alcohol regulation policies (Carpenter, Dobkin, and Warman 2016).

Furthermore, we are able to study the differential impact of the ban on violent and nonviolent crimes and contribute to the body of evidence on the time-varying effects of a prohibition. Most research studies on crime in India use annual level data (Luca, Owens, and Sharma 2015; Roy 2020). This paper is among a few that use monthly reported crime data, thereby allowing us to explore time-varying effects of such a policy at a finer timescale. Our findings also have policy relevance in light of a number of Indian states (such as Andhra Pradesh, Kerala, and Madhya Pradesh), which are exploring alcohol bans (*The Hindu* 2016). Furthermore, prohibition is a controversial topic among politicians and policymakers, with some studies predicting a rise in crime as an unintended consequence of prohibition (Kumar and Prakash 2016; Dar and Sahay

2018). Our paper contributes to this debate by presenting evidence on the effectiveness of the ban in controlling violent crime.

A related paper, Dar and Sahay (2018) (henceforth D&S) also examined the impact of the Bihar prohibition on crime rates in the state. Contrary to our findings, D&S found an increase in crime post the alcohol ban and attributed the rise in crime to the crime-displacement theory. Our paper differs from D&S in two critical ways.[4] First, D&S proposed a mechanism of increased police workload, reducing the ability of the police to control crimes other than prohibition. Our paper can directly contradict this assumption by providing evidence to suggest that police capacity increased in Bihar during the ban. We also substantiate our proposed mechanism of reduction in alcohol availability with the help of multiple analyses. Second, the analysis presented in D&S did not control for district-specific time trends, which we believe are crucial. In our context, district-specific time trends control for unobservable variables affecting crime that are likely to differ across districts and change over time.

The rest of the paper is organized as follows: in Section 2, we provide the policy background of the prohibition law in Bihar. Section 3 describes our data, followed by our empirical strategy and specifications. Section 4 describes our main results, and Section 5 discusses additional outcomes, including the state of policing in Bihar and the relationship between political representation and crime in the state. Lastly, we present some robustness checks in Section 6, and conclude with a discussion on the interpretation and caveats of our results in Section 7.

2. Alcohol Consumption and Institutional Background in Bihar

The past two decades have seen a rise in per capita alcohol consumption in India. Heavy alcohol consumption is a growing issue among low-income workers in India, having consequences for their income, savings, and labor market productivity. Within this context, different policies and commitment devices have been examined with a goal toward decreasing alcohol consumption. Before the 2016 Bihar alcohol ban,[5] other policies, such as high minimum level drinking age (MLDA) and total alcohol prohibition policies were also practiced in different states in the country with a goal of reducing alcohol consumption (Luca et al. 2019). Coincidentally, there is anecdotal evidence that there is substantial demand for alcohol regulation policies within India. This is supported by evidence within economics, as Schilbach (2019) found positive effects of financial incentives on increasing sobriety among low-income workers in India.

Alcohol regulation laws lie within the exclusive domain of state governments in India, and as such, alcohol regulation policies vary across states. This paper focuses on a particular regulation, that is, the Bihar Prohibition and Excise Act, 2016. Under this act, the Bihar government prohibited the manufacture, transport, sale, and consumption of alcohol throughout the state, with strict penal provisions for those found in violation of the ban. The alcohol prohibition was an electoral promise by Nitish Kumar, the incumbent chief minister of Bihar, who had pledged, while campaigning for the 2015 assembly elections, to purge alcoholism from the state. This was in response to repeated complaints of domestic violence and a demand for prohibition by the female electorate in the state (Singh 2015).

Starting in April 2016, the state enforced a draconian version of the prohibition, with strict penal provisions for any violations. For example, manufacturers and suppliers would be awarded the death penalty for any deaths reported as a result of consuming spurious liquor. Even drinking or being drunk in public spaces was punishable by a jail term of 5–10 years and a fine of up to INR 10 lakhs (US$16,000). People were encouraged to report cases of drinking and nuisance to the police by telephoning a toll-free number, which had been painted on walls throughout the city (Singh 2016). Furthermore, anecdotal evidence suggests that the government was strict in enforcing the Act—liquor manufacturers claimed in the Supreme Court of India that stocks of alcoholic beverages, worth INR 5 crore (US$1 million), were destroyed by the Bihar government in a "vindictive and arbitrary manner" (*Economic Times* 2017). In July 2018, however, more than two years after the Act came into force, the Bihar government decided to water down many of the stringent provisions of the prohibition. The new version allows first-time offenders to be released on bail and removes the provision allowing for seizing family property if liquor is found on the premises of a house.

The Indian state of Bihar provides an appropriate setting to study the impact of alcohol regulation on crime. Bihar is notorious for its high incidence of crime, reporting 10.4 percent of all violent crimes in India (NCRB 2016), among a national population share of only 8.5 percent. At the same time, the state ranks sixth among all Indian states in alcohol consumption with a per capita annual consumption of 14.7 liters (NSSO 2014). Apart from Bihar, complete alcohol prohibition, as a regulation policy, is currently practiced in only one other state in India, namely Nagaland.[6] However, medical reports indicate rampant prevalence of alcohol consumption in Nagaland (Tushi et al. 2018), which suggests a lax implementation of the ban. In comparison, "The Bihar Prohibition and Excise Act, 2016," which came into effect on April 1, 2016, offered a fertile setting to study the effect of alcohol prohibition on crime, especially because of the strict enforcement of the ban.

Policing also plays a key role in the implementation of the ban and its interaction with crime. In addition to controlling crime, state police forces in India also perform a key role in the implementation of any regulation policies, including bans and prohibitions. Police services are organized at the state level and headed by the Director General of Police (DGP), which is an administrative post appointed by state-level cabinet ministers. The DGP is in charge of managing Deputy Inspector Generals (DIGs). DIGs are, further, in charge of police ranges, which are geographic zones, covering three to six districts within a state. Due to the tight relationship between the state electoral government and the state police force, the effect of alcohol prohibition on crime may be moderated by the quality of policing in the state. We explore the descriptive relationship between policing and crime in Bihar at the time of the prohibition, included in Section 5. We also study how political representation at the district level differentially affected crime in Bihar.

3. Empirical Analysis

3.1 *Data*

The primary source of crime data for our analysis is the district-level monthly crime statistics published by the Bihar state police department. We use data for eight different crime categories for the time period from January 2013 to February 2019. For our difference-in-differences analysis, we use the neighboring state of Jharkhand as a control group and use district-level monthly crime statistics, published by the Jharkhand state police. We offer a number of reasons why Jharkhand is a good control group for our study.

Jharkhand has been used as a control group for Bihar by previous studies in economics (Muralidharan and Prakash 2017). Traditionally, the districts of what is now Jharkhand were part of the relatively underdeveloped southern region of Bihar (Figure 1). After a 50-year struggle by the tribal population of Bihar, the Parliament of India passed the Bihar Reorganisation Bill on August 2, 2000, to carve out 18 districts of Bihar to create the state of Jharkhand. Crime rates in both states have followed similar levels. The reported rate of cognizable crime (total cases per 100,000 population) in 2015 was 171.6 for Bihar and 135.1 for Jharkhand. At the same time, the percentage of violent crimes to total cognizable crimes in Bihar and Jharkhand was 20.2 percent and 18.9 percent, respectively (NCRB 2016). These data suggest that the proportion of violent crime in both states was similar before the alcohol ban in Bihar.[7] Furthermore, when the ban was introduced in Bihar in April 2016, the ruling party in Jharkhand imposed no such parallel ban.

<INSERT FIGURE 1 approximately HERE>

Examining the political scenario in Bihar and Jharkhand at the time of the ban, we do not find any other major policy development that could have affected crime.

We use the definitions of violent and nonviolent crime as per the National Crime Records Bureau of India to classify our crime categories (NCRB 2016). Violent crimes include those crimes where there is "bodily or property harm," or threat thereof. As per this definition, murder, rape, kidnapping, dacoity, robbery, and riots constitute violent crimes, whereas burglary and theft constitute nonviolent crimes. For our analysis, we create standardized indices of violent and nonviolent crimes using this classification[8] and use these as a measure of the reported incidence of crime.[9]

We use the fourth (2015–16) round of the National Family Health Survey (NFHS) to construct measures of pre-ban alcohol consumption and proportion of Muslim population for each district in Bihar.[10] The NFHS is conducted roughly every 10 years in representative samples of households across the districts of India. The survey collects information on various demographic and health characteristics, including fertility, mortality, religion, maternal, and child health outcomes. Using this data set, we generate binary indicators of high baseline alcohol consumption and low Muslim population across the districts of Bihar. To construct these measures, we tag districts as high baseline consumption if the alcohol consumption was higher than the average alcohol consumption for all districts of Bihar. An identical procedure is used for tagging districts as having low Muslim populations, with respect to the average proportion of Muslims in Bihar (Figures 2 and 3).

<INSERT FIGURES 2 and 3 approximately here>

Next, we obtain data from the 2011 Census of India for district-level demographic information to control for time-invariant, district characteristics that could have affected crime in both states. We construct five variables from the Census data for each district: the proportion of backward communities (Scheduled Castes and Tribes) among the population, sex ratio, male literacy rate, male employment rate, and the proportion of the working population engaged in agriculture. We use male literacy and employment rates, rather than the overall rates, because of the imbalance in alcohol consumption by gender. We also obtain the area and total population of each district from the Census. Using district names as identifiers, we merge the Census data with the crime data to obtain our final data set, which yields 4,588 observations for each crime category—62 districts (38 in Bihar and 24 in Jharkhand), over a period of 74 months.

We also study trends in alcohol consumption before and after the ban, using data from the Consumer Pyramid household survey published by the Centre for Monitoring Indian Economy (CMIE). The survey records monthly consumption and expenditure data for over 200,000 households in India for 153 specific expenditure categories. From this data set, we obtain the average household monthly expenditure on alcohol for all households in Bihar and Jharkhand for our study period: January 2014–February 2019. We aggregate the data to the state level and plot the monthly average expenditure on alcohol over time in order to study the first-stage effect of the Bihar prohibition on alcohol consumption (expenditure) in both states (Figure 4).

<INSERT FIGURE 4 approximately here>

3.2 *Empirical Strategy*

Our objective is to empirically determine the causal effect of alcohol prohibition on crime. We first conduct DiD analysis, looking at standardized crime indices, comparing the change in violent and nonviolent crimes in Bihar to the change in Jharkhand (the control group) after the ban. The key identifying assumption is that Bihar would have had similar trends in crime as Jharkhand, had the prohibition not happened. We test the validity of this assumption by studying crime trends in Bihar and Jharkhand in the pre-ban period using an event study (Figure 5). We use crime data from our entire study period of six years, with the event time as the second quarter of 2016 (the ban was implemented in April 2016). By this definition, we have 12 quarters that are treated and 13 that are untreated. In constructing the event study graph, we control for district, as well as month, fixed effects, and clustered standard errors at the district level. We note that, while there were no significant trends before the ban, the index of violent crimes declined after the ban (Figure 5).

<INSERT FIGURE 5 approximately here>

Our primary specification, as mentioned here, uses a DiD estimator. We include district-level demographics to account for time-invariant, district characteristics, calendar month fixed effects to control for seasonality, and district-specific time trends. Standard errors are clustered at the district level. The regression equation is:

$$y_{dt} = \alpha + \beta_1 Post_1 + \beta_2 Treat_d + \beta_3 Treat_d * Post_1 + \delta_d * t + \gamma X_d + \eta_t + e_{dt}\ , \qquad (1)$$

where y_{dt} is our main outcome of interest: an index of the reported incidence of violent or nonviolent crime in district d, in month t. $Treat_d$ and $Post_1$ are indicator variables for the treatment group (Bihar) and period (after April 2016), respectively. $\delta_d * t$ accounts for district-specific time trends, X_d for district-level demographics, and η_t for calendar-month fixed effects. β_3 is the main coefficient of interest, representing the causal estimate of the impact of the ban on crime.

3.3 *Heterogeneity Analyses*

In the second part of our analysis, we examine potential channels through which the alcohol ban could affect crime in Bihar, and test whether restricted alcohol availability is the primary operating channel for the ban. We consider variations in alcohol consumption from two sources—the first examines the impact of the ban in districts with higher baseline alcohol consumption in the pre-ban period, as compared to low baseline alcohol consumption districts. The second approach uses information on religious groups that prohibit consumption of alcohol and compares the effect of the ban in districts with high versus low concentrations of such groups.

If reduced alcohol availability drives the impact on crimes in the state, then we would expect to see a larger effect of the ban in those districts of Bihar that had higher levels of alcohol consumption before the ban. To test this hypothesis, we perform a heterogeneity analysis, looking at the differential effect of the alcohol ban in districts with high and low baseline alcohol consumption, using the following estimation strategy:

$$y_{dt} = \alpha + \beta_1 Post_t + \beta_2 I_d + \beta_3 I_d * Post_t + \delta_d * t + \gamma X_d + \eta_t + e_{dt} \quad (2)$$

In this specification, I_d is an indicator variable for districts in Bihar with high baseline alcohol consumption. β_3 is the coefficient of interest, which gives the differential effect of the ban on high alcohol-consuming districts in Bihar, compared to districts with low baseline alcohol consumption.

Our next analysis focuses on dividing districts of Bihar along religious lines that have different implications for alcohol consumption. Traditionally, alcohol consumption is considered sinful in Islam, and therefore, a large majority of Muslims in India do not consume alcohol (Bennett et al. 1998). If alcohol availability is the operating channel, then we would expect effects to be muted in districts with a greater proportion of Muslim population. As a second test of the hypothesis of alcohol availability, we conduct another heterogeneity analysis using equation (2), on the basis of Muslim population by district in Bihar. I_d now represents districts for which the Muslim population is less than the average Muslim population in Bihar. β_3 is once again the coefficient of interest that gives the differential effect of the ban on districts with fewer Muslims. It is worthwhile to note the absence of a one-to-one match between high alcohol-consuming districts and Muslim-minority districts in Bihar (Figures 2 and 3)—an important distinction, without which analysis along the religious group dimension would not add value over the initial baseline alcohol analysis.

Next, we perform a third heterogeneity analysis to understand the differential effects of the ban on the border and interior districts of Bihar.[11] Given that state borders are largely open and there is relatively free movement of people and goods across states, a state-wide ban might not be equally effective across all districts of the state. We hypothesize that the ban would be more effective in interior districts than in border districts, as it would be easier to enforce the ban in the absence of cross-border movement of alcohol or alcohol seekers. As a result, if the ban led to a reduction in crime by reducing the availability of alcohol, we could expect the reduction in crime to be much more pronounced in these interior districts. Using the indicator variable I_d to denote a district of Bihar that does not share a border with a district of another state or country, we repeat our heterogeneity analysis using equation (2). For example, Kishanganj is a district in Bihar that shares a border with both Nepal and West Bengal, while Patna is another district in the state, which is only bordered by other districts of Bihar (Figure 6). In this manner, we divide Bihar into 22 border districts (such as Kishanganj) and 16 interior districts (such as Patna).

<INSERT FIGURE 6 approximately here>

4. Impact of the Alcohol Ban on Crime

We first check whether the ban affected overall alcohol consumption in the state. We note that alcohol consumption, which was following similar trends in both Bihar and Jharkhand before the ban, declined to near zero levels after the ban in Bihar, providing strong evidence that alcohol consumption did decrease in Bihar post-April 2016 (see Figure 4). As mentioned earlier, we note a decline in the violent crime index post-ban in our event study graphs. This was further confirmed in Table 1, which reports the DiD estimate from regression (1). We find that the alcohol ban led to a 0.22 standard deviation reduction ($p < 0.1$) in violent crimes. There is no significant effect on nonviolent crimes. The relatively high R-squared on the regressions for violent and nonviolent crime indices (0.84 and 0.90, respectively) suggests that the factors included in our model explain most of the observed variation in crime. We also present disaggregated results for individual crime categories in Table 2. We find a significant decline for murder and robbery, both grouped in the violent crime category, in Bihar in the post-ban period. Furthermore, the point estimates for all violent crime categories are qualitatively negative, while the nonviolent categories are positive, albeit insignificant.

<INSERT TABLES 1 and 2 approximately here>

Along with the overall impact of the ban, we study the time-varying effects of the ban on crime over cumulative 6-month intervals in the post-ban period. We repeat our DiD analysis by restricting the sample up to the first half-year in the post-ban period, and subsequently adding cumulative half-years to our sample. We then plot the main coefficient of interest from regression (1) for violent and nonviolent crime indices for each cumulative half-year to observe the effect of the ban over time (Figure 7). Our analysis of the time-varying effects of the ban shows that the coefficient for violent crime remains fairly stable (between –0.20 to –0.27), approximately 3 years into the ban. This indicates that the ban reduced the reported incidence of violent crime within the state and remained effective, on average, for close to 3 years into its implementation. That said, it is also important to note that the effect on violent crime in each period declined over time after the implementation of the ban (Figure 5). Given the low power when considering only one time period at a time, the effect of the ban in later periods is small enough to be insignificant; however, the initial effect immediately after the ban is large enough that the average effect of the ban is negative, significant, and fairly stable, even as we consider more time periods after the ban.

<INSERT FIGURE 7 approximately here>

4.1 *Heterogeneity Results*

There could be multiple channels through which the alcohol ban reduced violent crime. One potential mechanism is the increased policing that was put in place for the effective implementation of the ban—one could argue that increased police deployment generated a greater sense of security and was an effective deterrent for criminal activities. The other plausible mechanism for a drop in violent crime could be the reduced availability and consumption of alcohol, which led to a drop in violent crimes by reducing tendencies of aggression, hostility, and present-bias (Steele and Josephs 1990; Zhang, Wieczorek, and Welte

1997). In this section, we describe heterogeneity tests we perform to isolate the channel—alcohol availability versus police deployment —through which the ban affected reported crime.[12]

First, we find that violent and nonviolent crime decreased by an additional 0.52 ($p < 0.05$) and 0.19 ($p < 0.10$) SD points, respectively, in districts with higher baseline alcohol consumption in the post-ban period (Table 3, columns 3 and 4). These results suggest that reduced alcohol consumption, resulting from a reduced availability, could be an important channel through which the policy affected crime in the state. A second analysis, based on the Muslim population, by district, reveals that violent crimes decreased by an additional 0.37 SD points ($p < 0.05$) in the post-ban period (with no significant effect on nonviolent crimes) in districts with a lower proportion of Muslims, confirming our alcohol availability hypothesis (Table 3, columns 1 and 2). Lastly, we also expect to see a stronger decline in violent crimes in the interior districts, compared to the border districts, due to potential cross-border movement of alcohol and alcohol-seekers. We find that the ban had a stronger impact in the interior districts, with violent crimes declining by an additional 0.53 SD points ($p < 0.01$), with no significant effect on nonviolent crimes (–0.093, $p > 0.1$) (Table 3, columns 5 and 6).[13]

<INSERT TABLE 3 approximately here>

These results indicate that the full effect of the ban was displayed only in the interior districts of Bihar, and it is plausible that only the interior districts of Jharkhand were completely unaffected by it. Anecdotal evidence suggests that there was cross-border movement by locals residing in border districts of Bihar in search of alcohol (Chamaria 2016; *NDTV* 2016). A concern is raised for our earlier DiD estimates, as they do not account for any spillover effects of the ban on crime in Jharkhand districts that border Bihar. Therefore, to get at the uncontaminated effect of the ban, we re-estimate regression (1) while restricting the sample to the interior districts of Bihar and the interior districts of Jharkhand.[14] We find that the ban reduced violent crime in the interior districts of Bihar by 0.53 ($p < 0.01$) SD (Table 4), with no significant effect on nonviolent crimes.[15] Comparing this coefficient to our main estimates, we find that the restricted sample displayed a significantly larger effect, nearly equal to that in the districts with high baseline alcohol consumption. This result suggests that the border districts were indeed suffering from spillover effects, which diluted the effect of the ban, lending further credence to our argument that the ban affected crime through the channel of alcohol availability.

<INSERT TABLE 4 approximately here>

Our results, thus far, could be confounded by potential changes in crime reporting. Although this is a possibility, our heterogeneity results shows it to be unlikely since reporting patterns would have to change differentially across districts to accommodate this view. Additionally, changes in policing could be driving our results. One could posit that if the drop in reported crime was due to improved policing, this effect should have been consistent across crime categories and geographical locations within Bihar. To the contrary, we observe a larger decline in interior districts in Bihar, districts with high baseline alcohol consumption, and those with lower-than-average Muslim population. The results suggest that the ban affects crime through the channel of reduced alcohol availability rather than through increased policing.

In the next section, we provide further evidence to help disentangle the alcohol availability mechanism from the channel of policing changes after implementation of the ban. We present new, descriptive evidence on the state of policing and police resources in Bihar during the ban and also, study how political climate affected crime in the state.

5. Additional Outcomes

5.1 *Police and the Prohibition*

It is crucial to separate the effects of the alcohol ban from potential changes in policing in Bihar. In this section, we consider two indicators of policing behavior: (1) police transfers, and (2) police infrastructure and resources in Bihar during the ban period. We gather new data on both of these measures and analyze them below.

5.1.1 *Police transfers:*

We manually create a data set of transfers of police officers in the Indian Police Service and the Bihar Police Service. For police transfers, we obtain digital copies of all transfer orders in the Indian Police Service (Bihar state) and the Bihar Police Service. From these documents, we create a data set of the total number of transfers per month over the period November 2014 (one year before the Bihar Assembly election) to April 2017 (one year after the alcohol ban came into effect). Using this data, we study trends of the number of police transfers per month for the state of Bihar.

Between November 2014 and April 2017, the number of transfers largely stayed stable, with an average of 27.5 transfers per month (Figure 8, Panel A). We observe no noticeable change in the number of transfers in the month of the election or of the alcohol ban. Our findings are qualitatively unchanged (Figure 8, Panel B), when we use another data source for prohibition-related transfers: transfer orders, from the Bihar Prohibition (Excise and Registration) Department.[16] We augment our visual inspection with an empirical test of changes in police transfers. To do so, we assemble a data set that records the probability of a transfer in any given month, as well as the monthly number of transfers per district in 2016. We then examine differences in police transfers before and after the prohibition (April 2016), using ancillary regressions of the form:

$$Y_{dt} = \beta_0 + \beta_1 D_d + \alpha PostBan_t + \gamma T_t + \epsilon_{dt} \,, \quad (3)$$

where Y_{dt} is the police response outcome and $PostBan_t$ is an indicator for post-period months (after April 2016). We include month fixed effects T_t to absorb year-invariant, month-specific batch transfers,[17] and district fixed effects, D_d, absorbed time-invariant differences across districts. Standard errors are clustered at the district level.

<INSERT FIGURE 8 approximately HERE>

Columns 1 and 4 in Table 5 report results from equation 3. There are no significant effects on the number of transfers in the post-ban period; however, the probability of transfer is significantly higher in the post-period. We note that a higher probability of transfer in the post-ban period was sensitive to the comparison month omitted while estimating the equation. Additionally, since the data are restricted to the year 2016, the estimating equation could be picking up a mechanical relationship wherein the probability of transfer increases as a function of the number of months in the year. We support this argument by highlighting the lack of difference in the number of transfers between the pre-ban and post-ban periods. We conclude that there were no significant differences in police transfers before and after the ban. Our results are qualitatively unchanged when we repeat the above exercise for the Bihar election in November 2015. We compile a district month-level data set for transfers of all district police chiefs. Using the election month as an event, we define a *PostElection* flag for October through December 2015, and test for differences in transfer of district police chiefs pre-election and post-election by comparing outcomes for the three months before and after the election. We use the same specification (equation 3) as above, but replace the *PostBan* indicator with the *PostElection* indicator. The results are presented in Table 6. We find no significant difference in probability of transfer or the number of transfers for officers in the pre-election, as compared to the post-election period. Thus, we confirm the preliminary observations from our plots in Figure 8 and are able to rule out significant differences in police transfers in Bihar before and after the election or the ban.

<INSERT TABLES 5 and 6 approximately here>

5.1.2 *Police infrastructure and resources*

To study trends in police infrastructure and resources, we collect new data from the Bureau of Police Resources and Development (BPRD), a national repository of police indicators for all Indian states, reported at the annual level. We collect data on six indicators: the number of police stations, transport facility per 100 policemen, population per policeman, area per policeman, total strength of the police force, and vacancies in the police force.

We plot changes in the previously described measures of police infrastructure for Bihar and Jharkhand over the time period of our study (Figures 8 and 9). We find that the number of police stations largely stayed stable over time for both Bihar and Jharkhand. However, transport facility per 100 policemen dipped significantly for Bihar in 2015 and 2016 (the year of the election and the alcohol ban, respectively), suggesting that the strength of the police force may have increased in Bihar. Furthermore, we find that the population per policeman and area per policeman also dipped sharply in Bihar in the prohibition year, suggesting that additional police force was recruited in 2016. Finally, we study police strength indicators and find that actual police strength increased sharply in 2016, and then returned to its previous levels, whereas the number of vacancies in the police force decreased in 2016. These trends suggest that overall police capacity increased in Bihar in 2016, perhaps, to meet the increased demands of the prohibition.

<INSERT FIGURES 8 and 9 approximately here>

One could argue that the increased police strength after the prohibition (and not the alcohol restriction) was responsible for reducing violent crimes in Bihar. We allay these concerns by analyzing district-level variation in police response, in combination with our heterogeneity results on crime.[18] We flag districts according to two characteristics: (1) border versus interior districts; and (2) high versus low alcohol-consuming districts and estimate the following equation:

$$Y_{dt} = \beta_0 + \alpha_1 PostBan_t + \alpha_2 PostBan_t * Treat_d + \gamma T_t + \epsilon_{dt} \tag{4}$$

This specification is motivated by time-invariant, district-level characteristics of interest, in which $Treat_d$ is either (1) border or interior districts (*InteriorDistrict* [= 1]) or (2) low- or high-alcohol-consuming districts (*HiAlcohol* [= 1]). Y_{dt} corresponds to the police response outcome, which is either (1) the probability of a transfer, or (2) the total number of transfers for a district *d* in month *t*. For both regressions, we include district-level fixed effects and calendar-month fixed effects, while clustering our standard errors at the district level. A significant coefficient of the interaction, $\alpha_{2,}$ would suggest a systematic difference in police response based on interior or border status as well as high or low alcohol status. Table 5 (columns 2–3, 5–6) reports the results from this estimation. We find no significant difference in the number of transfers or the probability of transfers between interior and border districts or between high and low alcohol-consuming districts. Thus, although overall police resources did increase for Bihar in 2016, they did not vary systematically across districts in a way that could explain the effect of the ban in reducing violent crime.

5.2 *Political Representation and Crime*

As mentioned earlier, the political system and the policing infrastructure are intertwined in India. In this section, we examine how the ban may have impacted crime along political lines. In particular, we check how local political representation differentially affected crime, by testing whether the impact of the ban is heterogeneous across districts, based on their level of exposure to the ruling party—that is, the number of elected representatives in a district affiliated with the ruling party. We compare districts with elected representatives aligned to the state ruling party against those with elected representatives belonging to opposition political parties. The 2015

Bihar state election is used to define ruling and opposition coalitions. State-level elections in India are held at the constituency level, whereas crime outcomes are reported at the district level, a more aggregated level. The election data is aggregated to the district level by using the number of constituencies[19] to which elected representatives belonged: (1) Janata Dal United (JDU), (2) Rashtriya Janta Dal (RJD), or (3) either JDU or RJD, to create a continuous treatment intensity variable. Note here that JDU and RJD comprised the winning coalition. All other parties' elected representatives are tagged as opposition coalition. The following empirical specification is implemented on data for Bihar only:

$$Y_{dt} = \alpha + \beta_1 Post_t + \beta_2 Treat_d + \beta_3 Treat * Post_{dt} + \delta_d * t + \gamma X_d + \eta_t + e_{dt} , \qquad (5)$$

where Y_{dt} is the crime index, as specified in the paper, and $\delta_d * t$ and γX_d control for district-specific time trends and district covariates. $Treat_d$ is a continuous variable capturing treatment intensity, defined as the exposure of a district to the party in power. Table 7 presents results from this estimation. The definition of treatment exposure is varied to account for major political parties within the winning coalition. The estimates suggest no difference in crime outcomes across districts with different exposures to the ruling party, suggesting that the political will to implement the ban is uniform across districts.

<INSERT TABLE 7 approximately here>

6. Robustness Checks

In addition to the heterogeneity analyses, we also perform a few robustness checks of our estimates. First, we check if our estimates are robust to exclude months immediately surrounding the ban. To do this, we drop three months leading up to and following the ban and rerun our main specification, with months from July 2016 constituting the ban period (Table 8). We observe qualitatively similar findings as our main estimates in Table 1. This result suggests that our estimates were not driven by secular trends that resulted from the announcement and implementation of the ban.

<INSERT TABLE 8 approximately here>

Second, we ensure that our estimates are robust to alternate approaches of constructing crime indices. For this, we construct a simple average of violent and nonviolent crime indices, when standardized with respect to the control state. We also construct standardized indices with respect to the overall crime in both states. We report our estimates in Table 9. We find that violent crime decreased in both instances (column 1 and column 5 of Table 9) and nonviolent crime is positive, though insignificant, in all instances.

<INSERT TABLE 9 approximately here>

Lastly, we check the robustness of our main estimates using an alternate estimator described in de Chaisemartin and D'Haultfoeuille (2022). This DiD estimator is relevant for designs with binary non-staggered treatments. The estimator computed a weighted average treatment effect by comparing the outcome evolution from t–1 to t for the control, as well as the treatment groups across all time periods. We present the average treatment effect we obtain using this procedure in Table 10. We find a statistically significant strong negative effect on violent crime and a positive effect on nonviolent crime. We also note that our main estimate (0.22) is not statistically different from the estimate we derived from the de Chaisemartin and D'Haultfoeuille (2022) technique, rendering further credibility to our findings.

<INSERT TABLE 10 approximately here>

7. Discussion

Alcohol consumption imposes many societal costs, including violence and alcohol-related crime. Literature studying various alcohol regulation policies (excise taxes, MLDA, zero tolerance laws, spatial restrictions) has found that higher restrictions and reduced availability of alcohol lower the reported incidence of violent crime, as well as property crime (Sloan, Reilly, and Schenzler 1994; Miron 1999; Cook and Moore 1993; Carpenter 2007). Our findings align with these observations. We find that the alcohol ban had a differential effect on violent crimes (murder, kidnapping, dacoity, robbery, rape, and riots), as opposed to nonviolent crimes (theft and burglary) in Bihar (Figure 1). The reduction in violent crimes is a consistent result in all our heterogeneity tests. In particular, we find that the decline was larger in interior districts of Bihar, districts with high baseline alcohol consumption, and in districts with a smaller Muslim population. We piece together this evidence to nail down alcohol availability, as a channel through which the ban operates.

We argue for the decreased availability hypothesis over that of increased police deployment on the basis of our analysis comparing border and interior districts. If anything, it is plausible to expect greater police deployment in border districts, given that state borders are porous to movement of alcohol-seekers and potentially even alcohol itself (*Hindustan Times* 2016). Attributing the greater reduction in violent crimes for interior districts to police infrastructure would suggest that police deployment functions in a perverse way. Thus, our border versus interior district result lends credence to the availability story over the channel of police deployment. It also mitigates concerns about other institutional changes driving the results, such as the effect of a newly elected government, or any attempts to massage crime statistics by the state police after enacting a prohibition. These effects are likely to be consistent across geographical locations and religious communities in Bihar, and are, therefore, not consistent with our heterogeneity results. Last, while overall police resources did increase for Bihar in 2016, we show that they did not vary systematically across districts in a way that could explain the heterogeneous effect of the ban across districts. All these analyses lead us to conclude that the likely channel here is reduced alcohol consumption rather than changes in institutional or policing capacity.

The analysis on the time-varying effects of the ban suggests that, on average, the ban was effective in reducing violent crime throughout the study period. The result is interesting in the historical context of past experiments with alcohol bans that failed and were eventually revoked, partly as a result of increased production of bootleg alcohol and smuggling (for example, in Haryana and Andhra Pradesh in the 1990s). Even within our context, the Bihar government decided to water down many of the stringent provisions of the ban in July 2018, approximately two years after its enactment (*Business Today* 2018). However, we find that the average impact of the ban on crimes remained stable, even as we extend the study period until February 2019, although the per-period effect does diminish over time and become insignificant due to a lack of power.

The fact that a full four months passed between the policy being announced and implemented implies that the populace of Bihar anticipated the policy. However, we posit that anticipatory reactions by the people of Bihar are unlikely to affect the validity of our results. Even if the people of Bihar correctly anticipated the ban and stocked up on alcohol, the only impact this would have on our results is that the ban would not have been as effective until later. If anything, crime would have remained higher until these illegal private stocks ran out, and therefore, our results are, in fact, lower bounds on the magnitude of change in crime due to the prohibition. In other words, if the ban had not been premeditated, violent crime might have declined by an even more considerable margin.[20]

Our results should be interpreted with certain caveats. First, alcohol belongs to a broad class of intoxicants that have similar impacts on outcomes of health, productivity, and social harm. In the presence of alternatives such as cannabis, sedatives, and opioids, the effect of an alcohol ban on crime will be limited by the potential availability of other intoxicants. Anecdotal evidence from hospitals across Bihar highlights increased cases of substance abuse, as compared to the pre-ban period (Chaudhary, Jha, and Mishra 2017; *Financial Express* 2017). Although changes in the consumption of other intoxicants may also affect crime, this paper is unable to comment on those effects. Second, the external validity of our results may depend on several factors other than alcohol regulation alone. Factors, such as implementation of the ban, initial crime patterns, and prevalence of baseline alcohol consumption, could affect crime differently in another context. Third, we are unable to conclusively comment on the welfare effects of a prohibition. Prohibition is usually associated with a significant loss in revenue for the state, not just because of the widespread shutdown of alcohol production, but also because of the increased state capacity for surveillance and police raids. Alcohol regulation policies have also been found to positively affect health outcomes (Barreca and Page 2015). We cannot qualitatively assess such welfare aspects of the prohibition in our paper. However, we examine additional outcomes, including the effect of the ban on gender-based violence, household consumption, and child welfare, which we elaborate in our Online Appendix.

Finally, although we find evidence to suggest that the ban affected crime through the channel of alcohol restriction, in the absence of disaggregated data on income, we are unable to distinguish between the behavioral and income effects of alcohol restriction, that is, the direct pharmacological effects from reduced consumption (Carpenter and Dobkin 2010), or a positive income effect by reduced spending on alcohol (Miguel 2005). We also acknowledge that we are unable to completely rule out changes in crime reporting patterns because of the policy. While it is possible that such changes may have contributed to our results, our heterogeneity analyses, as described herein, make such a scenario unlikely, since the reporting patterns would have to change differentially across districts for this to be the case. That said, our results should be interpreted with the caveat that some part of the results may be due to changing reporting patterns in the aftermath of the policy change. Avenues for future research include cost–benefit and cost-effectiveness analyses of such a policy and the exploring of other social, economic, and health implications of such a prohibition.

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Tables

Table 1. Effect of the alcohol ban on violent and nonviolent crimes

	Violent crime index	Nonviolent crime index
	(1)	(2)
Treat	–0.28	–0.23
	(0.31)	(0.27)
Post	–0.17**	–0.096**
	(0.07)	(0.04)
Treat x Post	–0.22*	0.043
	(0.11)	(0.06)
N	4,588	4,588
R^2	0.84	0.90

Notes: Data consists of district-level monthly reported crime data from January 2013 to February 2019, as obtained from Bihar Police and Jharkhand Police. The table reports coefficients of the specification estimated in eq. (1) of the main paper. Our outcome variables are indices for violent crimes (dacoity, kidnapping, murder, rape, riot, and robbery) and nonviolent crimes (theft and burglary). All specifications control for district covariates and include calendar month fixed effects and district-specific time trends. Standard errors, clustered at the district level, are shown in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 2. Effect of the alcohol ban on individual crime categories

	Dacoity	Kidnapping	Murder	Rape	Riot	Robbery	Burglary	Theft
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat x Post	–0.055	0.059	–0.17*	–0.065	–0.023	–0.36**	0.062	0.025
	(0.11)	(0.17)	(0.09)	(0.09)	(0.16)	(0.14)	(0.09)	(0.06)
N	4,588	4,588	4,588	4,588	4,588	4,588	4,588	4,588
R^2	0.31	0.85	0.62	0.48	0.73	0.60	0.82	0.89

Notes: Data consists of district-level monthly reported crime data from January 2013 to February 2019, as obtained from Bihar Police and Jharkhand Police. The table reports coefficients of the specification estimated in eq. (1) of the main paper. Our outcome variable is the number of crimes as indicated in the column heading. All specifications control for district covariates and include calendar month fixed effects and district-specific time trends. Standard errors, clustered at the district level, are shown in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3. Heterogeneity analyses

	Violent crime index (1)	Nonviolent crime index (2)	Violent crime index (3)	Nonviolent crime index (4)	Violent crime index (5)	Nonviolent crime index (6)
Post	–0.20	–0.032	–0.30***	–0.0081	–0.20**	–0.015
	(0.12)	(0.06)	(0.09)	(0.04)	(0.07)	(0.04)
LoMuslim	–0.71**	–0.44				
	(0.30)	(0.31)				
Post x LoMuslim	–0.37**	–0.037				
	(0.17)	(0.08)				
HiAlcohol			0.50	0.55		
			(0.31)	(0.45)		
Post x HiAlcohol			–0.52**	–0.19*		
			(0.24)	(0.10)		
Interior					0.086	0.52
					(0.30)	(0.38)
Post x Interior					–0.53***	–0.093
					(0.18)	(0.08)
N	2,812	2,812	2,812	2,812	2,812	2,812
R^2	0.86	0.91	0.86	0.91	0.85	0.91

Notes: Heterogeneous effects of the alcohol ban, based on three characteristics of a district: proportion of Muslim population, proportion of males consuming alcohol, and border status. A

LoMuslim district have a proportion of Muslims lower than the average proportion of Muslims in Bihar (0.13). A *HiAlcohol* district is one where the proportion of males consuming alcohol is higher than the Bihar average (0.35), and an *Interior* district of Bihar is one that does not border another state or country. Data consist of district-level monthly reported crime data from January 2013 to February 2019, as obtained from Bihar Police and Jharkhand Police. Information on baseline alcohol consumption and Muslim population was obtained from NFHS 2015. The table reports coefficients of the specification estimated in eq. (2) of the main paper. All specifications control for district covariates and include calendar-month fixed effects and district-specific time trends. Standard errors, clustered at the district level, are shown in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4. Effect of the ban with a restricted sample of interior districts

	Violent crime index	Nonviolent crime index
	(1)	(2)
Post	–0.15	–0.14**
	(0.09)	(0.06)
Treat	0.23	0.39
	(0.95)	(1.13)
Post x Treat	–0.53***	0.026
	(0.19)	(0.09)
N	2,220	2,220
R^2	0.89	0.93

Notes: The table reports results from our estimation of equation (1) using a restricted sample of districts in Bihar and Jharkhand that are not on the state border of Bihar (these districts are indicated as *Interior districts of Bihar* and *Districts in Jharkhand that do not share a border with Bihar* in Figure 6). Our outcome variables are indices for violent (includes dacoity, kidnapping, murder, rape, riot, and robbery) and nonviolent crimes (includes theft and burglary). Data consist of district-level monthly reported crime from January 2013 to February 2019, as obtained from Bihar Police and Jharkhand Police. All specifications control for district covariates and include calendar month fixed effects and district-specific time trends. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively. Standard errors, clustered at the district level, are shown in parentheses.

Table 5. Police response in Bihar

	Probability of transfer			Total number of transfers		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Ban	0.184**	0.227**	0.211**	0.868	0.927	0.899
	(0.088)	(0.093)	(0.092)	(0.643)	(0.634)	(0.634)
terior District		0.126			0.376	
		(0.089)			(0.259)	
ost-Ban X Interior District		–0.102			–0.138	
		(0.081)			(0.088)	
Alcohol			0.071			0.310
			(0.096)			(0.280)
ost-Ban X Alcohol			–0.067			–0.078
			(0.088)			(0.096)
onth fixed effect	X	X	X	X	X	X
istrict fixed effect	X			X		
Observations	456	456	456	456	456	456
R^2	0.317	0.198	0.188	0.241	0.066	0.064

Notes: Columns 1 and 4 of the table report results from our estimation of equation (3) using a month-level data set comprising of all police transfers across all districts of Bihar in the year 2016. Columns (2–3) and (5–6) of the table report results from our estimation of equation (4) using the same data set. *Post-ban* is a binary variable that is equal to 1 for all post-ban months in 2016, from April onward. *Interior District* is an indicator that equals 1 for districts in Bihar that do not share a border with another state. *Alcohol* is an indicator that equals 1 for districts in Bihar where the average alcohol consumption is higher than the average alcohol consumption across all districts in Bihar. This indicator is constructed using data from the 2015–2016 round of the National Family Health Survey. The outcome variable *Probability of transfer* is an indicator equal to one for districts in Bihar where a transfer occurred during that month. The outcome variable *Total number of transfers* is the total number of transfers in the district in each month of 2016. Transfer data is extracted from digital copies of all transfer orders in 2016 for the Indian Police Service and the Bihar Police Service. Standard errors, clustered at the district level, are shown in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 6. Election and police response

	Transfer	Number of Transfers
	(1)	(2)
Post-election	0.079	0.158
	(0.064)	(0.107)
Month fixed effect	X	X
District fixed effect	X	X
Observations	228	228
R^2	0.348	0.461

Notes: The table reports results from our estimation of equation (3) using a district month-level data set recording transfer information of police chiefs for all districts of Bihar in 2015. *Post-election* is an indicator equal to one for the months of November and December of 2015. The outcome variable *Transfer* is an indicator equal to 1 if there was a police chief transfer in that district-month in 2015. The outcome variable *Number of Transfers* records the total number of transfers of police chiefs in that district-month in 2015. Standard errors, clustered at the district level, are shown in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 7. Political representation and impact on crime

	JDU		RJD		JDU or RJD	
	Violent crime index	Non-violent crime index	Violent crime index	Non-violent crime index	Violent crime index	Non-violent crime index
	(1)	(2)	(3)	(4)	(5)	(6)
Post	–0.295*	–0.107*	–0.338***	0.005	–0.218*	–0.022
	(0.148)	(0.061)	(0.117)	(0.047)	(0.111)	(0.056)
Treat x Post	–0.067	0.028	–0.039	–0.028	–0.051	–0.008
	(0.061)	(0.023)	(0.059)	(0.023)	(0.034)	(0.014)
Treat	–0.249***	–0.243***	–0.121	–0.198	–0.286***	–0.341***
	(0.071)	(0.089)	(0.114)	(0.154)	(0.064)	(0.096)
Observations	2,812	2,812	2,812	2,812	2,812	2,812
R^2	0.858	0.915	0.853	0.909	0.861	0.925

Notes: The table reports results from our estimation of equation (5) using data from Bihar only. *Treat* is a continuous variable and measures the intensity of exposure to the ruling political party in the state and equals the number of constituencies (in a district), where the political party won in the 2015 state election. In the 2015 Bihar election, the winning coalition party was formed by Janata Dal United (JDU) and the Rashtriya Janta Dal (RJD). Our outcome variables are indices for violent (includes dacoity, kidnapping, murder, rape, riot, and robbery) and nonviolent crimes (includes theft and burglary). Data consist of district-level monthly reported crime data from January 2013 to February 2019, as obtained from the Bihar Police and constituency-level election data for the 2015 Bihar state election, as obtained from the Election commission. Vote shares are used to identify winning politicians and their party affiliations for each constituency. All specifications control for district covariates and include calendar month fixed effects and district-specific time trends. Standard errors, clustered at the district level, are shown in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 8. Effect of the ban excluding months pre-ban and post-ban

	Violent crime index	Nonviolent crime index
	(1)	(2)
Treat X Post	–0.27*	0.027
	(0.14)	(0.07)
N	4,216	4,216
R^2	0.84	0.90

Notes: The table reports results from our estimation of equation (1) using a restricted panel that excludes the months from January 2016 to June 2016 (the ban was implemented in April 2016). Our outcome variables are indices for violent (includes dacoity, kidnapping, murder, rape, riot, and robbery) and nonviolent crimes (includes theft and burglary). Data consist of district-level monthly reported crime data from January 2013 to February 2019 (excluding January-June 2016), as obtained from Bihar Police and Jharkhand Police. All specifications control for district covariates and include calendar month fixed effects and district-specific time trends. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively. Standard errors, clustered at the district level, are shown in parentheses.

Table 9. Robustness to different indices of violent and nonviolent crime

	Violent crime index (1)	Nonviolent crime index (2)	Violent crime index (3)	Nonviolent crime index (4)	Violent crime index (5)	Nonviolent crime index (6)
Treat x Post	–0.10	0.043	–0.22*	0.043	–0.088*	0.030
	(0.07)	(0.06)	(0.11)	(0.06)	(0.05)	(0.04)
N	4,588	4,588	4,588	4,588	4,588	4,588
R^2	0.86	0.90	0.84	0.90	0.82	0.90

Notes: The table reports results from our estimation of equation (1) using various transformations of the outcome variable as a robustness check. Our outcome variables are indices for violent (includes dacoity, kidnapping, murder, rape, riot, and robbery) and nonviolent crimes (includes theft and burglary). Columns (1) and (2) construct a simple average of standardized violent and nonviolent crime categories when standardized with respect to the control state, whereas columns (5) and (6) construct the same index, standardized with respect to the overall crime in both states. Columns (3) and (4) report original estimates from the paper. Data consist of district-level monthly reported crime data from January 2013 to February 2019, as obtained from Bihar Police and Jharkhand Police. All specifications control for district covariates and include calendar month fixed effects and district-specific time trends. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively. Standard errors, clustered at the district level, are shown in parentheses.

Table 10. Difference-in-differences estimator using de Chaisemartin and D’Haultfoeuille (2022)

	Estimate	SE	LB CI	UB CI
Violent crime	–0.3573691	0.113094	–0.5790333	–0.1357049
Nonviolent crime	0.0372294	0.1203697	–0.1986952	0.2731539

Notes: The table reports results of a difference-in-difference model based on the estimator described in de Chaisemartin and D’Haultfoeuille (2022) to account for any heterogeneous treatment effects in our setting. Our outcome variables are indices for violent crimes (includes dacoity, kidnapping, murder, rape, riot, and robbery) and nonviolent crimes (includes theft and burglary). Data consist of district-level monthly reported crime data from January 2013 to February 2019, as obtained from Bihar Police and Jharkhand Police. LB and UB refer to the lower-bound and upper-bound of the 95 percent confidence interval of the main estimate, and SE denotes standard error. All specifications control for district covariates and include calendar-month fixed effects and district-specific time trends. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively. Standard errors, clustered at the district level, are shown in parentheses.

Figure Legends

Figure 1. Location of Bihar and Jharkhand in India

Notes: Figure 1 presents the location of Bihar (the treated state) and Jharkhand (the control state) on a map of India. Jharkhand was created by splitting off several southern districts of Bihar in 2000; thus, Jharkhand has been conjectured to be fairly similar to Bihar in socioeconomic characteristics and used as a natural control state for Bihar in the literature (Muralidharan and Prakash 2017).

Figure 2. Districts in Bihar according to baseline alcohol consumption

Notes: Figure 2 presents the distribution of high and low alcohol-consuming districts across the state of Bihar. High (low) alcohol-consuming districts, shaded in dark (light), are identified using a binary indicator based on if alcohol consumption in the district was higher (lower) than the average alcohol consumption for all districts of Bihar. Alcohol consumption measures are obtained from the 2015–16 round of the National Family Health Survey, which uses a representative sample of households across districts in India.

Figure 3. Districts in Bihar according to baseline Muslim population

Notes: Figure 3 presents the distribution of Muslim minority and majority districts across the state of Bihar. Muslim minority (majority) districts, shaded in dark (light), are identified using a binary indicator based on if the Muslim population as a proportion of district total population was lower (higher) than the average Muslim population as a proportion of total population across all districts of Bihar. Population measures are obtained from the 2015–16 round of the National Family Health Survey, which uses a representative sample of households across districts in India.

Figure 4. Expenditure on liquor in Bihar and Jharkhand

Notes: Figure 4 plots the time-series of average monthly expenditure on all liquor products of households in Bihar and Jharkhand before and after the ban in April 2016. We use household monthly expenditure data from the Centre for Monitoring Indian Economy (consumption pyramid) for the periods from January 2014 to February 2019, averaged across households at the state-year-month level. The vertical line marks the year and month of the Bihar prohibition: April 2016.

Figure 5. Event study for violent and nonviolent crime

(A) Violent crimes

(B) Nonviolent crimes

Notes: Figure 5 reports regression estimates and their 95 percent confidence intervals from quarter-level event studies for the: (A) violent crime index and (B) nonviolent crime index. The crime indices are constructed using reported crime data for both Jharkhand and Bihar for the years 2013–2019. Estimation includes quarter and district fixed effects and district-specific time trends. Standard errors are clustered at the district level. The alcohol ban was implemented in April 2016. The solid black line indicates the quarter immediately prior to the ban, that is, January–March 2016. The ban was first announced in November 2015 (indicated by the dashed vertical line), which coincided with the elections in Bihar.

Figure 6. Interior and border districts of Bihar and Jharkhand

Notes: Figure 6 distinguishes the districts in Bihar and Jharkhand as to whether they lie along the state border of Bihar. The districts in Bihar that share a border with any other state are indicated as border districts of Bihar in the figure; we expect the ban to be less effective in these districts because of cross-border movement of alcohol. The other districts of Bihar that do not share a border with any other state are indicated as interior districts of Bihar. In a similar fashion, we also distinguish between districts in Jharkhand that do or do not share a border with Bihar. This distinction is relevant because districts that share a border with Bihar might experience spillover effects from the ban, as a result of alcohol seekers moving across the border.

Figure 7. Time-varying effects of the ban

(A) Violent crimes

(B) Nonviolent crimes

Notes: Figure 7 reports regression estimates and their 95 percent confidence intervals from OLS regressions of the (A) violent crime index and (B) nonviolent crime index for samples that include data up to the specified half-year. For example, the coefficient estimate for the violent crime index 2 half-years into the ban is derived from a regression using data for the entire pre-ban period and the first 2 half-years after the ban. Data consist of district-level monthly reported crime data from January 2013 to February 2019, as obtained from Bihar Police and Jharkhand Police. All specifications control for district covariates and include district-specific time trends and calendar month fixed effects. Standard errors are clustered at the district level.

Figure 8. Police transfers

(A) IPS & BPS officers

(B) Bihar Prohibition (Excise & Registration) Officers

Notes: Trends in the transfers of police officers over time in Bihar. Panel (A) plots the total transfers per month for all police officers in the Indian Police Service and the Bihar Police Service combined. Panel (B) plots the total transfers per month for all officers in the Bihar Prohibition (Excise and Registration) department. Transfer data is extracted from digital copies of all transfer orders, during November 2014–April 2017, for the police services and the Bihar Prohibition department. The vertical lines mark two events of interest within this time period: the dotted line marks the Bihar assembly election (November 2015), and the dashed line marks the alcohol prohibition coming into effect (April 2016).

Figure 9. Police infrastructure and resources

Notes: Trends in four measures of police infrastructure and resources for Bihar (dashed line) and Jharkhand (dotted line) from 2013 to 2019. Panel (A) plots the number of police stations, (B) plots the transport facilities per 100 policemen, (C) plots the population served per policeman, and (D) plots the area served per policeman in sq km. The data are at the state–annual level and are obtained from the Bureau of Police Resources and Development. The vertical line marks the year of the Bihar prohibition: 2016.

Figure 10. Police strength

(A): Actual police strength

(B): Vacancy in police strength

Notes: Trends in two indicators of police strength for Bihar (dashed line) and Jharkhand (dotted line) from 2013 to 2019. Panel (A) plots the actual police strength, which is defined as the number of police personnel employed by the state police force. Panel (B) plots the vacancy in police strength, defined as the difference between the sanctioned strength (positions meant to be filled) and the actual police strength (positions actually filled). The data are at the state–annual level and are obtained from the Bureau of Police Resources and Development. The vertical line marks the year of the Bihar prohibition: 2016.

Endnotes

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[1] Only 15 percent of all low-income countries reported having a written national alcohol policy, compared to 67 percent for high-income countries (WHO 2018).

[2] Hazardous drinking is characterized by bingeing and solitary consumption to the point of intoxication.

[3] For outcomes other than crime, see Pullabhotla (2017). They studied the effect of alcohol prohibition policies on education of children in India.

[4] A detailed discussion is presented in section 1 of the Online Appendix.

[5] Excise duties and taxes on liquor for human consumption are classified as items under the "State List" as per the Indian Constitution.

[6] Gujarat allows consumption of alcohol for nonresidents of the state, using a system of permits. At the time of this study, Mizoram had repealed its alcohol prohibition, which was reinstated

only recently, in 2019. Lakshadweep Islands, a union territory, has alcohol prohibition in place; however, this region is sparsely populated and was not an appropriate setting for our study.

[7] We formally test for parallel pre-trends between Jharkhand and Bihar in crime in Section 3.2.

[8] Standardization of each crime category is done with respect to the control group. The indices are generated using Principal Component Analysis (PCA).

[9]. We choose the violent versus nonviolent crime classification because the literature suggests that alcohol consumption is likely to impact violent crime more than nonviolent crime (Murdoch and Ross 1990; Cook and Moore 1993). Furthermore, this classification allows for the creation an index of crimes, instead of studying individual crimes, which address the issue of multiple hypothesis testing.

[10] Since alcohol is forbidden by Islamic dietary restrictions, the religious composition of districts creates a variation in pre-ban alcohol consumption levels.

[11] "Border" districts refer to those that share a border with another state or country such as Jharkhand, West Bengal, Uttar Pradesh, and Nepal. See Figure 6 for reference.

[12] We present further evidence on the state of policing in Bihar in Section 5.

[13] We also present heterogeneity analyses with continuous measures of alcohol consumption, Muslim population, and distance to the state border in Appendix A, Section 3.

[14] Note that "interior" means not sharing a border with Bihar; these districts of Jharkhand may share a border with other states or countries.

[15] This result, of reduced violent crime in the interior districts of Bihar, with no significant effect on nonviolent crimes, does not qualitatively change when we perform a triple difference specification using the unrestricted sample.

[16] Bihar Prohibition (Excise & Registration) is a state department responsible for handling alcohol excise revenue (before the prohibition) and enforcing the prohibition (after the ban was enacted).

[17] The transfer reports indicate that many transfers occur along with a promotion to a higher rank. A cornerstone of Indian bureaucracy is batch-level promotions, in which all officers in a batch are simultaneously promoted periodically, creating a high degree of seasonality in the transfer-posting of government officials within a year.

[18] Since the BPRD data are only available at the state–annual level, we do not have district-level information on police strength or resources. Therefore, we use police transfers as a proxy for police resources and use district information from the transfer orders.

[19] As an alternative specification, we also consider the fraction of constituencies in a district, and the results are qualitatively unchanged.

[20] The only other imaginable effect of an anticipatory reaction to the ban is a potential increase in crime in the months leading up to the ban. For example, people who anticipated a prohibition may have consumed alcohol in greater quantities in the months leading up to the ban, and as a result of the lowered inhibitions, may have committed more crimes. However, we find similar results to those in our paper when using a specification that excludes several months immediately before and after the ban. For further details, please refer to Section 6 of the Online Appendix. This result suggests that anticipatory reactions, if any, had a minimal impact on our estimates.

Online Appendix

Alcohol Ban and Crime: The ABC's of the Bihar Prohibition

Kalyani Chaudhuri, Natasha Jha, Mrithyunjayan Nilayamgode, and Revathy Suryanarayana

APPENDIX A: ADDITIONAL OUTCOMES

1. Contrast with Dar and Sahay (2018)
2. Alternate clustering of standard error
3. Heterogeneity tests with continuous measures of alcohol consumption
4. Placebo test
5. Effect of the ban on additional outcomes:
    - 5.1 Female voter support for the incumbent political party
    - 5.2 Gender-based violence
    - 5.3 Child welfare
    - 5.4 Women's participation in local elections
    - 5.5 Household consumption
6. First information reports
7. Residual of crime index
8. Summary statistics of district covariates
9. Month-level event study

1. Contrast with Dar and Sahay (2018)

We would like to briefly draw attention to and contrast our paper with the results of Dar and Sahay (2018) (henceforth, D&S). Both papers have dealt with the same question differently, leading to different conclusions. Contrary to our findings, D&S found an increase in crime after the alcohol ban and attributed the rise in crime to the crime-displacement theory.

Perhaps, the primary difference in the empirical specifications used by the two papers is in the choice of the dependent variable. We used standardized indices for crime numbers, whereas D&S used crime rates (crime per 1,000 of the population). The latter is problematic since they used older, time-invariant population data from the Indian Census (from five years before the ban), which could have biased and introduced a nonclassical measurement error in their outcome.

Another critical difference in the specifications employed by the two papers is the use of district-specific time trends, which we believe is required for accurate analysis; however, we showed that our results are robust to the inclusion and exclusion of these trends.

Finally, the two papers also differed in terms of the mechanisms used to explain the results. D&S argued (without evidence) that the prohibition increased police workload, reducing the ability of the police to control crimes other than prohibition. On the contrary, we found evidence to suggest that police capacity increased in Bihar in 2016 (Figures 8 and 9 in the paper), contradicting the police workload mechanism. Our paper found that the prohibition was effective in reducing the availability of alcohol in Bihar, which led to a reduction in violent crime (Figure 4 in the paper).

2. Alternate clustering of standard errors

In our paper, standard errors are clustered at the district level because districts are the primary administrative units in India. However, in Appendix Table 1, we showed that our estimates are robust to clustering at different levels. In columns (7) and (8), we adjusted our standard errors to account for spatial correlation. We calculated the Conley standard errors using a distance cutoff of 68 km and a serial autocorrelation cutoff of 3 months, with distances defined by a continuous geodesic measure of distance between district headquarters (HQ), calculated using Vincenty's formula. We noted that the Conley measure's standard errors were not too different from those presented in the paper, and accounting for spatial correlation does not appreciably change our results.

3. Heterogeneity tests with continuous measures

We tested the validity of our heterogeneity estimations using continuous measures of alcohol consumption, Muslim proportion, and distance to the Bihar state border. First, we constructed district-level measures for average alcohol consumption and the proportion of Muslims, using the National Family Health Survey 4 (NFHS) data. Next, we defined our continuous distance measure as the geographic distance from the center of a district to the nearest point on the state border.

Appendix Table 1. Effect of the ban on crime: Robustness to level of clustering

	Violent crime index (1)	Nonviolent crime index (2)	Violent crime index (3)	Nonviolent crime index (4)	Violent crime index (5)	Nonviolent crime index (6)	Violent crime index (7)	Nonviolent crime index (8)
Treat	–0.28	–0.23	–0.28	–0.23	–0.28	–0.23	–0.28	–0.23
	(0.31)	(0.27)	(0.21)	(0.17)	(0.35)	(0.26)	(0.16)	(0.10)
Post	–0.17**	–0.096**	–0.17**	–0.096*	–0.17*	–0.096***	–0.17***	–0.096**
	(0.07)	(0.04)	(0.07)	(0.06)	(0.08)	(0.03)	(0.06)	(0.04)
Treat	–0.22*	0.043	–0.22*	0.043	–0.22	0.043	–0.22**	0.043
x Post	(0.11)	(0.06)	(0.12)	(0.09)	(0.14)	(0.06)	(0.10)	(0.07)
SE clustering	district	district	district–year	district–year	state–year	state–year	Conley	Conley
N	4,588	4,588	4,588	4,588	4,588	4,588	4,588	4,588
R^2	0.84	0.90	0.84	0.90	0.84	0.90		

Notes: Data consist of district-level monthly reported crime data from January 2013 to February 2019, as obtained from Bihar Police and Jharkhand Police. The table reports coefficients of our main specification (eq. (1) in the main paper) on outcomes indicated in the column headings. Outcome variables are indices for violent crimes (dacoity, kidnapping, murder, rape, riot, and robbery) and non-violent crimes (theft and burglary). Standard errors (shown in parentheses) are clustered at the district level for columns (1) and (2), at the district–year level for columns (3) and (4), and at the state–year level for columns (5) and (6). In columns (7) and (8), we used Conley standard errors to adjust for spatial correlation. All specifications control for district covariates and include calendar month fixed effects and district-specific time trends. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Then, we interact these measures with the post variable as illustrated below:

$$y_{dt} = \alpha + \beta_1 Post_t + \beta_2 cont_d + \beta_3 cont_d * Post_t + \delta_d * t + \gamma_d + \eta_t + e_{dt} \qquad \text{(A1)}$$

We estimated equation A1 with three different continuous measures (*cont*) at the district level: average alcohol consumption, the proportion of the Muslim population, and distance to the state border. We present the combined results in Appendix Table 2. We found that the ban was more effective in those areas with higher baseline alcohol consumption (columns 1–2) and areas with a lower Muslim population (columns 3–4). We also noted that violent crime decreased more in those districts farther away from the state border (columns 5–6).

Appendix Table 2. Heterogeneity analyses using continuous measures

	Violent crime index (1)	Nonviolent crime index (2)	Violent crime index (3)	Nonviolent crime index (4)	Violent crime index (5)	Nonviolent crime index (6)
Post	0.40	0.27*	–0.59***	–0.12**	0.096	0.029
	(0.33)	(0.15)	(0.14)	(0.06)	(0.13)	(0.07)
Mean alcohol	4.24**	4.20				
	(1.85)	(3.03)				
Post x Mean alcohol	–2.74**	–1.08**				
	(1.19)	(0.51)				
Prop. of Muslim			2.55*	1.30		
			(1.31)	(1.26)		
Post x Prop. of Muslim			1.19**	0.46**		
			(0.45)	(0.20)		

Distance to border					–0.0027	0.00098
					(0.01)	(0.01)
Post x Distance to border					–0.013***	–0.0021
					(0.00)	(0.00)
N	2,812	2,812	2,812	2,812	2,812	2,812
R^2	0.86	0.91	0.85	0.91	0.85	0.91

Notes: Heterogeneous effects of the alcohol ban, based on three characteristics of a district: mean proportion of males consuming alcohol, mean proportion of Muslim population, and distance to the state border. Data consist of district-level monthly reported crime data from January 2013 to February 2019, as obtained from the Bihar Police and Jharkhand Police. Information on baseline alcohol consumption and Muslim population was obtained from the NFHS 2015. The table reports coefficients of the specification estimated in Appendix eq. (A1). All specifications control for district covariates and include calendar-month fixed effects and district-specific time trends. Standard errors, clustered at the district level, are shown in parentheses. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

4. Placebo test

A potential concern is that our regression specification may be picking up nonlinear, time-varying, district-specific effects on crime rather than the timing of the ban itself. To address this issue, we ran a placebo-like test, in which we randomly reassigned the post variable across all time periods while retaining the overall proportion of periods that are marked post-intervention (post = 1). In other words, 39 randomly selected months among the 74 months in our sample were marked as post = 0, and the other 35 were marked as post = 1. If the effect picked up by our main regression was indeed related to the ban timing, and not nonlinear, district-specific time variation in crime, then the coefficient of interest from this “placebo” regression must, on average, be insignificant. We tested this by repeating this process 100 times and applying a t-test to the distribution of coefficients (Appendix Table 3). We found that the "placebo" test returns, on average, a null effect on both violent and nonviolent crime, unlike the standard specification in which the ban reduced violent crime. This finding indicates that the placebo test does not find an effect where one should not exist, and therefore, our results are likely due to the ban affecting crime.

5. Effect of the ban on additional outcomes

Other than crime, we also tested for the effect of the Bihar prohibition on the following outcomes:

5.1 Female voter support for the incumbent political party

The incumbent party in Bihar before the 2015 Assembly Election was Janata Dal (United) [JD(U)]. To study the effect of the ban on female vote share for JD(U), we obtained constituency-level data on the number of female and male voters in the Bihar Assembly election of 2015, when the alcohol prohibition was an electoral promise by the incumbent chief minister.[1] Using data from the Election Commission, we created an assembly–constituency-level data set containing the number of voters and electors by gender, in the Bihar Assembly election of 2015. We also constructed variables on whether JD(U) contested and won that constituency. Although we knew the total number of women voters and electors, as well as the winning party in each constituency, the Election Commission does not release data on the number of women who voted for a particular party or candidate. As a proxy, therefore, we studied the number of female voters in constituencies in which JD(U) won in 2015 versus those in which JD(U) did not win.

We first restricted our sample to those constituencies where JD(U) contested the 2015 election. We then divided the constituencies into two groups based on whether their women voter turnout was above or below the median women voter turnout in Bihar in the 2015 Assembly election. Calling these two groups "hi-turnout" and "lo-turnout," we then tested the null hypothesis that JD(U) was equally likely to win a hi-turnout or a lo-turnout constituency, against the alternative that the chances of winning were higher for a hi-turnout constituency.

$$H_o : JDUwin_{hiturnout} - JDUwin_{loturnout} = 0$$

[1] The 2015 election was held before the actual ban came into effect. Thus, in this question, we are testing the effect of the *electoral promise* of the alcohol ban on political support for JD(U), rather than the effect of the ban itself.

$$H_a : JDUwin_{hiturnout} - JDUwin_{loturnout} > 0$$

With a p-value of 0.18, we failed to reject the null hypothesis that JD(U) was equally likely to win a constituency in the hi-turnout and lo-turnout groups (Appendix Table 4). Thus, under our assumptions, there is insufficient evidence to conclude that the promise of the alcohol ban significantly increased women voter shares for JD(U). The results are unchanged for alternate definitions of the high-turnout and low-turnout groups (when we define the turnout cutoff as the mean or 75th percentile of women voter turnout in the election).

Appendix Table 3. Women vote share for Janata Dal (United)

	Hi women-turnout constituency	Lo women-turnout constituency	Difference (hi-lo)
Proportion of constituencies won by JD(U)	0.75	0.66	0.085 [0.091]
N	51	50	

Notes: Data consists of electoral outcomes for the Bihar Assembly election in November 2015, where Janata Dal United (JD(U)) was the incumbent party. All data are obtained from the Election Commission of India. We divided all electoral constituencies into two groups based on whether their female voter turnout was above or below the median turnout of women voters in 2015. We then conducted a one-sided t-test of difference in likelihood of JD(U) winning the constituency. Our alternative hypothesis is that JD(U) had a higher chance of winning a constituency that had an above-median turnout of women voters. Standard errors are in parentheses.

5.2 Gender-based violence:

For these crimes, we used the only source for reported crimes against women in India—the National Crime Records Bureau (NCRB). The NCRB reports crimes against women under various categories: sexual assaults, insults, rape, cruelty by husband or his family, dowry deaths, kidnapping of girls, importation of girls from foreign countries, and acid attacks. Here, we focused on the subset of crimes related to domestic violence: sexual assaults, insult to modesty, cruelty by a husband or his family, and dowry-related deaths.

We collected annual district-level data for all districts of Bihar and Jharkhand from the NCRB. The data are reported for the years 2014–2016 and 2019; data for 2017 and 2018 are unavailable. We used the data to create a district-level panel and used standardized total crimes against women as the outcome variable. We applied a two-way fixed effects empirical strategy with the following specification:

$$y_{it} = \beta_o + \beta_1 Post\ * Treat + \beta_2 D_i + \beta_3 T_t + \epsilon_{it} \qquad \text{(A2)}$$

The main outcome of interest is y_{it}, which is the standardized reported crime for each category in district *i* and year *t*. D_i and T_t represent district and year fixed effects, respectively. Standard errors are clustered at the district level. This specification cannot distinguish between the effect of a general change in domestic violence crime trends versus a causal effect. This issue may be addressed by including district-specific time trends (Khurana and Mahajan 2018); however, given the gaps in the post-period, including a district-specific time trend may be inappropriate. In the absence of district-varying time trends, our analysis is akin to a correlational interpretation. We did this analysis separately for each category, as well as the constructed standardized index, and reported results in Appendix Table 4.

Appendix Table 4: Impact on the ban on gender-based violence

	Assault on women	Insult to modesty	Dowry death	Cruelty	Index
	(1)	(2)	(3)	(4)	(5)
Interact	–0.385**	0.259	–0.403**	–0.266	–0.199
	(0.160)	(1.619)	(0.197)	(0.219)	(0.422)
Observations	247	247	247	247	247
R^2	0.531	0.373	0.853	0.799	0.541

Notes: Data consists of reported crimes against women at the district-annual level for all districts of Bihar and Jharkhand over the time period 2014-2016 and 2019. The table reports coefficients from estimation of appendix equation (A2) on crimes related to domestic violence such as sexual assaults, insult to modesty, cruelty by a husband or his family, and dowry-related deaths. Columns (1), (2), (3), and (4) report estimation coefficients on the standardized reported crime for the categories: assault on women, insult to modesty, dowry deaths, and cruelty by a husband or his family respectively. Column (5) reports the estimation coefficient for an index of all four crime categories. Standard errors (shown in parentheses) are clustered at the district level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

Our results suggest that, compared to Jharkhand, the post-ban period in Bihar saw a significant reduction in crime categories of assault (0.385 SD) and dowry-related deaths (0.403 SD). We also found a reduction in reported cruelty by husbands or their families, but this effect is not statistically significant. Limited data in the post-period and the aggregate nature of the data prevent us from interpreting these coefficients as causal. However, these estimates suggest a reduction in domestic violence in the post-ban period in Bihar compared to Jharkhand.

5.3 Child welfare:

We studied the effect of the alcohol ban on child welfare, using data from the Center for Monitoring Indian Economy (CMIE) household panel survey. The survey tracks monthly household spending on several household-level items. In particular, we have monthly expenditure from January 2014 to February 2019, for Bihar and Jharkhand. For child welfare, we focused on expenditures under two headings—spending on baby food and on toys. We estimated the following equation to quantify the effect of the ban on household expenditure on child welfare.

$$y_{ht} = \beta_0 + \beta_1 Post * Treat + \beta_2 Post + \gamma_h + \delta_m + \lambda_d * t + \epsilon_{ht} , \qquad \text{(A3)}$$

where y_{ht} denotes total expenditure on child welfare by household h in time period t. We include household fixed effects, calendar-month fixed effects, and district-specific time trends. We observed a significant increase in spending on these items after the ban, suggesting a positive impact on child welfare. In particular, we estimated a 51.4 percent increase in spending on baby foods and a 181.4 percent increase in spending on toys in Bihar, compared to Jharkhand in the post-ban period (Appendix Table 5).

Appendix Table 5. Effect of the ban on child welfare

	Baby food	Toys
	(1)	(2)
Treat x Post	1.26***	7.53***
	(0.42)	(0.46)
Mean	2.45	4.15
N	241,946	241,946
R^2	0.14	0.16

Notes: The table reports results from the estimation of equation (A3). We use household monthly expenditure data from the Centre for Monitoring Indian Economy (consumption pyramid) for the periods from January 2014 to February 2019. Our outcome variables include monthly expenditure (in Rs) on baby foods and toys. All specifications control for household fixed effects, calendar-month fixed effects and district-specific time trends. Standard errors, shown in parentheses, are clustered at the household level. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent levels, respectively.

5.4 Women's participation in local elections:

For this outcome, we considered the state Assembly elections, which are held every five years. We used data on the two most recent Assembly elections in Bihar: 2020 (post-ban) and 2015 (pre-ban). We explored the following two indicators of women's political participation in Bihar: (1) the number of women who filed nominations, as a fraction of total nominations filed; and (2) the number of women contestants as a proportion of total contestants in the election. We collected these data at the Assembly-Constituency level for a total of 243 constituencies for two years: 2015 and 2020. We conducted a one-sided t-test of difference in means, using the following hypotheses for each indicator of political participation:

$$H_o : Participation(2015) - Participation(2020) = 0$$

$$H_a : Participation(2015) - Participation(2020) < 0$$

We found evidence to reject the null hypothesis in favor of the alternate for both measures of political participation (Appendix Table 6). The proportion of women who filed nominations increased from 8.3 percent in 2015 to 10.6 percent in 2020. Similarly, the proportion of women who contested the election increased from 7.9 percent (2015) to 10.2 percent (2020). Both these differences are statistically significant at the 1 percent level.

Appendix Table 6. Women's political participation in Bihar after the prohibition

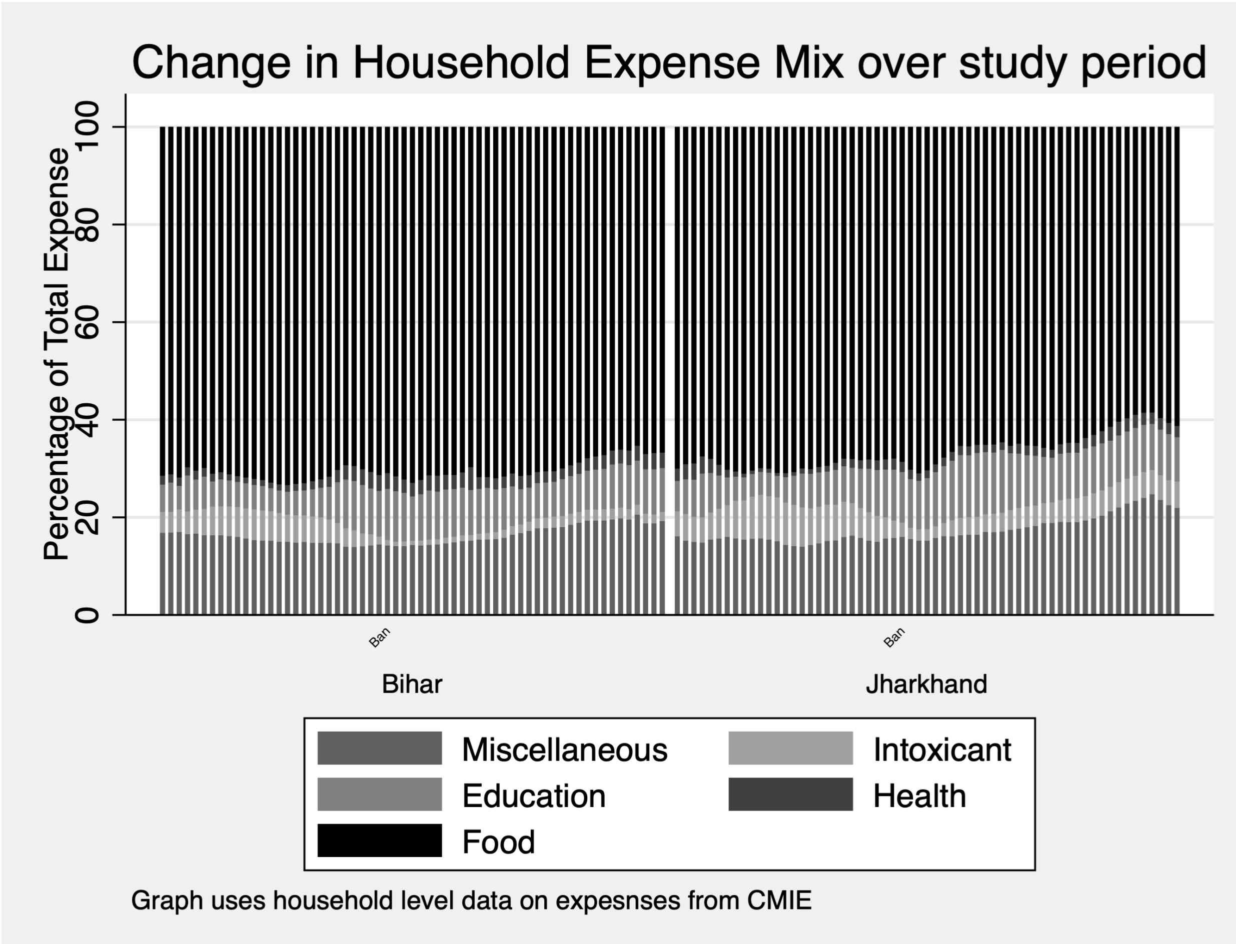
Indicator of women's political participation	2015	2020	Difference (2015–2020)
Women nominations/Total nominations	0.082632	0.105713	-0.023081
			(0.0076096)
Women contested/Total contested	0.078761	0.101614	-0.022854
			(0.0079277)
N	243	243	

Notes: Change in women's political participation in the Bihar Assembly elections after the prohibition. Two indicators of women's political participation: proportion of total nominations filed and proportion of total seats contested in the Bihar Assembly elections of 2015 (pre-prohibition) and 2020 (post-prohibition). Data source: Election Commission of India. We conducted a one-sided t-test of difference in mean political participation between 2015 and 2020. Our alternative hypothesis was that the mean political participation in 2020 was greater than that in 2015. Standard errors are in parentheses.

5.5 Household consumption:

We studied five different categories of household expenditure using the CMIE data—food, health, education, intoxicant, and other expenses. We plotted the proportion of household expenses on each of these items for every month over the period January 2014 to February 2019, for both Bihar and Jharkhand (Appendix Figure 1). As we move from top to bottom, the graph represents the proportion of total expenses spent on food, health, education, intoxicant, and other expenses, in that order, for the average household in a given month. As we move from left to right, the graph represents how this mix changed over our study period. The graph suggests no abrupt changes to the expenditure mix between the pre-ban and post-ban periods within each state, except for the decline in share of intoxicants for the Bihar post-ban period.

Appendix Figure 1. Change in household consumption



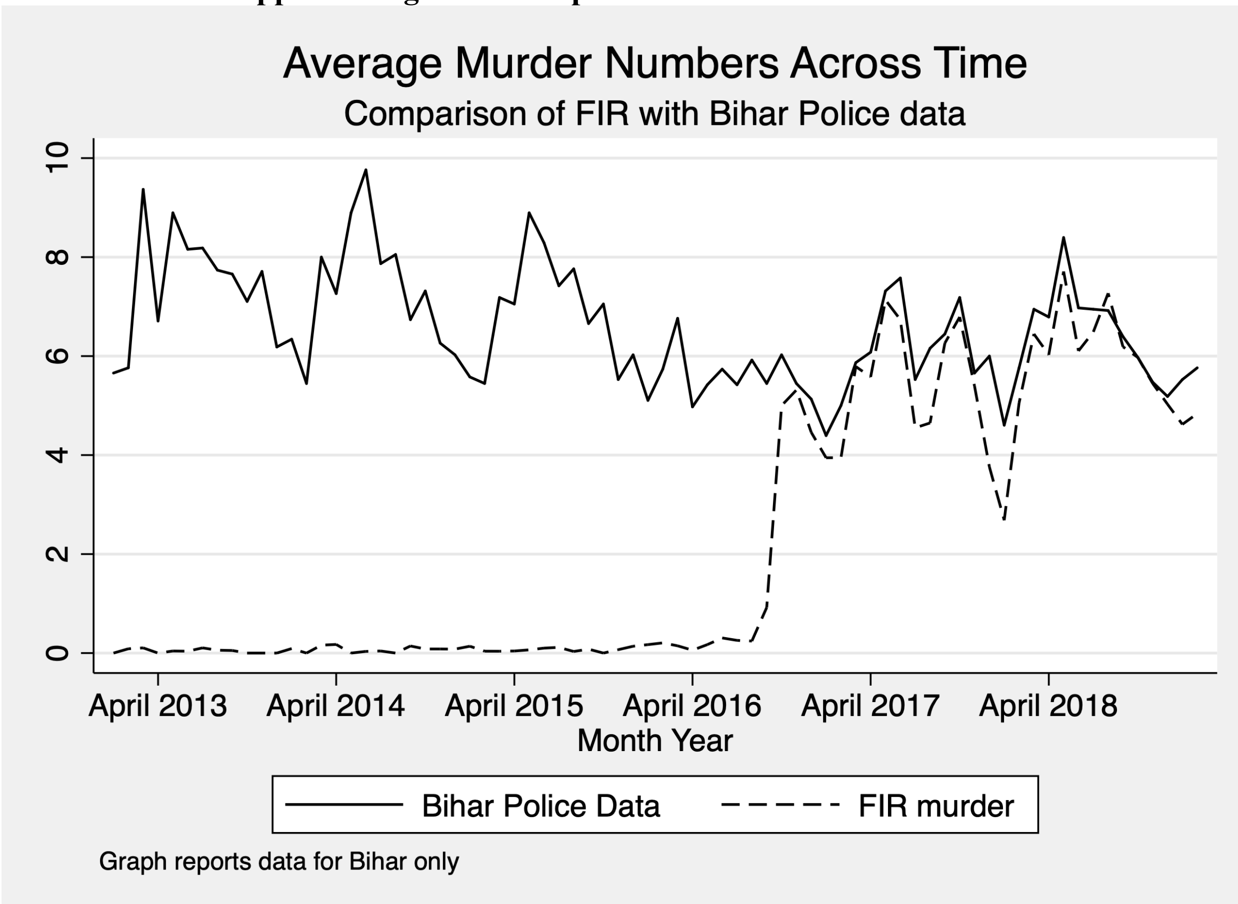
Notes: The figure plots the monetary value of monthly household consumption, by expense categories as a proportion of total monthly household expenditure for the time period of the study. Each bar graph is split into the monthly share of expense categories as a proportion of total monthly expense. Household monthly consumption data is obtained from the Centre for Monitoring Indian Economy (consumption pyramid) for the periods January 2014 to February 2019.

6. First Information Reports of crime

A First Information Report (FIR) is a written document prepared by the police when they receive information about the commission of a cognizable offense. We collected FIR data for 2013–2020, from the Bihar Police website and compiled a data set with the following information: FIR number and incident date, complainant and accused details, police station, and Indian Penal Code (IPC) section. Although FIR level information does not necessarily translate into arrests or indictment, we assume it to be a reasonable proxy of arrest data for certain types of crimes. As per Section 41 of the Code of Criminal Procedure, 1973, the police may arrest without warrant under the following categories: (a) persons involved in any cognizable offense; (b) against whom a reasonable complaint has been made, or credible information has been received. Using the information on IPC sections, we can flag all cognizable offenses. Moreover, filing an FIR, in itself, constitutes a "reasonable complaint" or "credible information."

Using murder-related FIRs, we employ the FIR data to execute a sanity check on the data we used for our primary analysis. Several reasons make murder an ideal choice for this exercise. First, murder is a cognizable offense. Second, an FIR for murder involves producing a dead body. Though macabre, this reduces any concerns of an extraneous FIR being filed. Appendix Figure 2 plots the average instances of murder (Section 302) filed in the FIR data for our study period. The line for FIR murder represents the average murder-related FIRs (Section 302) filed. Publishing of FIR details online increased during 2016, with data poorly captured prior to 2016. However, post-2016, the FIR data comes close to the data used in our analysis. This corroboration from an alternate data source provides confidence in our primary data analysis.

Appendix Figure 2. Comparison of FIR with Bihar Police data



Notes: The graph plots and compares the number of murders as recorded in two separate sources of data namely the list of First Information Reports (FIRs) and the crime incidence data released by the Bihar police (the main crime data used in the paper). The solid line reports the average number of murders across all districts in the Bihar police data. The dashed line reports the average number of First Information Reports pertaining to the Indian Penal Code Section 302, across all districts in Bihar. Section 302 of the IPC details punishment for the accused in the event of a murder. The Bihar police data is the data used in the main analysis and is obtained from aggregated district monthly crime reports published on the Bihar police website. The First Information Reports data is obtained from the Bihar police website for the period 2013-2020.

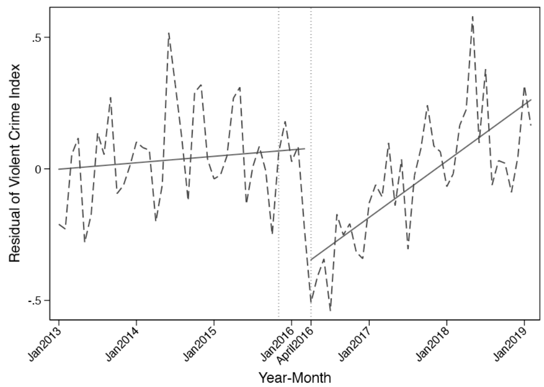
7. Residual crime

Appendix Figure 3 is a simple illustrative representation of the residual crime statistics in both states over time, after accounting for calendar-month fixed effects and district covariates. These figures were generated using the regression in equation (A2), separately for violent and nonviolent crime:

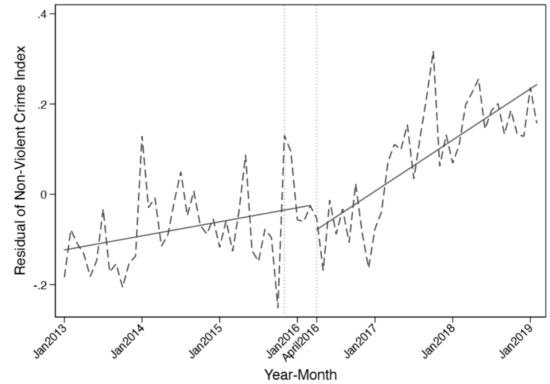
$$C_{dt} = \beta D_d + \gamma_m m_t + \epsilon_{dt} \tag{A4}$$

D_d is a vector of time-invariant district covariates, m_t is a categorical variable that tracks calendar months, and ϵ_{dt} is the residual of interest. We then averaged this residual across all districts in a state to generate the plots in Appendix Figure 3. These figures plot the residual trend of crime in Bihar, after accounting for the covariates that we also controlled for in our main regression specification, indicating that this trend graph combines the impact of the ban, the district-averaged residual from our main regression (which should, by standard assumption, be zero), and an averaged district-specific time trend for a sample restricted to the state of Bihar.

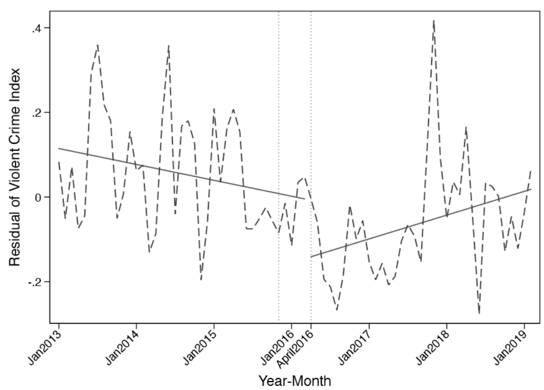
Appendix Figure 3. Residual of crime index over time



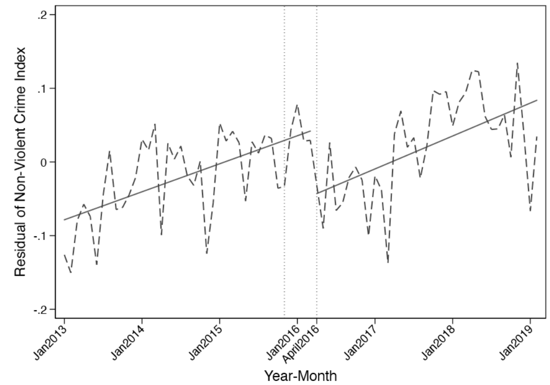
(a) Violent crimes, Bihar



(b) Nonviolent crimes, Bihar



(c) Violent crimes, Jharkhand



(d) Nonviolent crimes, Jharkhand

Notes: This figure reports the residual of crime indices in Bihar and Jharkhand, separately for violent and nonviolent crime indices. Data consist of district-level monthly reported crime data from January 2013 to February 2019, as obtained from the Bihar Police and the Jharkhand Police. The residuals were plotted, after extracting calendar-month fixed effects and district covariates. The alcohol ban was implemented in April 2016. The alcohol ban was first announced in November 2015, which coincided with the elections in Bihar.

8. Summary statistics of district covariates

We present the baseline summary statistics of district covariates used in our regression specifications for Bihar and Jharkhand in Appendix Table 7. We obtained district-wise data for the proportion of SC's (Scheduled Castes) and ST's (Scheduled Tribes) in the population, sex ratio, male literacy rate, male employment rate, and the proportion of population engaged in agriculture from Census of India, 2011. We used male literacy and employment rates rather than the overall rates because of the imbalance in alcohol consumption by gender. We also used the total area and total population of each district from the Census. Variables related to alcohol consumption and Muslim population were obtained from the National Family Health Survey (2015–16). In column (3) of Appendix Table 7, we report the mean difference between the two states in terms of these variables.

Appendix Table 7. Summary statistics

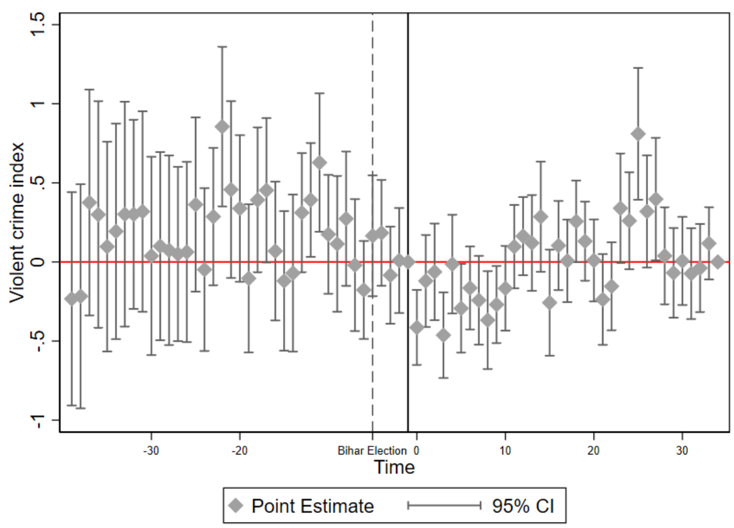
	Bihar	Jharkhand	Difference
SC/ST population	0.17	0.43	–0.253***
	(0.04)	(0.18)	
Sex ratio	0.94	0.95	–0.016***
	(0.02)	(0.02)	
Literacy rate–male	3.21	3.83	–0.619***
	(0.52)	(0.84)	
Employment rate–male	0.46	0.5	–0.038***
	(0.02)	(0.02)	
Agriculture workers	0.27	0.1	0.175***
	(0.07)	(0.04)	
Total area	2,477.97	3,321.5	–843.526**
	(1,069.73)	(1,403.8)	
Total population person	2,739,459	1,374,506	1,364,953.680***
	(1,278,796)	(681,960.6)	
Drinks alcohol (yes/no)	0.3	0.42	–0.117***
	(0.08)	(0.1)	
Drinks alcohol almost every day (yes/no)	0.14	0.15	–0.008
	(0.08)	(0.07)	
Proportion of Muslims	0.14	0.13	0.010
	(0.13)	(0.09)	

Notes: This table reports summary statistics for the district characteristics and district level variables used in our heterogeneity analyses separately for Bihar and Jharkhand. District-level characteristics were obtained from Census 2011 data. Data on baseline alcohol consumption and religious demographics for districts in Bihar and Jharkhand were obtained from National Family Health Survey 2015–16. The last column presents results from a t-test for differences between the two states for each variable.

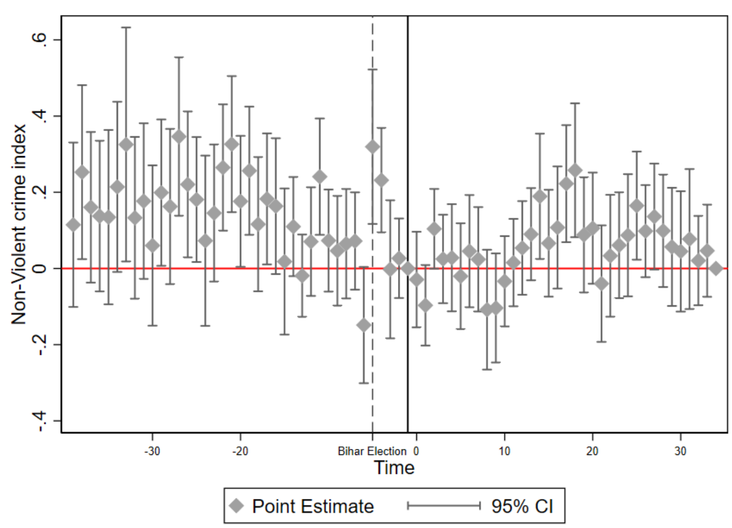
9. Month-level event study

As an alternative to the quarterly event study graphs shown in the main paper, we present here event study graphs at the month-level (Appendix Figure 4). As can be seen, the month-level data has much noise that does not readily allow for a clear graphical presentation. Thus, with clarity in mind, we used a more temporally aggregated version of the data in the form of a quarterly event study in the main paper. Discounting the greater level of short-term variation in the monthly graph, the general trends we observed are the same, regardless of the level at which the data is aggregated (monthly, quarterly, or annually).

Appendix Figure 4: Month-level event study for crime



(a): Violent crimes



(b): Non-violent crimes

Notes: Figure reports regression estimates and their 95 percent confidence intervals from month-level event studies for: (a) violent crime index and (b) nonviolent crime index. The crime indices are constructed using reported crime data for both Jharkhand and Bihar for the years 2013–2019. Estimation includes calendar month and district fixed effects and district-specific time trends. Standard errors are clustered at the district level. The alcohol ban was implemented in April 2016. The solid black line indicates the quarter immediately prior to the ban, i.e., January – March, 2016. The ban was first announced in November 2015 (indicated by the dashed vertical line), which coincided with the elections in Bihar.

APPENDIX B: DATA APPENDIX

In April 2016, the Indian state of Bihar implemented a statewide ban on the production, consumption, and possession of alcohol. Using a difference-in-differences approach, this paper presents our study of the effect of the alcohol prohibition on a portfolio of crimes in the state. We combined multiple sources of publicly available data to create a panel data set, recording district month-level crime information for a six-year period for Bihar and the neighboring control state of Jharkhand.

For Bihar, we also collected cross-sectional measures of pre-ban alcohol consumption and demographic characteristics at the district level. Finally, we also examined trends of policing outcomes, first-stage alcohol consumption, First Information Reports, and electoral outcomes in Bihar. This section describes the sources for all important variables in our paper, as well as additional outcomes studied in Appendix A.

1. Crime data

The main source of crime data for our analysis was the district-level monthly crime statistics, published by the Bihar state police department (http://police.bihar.gov.in/). For our difference-in-differences analysis, we used the neighboring state of Jharkhand as a control group and used district-level monthly crime statistics published by the Jharkhand state police. We used data for 8 different crime categories (categories for which data was available for both states) for the period

January 2013–February 2019. Thus, we created a panel of reported incidence of 8 crime categories for 62 districts (38 in Bihar and 24 in Jharkhand), over a period of 74 months.

Classification of crime categories: We used the definitions of violent and nonviolent crime as per the National Crime Records Bureau of India to classify our crime categories (https://ncrb.gov.in/sites/default/files/crime_in_india_table_additional_table_chapter_reports/Chapter3-15.11.16_2015.pdf). Violent crimes include those crimes with "bodily or property harm" or threat thereof. As per this definition, 6 crime categories in our sample (murder, rape, kidnapping, dacoity, robbery, and riots) constituted violent crimes, whereas burglary and theft constituted nonviolent crimes. Using this classification, we created a standardized index of reported violent and nonviolent crimes and used them as our outcome variables. Standardization of each crime category was done with respect to the control group. The indices were generated using Principal Component Analysis.

2. Baseline alcohol consumption and demographic data

We constructed measures of pre-ban alcohol consumption and Muslim population for each district in Bihar, using the fourth (2015–16) round of the National Family Health Survey (NFHS) of India. The NFHS is conducted roughly every 10 years in representative samples of households across the districts of India. The survey collects information on various demographic and health characteristics, including fertility, mortality, religion, maternal, and child health outcomes. Use of the survey enabled our generation of binary indicators of high baseline alcohol consumption and low Muslim population for each district of Bihar. We tagged districts as "high baseline consumption" if alcohol consumption was higher than the average alcohol consumption for all Bihar districts in our sample. An identical procedure was used for tagging districts as "low Muslim population," with respect to the average proportion of Muslims in Bihar. We also obtained data from the 2011 Census of India for district-level demographic information to control for time-invariant district characteristics that could have affected crime in both states. We constructed 5 variables from the Census data for each district: the proportion of backward communities (Scheduled Castes and Tribes) among the population, sex ratio, male literacy rate, male employment rate, and the proportion of the working population engaged in agriculture. We used male literacy and employment rates, rather than the overall rates, because of the imbalance in alcohol consumption by gender. We also obtained the area and total population of each district from the Census. Using district names as identifiers, we merged the Census data with the crime data to obtain our final panel data set.

3. Police outcomes

Other than our causal analysis, we also studied trends in two policing outcomes (police transfers and police infrastructure) in Bihar using multiple data sources. For police transfers, we obtained digital copies of all transfer orders in the Indian Police Service (Bihar state) and the Bihar Police Service (http://home.bihar.gov.in/CMS/archiveData/Transfer.aspx). From these documents, we created a data set of the total number of transfers per month over the period November 2014 (one year before the Bihar Assembly election) to April 2017 (one year after the alcohol ban came into effect). Using these data, we studied trends of the number of police transfers per month for the state of Bihar. For 2016 (the year of the prohibition), we also noted the district for each transfer order and assembled a data set recording (a) the probability of a transfer (an indicator for whether a transfer occurred that month); and (b) the total number of transfers per district per month in 2016. We then examined differences in police transfers in the months before and after the prohibition (April 2016).

For our second policing outcome, police infrastructure and resources, we collected new data from the Bureau of Police Resources and Development (BPRD), a national repository of police indicators for all Indian states reported at the annual level (https://bprd.nic.in/content/62_1_DataonPoliceOrganizations.aspx). We collected data on 6 indicators: the number of police stations, transport facility per 100 policemen, population per policeman, area per policeman, total strength of the police force, and vacancies in the police force. We used this data to visually examine trends in police infrastructure for Bihar and Jharkhand at the state–annual level for our study period 2013–2019.

4. Alcohol consumption

We studied trends in alcohol consumption before and after the ban using data from the Centre for Monitoring Indian Economy (Consumer Pyramid). This is a large household panel consisting of an all-India representative sample of over 200,000 households, with monthly consumption expenses for 153 expenditure categories. From the Consumer Pyramids data set, we obtained the average household monthly expenditure (INR) on alcohol for all households in Bihar and Jharkhand for our study period: January 2014–February 2019. We aggregated the data to the state level and plotted the monthly average expenditure on alcohol over time in order to study the first-stage effect of the Bihar prohibition on alcohol consumption (expenditure).

5. Additional variables

5.1 Gender-based Violence:

For this outcome, we used the only source for reported crimes against women in India—the National Crime Records Bureau (NCRB). NCRB reports crimes against women under various heads: sexual assaults, insults, rape, cruelty by husband or his family, dowry deaths, kidnapping of girls, importation of girls from foreign countries, and acid attacks. We focused on four categories: sexual assaults, insult to modesty, cruelty by a husband or his family, and dowry-related deaths. We collected annual district-level data for all districts of Bihar and Jharkhand from the NCRB. The data were reported for the years 2014–2016 and 2019; data for 2017 and 2018 are unavailable. We used the data to create a district-level panel and standardize the total crimes against women to create our outcome variables.

5.2 First Information Reports:

A First Information Report (FIR) is a written document prepared by the police when they receive information about the commission of a cognizable offense. We collected FIR data for 2013–2020 from the Bihar Police website and compiled a data set with the following information: FIR number and incident date, complainant and accused details, police station, and Indian Penal Code (IPC) section. Although FIR level information does not always translate into arrests or indictment, we assumed it to be a reasonable proxy of arrest data for certain types of crimes. Particularly, we used murder-related FIRs to execute a sanity check on the crime data used for our primary analysis.

5.3 Women's political participation:

We explored the effect of the ban on multiple outcomes for female political participation, such as (a) female vote share for the political party that promised to implement prohibition, and (b) women contesting in local elections. For (a), we obtained Constituency-level data on the number of female and male voters in the Bihar Assembly election of 2015, when alcohol prohibition was an electoral promise by the incumbent chief minister. Using data from the Election Commission, we created an Assembly–Constituency-level data set containing the number of voters and electors, by gender, in the Bihar Assembly election of 2015. We also constructed binary indicators for whether JD(U) contested and won that constituency. For (b), we used data on the two most recent Assembly elections in Bihar: 2020 (post-ban) and 2015 (pre-ban). We explored the following two indicators of women's political participation in Bihar: (1) number of women who filed nominations as a fraction of total nominations filed, and (2) number of women contestants as a proportion of total contestants in the election. From the Election Commission website, we collected data at the Assembly–Constituency level for a total of 243 constituencies for two years: 2015 and 2020.

5.4 Child welfare:

We studied the effect of the alcohol ban on child welfare using data from the Center for Monitoring Indian Economy (CMIE) household panel survey. The survey tracks monthly household spending on several household-level items. In particular, we have monthly household expenditure on several consumer items from January 2014–February 2019 for Bihar and Jharkhand. For child welfare, we used expenditure data (INR) on two outcomes—baby food and toys.

5.5 Political affiliation of districts

We tested whether the impact of the ban was heterogeneous across districts based on their level of exposure to the ruling party, that is, the number of elected representatives affiliated with the ruling party. We obtained the political affiliation data from the Trivedi Center for Political Data at Ashoka University, New Delhi (https://tcpd.ashoka.edu.in/data/). We compared districts with elected representatives aligned to the state ruling party against those with elected representatives belonging to the opposition political parties. The 2015 Bihar state election, when the Janata Dal United (JDU) and Rashtriya Janta Dal (RJD) comprised the winning coalition, was used to define ruling and opposition coalitions. State-level elections in India are held at the constituency level, whereas crime outcomes are reported at the district level, a more aggregated level. Thus, the election data was aggregated to the district level by using the number of constituencies to which elected representatives belonged to (1) JDU, (2) RJD, or (3) either JDU or RJD, to create a continuous treatment intensity variable.

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