Faith in Action: Does Ramadan Reduce Crime?

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Abstract

As a social institution, religion creates incentives or disincentives for 'appropriate' and 'inappropriate' social behaviour, including attitudes towards participation in criminal activities. The size of such an effect depends on the intensity of socio-religious norms regarding specific forms of crimes. Ramadan, a period of heightened religiosity among Muslims, involves expectations regarding socially desirable behaviour among individuals. Ramadan also involves mandated fasting, which affects local economic activity. How do such expectations and religious restructuring of daily life affect the incidence of crime among believers directly and/or indirectly? Using a difference-in-differences methodology and information from a unique dataset of criminal offences, we estimate the impact of Ramadan on criminal offences committed by those affected by it. Our identification strategy leverages the shifting timing of Ramadan through the Gregorian calendar to isolate the causal effect from confounding seasonality. We find that Ramadan leads to economically and statistically significant reductions in both violent and non-violent crimes, with estimated effect sizes ranging from 8 to 23 percent. We find suggestive evidence of these results being mediated by changes in religiosity and associated behavioural norms rather than by labour market channels. Our results provide suggestive evidence that informal institutions, such as religion, may complement formal state institutions in efforts to reduce crime.

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1 Introduction

"[F]ormal rules, even in the most developed economy, make up a small (although very important) part of the sum of constraints that shape choices; a moment's reflection should suggest to us the pervasiveness of informal constraints."

— Douglass C. North
Institutions, Institutional Change and Economic Performance (1990), pp. 36.

Becker (1968) conceptualises criminal behaviour not as a pathological deviation but as the outcome of rational choice, in which individuals offend when expected benefits exceed expected costs. While this framework emphasises legal sanctions, non-pecuniary costs, such as moral or psychological penalties, may also play an important role in shaping behaviour. Religion, one of the oldest social institutions, defines norms of right and wrong and may therefore increase the moral cost of deviance. A large literature has long studied the relationship between religiosity and anti-social behaviour (Durkheim, 1952, 1965; Berger, 1967; Hirschi and Stark, 1969). Recent experimental studies have found evidence of a positive relationship between aspects of religiosity and pro-social behaviour (Shariff and Norenzayan, 2007; Norenzayan and Shariff, 2008; Ahmed and Salas, 2008). However, religiosity is not static: periods of heightened religious salience may temporarily alter the non-pecuniary costs of deviance. Thus, these non-pecuniary motivations are heterogeneous across individuals and may vary over time for a given individual. This paper studies such variation by examining the impact of Ramadan-a month of intensified religious observance in Islam-on criminal behaviour among Muslims, using administrative crime data from Bihar, India.

Given that religiosity and adherence to religion are difficult to measure and are temporally persistent (over long durations), socially endogenous processes, establishing causal links between religion and crime, using long term temporal variation, is challenging. In the economics literature, after the early work of Heaton (2006), the preferred approach has been to focus on short-term or unexpected (and hence exogenous) shocks to religious participation or religiosity to generate causal estimates (Moreno-Medina, 2023; Johnston et al., 2025). We follow this approach by exploiting the shifting timing of Ramadan,

the ninth month of the Islamic calendar, as a source of plausibly exogenous variation in religious observance.

Ramadan is a period of heightened religiosity among Muslims across denominations, during which religious norms and practices become especially salient (Schielke, 2009; Balkaya-Ince et al., 2023). In addition to observing the fast from dawn to sunset, one of the Five Pillars of Islam, believers are encouraged to dedicate the month to introspection, spiritual discipline (piety), and increased acts of worship and charity. They are expected to refrain from sinful behaviour and cultivate empathy for the less fortunate (Encyclopaedia Britannica, 2026). Multiple Hadiths[1] indicate that those who observe Ramadan with sincerity and strive to live righteously may receive forgiveness for past sins (see *Sahih al-Bukhari*, Book of Fasting; *Sahih Muslim*, Book of Prayer).

Islam follows a lunar calendar consisting of 354 or 355 days, with Ramadan lasting 29 or 30 days. Because the Islamic year is shorter than the Gregorian year, Ramadan advances by approximately 10-12 days each year relative to the Gregorian calendar. This unique systematic rotation, arising from the use of a lunar calendar, generates a plausible exogenous variation in the timing of heightened religious observance across seasons, not observed for religious festivals of other religions that follow a solar or lunisolar calendar. Thus Ramadan provides a natural experiment that helps address the causal identification issue that confounds the study of the links between religious practices and crime. Similar identification strategies that exploit this temporal variation have been employed in previous work that examines the causal effect of Ramadan on various economic variables of interest, like maternal health (Almond and Mazumder, 2011), labour supply (Schofield, 2020), nutrition (Weiner, 2021), traffic accidents (Gulek, 2024), time use (Dasgupta and Datta, 2024), and education (Ito and Shonchoy, 2025). We extend this identification strategy to examine the effect of Ramadan on reported crime among Muslims, a setting in which causal evidence on the relationship between religious observance and crime remains relatively scarce, particularly in developing country contexts.

This paper uses a novel dataset that is an exhaustive list of all First Information Reports (FIRs) filed in Bihar - India, across 776 police stations in the state. FIRs are formal police

[1] Hadith refers to recorded sayings and actions of the Prophet Muhammad, which serve as an important source of guidance in most Islamic traditions, alongside the Qur'an.

records that document the initial report of a cognisable offence and trigger a criminal investigation. It provides detailed information on the date of reporting, incident date, accused names, district name, police station name, Indian Penal Code (IPC) sections, and an FIR number. Studies on crime outcomes in India have usually relied on data from the National Crime Records Bureau (NCRB), which provides yearly aggregates of crime incidence at a district level. Since Ramadan occurs at least once in every Gregorian year, such aggregated data cannot be used to study the effects of Ramadan. Our dataset provided information on individual incidents of crime and allows us to construct a dataset at a daily level. Secondly, our dataset provides the accused names, unlike most publicly available datasets. This allows us to use machine learning algorithms to predict the religion from the accused names, which helps us to construct data on crimes committed by Muslims and Non-Muslims every day in the year, including the days of Ramadan. Hence we are able to create crime data separately for a well defined treatment and control group. These two aspects of data allows us to create a dataset with the count of crimes reported about Muslim and non-Muslim accused for each (date, police station) tuple in the dataset. The temporal variation in the Ramadan period, as mentioned earlier, then allows us to use a difference-in-differences design comparing changes in crime involving Muslim accused relative to non-Muslim accused across Ramadan and non-Ramadan periods.

This paper provides evidence that Ramadan leads to a reduction in violent and non-violent crimes committed by Muslims. We document statistically and economically significant reductions across multiple violent and non-violent crime categories: a 19 percent decline in murder, 8 percent in riots, 23 percent in kidnapping, and 9 percent in theft. We subject these findings to a comprehensive set of falsification tests and robustness checks. Falsification tests involve a randomisation permutation test (involving random assignment of treatment periods and treated groups multiple times). We also try to estimate a Ramadan effect for non-Muslims and do not observe any statistically significant effect.[2] The results are also robust to alternative fixed-effects specifications, functional-form transformations, and exclusion of specific districts.

To explore the mechanisms underlying the observed decline in crime during Ramadan, we

[2]Note that this effect is not a causal DID estimate. This is the coefficient estimate of Ramadan in a regression restricted to Non-Muslims. Hence, we should be careful in making causal claims based on this result.

examine the impact of another significant Islamic month, *Dhu-al-Hijjah*—which encompasses *Eid al-Adha* and the *Hajj* pilgrimage —a period marked by heightened religious observance. We find comparable reductions in crime during *Dhu-al-Hijjah*, suggesting that the effects are likely driven by increased religiosity rather than by fasting alone or disruptions to daily routines. Moreover, the decline in crime remains consistent across the weeks of Ramadan, with no statistically significant variation across weeks, indicating a persistent behavioural response throughout the month. Finally, we draw on evidence from the literature (Schofield, 2020) documenting changes in employment, income, and other economic variables to offer suggestive support for the interpretation that the observed effects are not merely a consequence of economic restructuring but may also reflect moral decision-making influenced by increased religiosity. Our findings highlight the role of informal institutions such as Ramadan in shaping social outcomes. Periods of heightened religious observance may reinforce compliance alongside formal legal enforcement, suggesting that religious norms can complement state institutions in influencing behaviour.

To the best of our knowledge, this is the first paper to examine the impact of Ramadan on crime in a developing-country context. This gap in the literature is likely driven by the limited availability of granular crime data in such settings. Our study is most closely related to Birkholz and Gomtsyan (2023), which investigates the effect of Ramadan on criminal behaviour among migrants from Muslim-majority countries in Switzerland. However, our paper differs from theirs along several important dimensions.

First, while their analysis focuses on immigrant populations, we examine the behaviour of native residents in the Indian state of Bihar. This distinction is important, as migrant populations are typically subject to selection processes—both in terms of migration decisions and host-country sorting—that may limit the external validity of estimates for broader populations in origin countries. By focusing on a non-migrant population, our study provides evidence that is more directly representative of behaviour in a typical South Asian setting.

Second, whereas Birkholz and Gomtsyan (2023) infer religious affiliation indirectly through nationality, we employ machine learning techniques to classify individuals' religious identity based on names, enabling a more direct categorization of crimes by the religion of the accused. Third, the empirical strategies differ: their approach relies on cross-group com-

parisons by national origin, while we implement a difference-in-differences framework that compares changes in criminal behaviour among Muslims relative to non-Muslims during Ramadan.

Finally, the broader contextual setting of the two studies differs substantially. While their analysis is situated in a high-income European country with strong formal institutions, our study focuses on Bihar, one of India's poorest and most densely populated states. The setting is also demographically distinct: South Asia is home to a large share of the global Muslim population, and Muslims constitute a substantially larger proportion of the population in Bihar (approximately 18%) than in Switzerland (around 5%). These differences enhance the relevance of our context for understanding how religious practices operate in environments where such populations are more prevalent. Moreover, in contexts where formal institutional capacity may be comparatively limited, religious norms may play a more salient role in shaping behaviour. Accordingly, our analysis provides complementary evidence on the relationship between religiosity and crime from a South Asian developing-country perspective.

This study contributes to a growing body of literature in economics examining how religion and religious practices shape social and economic outcomes. In particular, recent work has leveraged variation in Ramadan fasting as a natural experiment to identify causal effects across a range of domains. Existing studies document impacts on outcomes such as subjective well-being, economic growth Campante and Yanagizawa-Drott (2015), gendered time use (Dasgupta and Datta, 2024), maternal health (Almond and Mazumder, 2011), education (Hornung et al., 2023), nutrition (Weiner, 2021), labour supply (Schofield, 2020), voting behaviour (Colussi et al., 2021), judicial decision-making (Mehmood et al., 2023), and traffic violations (Gulek, 2024). In addition to Birkholz and Gomtsyan (2023), few papers have explored the relationship between crime and religiosity directly. Heaton (2006) provided early evidence on this relationship, using an instrumental variable approach and finding little support for a statistically significant association between religious membership at the county level and crime rates. Moreno-Medina (2023) employs quasi-experimental variation in church attendance induced by rainfall shocks to examine its impact on crime. More recently, Johnston et al. (2025) exploits a city-wide shock to religious sentiment induced by a papal visit and provides evidence on its effects on less serious offences such as simple assaults, drug offences, and financial frauds. In a

related context, Poblete-Cazenave and Martínez (2025) studies a major religious festival in India and documents a sharp increase in violence against women during Holi.

The paper is organized in the following sections as follows. Section 2 describes the data used in the paper. Section 3 outlines the empirical strategy. Section 4 discusses the results, robustness checks, and potential mechanisms. Section 5 concludes.

2 Data

The data used in this paper are the universe of First Information Reports filed by the police department (the state's law enforcement agency) in the Indian state of Bihar from January 1, 2018, to August 11, 2023.[3] [4] An FIR is a written document recorded by the police under Section 154 of the Code of Criminal Procedure when they receive information about the commission of a cognisable offence, whether given orally or in writing. The filing of such a report by the officer in charge of a police station initiates the criminal law process. These reports provide the relevant details of each reported case, including the FIR number, date of reporting, incident date, accused names, district name, police station name, and relevant Indian Penal Code (IPC) sections.[5] These records constitute the most detailed publicly available dataset on criminal cases in India (Imbert et al., 2016; Poblete-Cazenave, 2020; Singh and Visaria, 2021). Unlike the National Crime Records Bureau (NCRB) data, which provides crime statistics aggregated at the district and annual levels or household surveys like the National Family Health Surveys that contain information on specific crimes like intimate partner violence, our data provides the universe of all cognisable offences committed during the study period at the highest level of disaggregation. This structure enables a more detailed and precise analysis of crime patterns, allowing us to study temporal and spatial variation that has not been possible with other crime data in India. With this as the initial data frame, we construct our dataset through the following steps:

[3] The data can be accessed from the following link: https://police.bihar.gov.in/

[4] We restrict the sample to police stations that are observed continuously between 2018 and 2023.

[5] This information was made available due to a mandate dictated by the Supreme Court of India in September 2016. Offences of a sensitive nature (e.g., sexual offences, insurgency-related crimes, terrorism-related offences, and cases under the Protection of Children from Sexual Offences Act) are not reported.

(i) *Mapping FIRs to crime categories:*

Using the IPC section reported, we mapped each FIR filed into eight crimes: riots, murder, rape, robbery, kidnapping and abduction, dacoity, theft, and burglary. We allow a one-to-many mapping: a single FIR can be mapped to multiple crime categories if multiple IPC sections are mentioned in the FIR. It is also possible that an FIR is not mapped to any of these eight categories. Each of these crime categories can further be grouped into violent and non-violent crimes using NCRB definitions: murder, rape, kidnapping, dacoity, robbery, and riots are grouped as violent crimes, whereas burglary and theft are grouped as non-violent crimes. This classification is well established and common in the literature on crime in India (Chaudhuri et al., 2024).

(ii) *Mapping accused names to religion*

FIRs do not contain information on the religious identity of the accused. Since Muslims and non-Muslims (primarily Hindus) have distinct names[6], in the second step, we map the names of the accused on an FIR to his/her religious identity: Muslims and Non-Muslims. Since this dataset contains approximately 0.84 million accused names, manual classification is infeasible. We employ the name-based classification model developed by Chaturvedi and Chaturvedi (2024), which uses character-sequence-based machine learning to distinguish between Muslim and non-Muslim names, achieving 97% accuracy. The model leverages convolutional neural networks (CNNs) and long short-term memory (LSTM) networks to capture linguistic patterns in Islamic and non-Islamic names. Layer-wise relevance propagation (LRP) further identifies the character sequences that drive classification, improving interpretability. Chaturvedi and Chaturvedi (2024) validated this approach using the Rural Economic and Demographic Survey (REDS), demonstrating its effectiveness in the Indian context.

For FIRs naming multiple accused individuals, we classify each accused separately based on the linguistic characteristics of their name. Thus, rather than assigning a single religion to the FIR, each accused contributes one observation with an indepen-

[6]According to the Bihar Caste-based Survey 2022, Hindus constitute 99.6 per cent of the non-Muslim population of Bihar.

dently predicted religion. This avoids the need to impose a religion-assignment rule on FIRs containing accused individuals from different religious groups and preserves the religious composition recorded in the FIR.

While the resulting religion variable may contain some measurement error due to imperfect classification of individual names, there is little reason to expect this error to be systematically correlated with the treatment or other explanatory variables. In a difference-in-differences framework, such measurement error in the dependent variable does not bias the estimated treatment effects, although it may reduce statistical precision. If, contrary to expectation, the measurement error were systematically related to the treatment, the estimated effects would most likely be attenuated toward zero.

It should be noted that approximately in 19 percent of the FIRs, the accused's names are missing. This is likely to be the case in situations involving specific crimes, such as theft, where the victim or the person filing the FIR is unaware of the perpetrator's identity. We show that such cases are likely in certain crime categories, and we assume that with such a category, the possibility of missing names is not correlated with our variables of interest. [7]

(iii) *Aggregating Data at (Police Station × FIR Date × Religion) level:*

After assigning crime categories and accused religion to each FIR observation, for each crime category c, we count the number of FIRs for category c across all unique values of the tuple (Police Station, FIR Date, Religion). Thus, we can create a dataset in which each observation corresponds to a unique value of (Police Station, FIR Date, Religion) and include a variable for each crime category. In other words, for every (date, police station) combination (e.g., *Jan 2nd, 2020-Gandhi Maidan Police Station*), the variable for crime category c has two values: one denoting FIRs filed against Muslims and one denoting FIRs filed against non-Muslims. If no FIRs for a particular crime category on a given data set in a specific police station, zero is assigned to both Muslim and non-Muslim observations.

It should be noted that we assign the count of crimes based on the date on which the FIR is filed. Although the dataset also records the date of the criminal incident,

[7] For a detailed discussion and supporting descriptive evidence, see the Appendix section A.1.

we do not use this variable to determine the timing of crimes because of concerns regarding its reliability. Approximately 16 percent of FIRs do not report an incident date, while some reported incident dates are inconsistent with the FIR filing date, including cases in which the reported incident occurs after the FIR was filed. In addition, the incident-date variable is recorded using inconsistent date conventions, including both day-month-year (DMY) and month-day-year (MDY) formats, with no systematic pattern that allows the convention to be reliably identified for every observation. While some dates can be unambiguously classified based on their values, such as 24/05/2018 or 3/31/2021, others, such as 8/2/2023, are inherently ambiguous and could refer to either 8 February 2023 or 2 August 2023. We therefore avoid imposing an arbitrary date convention on the incident-date variable and use the FIR filing date as the measure of crime timing throughout the analysis.

3 Empirical Strategy

The structure of our data allows us to employ a difference-in-differences estimation strategy by comparing changes in the number of crimes involving Muslim and non-Muslim accused during and outside the Ramadan period. Identification relies on the assumption that, absent the behavioural effects of Ramadan, the difference in crime involving Muslim and non-Muslim accused would not change systematically between Ramadan and non-Ramadan periods after conditioning on the included fixed effects. Given the richness of our dataset, we incorporate an extensive set of fixed effects to account for seasonal patterns, unobserved heterogeneity, and other time-varying confounding factors.

The main estimating equation is as follows:

$$Y_{gpt} = \beta_0 + \beta_1 \text{Ramadan}_t + \beta_2 \text{Muslim}_g + \beta_3 \left(\text{Muslim}_g \times \text{Ramadan}_t\right) + \tau_p + \theta_t + \epsilon_{gpt} \quad (1)$$

Note that the subscript $t = \{d, m, y\}$ denotes a specific calendar date, consisting of the day d, month m, and year y. Also note that because date fixed effects are included, the stand-alone Ramadan term is absorbed in estimation; it is shown in the equation only to make the difference-in-differences structure explicit.

In the equation above, Y_{gpt} denotes the number of accused individuals belonging to reli-

gious group g named in FIRs filed at police station p on date t. We estimate Equation (1) separately for each of the eight crime categories described in Section 2, with Y_{gpt} representing the corresponding outcome variable. $Ramadan_t$ is a dummy variable that takes the value 1 if the calendar date t falls within the Ramadan period and 0 otherwise. $Muslim_g$ is an indicator variable equal to one for the Muslim group and zero for the non-Muslim group. We include police station τ_p and date θ_t fixed effects. Police station fixed effects account for time-invariant characteristics at the station level, such as differences in law enforcement, infrastructure, demographic composition, and socioeconomic conditions. Date fixed effects absorb all shocks common to Muslims and non-Muslims on a given calendar date, including seasonal factors, political and economic events, national holidays, and other date-specific factors that may influence the likelihood of crime or crime reporting.

The inclusion of date fixed effects implies that identification comes from comparing the number of accused individuals belonging to the Muslim and non-Muslim groups on the same calendar date. The key source of variation is the timing of Ramadan, which follows the Islamic lunar calendar and therefore moves forward by approximately 10-12 days each year relative to the Gregorian calendar. This rotation helps distinguish the effect of Ramadan from seasonal variation that would otherwise be confounded with fixed calendar periods. Our coefficient of interest, β_3, therefore captures the differential change in the number of Muslim accused individuals during Ramadan relative to the corresponding change in the number of non-Muslim accused individuals on the same dates.

In this specification, β_2 represents the Muslim-non-Muslim gap in outcomes outside Ramadan. Our coefficient of interest, β_3, estimates the differential effect of Ramadan on Muslim crime behaviour relative to non-Muslims. Equation (1) is estimated using ordinary least squares, with standard errors clustered at the police station level to allow for arbitrary serial correlation in the error terms within police stations over time.

While Equation (1) presents the baseline difference-in-differences framework for estimating the effect separately for each crime category, we also estimate a pooled specification by stacking the data across the eight crime categories.

The estimating equation is

$$Y_{cgpt} = \beta_0 + \beta_1 Ramadan_t + \beta_2 Muslim_g + \beta_3 (Muslim_g \times Ramadan_t) + \lambda_c + \tau_p + \theta_t + \epsilon_{cgpt}, \quad (2)$$

where all notation is identical to that in Equation (1), except that the additional subscript c indexes the crime category and λ_c denotes crime category fixed effects. The pooled specification accounts for time-invariant differences across crime categories while maintaining the same difference-in-differences design. The coefficient of interest, β_3, captures the differential change in crime during Ramadan for Muslim-related observations relative to non-Muslim observations, pooling information across the eight crime categories. This specification therefore provides a complementary estimate to the crime-specific estimates presented in Equation (1).

4 Results

4.1 Main Results

Table 1 reports the estimated effects of Ramadan (captured by the coefficient of interest β_3) across eight categories of crime. The results exhibit substantial heterogeneity across offence categories. The coefficient is negative and statistically significant at the 5 percent level or better for murder, kidnapping, and theft, and at the 10 percent level for riots. It is positive and statistically significant for rape, while the estimates for robbery, dacoity, and burglary are statistically indistinguishable from zero.

The estimated coefficients imply declines of 0.0025, 0.0037, 0.0180, and 0.0108 in the number of Muslim accused persons recorded for murder, kidnapping, theft, and riots, respectively. Relative to the overall sample means, these estimates correspond to reductions of approximately 19%, 23%, 9%, and 8%, respectively. Relative to the corresponding mean outcomes for Muslim observations outside Ramadan, these estimates represent reductions of approximately 73%, 75%, 15%, and 24%. The evidence is strongest for kidnapping, murder, and theft; the estimate for riots is less precisely estimated and is statistically significant only at the 10 percent level.

For rape, the estimated coefficient is positive and statistically significant. The increase of 0.0007 is large relative to the very low baseline frequency of rape cases in the publicly available data. This result should be interpreted cautiously. FIRs involving sexual offences are not consistently disclosed through the public system from which our data are obtained, and the observed rape series may therefore represent only a selected subset of the cases registered by the police.[8] In addition, the low baseline mean implies that a small absolute change translates into a large percentage estimate. The available data do not allow us to determine whether the coefficient reflects a genuine change in offending, changes in reporting or police recording, or limitations in the public availability of administrative records.

The baseline specification of Table 1 excludes observations from the year 2020 because the COVID-19 pandemic and the associated restrictions substantially altered mobility, economic activity, policing, and access to the criminal justice system. Table B.1.1, in the Online Appendix, reports estimates from the full sample, including 2020. The negative estimates for murder, riots, and theft remain statistically significant, as does the positive estimate for rape. However, the negative estimate for kidnapping is no longer statistically significant, while the coefficients for robbery and dacoity become positive and statistically significant. Thus, the results for murder, riots, theft, and rape are qualitatively robust to the inclusion of 2020, whereas those for kidnapping, robbery, and dacoity are sensitive to the pandemic year. Because 2020 represents an exceptional institutional and behavioural regime, we retain the specification excluding that year as our baseline.

Overall, the estimates indicate that the effects of Ramadan differ across offence categories. The clearest evidence of a decline is found for murder, kidnapping, and theft, with weaker evidence for riots. These negative estimates are consistent with a broader literature linking religious observance to prosocial behaviour and lower criminal activity (Hirschi and Stark, 1969; Johnson and Jang, 2010; Adamczyk et al., 2017). However, the baseline estimates do not, by themselves, distinguish between reductions in crime arising

[8]The FIR data used in this study are obtained from the Bihar Police public portal, which was established following the Supreme Court's directions on the online disclosure of FIRs. Under the applicable disclosure rules, FIRs relating to certain sensitive offences, including sexual offences, are not consistently made publicly available. Consequently, the publicly observed rape series may understate the number of registered rape cases.

from heightened religious observance and moral restraint during Ramadan (the hellfire hypothesis) and reductions arising from changes in economic and social routines associated with the observance of Ramadan. We examine these alternative mechanisms in the subsequent analysis.

We also provide complementary evidence on the effect of Ramadan on crime using a stacked regression. Specifically, we estimate the regression specified in Equation (2) by stacking the data across the eight crime categories. The results are presented in Table 2. Column (1) reports the baseline specification, while Columns (2) and (3) progressively add police-station and date fixed effects. Our preferred specification in Column (4) additionally includes crime-category fixed effects. Across all four specifications, the coefficient on Ramadan $\times$ Muslim remains statistically significant at the 5 percent level, implying a reduction of 0.0040 in the number of Muslim accused persons. Relative to the sample mean, this estimate corresponds to approximately a 6.6% reduction. Thus, the pooled estimate is consistent with the pattern of results obtained from the crime-specific regressions and provides further evidence of a decline in crime during Ramadan.

4.2 Robustness Checks and Falsification

This section first examines the suitability of the non-Muslim comparison group and then presents a series of robustness checks and falsification exercises to assess the credibility of the baseline estimates. Specifically, we consider alternative fixed-effects specifications and functional forms of the outcome variable, assess whether the results are driven by any particular district through a leave-one-district-out exercise, and finally conduct randomisation inference to evaluate the statistical significance of our estimates under random assignment of treatment.

4.2.1 Evidence on the Comparison Group

Our baseline specification includes date fixed effects, which absorb the main effect of Ramadan. As a result, the baseline specification cannot identify whether the daily number of

non-Muslim accused persons changes during Ramadan. To examine this issue, we estimate the following specification using only observations involving non-Muslim subsample:

$$Y_{pt} = \beta_0 + \beta_1 Ramadan_t + \tau_p + \mu_{my} + \epsilon_{pt}, \tag{3}$$

where Y_{pt} denotes the daily number of non-Muslim accused individuals at police station p on date t, μ_{my} denotes month $\times$ year fixed effects, and the remaining notation follows the baseline specification. Unlike the baseline specification, date fixed effects are not included because they would absorb the Ramadan indicator, which is the coefficient of interest in this regression. This exercise should not be interpreted as identifying the causal effect of Ramadan on crime among non-Muslims. Rather, it serves as a diagnostic exercise examining whether the daily number of non-Muslim accused persons changes systematically during Ramadan.

Table 3 shows that the estimated coefficients are small in magnitude, exhibit no consistent pattern across crime categories, and are generally close to zero. These findings provide supportive evidence that the number of non-Muslim accused persons recorded in FIRs does not change systematically during Ramadan, suggesting that Ramadan is not associated with systematic changes in the observed outcomes for the comparison group. This finding is consistent with, although it does not establish, the identifying assumption underlying the baseline specification.

4.2.2 Alternative Specification

We first examine whether our results are sensitive to the choice of fixed-effects specification. Our baseline specification includes police station and date (day $\times$ month $\times$ year) fixed effects, providing a highly flexible control for time-specific shocks by allowing each calendar date to have its own intercept. While this specification places minimal restrictions on the evolution of temporal shocks, it may also absorb a substantial amount of variation. We therefore re-estimate the model using a range of alternative fixed-effects structures that impose different assumptions on the temporal dimension while allowing seasonal and annual variation to differ across police stations and districts. Specifically, we estimate specifications with (police station $\times$ month) and year fixed effects (Table 4),

(police station × year) and month fixed effects (Table 5), (district × month) and year fixed effects (Table 6), and (district × year) and month fixed effects (Table 7). These alternative specifications account for unobserved heterogeneity that may vary across locations over time at both the police station and district levels. Across all specifications, the estimated effects remain qualitatively similar to our baseline results. Together, these alternative specifications provide a useful assessment of whether the estimated Ramadan effect is robust to different ways of modelling spatial and temporal heterogeneity.

4.2.3 Alternative Functional Forms

Our baseline specification models the daily number of accused persons in levels. While the levels specification permits a direct interpretation of the estimated effects in terms of changes in the daily number of accused persons, crime counts are highly skewed and contain a substantial mass of zero observations. We therefore examine whether the substantive conclusions are sensitive to the functional form of the dependent variable. We re-estimate Equation (1) using two alternative transformations of the outcome variable. First, we use the natural logarithm of one plus the crime count, which accommodates zero observations. Second, we use the inverse hyperbolic sine (IHS) transformation, which is well-defined at zero and closely approximates the logarithmic transformation for larger values.

Tables 8 and 9 report the corresponding estimates. Across both transformations, the direction and statistical significance of the principal estimates remain broadly consistent with the baseline results. The only notable difference concerns robbery, where the estimated coefficient remains small and positive but becomes statistically significant at the 10% level under both transformations. Overall, these results indicate that the substantive conclusions are not sensitive to the choice of functional form.

4.2.4 Excluding One District at a Time

Next, we assess whether our results are driven by observations from any individual district. For each of the 34 districts represented in the estimation sample, we sequentially exclude

all observations from that district and re-estimate the baseline specification. Figures 1-4 report the resulting estimates for murder, rape, kidnapping, and theft.

The point estimates are generally stable in sign and magnitude across the leave-one-district-out samples. The estimates for kidnapping remain negative and statistically significant throughout, while the positive estimates for rape are similarly stable across district exclusions. The theft estimates also remain negative and close to the baseline estimate, although their confidence intervals include zero in some leave-one-out samples. For murder, the coefficient remains negative and changes only modestly, but is no longer statistically significant when East Champaran, Nalanda, Sitamarhi, Siwan, or Supaul is excluded. Thus, the precision of the murder estimate is somewhat sensitive to the exclusion of particular districts, even though its sign and magnitude remain broadly stable. Overall, the exercise provides little evidence that the principal estimates are driven by observations from any single district.

4.2.5 Randomisation Inference

Fourth, we conduct randomisation inference following Bharadwaj et al. (2014). The logic is that if the estimated treatment effects arise purely by chance, similar estimates should be obtained under random assignment of the treatment variables. We therefore implement two complementary placebo exercises. In the first, we randomly assign placebo Ramadan periods while preserving the baseline specification and re-estimate Equation (1). In the second, we randomly reassign the Muslim indicator and again estimate the baseline model. Each placebo exercise is repeated 1,000 times for every crime category to obtain the empirical distribution of placebo estimates. Figures 5 and 6 compare the baseline estimates with the corresponding placebo distributions. Across all four outcomes, the placebo distributions are centred around zero, whereas the baseline estimates (shown by the vertical red lines) lie well into the tails of the simulated distributions. These findings provide strong evidence that the estimated treatment effects are unlikely to arise from random assignment of either the timing of Ramadan or the religious identity of the accused.

4.3 Exploring Potential Mechanisms

The baseline estimates establish that crime involving Muslim accused persons declines during Ramadan but do not, by themselves, identify the underlying reasons for this pattern. In this section, we examine evidence consistent with two broad explanations. The first is increased religious observance during Ramadan, which may strengthen prosocial behaviour and moral restraint. The second is changes in labour supply and economic activity during Ramadan, which may alter the opportunities or incentives for criminal behaviour.

4.3.1 Evidence from Other Periods of Religious Observance: Dhu al-Hijjah and Fridays

To provide further evidence on the role of religiosity, we examine the first ten days of *Dhu al-Hijjah*, the final month of the Islamic lunar calendar. These days are regarded as among the holiest in Islam and are associated with increased prayer, charity, and religious devotion among many Muslims. Unlike Ramadan, however, they do not involve the month-long obligatory fasting or many of the broader behavioural changes that characterise the holy month. If the reductions in crime observed during Ramadan partly reflect heightened religious observance rather than Ramadan-specific practices, we might expect qualitatively similar, although potentially smaller, effects during this period. We focus on the first ten days because they are traditionally regarded as the holiest part of *Dhu al-Hijjah*[9] Observations during Ramadan are excluded from the estimation sample so that the estimated effects reflect the association between crime and *Dhu al-Hijjah*, rather than differences between this period and another major episode of heightened religious observance.

We estimate a specification analogous to Equation (1), replacing the Ramadan indicator with an indicator for the first ten days of *Dhu al-Hijjah* and interacting it with the Muslim indicator. Table 10 reports the corresponding estimates. We find statistically significant declines in murder, riot, kidnapping, burglary, and theft while the remaining crime categories show no statistically significant changes. The estimated effects display

[9]We also conduct the same exercise with the entire month of Dhu al-Hijjah, results of which are reported in Table A.0.1 of the appendix.

substantial overlap with those observed during Ramadan, although the pattern is not identical across all crime categories. The similarity in the declines for several offences is consistent with the possibility that heightened religious observance contributes to reductions in criminal activity. Although this exercise cannot exactly identify the underlying mechanism, the findings provide suggestive evidence that increased religiosity may be one factor contributing to the reductions in crime observed during Ramadan.

As a further exercise, we replace the Ramadan indicator with an indicator for Fridays and re-estimate the baseline specification. Fridays occupy a special place in Islam because of the congregational *Salat al-Jum'ah* prayer, but unlike Ramadan or the first ten days of *Dhu al-Hijjah*, they represent a recurring weekly observance rather than a sustained period of heightened religious activity. As shown in Table 11, we find little evidence of systematic changes in crime on Fridays. The estimated coefficients are statistically insignificant for seven of the eight crime categories, with the exception of murder, for which the coefficient is negative and statistically significant.

Taken together, these exercises provide only qualified evidence regarding the religiosity channel. The results from *Dhu al-Hijjah* are consistent with the possibility that sustained periods of heightened religious observance contribute to reductions in multiple categories of crime. At the same time, the absence of comparable effects on Fridays suggests that routine weekly religious observance alone is unlikely to account for the broad reductions in crime observed during Ramadan. One possible explanation is that multi-day periods of intensified religious practice generate more persistent changes in individual behaviour and social interactions than a recurring weekly observance. Although these exercises cannot identify the underlying mechanism, they suggest that if religiosity contributes to the Ramadan effect, it is more likely to operate through sustained periods of heightened religious engagement than through routine weekly worship.

4.3.2 Timing of the Ramadan Effect

To examine whether the effects of Ramadan are concentrated at the beginning of the month or persist throughout the fasting period, we divide Ramadan into four weekly intervals and estimate separate treatment effects for each week. If the observed reductions

in crime simply reflect a short-lived behavioural response to the onset of Ramadan, we would expect the estimated effects to be strongest during the first week and to weaken thereafter.

We do not find evidence that the effects are concentrated at the onset of Ramadan. Instead, there is some indication that the reductions in several crime categories (for which we have a significant negative effect in the baseline of Table 1) emerge more strongly in the latter part of the month, whereas the increase in rape is concentrated earlier. However, with the exception of theft (and weaker evidence for riots), the differences across weeks are not statistically distinguishable, so these temporal patterns should be interpreted cautiously.

Overall, the estimates suggest that the reductions in crime are not merely an immediate response to the onset of Ramadan. Instead, for several offences the effects persist, and in some cases become stronger, as Ramadan progresses. Although these results cannot distinguish between alternative mechanisms, they are consistent with the possibility that sustained exposure to Ramadan, rather than its initial onset alone, contributes to changes in criminal behaviour.

4.3.3 No Change in Employment and Earnings

An alternative explanation for the observed decline in crime is that Ramadan affects labour supply or earnings, thereby changing the economic incentives or opportunities for criminal activity. Although we cannot examine these channels directly, existing evidence suggests that Ramadan has little effect on labour market outcomes. Using data from the National Sample Survey (NSS) and the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Schofield (2020) find no statistically significant changes in labour supply or earnings among Muslims during Ramadan. Employment remains stable, while earnings are either unchanged or increase slightly, although the latter estimates are generally imprecise.

Although these findings do not rule out other economic channels through which Ramadan might affect crime, they suggest that changes in labour supply or earnings are unlikely to be the primary mechanism underlying our results. Taken together with the evidence from

other periods of religious observance, this interpretation is consistent with the possibility that behavioural changes associated with heightened religiosity contribute to the observed decline in crime.

5 Conclusion

In this paper, using granular data from daily FIR records across police stations in the Indian state of Bihar, we estimate the effect of Ramadan, a period of heightened religious observance, on recorded crime. We employ a difference-in-differences design that compares Muslim and non-Muslim accused persons and exploits the shifting timing of Ramadan relative to the Gregorian calendar. We find statistically significant reductions in murder, kidnapping, and theft during Ramadan, together with weaker evidence of a reduction in riots. The estimated effect for rape is positive and statistically significant, although this result should be interpreted cautiously because FIRs involving sexual offences are not consistently disclosed in the public data. For robbery, dacoity, and burglary, the estimated effects are statistically insignificant. Taken together, these results indicate substantial heterogeneity across offence categories and caution against interpreting the Ramadan effect as a uniform reduction in crime.

We find that the principal negative estimates are broadly and qualitatively robust to alternative specifications and functional forms and are not driven by individual districts. Randomisation exercises provide further evidence that the estimates are unlikely to arise from chance assignment of Ramadan timing or religious identity.

The paper undertakes a number of additional exercises and draws on existing evidence to provide suggestive evidence on the mechanisms through which Ramadan may affect crime. We find that the first ten days of Dhu al-Hijjah, another period of heightened religious observance, are associated with reductions in several crime categories, while we find little evidence of a systematic effect on Fridays, the weekly holy day in Islam. The latter does not necessarily contradict a religiosity channel, since a recurring weekly holy day may generate different behavioural responses from a sustained period of heightened religious observance. Importantly, unlike Ramadan, Dhu al-Hijjah does not involve month-long fasting and the associated changes in daily routines, providing suggestive evidence

that heightened religiosity itself may contribute to the observed reductions in crime. We also examine how the Ramadan effects evolve over the course of the month. While the estimated effects vary across weeks for some crime categories, most pairwise differences are statistically insignificant, providing little evidence that the effects dissipate as Ramadan progresses. Finally, existing evidence from India finds no significant decline in employment or earnings among Muslims during Ramadan. While this cannot rule out other economic mechanisms, it makes changes in labour supply and earnings a less likely explanation for our findings. Taken together, these results are consistent with heightened religiosity and the associated behavioural norms contributing to the observed effects of Ramadan on crime, although they do not allow us to identify the underlying mechanism conclusively.

Our findings highlight the potential importance of informal institutions in shaping socially consequential behaviour. Cooperation and social order require individual choices to be directed towards socially desirable outcomes through the constraints, benefits, and costs imposed by institutions. While formal institutions, drawing on the legitimised coercive power of the state, constrain criminal behaviour through law enforcement, policing, and the judiciary, informal institutions such as religion may influence behaviour through moral constraints and social norms, without relying exclusively on formal enforcement. Such informal institutions may be particularly important in developing countries, where formal institutions often have limited capacity to monitor and enforce socially desirable behaviour. Our findings therefore suggest that religion and other informal institutions need not be viewed as substitutes for formal institutions; rather, they may complement them in promoting socially desirable behaviour. In the context of crime, this suggests that religious norms can reinforce the constraints imposed by formal law and law enforcement.

Conflict of Interest

The authors declare that they have no competing interests or conflicts of interest that could have influenced the work reported in this paper.

Declaration of AI Usage

Generative AI tools were used during the preparation of this manuscript to improve language, clarity, and presentation, assist with code debugging, and provide feedback on the exposition and logical consistency of the manuscript. All AI-generated suggestions were critically evaluated by the authors. The authors are solely responsible for the study design, data collection, empirical analysis, interpretation of the results, and the conclusions of the paper.

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Table 1 Effect of Ramadan on Recorded Crimes

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Ramadan × Muslim	-0.0025**	0.0007***	-0.0108*	0.0008	0.0007	-0.0037***	0.0006	-0.0180**
	(0.0012)	(0.0003)	(0.0059)	(0.0005)	(0.0006)	(0.0011)	(0.0007)	(0.0077)
Observations	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016
R^2	0.0043	0.0022	0.0195	0.0022	0.0022	0.0082	0.0025	0.0585
Dep. Var. Mean	0.0129	0.0014	0.1215	0.0028	0.0028	0.0159	0.0042	0.3257
Mean (Muslims, Non-Ramadan)	0.0034	0.0007	0.0436	0.0009	0.0008	0.0049	0.0016	0.1181
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficient estimates from Equation (1) in the main text. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include police station fixed effects and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2 Effect of Ramadan on Recorded Crime

	(1) Crime	(2) Crime	(3) Crime	(4) Crime
Ramadan × Muslim	-0.0040**	-0.0040**	-0.0040**	-0.0040**
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Observations	20,896,128	20,896,128	20,896,128	20,896,128
R-squared	0.0027	0.0089	0.0099	0.0305
Dep. Var. Mean	0.0609	0.0609	0.0609	0.0609
Police Station FE	No	Yes	Yes	Yes
Date FE	No	No	Yes	Yes
Crime Type FE	No	No	No	Yes

Notes: The unit of observation is a police station-day-religion-crime category cell. The original data are organised in a wide format, with separate variables recording the daily number of offences committed by Muslims and non-Muslims for each crime category within a police station. These data are reshaped into a long format in which each observation corresponds to a unique combination of police station, date, religion group, and crime category. The religion dimension distinguishes offences committed by Muslims and non-Muslims, while the crime-category dimension consists of eight offence types: murder, rape, riots, robbery, dacoity, kidnapping, burglary, and theft. Consequently, each police station-day contributes 16 observations, corresponding to two religion groups and eight crime categories. The sample excludes observations from the year 2020. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3 Ramadan and Recorded Crime among Non-Muslims

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Ramadan	-0.0000	-0.0005	-0.0062	0.0001	-0.0008	-0.0011	0.0007	-0.0018
	(0.0018)	(0.0004)	(0.0087)	(0.0006)	(0.0008)	(0.0018)	(0.0008)	(0.0121)
Observations	1,306,008	1,306,008	1,306,008	1,306,008	1,306,008	1,306,008	1,306,008	1,306,008
R^2	0.0040	0.0023	0.0211	0.0020	0.0020	0.0088	0.0023	0.0608
Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include month × year fixed effects, and police station fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4 Robustness: Police Station-Month and Year Fixed Effects

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Ramadan × Muslim	-0.0025**	0.0007***	-0.0108*	0.0008	0.0007	-0.0037***	0.0006	-0.0180**
	(0.0012)	(0.0003)	(0.0059)	(0.0005)	(0.0006)	(0.0011)	(0.0007)	(0.0077)
Observations	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016
R^2	0.0070	0.0053	0.0225	0.0053	0.0054	0.0109	0.0055	0.0604
PS × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimates from Equation (1). The dependent variable is the daily number of accused individuals belonging to the Muslim and non-Muslim groups within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include police station × month fixed effects, and year fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5 Robustness: Police Station-Year and Month Fixed Effects

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Ramadan × Muslim	-0.0025**	0.0007***	-0.0108*	0.0008	0.0007	-0.0037***	0.0006	-0.0180**
	(0.0012)	(0.0003)	(0.0059)	(0.0005)	(0.0006)	(0.0011)	(0.0007)	(0.0077)
Observations	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016
R^2	0.0054	0.0044	0.0263	0.0035	0.0031	0.0108	0.0038	0.0689
PS × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimates from Equation (1). The dependent variable is the daily number of accused individuals belonging to the Muslim and non-Muslim groups within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include police station × year fixed effects, and month fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 6 Robustness: District-Month and Year Fixed Effects

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Ramadan × Muslim	-0.0025**	0.0007***	-0.0108*	0.0008	0.0007	-0.0037***	0.0006	-0.0180**
	(0.0012)	(0.0003)	(0.0059)	(0.0005)	(0.0006)	(0.0011)	(0.0007)	(0.0077)
Observations	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016
R^2	0.0021	0.0010	0.0094	0.0008	0.0007	0.0040	0.0008	0.0311
District × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimates from Equation (1). The dependent variable is the daily number of accused individuals belonging to the Muslim and non-Muslim groups within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include district × month fixed effects, and year fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 7 Robustness: District-Year and Month Fixed Effects

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Ramadan × Muslim	-0.0025**	0.0007***	-0.0108*	0.0008	0.0007	-0.0037***	0.0006	-0.0180**
	(0.0012)	(0.0003)	(0.0059)	(0.0005)	(0.0006)	(0.0011)	(0.0007)	(0.0077)
Observations	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016
R^2	0.0023	0.0015	0.0113	0.0009	0.0007	0.0044	0.0008	0.0363
District × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimates from Equation (1). The dependent variable is the daily number of accused individuals belonging to the Muslim and non-Muslim groups within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include district × year fixed effects, and month fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 8 Robustness: Logarithmic Transformation of Accused Counts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(1+Murder)	Log(1+Rape)	Log(1+Riot)	Log(1+Robbery)	Log(1+Dacoity)	Log(1+Kidnapping)	Log(1+Burglary)	Log(1+Theft)
Ramadan × Muslim	-0.0012***	0.0003**	-0.0040***	0.0003*	0.0002	-0.0016***	0.0002	-0.0057***
	(0.0004)	(0.0001)	(0.0012)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0019)
Observations	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016
R^2	0.0055	0.0027	0.0270	0.0028	0.0028	0.0106	0.0036	0.0826
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficient estimates from Equation 1 in the main text. The dependent variable is the natural logarithm of one plus the daily number of accused persons in a given religious group recorded at a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include police station fixed effects, and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9 Robustness: Inverse Hyperbolic Sine transformation of Accused Counts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Murder	Rape	Riot	Robbery	Dacoity	Kidnapping	Burglary	Theft
Ramadan × Muslim	-0.0015***	0.0003**	-0.0051***	0.0004*	0.0003	-0.0021***	0.0002	-0.0073***
	(0.0005)	(0.0001)	(0.0015)	(0.0002)	(0.0002)	(0.0006)	(0.0003)	(0.0024)
Observations	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016
R^2	0.0056	0.0027	0.0272	0.0028	0.0028	0.0106	0.0036	0.0831
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficient estimates from Equation 1 in the main text. The dependent variable is the inverse hyperbolic sine transformation of the daily number of accused persons in a given religious group recorded at a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include police station fixed effects and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10 Effect of Dhu al-Hijjah on Crimes (Excluding Ramadan Period)

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Dhu-al-Hijjah × Muslim	-0.0033*	-0.0004	-0.0147*	-0.0010	-0.0001	-0.0048**	-0.0021**	-0.0648***
	(0.0020)	(0.0006)	(0.0082)	(0.0008)	(0.0007)	(0.0020)	(0.0009)	(0.0116)
Observations	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320
R^2	0.0043	0.0023	0.0195	0.0023	0.0022	0.0082	0.0027	0.0584
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include police station fixed effects, and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 11 Effect of Fridays on Crime (Excluding Ramadan Period)

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Friday × Muslim	-0.0021**	-0.0004	0.0036	0.0002	0.0001	0.0006	-0.0001	0.0024
	(0.0010)	(0.0003)	(0.0041)	(0.0004)	(0.0004)	(0.0009)	(0.0005)	(0.0056)
Observations	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320
R^2	0.0043	0.0023	0.0195	0.0023	0.0022	0.0082	0.0027	0.0584
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

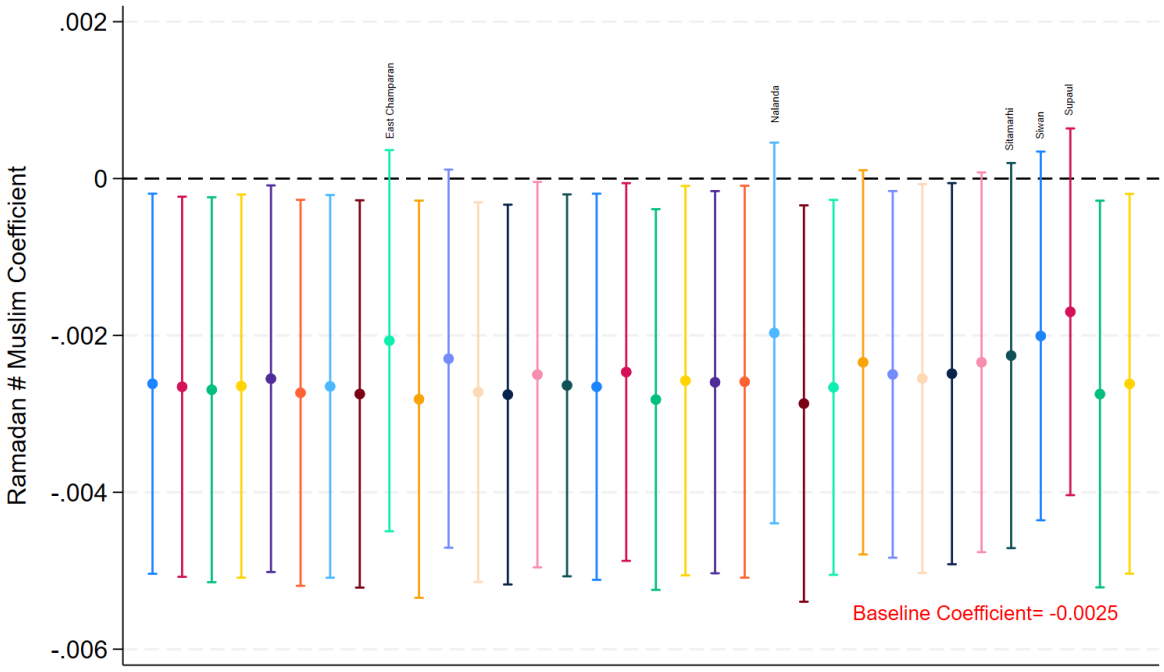
Notes: The dependent variable is the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include police station fixed effects, and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 12 Persistent Religiosity

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Week 1 × Muslim	-0.0003	0.0011***	-0.0036	0.0020***	-0.0001	-0.0018	0.0027	0.0051
	(0.0022)	(0.0003)	(0.0112)	(0.0005)	(0.0010)	(0.0020)	(0.0019)	(0.0133)
Week 2 × Muslim	-0.0016	0.0008**	0.0068	-0.0002	0.0015	-0.0055**	-0.0005	0.0108
	(0.0023)	(0.0004)	(0.0115)	(0.0012)	(0.0015)	(0.0024)	(0.0011)	(0.0151)
Week 3 × Muslim	-0.0055**	0.0005	-0.0218**	0.0002	0.0006	-0.0020	-0.0005	-0.0282*
	(0.0025)	(0.0005)	(0.0106)	(0.0009)	(0.0012)	(0.0021)	(0.0009)	(0.0149)
Week 4 × Muslim	-0.0027	0.0006	-0.0222**	0.0012	0.0007	-0.0052**	0.0008	-0.0519***
	(0.0021)	(0.0005)	(0.0097)	(0.0008)	(0.0008)	(0.0022)	(0.0008)	(0.0142)
$\beta_{week1} = \beta_{week2}$	[0.659]	[0.590]	[0.513]	[0.072]	[0.365]	[0.220]	[0.134]	[0.783]
$\beta_{week1} = \beta_{wee3}$	[0.101]	[0.306]	[0.228]	[0.067]	[0.653]	[0.952]	[0.126]	[0.102]
$\beta_{week1} = \beta_{week4}$	[0.415]	[0.393]	[0.189]	[0.378]	[0.562]	[0.260]	[0.362]	[0.003]
$\beta_{week2} = \beta_{week3}$	[0.256]	[0.524]	[0.045]	[0.757]	[0.659]	[0.248]	[0.978]	[0.039]
$\beta_{week2} = \beta_{week4}$	[0.724]	[0.660]	[0.050]	[0.318]	[0.649]	[0.928]	[0.319]	[0.003]
$\beta_{week3} = \beta_{week4}$	[0.377]	[0.844]	[0.977]	[0.394]	[0.981]	[0.253]	[0.241]	[0.228]
Observations	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016	2,612,016

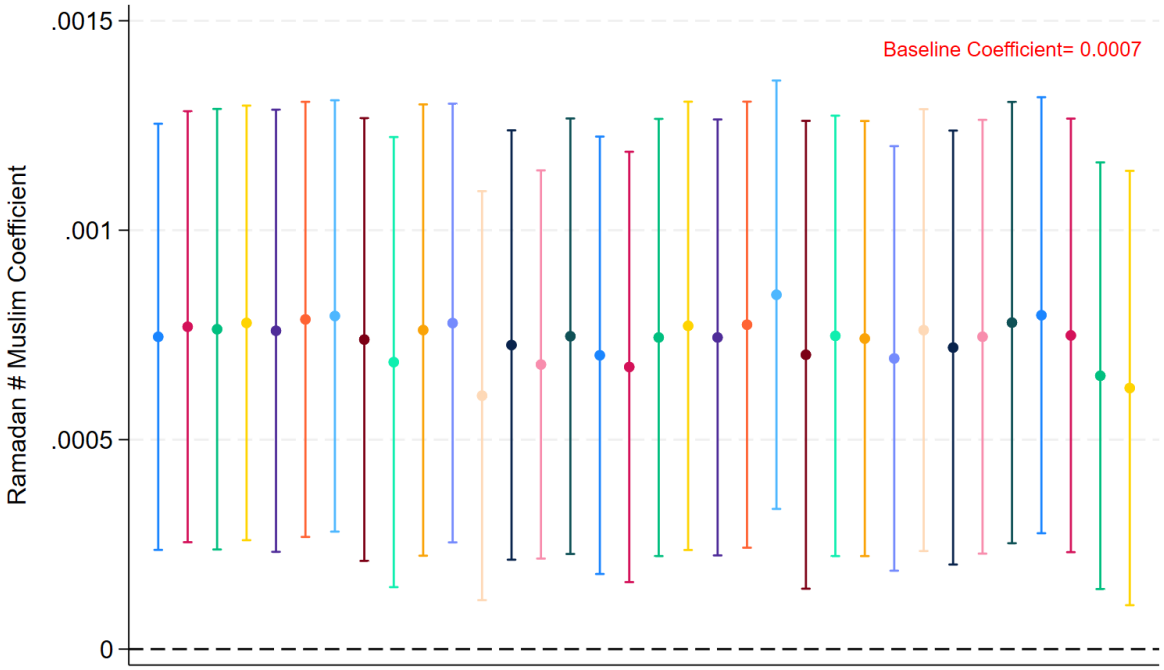
Notes: The dependent variable is the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include police station fixed effects and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. Values reported in square brackets are p-values from hypothesis tests of equality between coefficients across Ramadan weeks. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 1 Dropping one district at a time: Murder



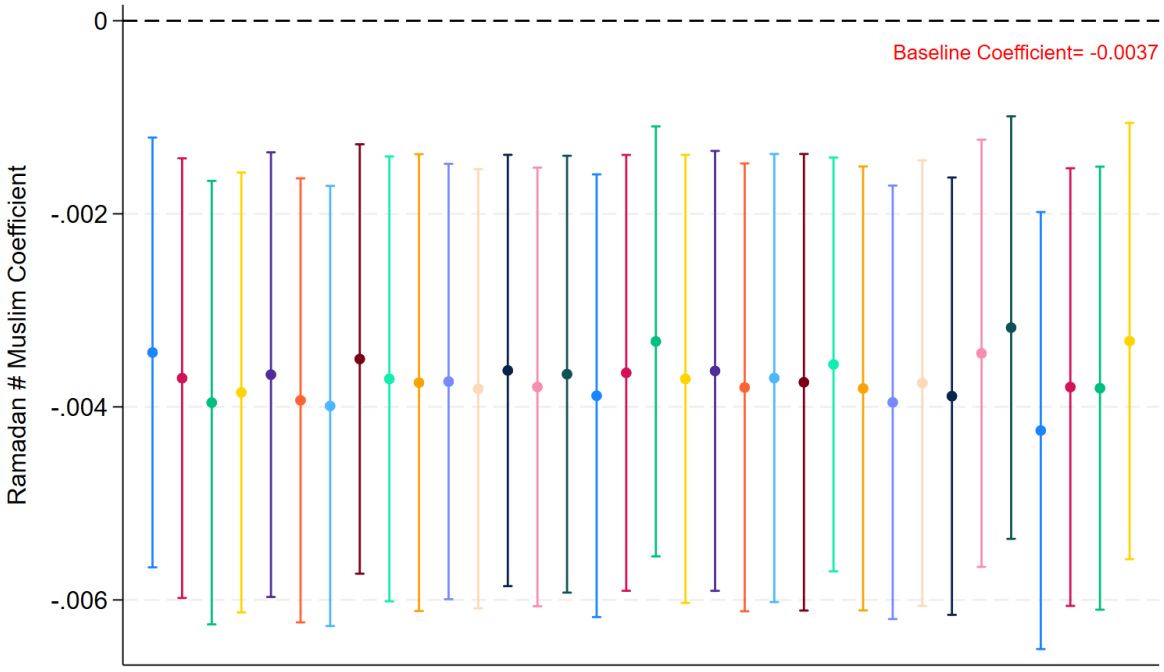
Notes: This figure illustrates the leave-out-one-district estimates of the coefficient on the Ramadan × Muslim. Each point corresponds to the estimated coefficient obtained after excluding all observations from a single district with all the baseline fixed effects. Error bars denote 95% confidence intervals. Standard errors are clustered at the police station level.

Figure 2 Dropping one district at a time: Rape



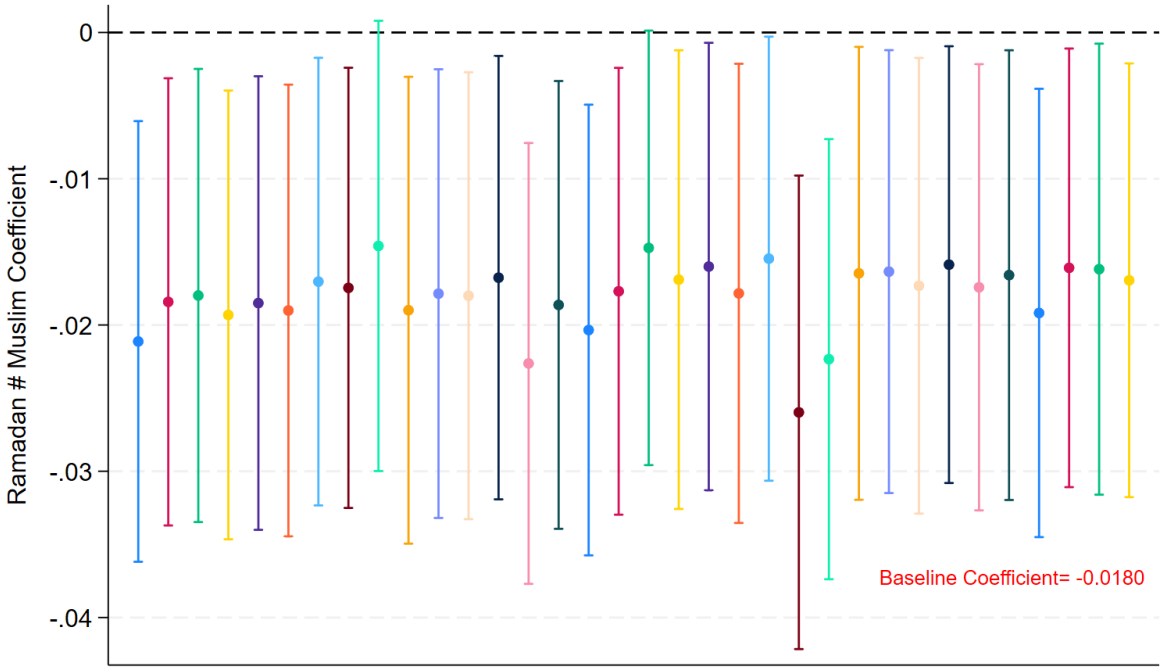
Notes: This figure illustrates the leave-out-one-district estimates of the coefficient on the Ramadan × Muslim. Each point corresponds to the estimated coefficient obtained after excluding all observations from a single district with all the baseline fixed effects. Error bars denote 95% confidence intervals. Standard errors are clustered at the police station level.

Figure 3 Dropping one district at a time: Kidnapping



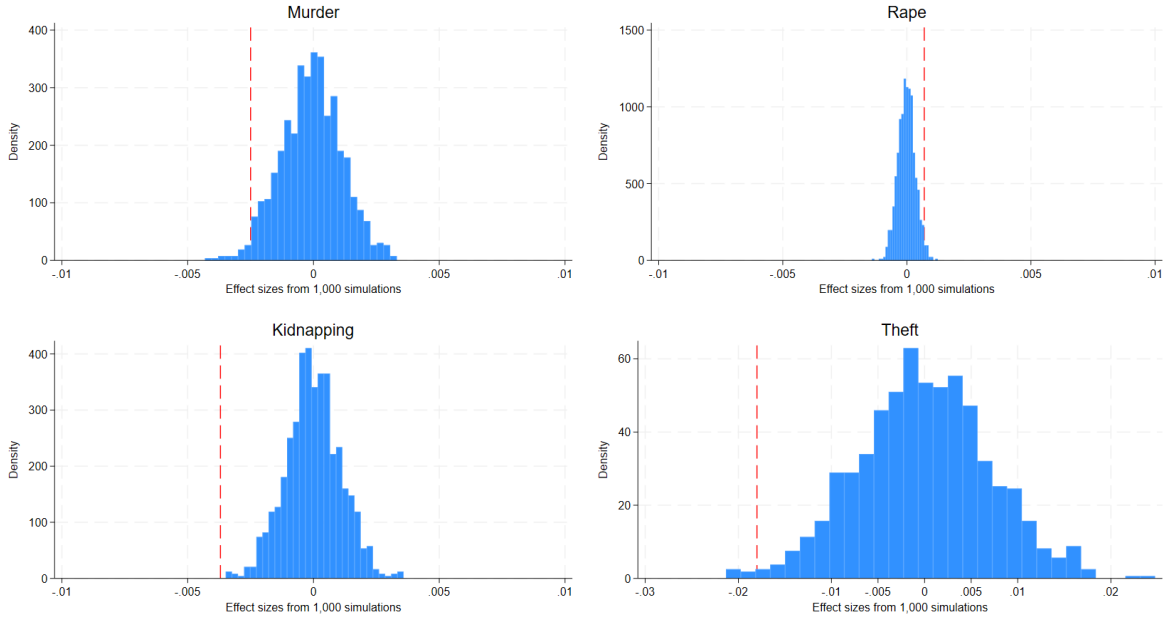
Notes: This figure illustrates the leave-out-one-district estimates of the coefficient on the Ramadan × Muslim. Each point corresponds to the estimated coefficient obtained after excluding all observations from a single district with all the baseline fixed effects. Error bars denote 95% confidence intervals. Standard errors are clustered at the police station level.

Figure 4 Dropping one district at a time: Theft



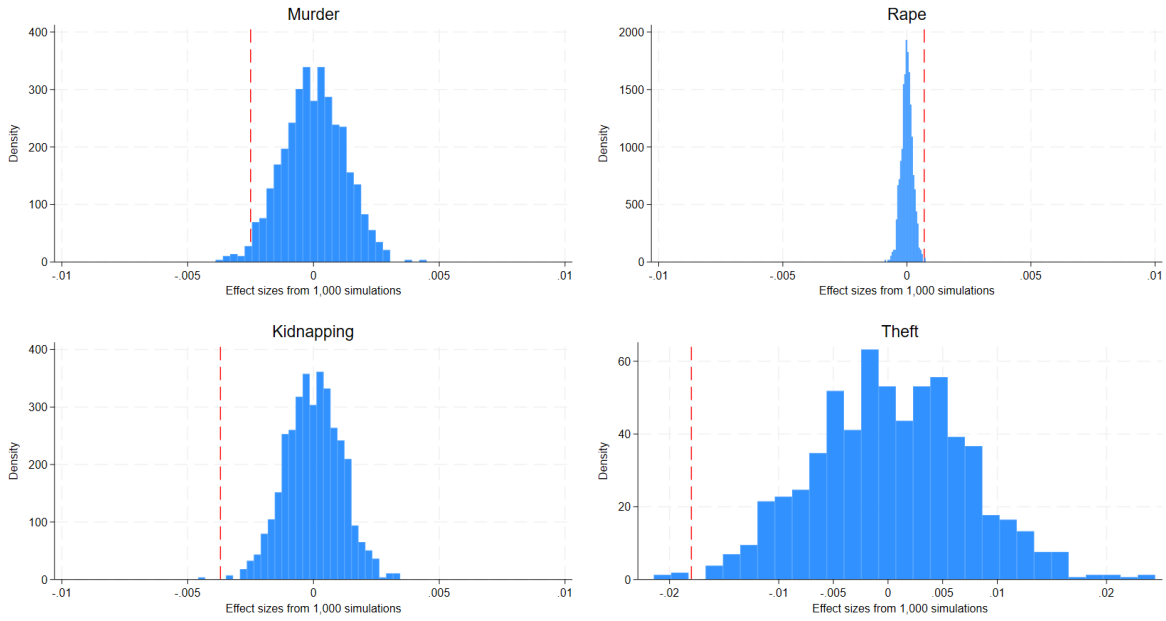
Notes: This figure illustrates the leave-out-one-district estimates of the coefficient on the Ramadan × Muslim. Each point corresponds to the estimated coefficient obtained after excluding all observations from a single district with all the baseline fixed effects. Error bars denote 95% confidence intervals. Standard errors are clustered at the police station level.

Figure 5 Randomisation of Ramadan



Notes: This figure shows the distribution of estimated effects from 1000 random simulations of accused religion assignment. The red vertical line represents the actual estimated effect from the data. Simulations are based on the null hypothesis of no effect.

Figure 6 Randomisation of Muslim



Notes: This figure shows the distribution of estimated effects from 1000 random simulations of the Muslim dummy. The red vertical line represents the actual estimated effect from the data. Simulations are based on the null hypothesis of no effect.

A Appendix

Table A.0.1 Effect of Dhu al-Hijjah on Crimes (Excluding Ramadan Period)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Murder	Rape	Riot	Robbery	Dacoity	Kidnapping	Burglary	Theft
Dhu-al-Hijjah × Muslim	-0.0013	0.0005	0.0048	-0.0012*	0.0001	-0.0022*	-0.0012**	-0.0244***
	(0.0012)	(0.0003)	(0.0054)	(0.0006)	(0.0005)	(0.0011)	(0.0005)	(0.0076)
Observations	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320	2,382,320
R^2	0.0043	0.0023	0.0195	0.0023	0.0022	0.0082	0.0027	0.0584
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. The sample excludes observations from the year 2020. All columns include police station fixed effects, and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

A.1 Data Concerns

Table A.1.1 compares the distribution of crime categories between FIRs with available accused identifiers and FIRs in which the accused's identity is unavailable. The comparison reveals substantial differences in the composition of the two samples. In particular, FIRs with missing accused identifiers are overwhelmingly concentrated in property-related offences. Nearly 70 percent of FIRs with missing accused information involve theft, compared with approximately one-third of FIRs for which accused identifiers are available. Burglary also accounts for a substantially larger share of the missing-accused sample (6.2 percent versus 0.7 percent), while robbery and kidnapping are modestly overrepresented among FIRs without accused identifiers.

By contrast, serious violent offences constitute only a small fraction of FIRs with missing accused information. Murder accounts for roughly similar shares in the two samples (1.32 percent among FIRs with available accused identifiers and 1.38 percent among FIRs with missing accused identifiers), while dacoity also exhibits little difference. Rape represents an extremely small share of the missing-accused sample, suggesting that FIRs involving such offences are typically registered with identified accused. Riots are considerably less common among FIRs with missing accused information than among FIRs with available accused identifiers.

These differences are consistent with the institutional process through which FIRs are registered. In offences such as theft and burglary, victims frequently report the incident without knowing the identity of the offender, making the absence of accused identifiers relatively common. In contrast, offences involving interpersonal violence or disputes often involve victims who are able to identify the alleged offender at the time the FIR is lodged. Consequently, the likelihood of missing accused information naturally varies across crime categories.

Importantly, these descriptive patterns should not be interpreted as evidence that missing accused identifiers are randomly distributed across offences. Rather, they suggest that the likelihood of missing accused information varies systematically across crime categories, reflecting differences in the nature of the underlying offences and the circumstances under which FIRs are registered.

Table A.1.1 Distribution of FIRs Across Crime Categories

	Share (%)	
Crime Category	Accused Available	Accused Missing
Murder	1.32	1.38
Rape	0.17	0.01
Riot	7.99	0.69
Robbery	0.54	2.97
Dacoity	0.27	0.29
Kidnapping	2.07	3.81
Burglary	0.74	6.21
Theft	33.14	69.46

Notes: The table reports the distribution of FIRs across crime categories separately for FIRs with available accused identifiers and FIRs with missing accused identifiers.

Table A.1.2 examines the annual distribution of FIRs with available and missing accused identifiers over the study period. In contrast to the differences observed across crime categories, the temporal distribution of the two samples is remarkably similar. The proportion of FIRs with missing accused identifiers closely tracks that of FIRs with available accused identifiers in every year between 2018 and 2023. Although there are modest differences in individual years-for example, FIRs with missing accused identifiers account for a slightly larger share in 2019 and 2021 and a slightly smaller share in 2022—the overall pattern remains highly stable over time.

The similarity in the annual distributions suggests that missing accused identifiers are not concentrated in any particular year of the sample period. Instead, the prevalence of missing accused information appears to be a persistent feature of the FIR registration process rather than the result of changes in reporting practices or data recording over time. Together with the evidence from the previous table, these findings indicate that while missing accused identifiers vary systematically across crime categories, they do not exhibit substantial year-to-year variation.

Table A.1.3 compares the monthly distribution of FIRs with available accused iden-

Table A.1.2 Distribution of FIRs by Year

	Share (%)	
Year	Accused Available	Accused Missing
2018	14.94	14.36
2019	15.04	16.33
2020	16.06	16.05
2021	17.71	18.70
2022	22.42	20.51
2023	13.82	14.06

Notes: The table reports the distribution of FIRs by year separately for FIRs with available accused identifiers and FIRs with missing accused identifiers.

tifiers and FIRs with missing accused identifiers. Similar to the annual distribution, the monthly composition of the two samples is highly comparable. The share of FIRs with missing accused identifiers closely follows the distribution observed among FIRs with available accused identifiers throughout the calendar year. Although minor differences are observed in some months, these differences are small and do not indicate any systematic concentration of missing accused information in particular months.

Taken together, the evidence from Tables A.1.1, A.1.2, and A.1.3 suggests that the incidence of missing accused identifiers exhibits different patterns across different dimensions. While missingness is clearly concentrated in particular crime categories-most notably theft-it does not display substantial variation across years or calendar months. These findings indicate that missing accused information primarily reflects differences in the characteristics of offences rather than systematic temporal patterns in the recording of FIRs.

Table A.1.3 Distribution of FIRs by Months

	Share (%)	
Month	Accused Available	Accused Missing
January	7.84	8.46
February	7.88	8.83
March	9.52	9.08
April	7.69	7.79
May	9.04	8.64
June	9.92	9.14
July	10.00	9.54
August	8.21	8.04
September	7.41	7.63
October	7.24	7.54
November	7.45	7.29
December	7.81	8.02

Notes: The table reports the distribution of FIRs by calendar month separately for FIRs with available accused identifiers and FIRs with missing accused identifiers.

B Online Appendix

B.1 Results using Full Sample

Table B.1.1 Effect of Ramadan on Recorded Crimes

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Ramadan × Muslim	-0.0029**	0.0005**	-0.0152***	0.0008**	0.0009*	-0.0015	0.0007	-0.0235***
	(0.0012)	(0.0002)	(0.0056)	(0.0004)	(0.0005)	(0.0010)	(0.0006)	(0.0074)
Observations	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048
R^2	0.0042	0.0021	0.0193	0.0020	0.0021	0.0078	0.0024	0.0587
Mean Dep. Var.	0.0127	0.0013	0.1224	0.0026	0.0027	0.0149	0.0041	0.3252
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficient estimates from Equation 1 in the main text. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. All columns include police station fixed effects, and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.1.2 Effect of Ramadan on Recorded Crime

	(1)	(2)	(3)	(4)
	Crime	Crime	Crime	Crime
Ramadan × Muslim	-0.0050***	-0.0050***	-0.0050***	-0.0050***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Observations	25,440,384	25,440,384	25,440,384	25,440,384
R-squared	0.0028	0.0089	0.0098	0.0306
Dep. Var. Mean	0.0607	0.0607	0.0607	0.0607
Police Station FE	No	Yes	Yes	Yes
Date FE	No	No	Yes	Yes
Crime Type FE	No	No	No	Yes

Notes: The unit of observation is a police station-day-religion-crime category cell. The original data are organized in a wide format, with separate variables recording the daily number of offences committed by Muslims and non-Muslims for each crime category within a police station. These data are reshaped into a long format in which each observation corresponds to a unique combination of police station, date, religion group, and crime category. The religion dimension distinguishes offences committed by Muslims and non-Muslims, while the crime-category dimension consists of eight offence types: murder, rape, riots, robbery, dacoity, kidnapping, burglary, and theft. Consequently, each police station-day contributes 16 observations, corresponding to two religion groups and eight crime categories. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.1.3 Ramadan and Recorded Crime among Non-Muslims

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Ramadan	0.0001	-0.0004	-0.0074	0.0001	-0.0010	-0.0009	0.0004	0.0053
	(0.0016)	(0.0003)	(0.0081)	(0.0005)	(0.0007)	(0.0015)	(0.0007)	(0.0108)
Observations	1,590,024	1,590,024	1,590,024	1,590,024	1,590,024	1,590,024	1,590,024	1,590,024
R^2	0.0038	0.0021	0.0212	0.0018	0.0020	0.0083	0.0021	0.0618
Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the daily count of offences committed by non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. All columns include month × year fixed effects, and police station fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.1.4 Effect of Holydays on Crimes Excluding Ramadan Period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Murder	Rape	Riot	Robbery	Dacoity	Kidnapping	Burglary	Theft
Friday × Muslim	-0.0021**	-0.0004	0.0068*	0.0001	0.0001	0.0001	-0.0001	0.0075
	(0.0009)	(0.0003)	(0.0038)	(0.0003)	(0.0004)	(0.0008)	(0.0004)	(0.0050)
Observations	2,903,792	2,903,792	2,903,792	2,903,792	2,903,792	2,903,792	2,903,792	2,903,792
R^2	0.0042	0.0021	0.0191	0.0021	0.0022	0.0077	0.0025	0.0583
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. All columns include police station fixed effects, and date fixed effects. Standard errors clustered at the police station level are reported in parentheses.$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.1.5 Robustness: Police Station-Month and Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Murder	Rape	Riot	Robbery	Dacoity	Kidnapping	Burglary	Theft
Ramadan × Muslim	-0.0029**	0.0005**	-0.0152***	0.0008**	0.0009*	-0.0015	0.0007	-0.0235***
	(0.0012)	(0.0002)	(0.0056)	(0.0004)	(0.0005)	(0.0010)	(0.0006)	(0.0074)
Observations	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048
R^2	0.0062	0.0044	0.0216	0.0044	0.0046	0.0097	0.0047	0.0601
PS × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficient estimates from Equation 1 in the main text. The dependent variable is the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. All columns include police station × month fixed effects, and year fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.1.6 Robustness: Police Station-Year and Month Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Murder	Rape	Riot	Robbery	Dacoity	Kidnapping	Burglary	Theft
Ramadan × Muslim	-0.0029**	0.0005**	-0.0152***	0.0008**	0.0009*	-0.0015	0.0007	-0.0235***
	(0.0012)	(0.0002)	(0.0056)	(0.0004)	(0.0005)	(0.0010)	(0.0006)	(0.0074)
Observations	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048
R^2	0.0052	0.0043	0.0259	0.0034	0.0031	0.0103	0.0037	0.0684
PS × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficient estimates from Equation 1 in the main text. The dependent variable is the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. All columns include police station × year fixed effects, and month fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.1.7 Robustness: District-Month and Year Fixed Effects

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Ramadan × Muslim	-0.0029**	0.0005**	-0.0152***	0.0008**	0.0009*	-0.0015	0.0007	-0.0235***
	(0.0012)	(0.0002)	(0.0056)	(0.0004)	(0.0005)	(0.0010)	(0.0006)	(0.0074)
Observations	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048
R^2	0.0020	0.0009	0.0095	0.0007	0.0006	0.0037	0.0008	0.0312
District × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficient estimates from Equation 1 in the main text. The dependent variable is the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. All columns include district × month fixed effects, and year fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.1.8 Robustness: District-Year and Month Fixed Effects

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Ramadan × Muslim	-0.0029**	0.0005**	-0.0152***	0.0008**	0.0009*	-0.0015	0.0007	-0.0235***
	(0.0012)	(0.0002)	(0.0056)	(0.0004)	(0.0005)	(0.0010)	(0.0006)	(0.0074)
Observations	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048
R^2	0.0022	0.0014	0.0113	0.0009	0.0007	0.0042	0.0008	0.0361
District × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficient estimates from Equation 1 in the main text. The dependent variable is the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. All columns include district × year fixed effects, and month fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.1.9 Robustness: Inverse Hyperbolic Sine transformation of Crimes

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Ramadan × Muslim	-0.0014***	0.0002*	-0.0073***	0.0005**	0.0004**	-0.0009*	0.0003	-0.0098***
	(0.0005)	(0.0001)	(0.0015)	(0.0002)	(0.0002)	(0.0005)	(0.0002)	(0.0023)
Observations	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048
R^2	0.0055	0.0026	0.0270	0.0027	0.0027	0.0101	0.0034	0.0832
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficient estimates from Equation 1 in the main text. The dependent variable is the inverse hyperbolic sine transformation of the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. All columns include police station fixed effects, and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.1.10 Robustness: Logarithmic Transformation of Accused Counts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(1 + Murder)	Log(1+ Rape)	Log(1 + Riot)	Log(1+ Robbery)	Log(1+ Dacoity)	Log(1+ Kidnapping)	Log(1+ Burglary)	Log(1+ Theft)
Ramadan × Muslim	-0.0011***	0.0002*	-0.0057***	0.0004**	0.0003**	-0.0007*	0.0002	-0.0077***
	(0.0004)	(0.0001)	(0.0012)	(0.0001)	(0.0001)	(0.0004)	(0.0002)	(0.0018)
Observations	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048
R^2	0.0055	0.0026	0.0268	0.0027	0.0027	0.0101	0.0034	0.0827
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficient estimates from Equation 1 in the main text. The dependent variable is the natural logarithm of the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. All columns include police station fixed effects, and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.1.11 Effect of Dhu-al-Hijjah on Crimes Excluding Ramadan Period

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Dhu-al-Hijjah × Muslim	-0.0016	0.0004	-0.0039	-0.0010*	0.0004	-0.0011	-0.0013***	-0.0303***
	(0.0011)	(0.0003)	(0.0050)	(0.0006)	(0.0005)	(0.0010)	(0.0004)	(0.0073)
Observations	2,903,792	2,903,792	2,903,792	2,903,792	2,903,792	2,903,792	2,903,792	2,903,792
R^2	0.0042	0.0021	0.0191	0.0021	0.0022	0.0077	0.0025	0.0583
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Police Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

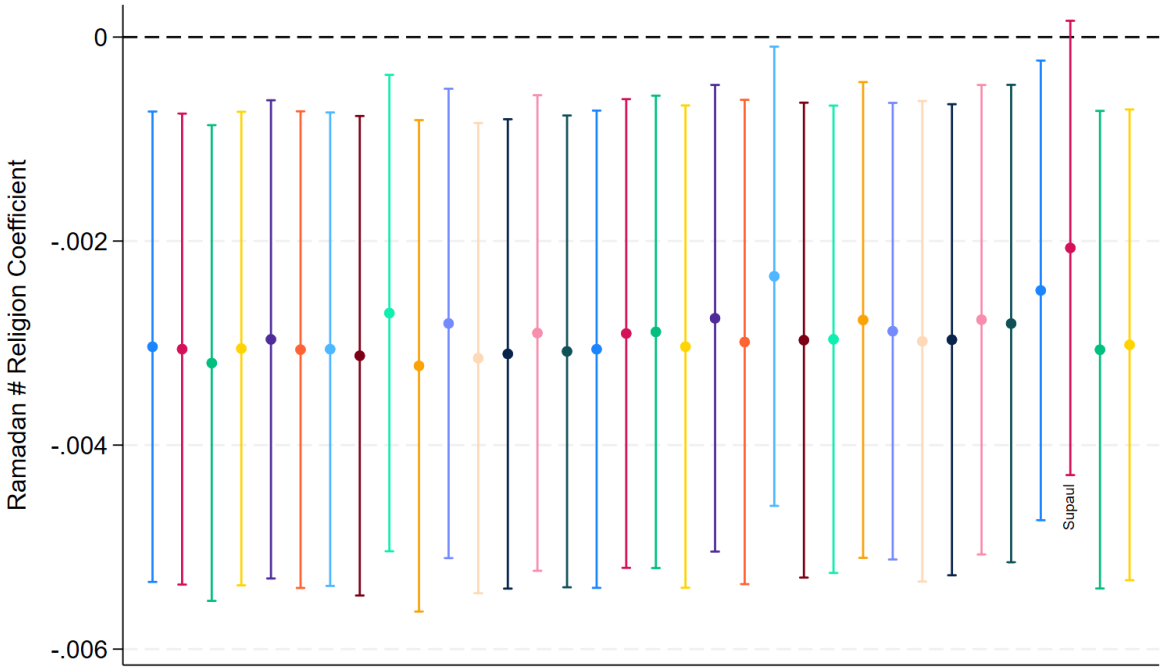
Notes: The dependent variable is the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. All columns include police station fixed effects, and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.1.12 Persistent Religiosity

	(1) Murder	(2) Rape	(3) Riot	(4) Robbery	(5) Dacoity	(6) Kidnapping	(7) Burglary	(8) Theft
Week 1 × Muslim	0.0006	0.0010***	-0.0024	0.0019***	0.0005	0.0005	0.0025	0.0038
	(0.0019)	(0.0003)	(0.0106)	(0.0005)	(0.0009)	(0.0017)	(0.0016)	(0.0130)
Week 2 × Muslim	-0.0023	0.0006*	-0.0067	-0.0001	0.0011	-0.0031	-0.0003	-0.0126
	(0.0021)	(0.0003)	(0.0105)	(0.0010)	(0.0012)	(0.0020)	(0.0009)	(0.0133)
Week 3 × Muslim	-0.0061**	0.0002	-0.0173*	0.0004	0.0010	0.0001	-0.0003	-0.0201
	(0.0024)	(0.0005)	(0.0099)	(0.0007)	(0.0010)	(0.0018)	(0.0008)	(0.0135)
Week 4 × Muslim	-0.0036*	0.0004	-0.0307***	0.0011	0.0007	-0.0033*	0.0009	-0.0573***
	(0.0020)	(0.0004)	(0.0092)	(0.0007)	(0.0007)	(0.0019)	(0.0007)	(0.0135)
$\beta_{week1} = \beta_{week2}$	0.266	0.337	0.761	0.044	0.663	0.159	0.121	0.382
$\beta_{week1} = \beta_{week3}$	0.023	0.156	0.296	0.057	0.688	0.848	0.126	0.198
$\beta_{week1} = \beta_{week4}$	0.120	0.226	0.038	0.303	0.838	0.141	0.371	0.001
$\beta_{week2} = \beta_{week3}$	0.236	0.483	0.419	0.664	0.953	0.229	0.958	0.648
$\beta_{week2} = \beta_{week4}$	0.659	0.685	0.074	0.286	0.778	0.929	0.271	0.015
$\beta_{week3} = \beta_{week4}$	0.419	0.761	0.314	0.428	0.805	0.169	0.243	0.036
Observations	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048	3,180,048

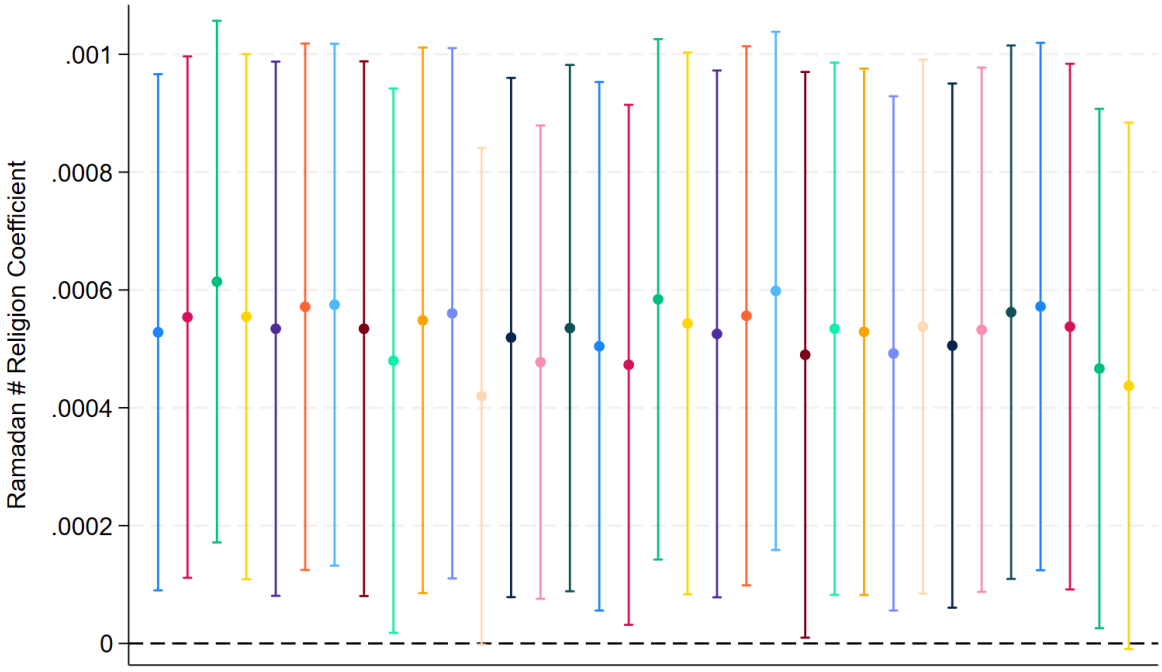
Notes: The dependent variable is the daily count of offences committed by Muslims and non-Muslims within a police station. The specific crime outcome analysed in each regression is indicated by the corresponding column heading. All columns include police station fixed effects, and date fixed effects. Standard errors clustered at the police station level are reported in parentheses. Values reported in square brackets are p-values from hypothesis tests of equality between coefficients across Ramadan weeks. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure B.1.1 Dropping one district at a time: Murder



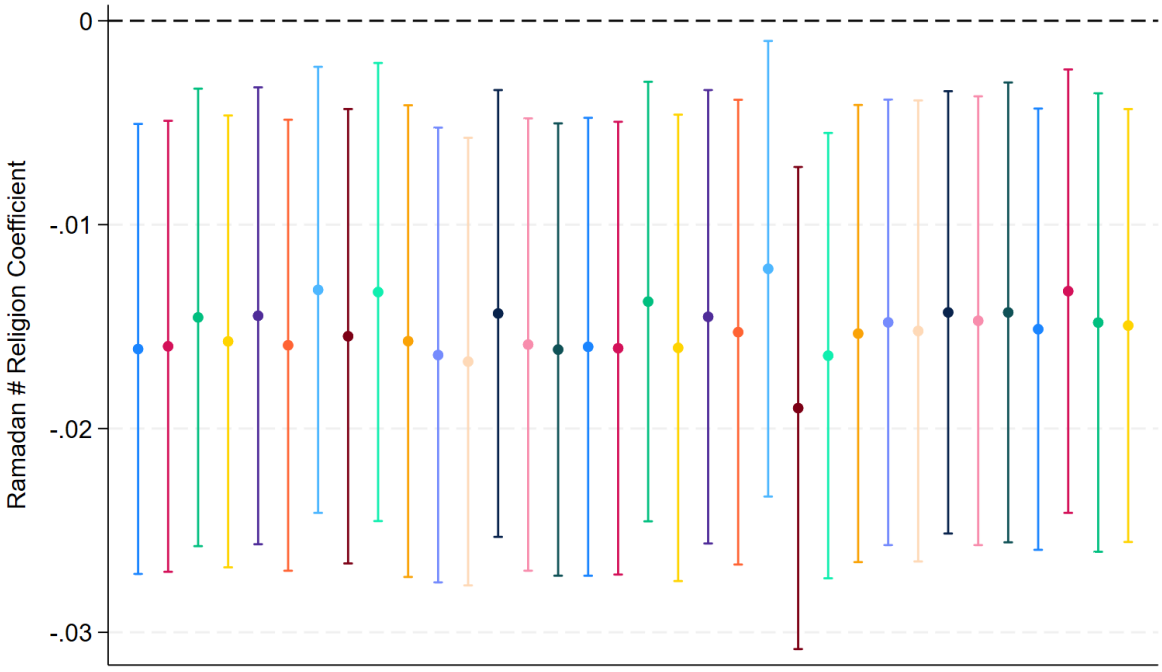
Notes: This figure illustrates the leave-out-one-district estimates of the coefficient on the Ramadan × Muslim. Each point corresponds to the estimated coefficient obtained after excluding all observations from a single district with all the baseline fixed effects.Error bars denote 95% confidence intervals. Standard errors are clustered at the police station level.

Figure B.1.2 Dropping one district at a time: Rape



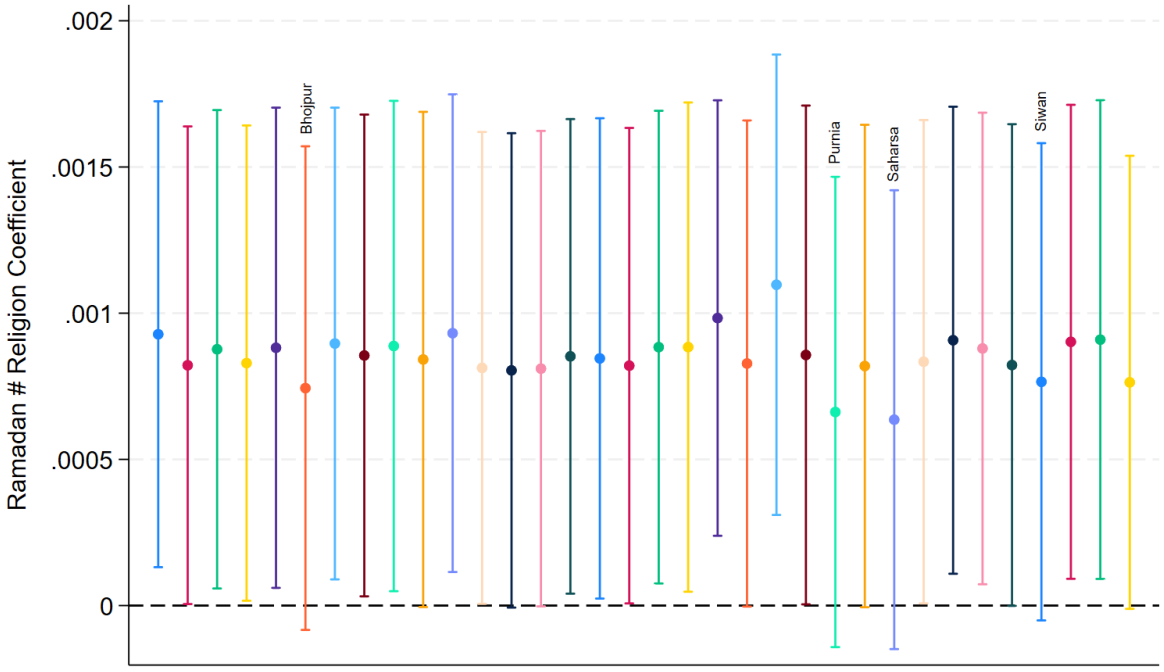
Notes: This figure illustrates the leave-out-one-district estimates of the coefficient on the Ramadan × Muslim. Each point corresponds to the estimated coefficient obtained after excluding all observations from a single district with all the baseline fixed effects.Error bars denote 95% confidence intervals. Standard errors are clustered at the police station level.

Figure B.1.3 Dropping one district at a time: Riot



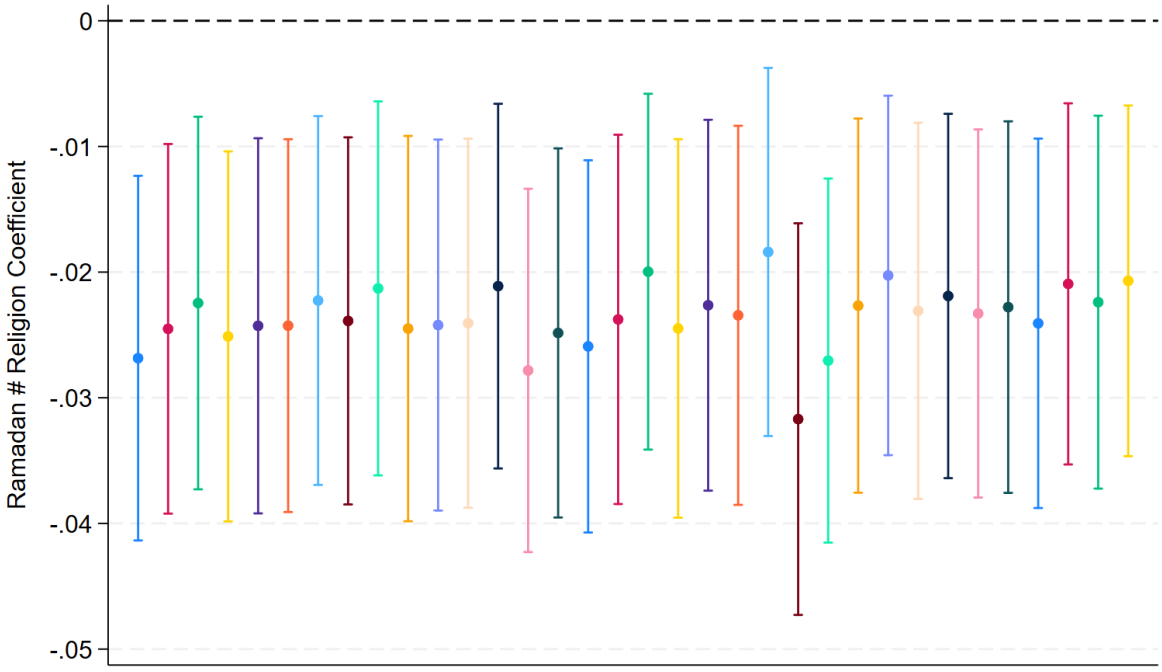
Notes: This figure illustrates the leave-out-one-district estimates of the coefficient on the Ramadan × Muslim. Each point corresponds to the estimated coefficient obtained after excluding all observations from a single district with all the baseline fixed effects.Error bars denote 95% confidence intervals. Standard errors are clustered at the police station level.

Figure B.1.4 Dropping one district at a time: Robbery



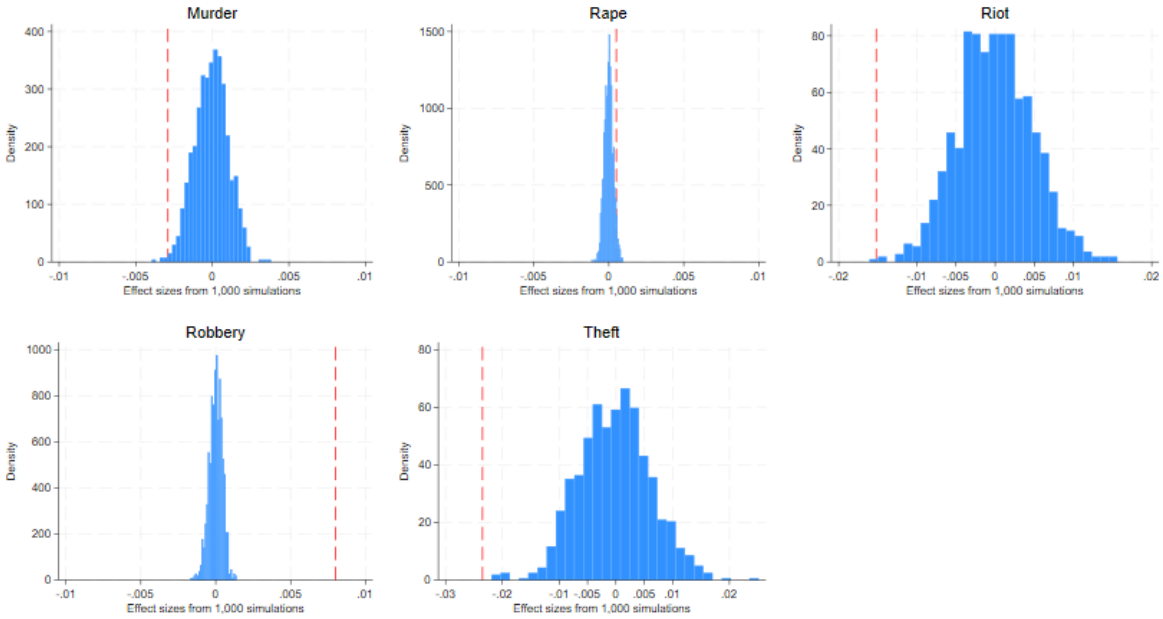
Notes: This figure illustrates the leave-out-one-district estimates of the coefficient on the Ramadan × Muslim. Each point corresponds to the estimated coefficient obtained after excluding all observations from a single district with all the baseline fixed effects.Error bars denote 95% confidence intervals. Standard errors are clustered at the police station level.

Figure B.1.5 Dropping one district at a time: Theft



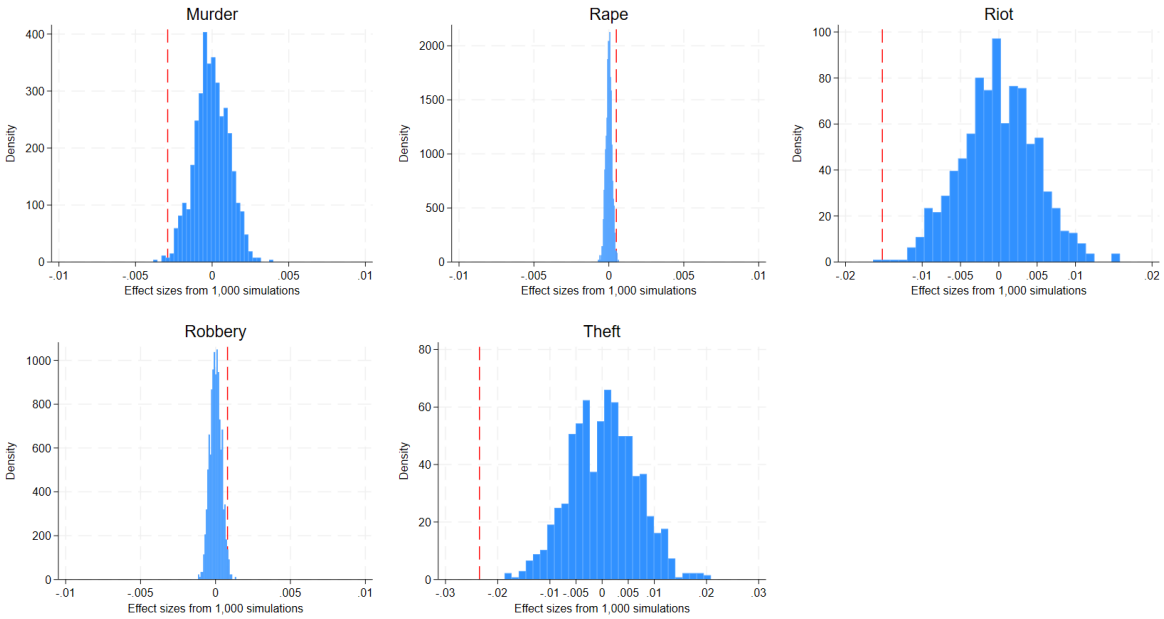
Notes: This figure illustrates the leave-out-one-district estimates of the coefficient on the Ramadan × Muslim. Each point corresponds to the estimated coefficient obtained after excluding all observations from a single district with all the baseline fixed effects.Error bars denote 95% confidence intervals. Standard errors are clustered at the police station level.

Figure B.1.6 Randomization of Ramadan



Notes: This figure shows the distribution of estimated effects from 1000 random simulations of accused religion assignment. The red vertical line represents the actual estimated effect from the data. Simulations are based on the null hypothesis of no effect.

Figure B.1.7 Randomisation of Muslim



Notes: This figure shows the distribution of estimated effects from 1000 random simulations of Muslim dummy. The red vertical line represents the actual estimated effect from the data. Simulations are based on the null hypothesis of no effect.