Measuring Religion from Behavior: Violence, Climate Shocks and Religious Adherence in Afghanistan*

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Abstract

Religion plays a fundamental role in society but is often difficult to measure. We develop a novel method for measuring religious adherence that is based on decreases in digital activity during periods set aside for prayer. We apply this approach to a dataset of roughly 23 billion phone calls to study the determinants of religious practice in Afghanistan. We find that religious adherence declines after violent attacks by Islamist insurgents but increases in response to droughts in agricultural regions. This approach creates new avenues for studying religious behavior in contexts where conventional data are unavailable or unreliable.

JEL classification: Z10, Z12, Q10, Q15, Q54, O13, C55, D74

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1 Introduction

Religion plays a fundamental role in human society. Religions shape cultural norms and values, influence the organization of social groups, and define the contours of political and economic power (Berman, 2000; Becker, Rubin, and Woessmann, 2021). Economic research also consistently demonstrates the centrality of religion in economic life (Iannaccone, 1998; McCleary and Barro, 2006; Barro and McCleary, 2019). These dynamics underscore the importance of understanding the determinants of religious practice and adherence.

In this study, we develop a scalable empirical method to measure religious adherence from passively collected digital data. This measure can be constructed at very high frequency and for very fine-grained geographic areas, even in environments — such as active conflict zones — where surveys are dangerous or infeasible. We then use this measurement approach to shed light on how insurgent violence and climate shocks shape religiosity in Afghanistan. Our empirical analysis is uniquely enabled by this measure, as it requires observations of religious behavior at a spatial and temporal resolution that would otherwise be nearly impossible to obtain.

Our paper has two main parts, one methodological and the other applied. In the first part, we demonstrate how digital trace data can be used to measure religious adherence. Our measurement approach is based on a simple insight: a core tenet of Islam is to pray five times a day during specific periods of time. We therefore posit that decreases in digital activity during prayer windows can provide an indication of the religious adherence of the population. We implement and validate this measurement approach in Afghanistan, using anonymized mobile phone data from one of Afghanistan's largest mobile phone operators. Leveraging data from over 10 million unique phone users, who collectively made 22.6 billion phone calls between 2013-2020, we observe that, on average, call volume falls by roughly 24% about 15 minutes into the Maghrib prayer window.[1] We refer to this decrease as the

[1] This dip in phone calls is consistent with the strong Islamic norm that talking to others – including on the phone – is widely considered to invalidate prayer. This norm is laid out explicitly in a series of religious texts and rulings, including sayings of Muhammad collated in the *Book of Prayers*. See Figure A1 for an example of a poster establishing this norm. Other prayer windows (including Zuhr and Asr) also exhibit

"Maghrib dip."

We use a variety of approaches to validate the Maghrib dip as a measure of religious adherence. First, we exploit the timing of the dip to separate reductions in call activity caused by Maghrib from reductions related to the end of the workday, rush hour, and other daily events. This is possible because the Maghrib prayer window begins exactly at sunset, which varies by season and by geographic region. Since mobile phone metadata are recorded every second by thousands of unique cell towers throughout the country, it is possible to measure the magnitude of the Maghrib dip in very fine-grained geographic regions, on every day of the year. By disaggregating in this way, we show that the Maghrib dip perfectly tracks the timing of sunset across seasons and space.[2]

Second, we provide evidence that individuals who self-report being more religious are more likely to reduce calls during the Maghrib window. This exercise is possible because we conducted surveys with a small sample of mobile phone subscribers, and with their informed consent, linked their survey responses to their mobile phone records (Blumenstock et al., 2024). Thus, for these individuals, we have a survey-based index of religiosity as well as a measure of their Maghrib dip based on their mobile phone activity. We find that these two variables are strongly correlated: in our sample, a one standard deviation increase in the survey religiosity index is associated with a 27% increase in the Maghrib dip.

Finally, we show that geographic variation in the Maghrib dip across Afghanistan correlates with existing data related to religious norms. In particular, when we aggregate our measure at the regional level, we observe that predominantly Pashtun districts exhibit larger Maghrib dips. This is reassuring since the Pashtun are widely regarded as more religiously conservative than other ethnic groups in Afghanistan.

As with more traditional measures of religiosity, our Maghrib dip measure likely reflects both a private component motivated by intrinsic factors such as piety (cf. Allport and Ross, 1967), as well as a range of more extrinsic and social considerations (e.g., Iannaccone, 1992; Berman, 2000; McBride, 2007; Chen, 2010; Berman, 2011; Levy and Razin, 2012; Carvalho,

dips, but as we discuss later, we focus on Maghrib as the window is shortest and most precisely defined.

[2]This approach resembles that of Campante and Yanagizawa-Drott (2015), who use both seasonal and geographic variation in daylight hours to study how the duration of daytime fasting during Ramadan affects economic growth, finding that longer fasting hours reduce growth.

2013; Levy and Razin, 2014; Carvalho, 2019; Levy, 2019; Iyer and Weeks, 2020; Cavalcanti et al., 2022; Seabright, 2024). For example, individuals may refrain from calling others in their social network out of a desire to appear pious, or because they wish to avoid interrupting others while they are praying. One advantage of our data is that we can observe several different types of transactions that vary in the extent to which they are publicly observed, and the extent to which they require a counterpart's active participation. This includes shortcode calls, which are voice calls made to automated services (e.g., managing account balances) and to semi-anonymous entities (e.g., customer care), as well as text messages and data services. We observe a significant reduction in all types of transactions during the Maghrib prayer window, which suggests that the Maghrib dip is unlikely to reflect social considerations alone.[3]

In the second part of the paper, we use this new measure to study the effects of conflict and economic adversity on religious adherence. We present two case studies that are particularly relevant to the Afghan context, which help illustrate how this measure can be used in environments where other measures of religiosity would be prohibitively difficult to collect.

Our first case study examines the effect of violent conflict on religious adherence. This builds on past work that emphasizes how threats can lead people to adhere more tightly to social norms (Henrich et al., 2019), and how people turn to religion for psychological solace in uncertain environments (Pargament et al., 1998; Vail et al., 2010; Sosis and Handwerker, 2011; Bryant-Davis and Wong, 2013; Bentzen, 2019, 2021), including due to trauma from combat (Cesur, Freidman, and Sabia, 2020; Mill et al., 2024).[4] Conflict that pits one religious group against another may also increase religious behavior by reinforcing group cleavages (Zussman, 2014; Atkin, Colson-Sihra, and Shayo, 2021). Alternatively, religious violence may reduce adherence by provoking disillusionment or backlash, or by imposing logistical constraints on religious practice.

We use our Maghrib dip measure to empirically study how violence by Islamist insurgents shapes religious adherence in Afghanistan. To do so, we link billions of mobile phone call

[3]For example, a reduction in internet data use during the Maghrib window is unlikely to occur because the subscriber merely wants to appear pious or avoid interrupting others.

[4]Related work also shows that religious participation can mitigate the adverse impact of shocks on mental health outcomes (Fruehwirth, Iyer, and Zhang, 2019; Bahal et al., 2023; Iyer et al., 2025).

records to tens of thousands of geocoded violent events over 2013-2014, and estimate the impact of violence on the Maghrib dip at the district-month level, controlling for district and month fixed effects. We find that insurgent violence leads to *lower* religious adherence. Consistent with backlash resulting from exposure to war's destructive effects (Condra and Shapiro, 2012; Dell and Querubin, 2018; Mahmood and Jetter, 2023), insurgent activity associated with intended but unrealized attacks (for example, unexploded IEDs) does not produce similar effects. In addition, neither state-led attacks nor other state-led military activities alter religious adherence. In other words, the tendency to turn away from religion emerges specifically when attacks are perpetrated by religious extremist groups.

Our second case study examines how religious behavior is affected by quasi-random climate shocks, which can be particularly disruptive to the rural Afghan economy (UNEP, 2016; Kochhar and Knippenberg, 2023). Empirically, we estimate the impact of changes in rainfall, derived from the Standardized Precipitation-Evapotranspiration Index (SPEI) (Vicente-Serrano, Beguería, and López-Moreno, 2010; Harari and La Ferrara, 2018) on religious adherence, at the level of 10 km x 10 km grid cells (the native resolution of the SPEI data). Across a variety of empirical specifications, we find robust evidence that adverse changes in climate conditions significantly *increase* religious adherence.

Exploring the possible mechanisms behind this effect, we find suggestive evidence that climate conditions affect religiosity — at least in part — through economic channels.[5] In particular, we find that climate shocks have the largest impact on religious adherence in rainfed croplands that lack access to irrigation, which are precisely the areas where agricultural productivity is most affected by drought. We further find, when disaggregating impacts by season, that climate shocks during the growing season have the greatest impact on religious adherence during the growing and post-harvest seasons, but have no effect during the harvest season itself. This particular pattern is consistent with the idea that individuals might

[5] Prior work highlights the ambiguous nature of the relationship between economic adversity and religiosity: On the one hand, adverse income shocks may reduce religious adherence if they weaken people's faith — particularly if they expect God to protect against such shocks (Auriol et al., 2020, 2021a; Seabright, 2024). On the other hand, adverse income shocks may increase religious adherence if they lower the opportunity cost of time (Azzi and Ehrenberg, 1975) or create a need for social insurance (Iannaccone, 1992; Berman, 2000; Dehejia, DeLeire, and Luttmer, 2007; Chen, 2010). Individuals may also turn to religion when they experience negative income shocks if religion provides psychological support (Hume, 1757; Wesley, 1760; Weber, 1905; Freud, 1927; Marx, 1970).

pray to cope psychologically with income shocks (Hume, 1757; Wesley, 1760; Weber, 1905; Freud, 1927; Marx, 1970), but not with the hypothesis that income shocks increase religious adherence by lowering the opportunity cost of time (Azzi and Ehrenberg, 1975).

After presenting our main results using regional aggregates of the Maghrib dip, we provide more suggestive analysis based on individual-specific measures of the Maghrib dip. This requires aggregating individual activity over longer time horizons, which is only appropriate for the second case study, for which we have nearly a decade of data. In this analysis, we can condition on individual fixed effects, effectively asking whether an individual's exposure to climate shocks causes them to change religious practices. Here, we find that individuals who are initially more religiously adherent become even more adherent when exposed to adverse economic shocks. This result is consistent with earlier results suggesting that religious adherence might help people cope with adverse events.

Taken as a whole, our paper makes two distinct types of contributions. First, we contribute a novel measurement instrument that helps address several well-documented challenges that arise in the empirical study of religion (Hadaway, Marler, and Chaves, 1998; Brenner, 2011; Brenner and DeLamater, 2016). In particular, the Maghrib dip measure is passively collected and "incidental", in the sense that the subject does not realize that the behavior of interest is under observation. As with recent work by Livny (2021) and Pope (2024), this helps address the biases that can arise when surveys are used to elicit self-reports of religious practices (cf. Hadaway, Marler, and Chaves, 1993; Brenner, 2014).[6] The measure also has several attractive empirical properties: it makes it possible to observe religious behavior in times and places where it would be infeasible to conduct surveys (such as during the conflict in Afghanistan); it can be observed at very high frequency for individual subscribers or aggregated over arbitrarily granular units of space and time — and this, in turn, makes it possible to conduct econometric analysis that would be impractical with conventional data. Moreover, unlike other passive measures of religious adherence, the Maghrib dip separately captures religious behaviors across a spectrum ranging from very public behaviors (such as

[6] Livny (2021) uses satellite imagery to track Ramadan observance via nighttime illumination, and Pope (2024) analyzes geolocated smartphone data to study church attendance. Other creative strategies to address measurement challenges include Bentzen (2021), which uses Google searches of prayer, and Atkin, Colson-Sihra, and Shayo (2021), which uses consumption of taboo goods (e.g., beef consumption among Hindus) as a measure of religious identity.

talking on the phone), which likely reflect a degree of external, social considerations, to more private behaviors (such as using internet data) that are more likely to reflect intrinsic motivations.

There are also clear limitations to the measure. For example, it does not tell us about people's internal sentiments, such as their emotional connection to their religious community, their private reflections on religious belief, or the personal salience of religion in their life. For these reasons, among others summarized in subsection 3.4, it should be viewed not as a replacement for but rather as a complement to traditional survey-based measures of religious adherence and beliefs.

Our second type of contribution, made via the case studies, is to the substantive literature on the relationship between conflict, economic adversity, and religious behavior. To the best of our knowledge, our violence case study is the first to find a negative relationship between insurgent violence and religious adherence. This finding also carries an important implication for understanding religious extremism: it suggests that violence may be strategically counterproductive for Islamist insurgent groups seeking to foster a more religious society.

The results of our second case study are consistent with previous work documenting a negative relationship between religiosity and economic conditions (McCleary and Barro, 2006; Chen, 2010; Costa, Marcantonio, and Rocha, 2019),[7] and relate to recent papers showing that environmental change can affect religiosity through social and political dynamics, with effects that persist for years and decades (Chaney, 2013; Ager and Ciccone, 2018). We build on this work by examining the impact of economic conditions that change at high frequency and by leveraging data from millions of individual users to examine how baseline religious adherence shapes individual responses to adverse shocks.

Pairing these two case studies together also highlights that some adverse shocks increase religious adherence, while others diminish it. When a shock is explicitly connected to religion, such as violence by Islamist insurgents, people are less likely to turn to religion as a coping mechanism. In contrast, when a shock is not explicitly tied to religion, as with income shocks, religious adherence may increase as a means of coping with the situation.

[7] An exception is Buser (2015), which instead finds a positive relationship between cash transfers and church attendance.

In developing this measure of religious adherence, we hope to foster further work on the burgeoning literature around how religiosity is shaped by different types of organizational structures such as schooling (Bazzi, Hilmy, and Marx, 2020), charity (Gruber, 2004), group ties (Berman, 2000), and other Islamic institutions (Bazzi, Koehler-Derrick, and Marx, 2020). We also believe our work connects to the literature examining the economic consequences of religion.[8] Recent empirical work in this area has examined the consequences of particular institutional features of religion, such as the Hajj (Clingingsmith, Khwaja, and Kremer, 2009), religious holidays (Montero and Yang, 2022), and programs aimed at promoting Protestant theology (Bryan, Choi, and Karlan, 2021). Campante and Yanagizawa-Drott (2015) studies how fasting during Ramadan affects economic growth. These papers present important advances; we hope that broadening the data sources and methods used to measure religious behavior can help advance the study of religion in economics, where it is a relatively new but growing topic of study (Iyer, 2016).

The remainder of the paper is organized as follows. In Section 2, we provide relevant details on Islamic prayer norms and the Maghrib prayer window. In Section 3, we describe our mobile phone metadata and present and validate the Maghrib dip measure. In Section 4, we use our Maghrib dip measure to examine how insurgent violence affects religious adherence. In Section 5, we examine how climate shocks affect religious adherence. Section 6 concludes.

2 Islamic Prayer Norms and the Maghrib Prayer

This section provides background on Islamic prayer norms, with a particular focus on how they relate to the daily Maghrib prayer window.

[8]Among others, this literature includes work by: Barro and McCleary (2003); Gruber (2004); Gruber and Hungerman (2008); Becker and Woessmann (2009); Chaudhary and Rubin (2011); Bottan and Perez-Truglia (2015); Cantoni (2015); Michalopoulos, Naghavi, and Prarolo (2016); Chaney (2016); Chaudhary and Rubin (2016); Rubin (2017); Cantoni, Dittmar, and Yuchtman (2018); Esteban, Levy, and Mayoral (2018); Kuran (2018); Chaney (2019); Esteban, Levy, and Mayoral (2019); Naghavi (2019); Auriol et al. (2021b); Bénabou, Ticchi, and Vindigni (2022); Rubin (2022); Butinda et al. (2023); Cinnirella, Naghavi, and Prarolo (2023); Becker, Rubin, and Woessmann (2024); Le Rossignol, Lowes, and Nunn (2024); Rubin (2024).

Prayer Norms in Islam Engaging in prayer five times a day is one of the five pillars of Islam. These prayers must occur during specific windows of time. Muezzins issue the call to prayer from loudspeakers at the beginning of the prescribed times, and more recently, though mobile phone applications that alert users when the prayer window begins. The prayers are only considered valid if they are completed before the window closes.

Prayers may be performed individually or collectively. While men are expected to attend a congregational prayer on Fridays (the Jummah prayer), which often takes place in mosques, the other daily prayers may be conducted privately. Women rarely pray in mosques. In Afghanistan, most prayer activity occurs within homes or other private spaces.

A large body of religious texts and rulings has established that talking during prayer invalidates it. For example, *The Book of Mosques and Places of Prayer* draws on hadiths — records of the sayings of Muhammad that serve as a major source of religious law and moral guidance — to codify this rule. Chapter 7 of that text, entitled "The prohibition of speaking during the prayer, and the abrogation of its former permissibility", draws on several hadiths from Sahih Muslim (circa 840 A.D.), illustrating how silence during prayer became the norm.[9] One such hadith (Book 5, Number 43) states:

> Zaid b. Arqam reported: We used to talk while engaged in prayer and a person talked with a companion on his side in prayer till (this verse) was revealed: "Stand before Allah in devout obedience" (ii, 238) and we were commanded to observe silence (in prayer) and were forbidden to speak.

A similar passage (Book 5, Number 46) recounts:

> Jabir reported: The Messenger of Allah (may peace be upon him) sent me (on an errand) while he was going to Banu Mustaliq. I came to him and he was engaged in prayer on the back of his camel. I talked to him and he gestured to me with his hand... When he completed the prayer he said: What have you done (with regard to that business) for which I sent you? I could not talk with you but for the fact that I was engaged in prayer.

The principle of not talking during prayer has also been reaffirmed through numerous legal rulings (fatwas) regarding elements of Sharia law.[10] For example, one fatwa (Majmu' al-Fatawa 12/93) by the theologian Ibn Taymiyyah, states:

[9] A translation can also be found here: `https://sunnah.com/muslim/5`.

[10] See `http://www.fiqhonline.com/articles/fxefabv-the-ruling-on-speaking-during-the-prayer.cfm` for a summary of fatwas relevant to this issue.

> It has been established by both textual evidence and consensus that when one speaks with the speech of men, deliberately, [with speech that is not for the] beneficial interest of the prayer, knowing of its unlawfulness, his prayer becomes invalid.

Another fatwa (Majmu Fatwa 6/47) rules:

> Deliberate speech during the prayer invalidates it except in the case of the ignorant one and the forgetful.

In summary, talking during prayer — whether in person or on the phone — is strictly prohibited. Accordingly, mosques around the world display signs prohibiting phone use during prayer. Appendix Figure A1 provides an illustrative example.

The Maghrib Prayer Window Much of our analysis focuses on the Maghrib ("sunset") prayer window, the fourth daily prayer window, which begins immediately after sunset. Under Sunni Islam, the branch practiced by 90% of Afghans, the Maghrib window opens precisely at sunset and must be completed by dusk.[11] While "dusk" is not clearly defined, most Muslims aim to complete the Maghrib prayer before darkness sets, which requires starting the prayer within 15 minutes of the prayer window opening. Delaying the Maghrib prayer beyond this point without valid reason is considered *Makruh* (disliked or offensive).[12]

Maghrib has three important characteristics that will be relevant to our empirical analysis. First, in the Sunni tradition the Maghrib window is short, lasting less than an hour. By contrast, the Zuhr (noon) and Asr (afternoon) prayer windows are three hours long, and the Isha (night) prayer window starts after Maghrib and lasts until sunrise. Second, the Maghrib window occurs when most people are awake and active, whereas the Fajr (dawn) and Isha prayers occur when many people are asleep. Third, the exact timing of the Maghrib window varies by location and season, so it doesn't consistently overlap with other fixed daily activities, such as the end of the workday or rush hour in urban areas.[13]

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[11] The Maghrib window is different under Shia Islam: it begins 5 to 15 minutes later and extends longer, as it is merged with the Isha prayer window. Thus, we should not expect to observe sharp changes in call volume during the Sunni Maghrib prayer window in predominantly Shia areas, as discussed in Section 3.

[12] For example, see the guidance on prayer times: `https://www.moonsighting.com/faq_pt.html`.

[13] We calculate daily prayer times using the Python library `prayertimes` (`http://praytimes.org/calculation`).

3 Measuring Religious Adherence with Mobile Phone Metadata

The first contribution of this paper is to develop and validate a behavioral measure of religious adherence derived from anonymous mobile phone transaction logs. This builds on a substantial social science literature that has explored the methods and challenges involved in measuring religiosity, both across countries and over time (Hadaway, Marler, and Chaves, 1998; Brenner, 2011; Brenner and DeLamater, 2016). Traditional survey-based indicators often overstate religious participation. For example, church attendance is frequently over-reported in surveys, with estimates of the degree of over-reporting in the US ranging from 100% (Hadaway, Marler, and Chaves, 1993) to over 400% (Pope, 2024). In Muslim societies, prayer observance is also frequently over-reported, particularly among women and among respondents who self-identify as highly religious (Brenner, 2014).[14] Such biases arise because questions on religious practice can carry risks or moral connotations, making responses sensitive to social desirability bias and selective disclosure (Tourangeau and Yan, 2007).

The key insight behind the passive measure that we use is that Islamic religious norms forbid talking during the Maghrib prayer window (see Section 2), the timing of which is precisely specified. We therefore interpret the drop in call volume that occurs during the Maghrib prayer window, relative to the volume immediately before Maghrib, as an indication of local religious adherence. This section introduces the mobile phone data in more detail, formally defines the Maghrib dip measure, and provides both visual and quantitative validation using conventional sources of data.

3.1 Mobile Phone Metadata (Call Detail Records)

Mobile phones are a widespread form of communication in Afghanistan, with estimates of adult cell phone penetration ranging from 60% - 70% (Gonzalez, 2021; World Bank, 2021). We observe the complete transaction logs of mobile phone activity on one of Afghanistan's

[14] Even modest changes to the survey collection process, such as whether the enumerator wears a religious headscarf (Blaydes and Gillum, 2013) or whether respondents fill in their own survey instead of speaking to an enumerator (Pew Research Center, 2021), substantially affect measures of religious adherence.

largest mobile phone networks during the eight-year period 2013-2020. These logs cover 6.0-7.7 million unique phone numbers each year (out of a total population of 39 million), who collectively made 22.6 billion calls during this period. Geographically, the phone company operates 1,739 cell phone towers across 292 of Afghanistan's 398 districts (Appendix Figure A2). Tower density is roughly proportional to population density, and the number of subscribers in a district is highly correlated (Pearson $\rho = 0.94$) with the district population (Tai, Mehra, and Blumenstock, 2022).

Our analysis relies on Call Detail Records (CDR), which are the metadata of phone calls collected by mobile phone operators for billing purposes. For each call placed, we observe an anonymized unique ID for the caller and the receiver, the date and time when the call was made, and the identifier for the calling party's cell phone tower. This tower is typically the tower closest to the calling party at the time of the call, with minor variations due to network load balancing and signal interference. Because we have the geographic coordinates of all towers, we can approximate the caller's location at the time of the call, typically within a few hundred meters in urban areas and a few kilometers in rural areas. We do not observe tower information for the receiving party, so location data are only available for outgoing calls. For this reason, our analysis focuses on outgoing calls, though we also provide supporting results using other forms of network activity.[15]

Data Access and Data Privacy While our main analysis uses aggregated data, and while the CDR include only metadata rather than the *content* of communications, the raw data are nonetheless confidential and sensitive (Mayer, Mutchler, and Mitchell, 2016). To protect subscriber privacy, our research and data management protocols were reviewed and approved by the U.C. Berkeley Committee for the Protection of Human Subjects (protocols #2018-03-10929 and #2016-10-9212). These protocols include strict data security measures that regulate access to the data, as well as anonymization procedures that remove any personally identifying information prior to analysis.

More broadly, Blumenstock (2018), de Montjoye et al. (2018), Oliver et al. (2020), and

[15] Outgoing calls are also more complete. We observe all outgoing calls placed on this operator's network, whether the calls are made to the same or other networks. In contrast, we only observe incoming calls that are within-network. We do not observe calls between subscribers of other networks.

Kohli, Aiken, and Blumenstock (2024) discuss important considerations that arise in the use of mobile phone data. Although access to such data has historically been limited, they are now increasingly used in social science research and public policy (cf. Blondel et al., 2012; United Nations, 2019). Examples include phone companies sharing CDR with governments, researchers, and NGOs to guide social protection policy (cf. Gentilini et al., 2020; Aiken et al., 2022), public health interventions (Milusheva et al., 2021), disaster response (Lu, Bengtsson, and Holme, 2012), and transport planning (Hanna, Kreindler, and Olken, 2017).

3.2 The 'Maghrib Dip' as a Measure of Religious Adherence

Our measure of local religious adherence quantifies the drop in outgoing call volume during the Maghrib prayer window. To provide intuition for this approach, Figure 1 shows total countrywide call volume in each minute relative to the start of Maghrib, averaged across all days in our 2013-2020 sample. The top axis shows the time of day for an illustrative day in which sunset — and thus the start of the Maghrib prayer window — occurs at 18:00.

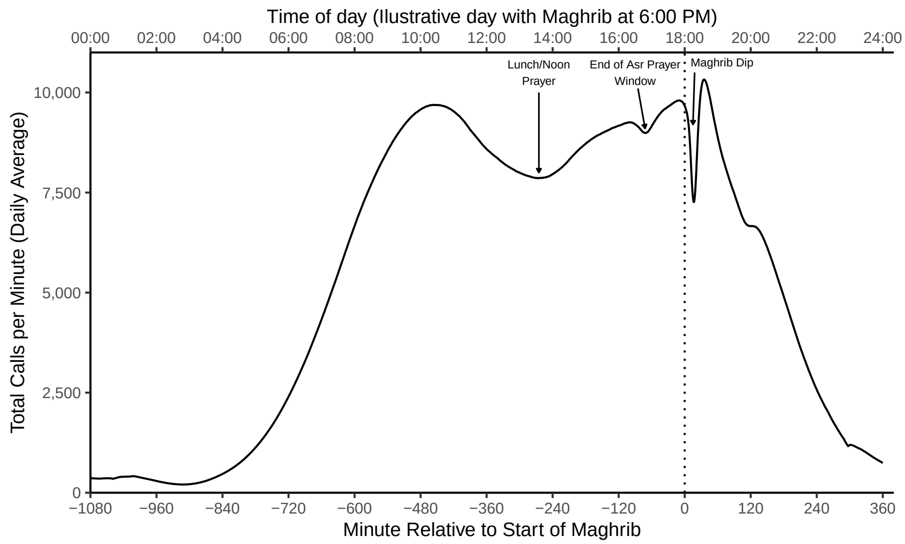
Figure 1a reveals several distinct patterns of daily call activity. First, call volumes are low at night when most people sleep, then rise steadily as people awaken. Call volumes peak around 9:00 - 11:00 am, before falling to a midday minimum around 13:00. This lull likely reflects a combination of people eating lunch and the noon (Zuhr) prayer. Call volumes increase again in the afternoon, with a small dip around 17:00, which likely corresponds to the end of the Asr prayer window.

Immediately after the Maghrib prayer window opens (indicated by the vertical dashed line), there is a sharp decrease in call volume. We refer to this decline as the "Maghrib dip," as it captures the temporary pause in phone use as individuals perform the Maghrib prayer. The Maghrib dip can be seen more clearly in the enlargement in Figure 1b, which displays the 140-minute period before and after sunset. The lowest point in the dip occurs 17 minutes after the start of Maghrib, when call volume per minute is approximately 25% lower than at the start of the window.[16] Call activity then returns to its pre-Maghrib level after roughly

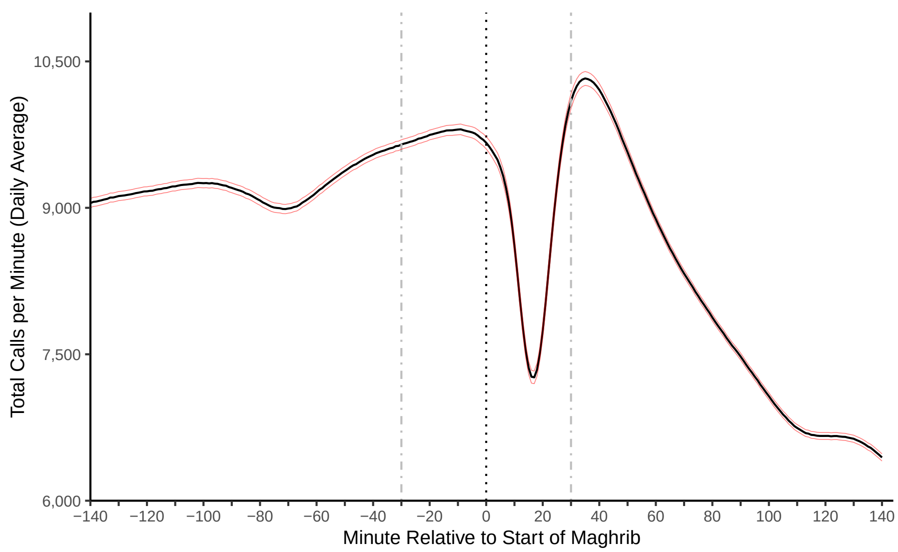
[16]The size of the Maghrib dip varies across space and time. If we divide tower-months in our sample into quartiles based on the dip, the first quartile exhibits a fall of 13%; the second quartile of 21%; the third quartile of 27%; and the fourth quartile of 36%.

30 minutes and declines gradually through the evening as individuals retire for the night.

Figure 1: Call Volume Throughout the Day



(a) One full day of activity



(b) Enlargement of period around Maghrib window

Notes: These figures show the average call volume for each minute of the day, averaged across all days between 2013-2020. Data from different towers and different days are aligned to display call volume relative to the start of Mahgrib (bottom x-axis). The top figure provides an illustrative timeline from a day in which Maghrib starts at 18:00 (6pm). The top figure shows a 24-hour window; the bottom figure shows roughly 4 hours around the start of Maghrib. The black dotted vertical lines indicate the start of Maghrib; dashed grey lines on the bottom figure mark 30 minutes before and after Maghrib; and red lines on the bottom figure show the 99% confidence intervals.

To quantify the reduction in call volume that occurs during the Maghrib period, we define the Maghrib dip as:

$$\text{MaghribDip} = \frac{\text{CallVolume}^{Before} - \text{CallVolume}^{After}}{\text{CallVolume}^{Avg(Before,After)}} \tag{1}$$

Since the Maghrib prayer takes approximately 15 minutes to complete, our main specification compares call volume 30 minutes before and 30 minutes after the start of Maghrib. We scale this difference by the average of the pre- and post-window volumes ($\text{CallVolume}^{Avg(Before,After)}$), to ensure the ratio is defined when call volume before Maghrib is zero.

In robustness analysis, we confirm that our results hold for other reasonable time frames, including 25-minute and 40-minute windows around the start of Maghrib.[17] We also show robustness to alternative methods for quantifying the dip, such as scaling (1) by a different denominator.

Temporal variation in the Maghrib dip One potential concern with the measure defined in Equation (1) is that it may capture other events that occur in the evening that do not have to do with religiosity *per se*. To examine this possibility, Figure 2 shows how call volume varies by time of day and day of year. As shown in Figure 2a, call activity increases with sunrise as people begin their daily activities. The light undulating wave-like band is the Maghrib dip, the timing of which varies with sunset, which occurs between 17:00 and 19:30 over the course of the year. When sunset occurs later, in summer months like August, the dip occurs later; when sunset occurs earlier, the dip also shifts earlier. This pattern helps confirm that the fall in call volume is not a "5 pm effect," but rather, corresponds precisely to the start of the prayer window.

Figure 2a displays other interesting signatures of Islamic religious observance. For instance, the two light vertical bands around June-July correspond to the holy months of Ramadan. Annual observance of Ramadan is another of the five pillars of Islam, and Muslims observe the religious holiday through fasting, prayer, and reflection. During Ramadan,

[17] Our main analysis uses the 30-minute window because smaller windows miss some of the reduction in call volume during Maghrib and larger windows capture calls reductions unrelated to prayer, as people wind down for the night. See Figure 1b.

we observe lower overall call activity and larger Maghrib dips, indicating higher religious observance during these periods. Figures 2a and 2b also display midday reductions in activity around the Zuhr prayer and lunch hour. The vertical striations in Figure 2a, enlarged in Figure 2b, show consistent drops in mobile phone activity on Fridays, the holiest day of the week in Islam (and also a weekend day in Afghanistan). On Fridays, the noon prayer is replaced by the Jummah prayer, which is typically preceded by a sermon and followed by another prayer delivered by the imam. In Figure 2b, we observe a longer and sharper drop in call volume around around the Zuhr prayer on Fridays.

Finally, Figure 2 also captures non-religious activities. For example, the sharp increase in calls on October 26, 2015 (the dark vertical patch in the top panel) coincides with the Hindu Kush earthquake, which struck Afghanistan at 13:39. Conversely, white gaps — periods of zero call volume — typically reflect cell tower outages, an issue we discuss further below.

What is the nature of religious adherence captured by the Maghrib dip? As noted in Section 1, religious behavior reflects a complex interplay of several motivations. On the one hand, individuals who observe religious practices may do so for deeply intrinsic motivations, reflecting individual piety, beliefs, and preferences. As Allport and Ross (1967) describes: "Persons with [an intrinsic] orientation find their master motive in religion. [Such a person] endeavors to internalize it and follow it fully. It is in this sense that he lives his religion."[18] On the other hand, there are a range of more social, extrinsic considerations that lead people to observe religious norms. In some societies, religious practices are explicitly mandated in laws or implicitly enforced through norms. Afghanistan provides stark examples with the Taliban's imposition of strict rules requiring women to wear burqas and abstain from singing in public. (A less extreme example might be businesses that limit hours during Ramadan). However, even in the absence of mandates, individuals may practice religion to conform or to foster a sense of belonging.[19] Closely related, religious observance may

[18] Allport and Ross (1967) contrasts these intrinsic motivations with extrinsic motivations: "Persons with [an extrinsic] orientation are disposed to use religion for their own ends...Extrinsic value is always instrumental and utilitarian. Persons with this orientation may find religion useful in a variety of ways – to provide security and solace, sociability and distraction, status and self-justification...The extrinsic type turns to God, but without turning away from self."

[19] Such expressions of identity respond to experimental manipulation of beliefs about the observability of behavior (Bursztyn and Jensen, 2015, 2017; Bursztyn, Egorov, and Jensen, 2019; Bursztyn et al., 2020).

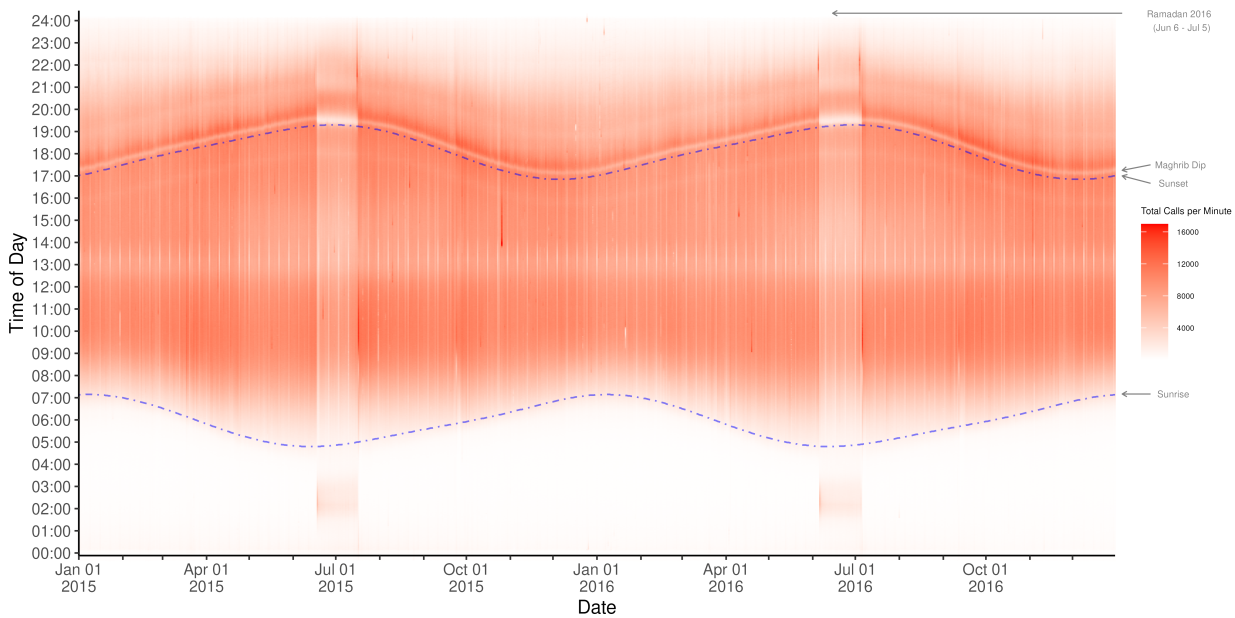
also yield instrumental benefits, both direct — such as the personal fulfillment derived from shared rituals and experiences (Allport and Ross, 1967) — or indirect, by providing access to social networks and shared "club goods" (Iannaccone, 1992; Berman, 2000, 2011; Dehejia, DeLeire, and Luttmer, 2007; Chen, 2010; Ager and Ciccone, 2018; Auriol et al., 2020).

The nuanced nature of religious behavior highlights several key methodological considerations in the measurement of religious adherence. First, revealed-preference measures of religious activity are likely to be more accurate than self-reports, given the well-documented over-reporting of religiosity across societies and decades. Second, it is helpful if the measure is "incidental" or unobtrusive — that is, collected without subjects' awareness of being observed — thus minimizing social desirability bias.[20] Third, when studying individual decisions and personal beliefs, it is important that the measure captures behavior at the individual level. Finally, it can be useful to distinguish between decisions driven by extrinsic versus intrinsic motivations.

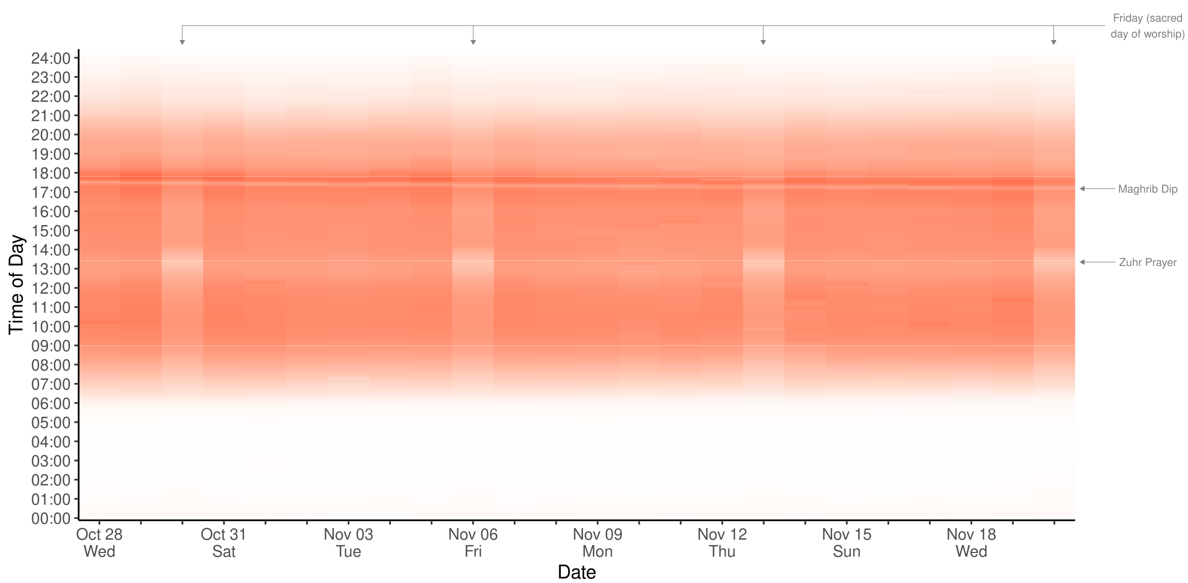
To our knowledge, the Maghrib dip is the only measure of religious adherence that meets all of these considerations: it is passively collected, observable at both individual and aggregate levels, and can be derived from different types of behavior that vary in their degree of public visibility. More pragmatically, the measure is available in settings where violence, conflict, and other institutional factors would make survey collection infeasible or impractical. These features make it particularly well-suited to the two empirical applications in this paper, where our causal analysis requires a panel dimension. In conflict settings like Afghanistan, conventional longitudinal surveys are nearly impossible to sustain, due to high population mobility and shifting accessibility. Indeed, we are unaware of any large-scale individual panel survey successfully implemented during the Afghan Republic period.

[20] This approach is exemplified by Livny (2021), who uses satellite imagery to track Ramadan observance via nighttime illumination, and by Pope (2024), who analyzes geolocated smartphone data to study church attendance.

Figure 2: Intensity of Mobile Phone Calls over Time



(a) Two years of mobile phone activity



(b) Four weeks of mobile phone activity

Notes: The top panel of this figure plots the total call volume for every minute of every day for two years in our sample (from January 2015 to December 2016). The bottom panel plots the equivalent call volume for a four-week period in 2015 (from Oct. 28 to Nov. 20). The dashed blue lines in the top figure demarcate the start of sunset and the start of sunrise.

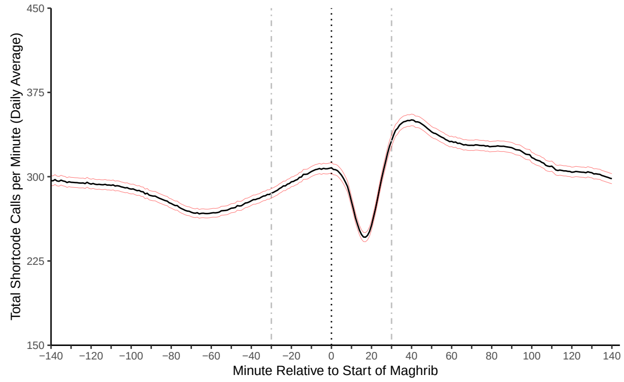
More and less private Maghrib dips One advantage of using mobile transactions to measure the Maghrib dip is that different types of transactions vary in how publicly observable they are. Our dataset contains four different types of phone-based transactions that vary in the degree to which they are visible to others or shaped by external considerations. In our context, these include a desire to appear religious, the risk of disturbing others during prayer, and the practical concern that other people might be less likely to answer the phone during the prayer period. In addition to standard voice calls, the three transaction types are: (a) shortcode calls, which are toll-free numbers used for customer care, account management (e.g., airtime top-ups, bill payments, and mobile money), and emergency or information services — many of which are handled by automated systems; (b) data packet transfers, which facilitate internet use; and (c) text messages (SMS).

Figure 3 shows how average volume per minute varies during the period around the Maghrib prayer window for these three additional transaction types. Although the overall daily patterns differ—text and data transactions typically rise into the evening while call volume falls—all types exhibit a clear decline following the start of Maghrib. Between the peak volume prior to Maghrib and the minimum volume in the 30 minutes after Maghrib, shortcode call volume falls by 20%, data volume falls by 11%, SMS volume falls by 11%; all reach minima approximately 17 minutes into the Maghrib window.

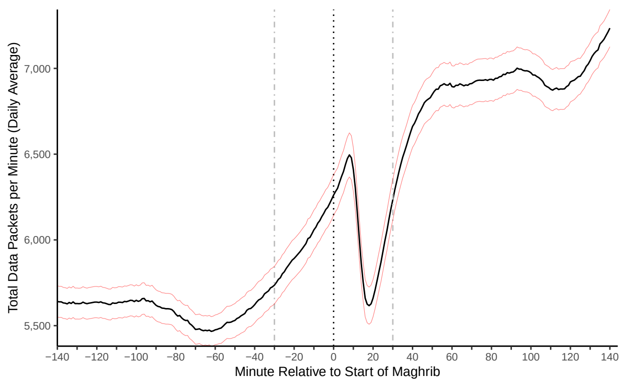
The fact that all transaction types decline during Maghrib suggests that the drop in call volume is not driven solely by a desire to reduce socially observable activity or other types of external considerations. In particular, reductions in data transfers — transactions not observable to others — cannot be explained by a desire to appear religious or a desire to avoid interrupting others during the prayer window. However, the larger decrease in voice calls relative to less observable transactions suggests that social or extrinsic considerations do play a role in the overall Maghrib dip.[21]

[21] For example, the average volume of non-shortcode calls is 12% lower during the 30 minutes after Maghrib than in the 30 minutes before, compared with a 5% reduction for shortcode calls. (These averages differ from the peak-to-trough decline of 20% reported above because they compare mean call volumes over the full 30-minute windows.) As shown in Appendix Table A1, the difference in dips between shortcode and other calls is statistically significant. To construct the table, we regress the Maghrib dip in phone calls (constructed at both the grid-month and district-month levels) on an indicator for whether the measure is based on shortcode calls versus standard calls, controlling for location and time fixed effects.

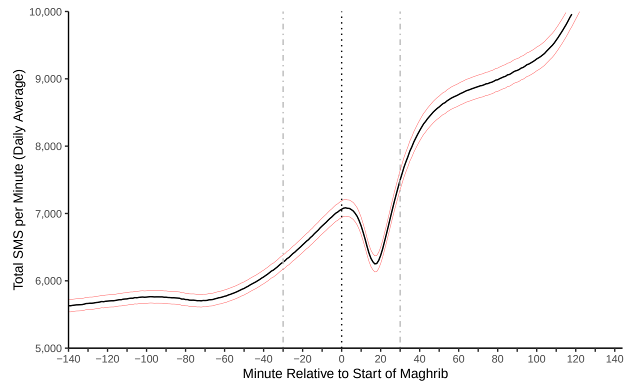
Figure 3: Shortcode Call, Data and SMS Volume around the Maghrib Window



(a) Shortcode Calls



(b) Data Transactions



(c) Text Messages

Notes: Panel A plots the average number of shortcode calls in each minute defined relative to the start of Maghrib, zooming in on the 140 minutes before and after the start of the prayer window. Panel B plots the average number of data packets transacted in each of these minutes. Panel C plots the average text messages sent. In all panels, the red lines show the 99% confidence intervals.

In summary, individuals reduce both public and private forms of phone activity during Maghrib. The larger decline in standard voice calls suggests that extrinsic motivations and social considerations contribute to the effect, while the decline in even the most private transactions implies that intrinsic religious motivations are also at work.[22]

Although all four types of transaction types exhibit dips, we focus our analysis on standard voice calls, with a few checks performed on shortcode calls, for four reasons. First, phone calls are by far the most common and representative mode of communication in Afghanistan. Appendix Figure A3 shows that, on average, 95% of unique monthly subscribers place phone calls, whereas only 32% send text messages and only 29% use data.[23] Second, each phone call is associated with a specific cell phone tower, which we use to roughly locate people when they place calls. By contrast, no geographic information is included in the text message activity logs. We infer locations for text messages based on the most recent call by the same subscriber, but this introduces measurement error.[24] Third, a great deal of mobile data traffic occurs automatically in the background (e.g., app updates or email synchronization), and does not require the active attention of the subscriber. Moreover, data use is 'lumpy' in the sense that a single action (such as downloading an image) often requires transmitting multiple data packets, which appear as multiple consecutive transactions in the logs.[25] Thus, a user who initiates a download before Maghrib may still generate packet activity after the window begins. Finally, while 72% of subscribers make at least one shortcode call during the year, these calls constitute only 3% of total call volume, limiting their usefulness for aggregate analysis.

[22] More precise quantitative decomposition, while attractive in principle, is complicated by the many factors that influence how each transaction type is generated. For instance, data usage intuitively seems like a very private transaction, but a significant portion of data packets are transmitted in the background, without the subscriber having to take any action. As discussed below, text and data usage are also far less common than voice and shortcode calls.

[23] These numbers are influenced by the country's low adult literacy rate (43%) and limited smartphone penetration. Consequently, inferences made from text messages and data use would be less representative of the general Afghan population.

[24] To construct Figure 3c, we assume each text message is sent from the same tower as the most recent call placed by that subscriber. We believe this is a reasonable approximation for active subscribers, but is less appropriate for the large number of subscribers who make calls infrequently. For example, only 16% of SMS transactions could be interpolated using a phone call that was made in the same hour; 47% within the same day; and 37% had to be within the same month.

[25] On average, 43% of a user's data transactions occur within 5 seconds of each other and 47% occur within one minute.

Addressing Tower Outages Cell phone towers in Afghanistan occasionally go offline, either due to routine maintenance, technical failures, or deliberate shutdowns ordered by the Taliban.[26] If these tower outages overlap with the Maghrib dip, it could distort our measure. For instance, an outage that begins during or immediately after the Maghrib period would artificially increase the observed decline in call volume, whereas an outage that begins shortly before Maghrib would reduce the apparent decline. To address this issue, we systematically identify and exclude all tower-days with potential outages. Specifically, we flag any tower-day with a period of zero call volume that starts as late as 30 minutes after Maghrib (or anytime before) and extends until at least midnight (or later). We then remove these tower-days from the dataset.

3.3 Validating the CDR-Based Measure of Religious Adherence

Until this point, we have argued that the Maghrib dip can be interpreted as a measure of religious adherence, based on established Islamic norms and a visual inspection of aggregate mobile phone activity. The fact that call volume drops not only during Maghrib but also during other sacred periods such as Ramadan provides encouraging evidence that changes in call activity can serve as a measure of religious behavior. In this section, we bring in additional data sources to validate the Maghrib dip measure using two complementary approaches. The first compares self-reports of religiosity from survey data to the Maghrib dip we observe for those same individuals. The second examines whether regional averages of the Maghrib dip correlate with independent regional indicators of religious adherence.

Validation Using Surveys Ideally, we would like to validate the Maghrib dip using a large, nationally representative survey that measures religiosity regularly over time and space. However, no such data exist in Afghanistan: While there have been a few national surveys in Afghanistan in the past decade — such as the Afghan National Quarterly Assessment Research (ANQAR), the Survey of the Afghan People, and the National Risk and Vulnerability Assessment (NRVA) — none include detailed measures of religiosity, and most

[26] See "Cell Carriers Bow to Taliban Threat" (`https://www.wsj.com/articles/SB10001424052748704117304575137541465235972`).

are conducted irregularly.

Instead, we draw on a smaller household survey of 1,090 individuals conducted in Parwan and Kabul provinces in 2015 (Blumenstock et al., 2024). Although this survey was not primarily focused on religious beliefs, it included questions on six common Islamic practices: fasting during Ramadan, giving Zakat (charity), performing namaz (prayer) five times daily, abstaining from alcohol, refraining from listening to music, and reading the Quran daily. Importantly, respondents provided informed consent to link their survey responses to their mobile phone records from the mobile phone company that shared data with us.

The distribution of survey responses, shown in Appendix Figure A4, highlights how almost every respondent described each religious practice as "important" or "very important." While this pattern suggests a high degree of religiosity, it also highlights the limitations of survey-based measures in highly devout societies: self-reports may be subject to social desirability bias and may not reflect actual practice. Afghanistan is among the most religiously observant societies in the world (Pew-Templeton Global Religious Futures, 2022), and observance is deeply embedded in centuries-old norms (Barfield, 2022).

Nonetheless, we find a strong positive correlation between self-reported religious practices and our measure of the Maghrib dip. We construct a religiosity index for each individual by grouping the responses "important" and "very important", standardizing each indicator, and averaging across the six practices.[27] We then compute an individual-level measure of the Maghrib dip using Equation (1), calculated using data from a 48-month period around the time of the survey.[28] The individual-level Maghrib dip measure is somewhat noisy because the median individual in our sample only makes only three calls per day. (Given the sparsity of the data at the individual level, our main analysis in later sections aggregates calls across all individuals in different geographic regions).

Table A2 reports regressions of the individual Maghrib dip on survey religiosity, controlling for district fixed effects in the first column and also household demographic characteristics in the second column. The top row examines the correlation with the Survey Religiosity

[27]The results are not dependent on this grouping and look similar if we instead generate an indicator that takes on the value one for 'very important' and zero for the other responses, 'important', 'a little important' and 'unimportant'.

[28]The survey was conducted in October 2015; we use CDR data spanning from January 2015 to December 2016.

Index. The coefficient in Column (2) indicates that a one standard deviation (SD) increase in the index is associated with a 29% increase in the Maghrib dip ($p < 0.05$).[29] The other rows of the table present analogous regressions for each survey question separately, and show that the correlation is positive for all the questions, and strongest for the component "Reading the Quran Daily". These results indicate that people who believe in the importance of Islamic religious practices are also less likely to make calls during the Maghrib prayer window.

Our survey-linked mobile phone records also allow us to explore how observable characteristics correlate with the Magrib Dip. Table A3 presents these results. We find a clear age gradient: older individuals exhibit stronger adherence, consistent with prior theoretical and empirical work linking age and religiosity (Azzi and Ehrenberg, 1975; Iannaccone, 1998; McCleary and Barro, 2006). We also find a strong positive association between land ownership and adherence, consistent with patterns of elite religiosity documented in Afghanistan (Afghan Analysts Network, 2025). By contrast, literacy is not significantly related to the Maghrib dip. Finally, as discussed in the next section, Pashtun respondents are significantly more observant than members of other ethnic groups in our sample.[30] While these are just correlations and open to multiple interpretations, they provide additional evidence that the Maghrib dip captures meaningful variation in religious observance.

Validation using district-level correlations Our second validation exercise examines whether the Maghrib dip correlates, at the district level, with other features that we expect to correlate with religious norms. We construct a cross-sectional measure of the Maghrib dip at the district level by aggregating call traffic across all cell phone towers in a district. We then standardize this measure by subtracting the national mean and dividing by the standard deviation, so that it is expressed as a Z-score in standard deviation units. Figure 4 maps this measure, highlighting districts where religious adherence is above and below the nation-wide average.

The map shows dark clusters in the South and East, indicating that the reduction in call

[29]The coefficient shows that a one SD increase in the survey index increases the Maghrib dip by 3.78, which represents a 29% increase above 12.94, the mean of the Maghrib dip measure in this regression.

[30]Our survey includes 71% Tajiks, 17% Pashtuns, 9% Hazaras, and 3% from other smaller ethnic groups. This sample is not representative of Afghanistan as a whole, given its locational specificity to Parwan and Kabul.

volume during Maghrib is greater in these regions. These are areas are home to the Pashto-speaking Pashtun ethnic group. To make this point explicit, districts with a Pashto-speaking majority are outlined in yellow.[31]

On average, Pashto-speaking districts exhibit a Maghrib dip 0.52 standard deviations above the national mean. This pattern corroborates the survey-based results from Table A3, which show that Pashtun respondents exhibit larger Maghrib dips, but extends this pattern to a country-wide scale. These results also reaffirm the validity of the measure, as the Pashtun — who constitute the core of the Taliban movement (Central Asian Cultural Intelligence for Military Operations) — are widely recognized as among the most religiously conservative groups in Afghanistan (Barfield, 2022).

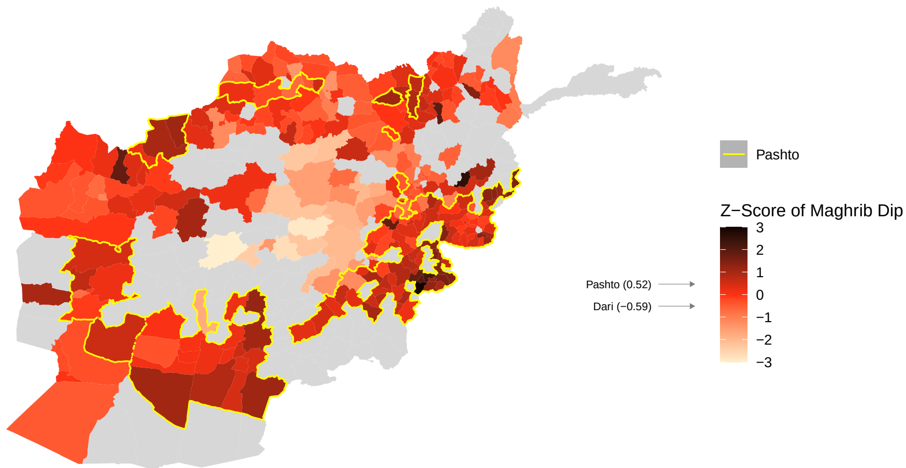
In contrast, Dari-speaking populations such as the Tajiks have historically adhered to less strict interpretations of Sharia law and are generally less religiously observant. Tajik women, for instance, have traditionally enjoyed greater social freedoms (Joshua Project, 2023). Dari speakers are concentrated in central and northwestern Afghanistan, which is also the lightest region shown in the map.[32]

To further corroborate these visual results, column (1) of Table A4 presents district-level regressions of the district's average Maghrib dip over 2013-2020 on an indicator of whether the largest number of villages in the district are predominantly Pashto-speaking (controlling for province fixed effects and if the plurality of villages in the district are Hazara). The coefficient indicates that the Maghrib dip is significantly larger in Pashto districts than in others. Column (2) repeats this analysis using 10 km grid-cell–level observations, yielding similar results. The consistent significance across both specifications provides additional validation that the Maghrib dip captures meaningful spatial variation in religious adherence.

[31] To demarcate these districts, we use data the ethnic composition of each village from 2012, compiled by the Afghanistan Information Management Service, the Central Statistics Organization, United States Agency for International Development, and Yale University. For each cell tower in our data, we consider all villages within a 10 km radius and compute the fraction in which each ethnic group (defined by primary language) constitutes the majority. We then average across towers within each district to identify the dominant ethnic group.

[32] The central areas are also home to the Hazaragi-speaking Hazara ethnic group, a Shia minority whose prayer schedule differs from that of the Sunni majority. For Shia Muslims, the Maghrib window begins later and merges with the Isha prayer period, which continues through the night. Hence, a pronounced Maghrib dip is not expected among this group. However, Afghanistan is close to 90% Sunni, and the Hazara constitute a relatively small share of the population, and only one district has a Hazara majority.

Figure 4: Religious Adherence by District



Notes: This map of Afghanistan indicates the average Maghrib dip for each district, calculated over the period from 2013-2020. For display purposes, district averages are standardized to have mean zero and standard deviation one, with darker red shading indicating a larger reduction in call volume during the Maghrib prayer window. Districts shown in grey have no active cell phone towers during the period of study. The thick yellow line demarcates the set of districts in which Pashto-speakers constitute the largest of the ethnic groups.

3.4 Summary of the Maghrib Dip Measure

Up to this point, we have developed and validated a behavioral measure of religious adherence based on mobile phone metadata. The measure captures the extent to which individuals reduce outgoing call volume during the Maghrib prayer window, and thus comply with the religious norm of prayer during this time. This approach yields a measure that can be aggregated flexibly across units — such as provinces, districts, villages, or grid cells of various sizes — and computed at different frequencies, such as years, months, weeks or even days. As described above, the measure offers several advantages: it is passively collected, does not rely on self-reports, and remains available even in insecure or hard-to-access areas.

This approach also has important limitations. First, as discussed in Section 3.1, there are constraints to accessing mobile phone data. We can imagine future extensions of this approach to other digital data sources (such as social media data, or internet router traffic), but we do not pursue those extensions here. Second, as noted in Section 3.2, the Maghrib dip captures a particular type of religious adherence, but the motivations underlying that adherence are not self-evident — for instance, the dip does not indicate what people were thinking about during the prayer window, or whether they felt connected to God at the time of prayer.

In the next two sections, we demonstrate how the measure can be used to investigate substantive social science questions that would be difficult to study with conventional data. More broadly, we expect that the most powerful applications of this approach will be in conjunction with surveys and other traditional methods of data collection, which offer complementary strengths and weaknesses, and can provide essential context on the motivations and meanings underlying religious behavior.

4 Using the Maghrib Dip Measure to Study How Insurgent Violence Shapes Religious Adherence

Our first case study examines the relationship between violent conflict and religious adherence. As discussed in Section 1, prior work suggests several reasons why violence could increase religious observance. For example, war may lead to stricter norm adherence — including in religious practices — as an evolutionary response to threat (Henrich, 2020; Winkler, 2021). Experiencing violence can also reshape preferences in ways that lead to greater religiosity, for instance, by leading people to seek certainty and stability (Callen et al., 2014). Religious devotion itself can provide a source of comfort (Bentzen, 2019, 2021; Isaqzadeh, 2024). Similarly, conflict between two religious groups can intensify religiosity by reinforcing group identity and intergroup boundaries (Zussman, 2014; Atkin, Colson-Sihra, and Shayo, 2021).

Yet there are also compelling reasons why violence perpetrated by religious extremists might instead *reduce* religious adherence, particularly in contexts such as Afghanistan. The Taliban impose — often with extraordinary brutality — a strict, sharia-based interpretation of Islam that imposes some of the most draconian religious restrictions in the world, including mandatory mosque attendance for men, severe limitations on women's public presence, and a rejection of music, poetry, and secular education (Berman, 2003, 2011).

When religious commitment is imposed through violence, it may lose its role as a source of comfort or moral guidance, prompting individuals to disengage from religious practice (Pargament et al., 1998; Litz et al., 2009; Juergensmeyer, 2017). Civilian casualties caused in the name of religion can likewise provoke moral revulsion (Condra and Shapiro, 2012). A turn away from religion may also reflect subtle forms of resistance, as qualitatively documented by Scott (1985), who finds that coercion can provoke everyday acts of defiance. In this context, reduced prayer or ritual observance may function as symbolic dissent. Furthermore, civilians may deliberately curtail outward observance to avoid being misidentified as Taliban supporters, even if their private beliefs remain unchanged (Kuran, 1995). Taken together, these mechanisms suggest that religious violence can generate *backlash* against religious adherence. Such backlash has been documented in other settings where harmful actions were carried out by religious actors, including the Catholic Church abuse crisis (Grosfeld et al., 2024).[33]

Beyond these psychological and strategic channels, violence can also suppress religious participation through purely *logistical* constraints. The Taliban often impose curfews, roadblocks, and security checkpoints, which can make it difficult to access mosques (Berman et al., 2011). Religious gatherings — especially those associated with sects opposed to the Taliban — may become deliberate targets of violence, which could deter communal religious practice.[34] Even absent direct repression, insecurity can cause people to prioritize safety and subsistence over collective ritual, thus raising the opportunity cost of religious observance increases with violence.

Below, we show that the net effect of violence is to reduce religious adherence. While the nature of our data limits our ability to adjudicate between the mechanisms driving the

[33] A more subtle possibility is that the Taliban may use violence as a screening device to identify committed believers who, despite the higher costs of public observance when religion is associated with violence (and when such practice implies their alignment with the perpetrators), continue to visibly practice (Iannaccone, 1992; Berman, 2003, 2011). By the same token, less-committed civilians may deliberately curtail visible religious observance to avoid being misidentified as Taliban supporters, even though their internal beliefs remain unchanged (Kuran, 1995).

[34] Condra et al. (2018) provide evidence that the Taliban strategically attack travel arteries to prevent voting, while avoiding civilian casualties, before elections.

reduction, the evidence collectively suggests that backlash is a key channel linking exposure to religious violence with decreased religious observance.

4.1 Empirical Strategy

Our granular data provide a unique opportunity to determine how violence shapes religious behavior. We combine detailed, geocoded data on insurgent violence and other wartime activities with our high-frequency Maghrib dip measure to identify how religious adherence responds to different types of conflict.

Measuring Violence in Afghanistan

By 2013, the beginning of our study period, Afghanistan had endured over three decades of near-continuous conflict. This period began with the 1978 military coup by the communist People's Democratic Party of Afghanistan and the subsequent Soviet invasion in 1979. Violence in our period of analysis reached levels not seen since the bloody civil war following the Soviet withdrawal in 1989 and preceding the Taliban takeover in 1996. Between April 2013 and 2014, violence intensified, marked by frequent Taliban attacks, improvised explosive device (IED) incidents, and targeted assassinations. This period coincided with the planned withdrawal of international forces at the end of 2014, during which the Taliban escalated operations, leading to substantial casualties for both Afghan National Security Forces (ANSF) and civilians.

For the 2013-2014 period, we use precisely geocoded data on violence to complement our mobile phone CDR data. The violence data come from incident records of the International Security Assistance Force (ISAF), a multilateral military body present since December 2001.[35] The ISAF dataset provides event locations at five-decimal precision (accurate to within one meter at the equator) and captures all types of violence reported to ISAF, including the nature of each incident. Although the ISAF data cover only the first two years for which mobile phone data are available, they nonetheless cover 95,231 incidents during this period in regions that overlap with the CDR.

[35] The dataset we use is available at `https://github.com/knapply/data4ds4da/blob/master/data/sigacts_afghanistan_df.rda`

We classify incidents into four categories. First, 'Insurgent Violence' includes salient acts of violence initiated by insurgent groups (including direct fire, IED explosions, indirect fire, surface-to-air fire, murder, mine strikes, other explosions, explosive remnants of war, and assassination). Second, 'Other Insurgent Activity' includes a collection of threats, unexploded IEDs, mines, and explosives, as well as a range of other activities undertaken by these groups.[36] Although the ISAF data do not explicitly list the groups carrying out insurgent attacks, most of these attacks were carried out by the Taliban. The third category, 'State-led Violence', we group together violent incidents initiated by state-led forces (primarily ISAF, but also the Afghan army and police), including escalation of force, direct fire, close air support, and indirect fire. Lastly, 'Other State-led Activity' includes clearing enemy weapons caches, detention, arrest, surveillance, medical evacuation, police actions, and releasing detainees. We observe 27,931 insurgent violence incidents, 57,629 other insurgent activities, 4,285 violence incidents led by state forces, and 27,155 other state-led activities. Appendix Figure A5 shows the spatial distribution of these incidents in Afghanistan.

Econometric Specification

Our aim is to test whether insurgent violence, as opposed to other types of wartime activities, impacts religious adherence. We thus estimate:

$$\begin{aligned} d_{d,m} = \alpha_d + \theta_m &+ \beta_1(\text{Insurgent Violence})_{d,m} + \beta_2(\text{Other Insurgent Activity})_{d,m} \\ &+\beta_3(\text{State-led Violence})_{d,m} + \beta_4(\text{Other State-led Activity})_{d,m} + \varepsilon_{d,m} \end{aligned} \tag{2}$$

where $d_{d,m}$ is the Maghrib dip in district d and month m; Insurgent Violence$_{d,m}$ and State-led Violence$_{d,m}$ denote the number violent incidents initiated by insurgents and state forces, respectively; Other Insurgent Activity$_{d,m}$ and Other State-led Activity$_{d,m}$ are other types of incidents initiated by insurgents and state forces, respectively; and α_d and θ_m are

[36] Specifically, 'threat' incidents include: attack threat, IED threat, indirect fire threat, direct fire threat, safire threat, assassination threat, and murder threat. Unexploded apparatus incidents include: unexploded IEDs, mines, explosives - IED found and cleared, suspected IED, mine found and cleared, unexploded ordinance, IED turn-in, and false IEDs. Other activities include: meetings, accidents, kidnappings, weapons transport, intimidation, illegal checkpoints, corruption, smuggling, theft, demonstrations, narcotics, surveillance, terrorist tactics and procedures, terrorist recruitment, defecting, assault, terrorist training, arson, counterfeiting, sabotage.

district and month fixed effects. $\varepsilon_{d,m}$ is an idiosyncratic error term that we cluster on district.

Appendix Table A5 presents descriptive statistics of the key variables that are used in our analysis and which appear in the main tables. Appendix Table A6 summarizes additional variables that are used for robustness checks later in the paper.

4.2 Results: Insurgent Violence and Religious Adherence

Table 1 reports the impact of violence on religious adherence from estimating equation (2), using the Maghrib dip in phone calls as the dependent variable. Column (1) indicates that insurgent violence significantly reduces the Maghrib dip. In other words, violence perpetrated by religious extremist groups lowers religious adherence. Although the specification includes location and time fixed effects, the estimates may still be endogenous if changes in religiosity influence levels of violence. For example, if increased adherence led to more violence, the estimates in column (1) would under-state the true negative effect of violence on religiosity. To assess this possibility, column (2) adds two monthly leads of insurgent violence to the specification.[37] The coefficients on the lead terms are both small and statistically insignificant, indicating that greater religious adherence today does not predict future increases in violence. This pattern suggests that the main result is unlikely to be driven by unobserved factors that simultaneously predict religious adherence and rising violence.

Since the Maghrib dip is measured in units that do not have a natural interpretation, we benchmark the magnitude of this effect against other meaningful comparisons. Specifically, we compare the change in religious adherence associated with insurgent violence (column (1) of Table 1) to the difference in adherence between Pasthun-majority and other districts (Table A4). Moving from a district-month at the 50th percentile of insurgent violence (with 2 violent incidents) to one at the 90th percentile (with 16 violent incidents) decreases religious adherence by roughly 23% of the gap between Pashtun and non-Pashtun districts.[38]

[37] Including two leads in the regression shortens the estimation window by two months and removes two districts that only appear in the data for two months.

[38] Multiplying the coefficient (-.078) by the change in violent incidents (14) implies that the Maghrib dip would fall by -1.09. Column (1) of Table A4 shows that being in a plurality Pashtun district changes the Maghrib dip by 4.75. Scaling -1.09 by 4.75 produces the implied effect of 23%.

Why Does Violence Reduce Religious Adherence? Above, we discussed two potential channels through which violence could reduce religious adherence: that violence may logistically suppress observance by disrupting prayer, and that people may turn away from religious practice as a form of backlash. Although the data cannot conclusively disentangle these mechanisms, the evidence suggests that the reduction in adherence is unlikely to be driven by logistical factors. In particular, column (3) of Table 1 shows that state-initiated violence and other types of war-related activity initiated by the state have no significant effect on the Maghrib Dip. These estimates are imprecise, since there are only 4,285 state-initiated violent events. Nonetheless, the null effects suggest that the observed decline is not simply due to the logistical disruptions that result from conflict.

Instead, the empirical evidence is more consistent with the backlash mechanism. Column (3) shows that people respond differently to violence by insurgents than to violence by the state — an asymmetry difficult to reconcile with a logistical story. Columns (4) and (5) of Table 1 further test this interpretation by examining non-violent events, including threats of attacks, attacks that are not actualized, and measures such as setting up checkpoints. These activities have no measurable effect on the Maghrib dip; only realized insurgent violence drives the decline. This pattern indicates that it is the experience of actual Taliban-perpetrated violence, rather than the general presence of insurgent forces, that reduces religious adherence.

The reduction in religiosity is not limited to just forms of religious adherence that reflect external, or social considerations. Column (1) of Appendix Table A7 estimates the effect of violence on shortcode calls — one-way calls to automated or emergency services (see Section 3.2). The coefficient (-.112, $p < 0.05$) indicates that insurgent violence also reduces this more private form of religious adherence. The magnitude of this effect is qualitatively larger than the baseline effect on the Maghrib dip calculated using all calls.[39] This finding implies that the effect is not confined to public, outward-facing behaviors but reflects changes in more private religious activity as well.[40]

[39]Moving from the median to the 90th percentile of insurgent violence produces a decline equal to 41% of the Pashtun effect, based on Column (3) of Table A4.

[40]The substantial decline in private observance also suggests that the screening mechanism (see footnote 33) is unlikely to drive the reduction in the Maghrib dip.

Table 1: Insurgent Violence and Religious Adherence

	Maghrib Dip				
	(1)	(2)	(3)	(4)	(5)
Insurgent Violence	–0.078***	–0.058**	–0.077**	–0.072***	–0.072**
	(0.029)	(0.029)	(0.030)	(0.028)	(0.028)
Insurgent Violence (1 lead)		–0.028			
		(0.034)			
Insurgent Violence (2 leads)		–0.015			
		(0.025)			
State-led Violence			–0.022		–0.021
			(0.047)		(0.048)
Other State-led Activity			0.015		0.053
			(0.034)		(0.053)
Other Insurgent Activity				–0.012	–0.015
				(0.014)	(0.015)
Observations	4703	4153	4703	4703	4703
Mean of Dependent Variable	12.965	13.328	12.965	12.965	12.965
Number of Districts	235	233	235	235	235
Number of Months	21	19	21	21	21
District Fixed Effects	Y	Y	Y	Y	Y
Month Fixed Effects	Y	Y	Y	Y	Y

Notes: Each column is a separate regression. One observation is included for each month for each district. Column (1) regresses the Maghrib dip measure of religious adherence on the number of insurgent violence incidents. Column (2) controls for insurgent violence one and two months in advance. Column (3) controls for state-led violence (including escalation of force, direct fire, close air support, and indirect fire) and other state-led activity (including clearing enemy weapons caches, detention, arrest, surveillance, medical evacuation, police actions, and releasing detainees). Columns (4) and (5) control for other insurgent activity (including threats, unexploded IEDs/mines/explosives, meetings, accidents, kidnappings, weapons transport, intimidation, illegal checkpoints, corruption, smuggling, theft, demonstrations, narcotics, surveillance, terrorist tactics and procedures, terrorist recruitment, defecting, assault, terrorist training, arson, counterfeiting, and sabotage). All regressions include district and month fixed effects. The number of districts and months appearing in each regression is shown separately in each column. Standard errors clustered on district shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Robustness We next assess the robustness of our results to alternative econometric specifications, variable definitions, and sample restrictions. For these checks, we focus on our preferred specification from Table 1, column (5), which incorporates all four measures of war activity.

Table A8 shows that our main results do not depend on the set of control variables included in the regression, or the exact way in which we define the Maghrib dip outcome. Since religious adherence may be serially correlated, column (1) controls for a one-period lag of the measure. Column (2) controls for the total daily call volume, to account for time-varying factors related to population and network size. Incorporating this variable helps address the concern variation in the dip might simply reflect changes in overall call volume, including in the pre-Maghrib window. We find that our results are unchanged with these additional controls.

Columns (3)-(5) confirm that our results are not sensitive to the duration of the time window used to measure the dip. The effects remain qualitatively similar when the window is adjusted to 25, 35, or 40 minutes around the start of the prayer period rather than the 30-minute baseline. In column (6), we scale the change in call volume 30 minutes before and after Maghrib using only the call volume before (rather than the average volume over the before and after periods, as in equation (1)). Column (7) applies an inverse hyperbolic sine (IHS) transformation to the ratio of pre-Maghrib call volume relative to total volume to mitigate the influence of outliers. We find that the results are robust across these specifications.

Appendix Table A9 further confirms that our findings are robust to changes in sample composition. Because religious adherence peaks during Ramadan (Figure 2), column (1) reconstructs our baseline Maghrib dip measure (using all types of phone calls) after excluding Ramadan days. The results are unchanged, which suggests that violence does not simply reduce adherence due to religious responses during the holiest months. Since the Maghrib prayer window differs between Sunni and Shia Islam, column (2) excludes districts with sizable Shia populations, proxied by the share of villages where Hazaras constitute the majority.[41] Finally, columns (3) and (4) exclude the 5% of districts with the fewest users

[41] We drop districts in which at least 5% of the villages are majority Hazara. In results not presented, we also verify that the results remain unchanged when using stricter thresholds of 1% or 10%.

or lowest call volumes, respectively, to ensure that sparse CDR coverage does not drive the results. In all cases, the estimated effects of insurgent violence on religious adherence remain statistically and economically stable.

Alternative Accounts We briefly consider several alternative accounts for the observed effect of violence on religious adherence.

First, population mobility could bias our results if religious individuals systematically relocate following violence. In that case, a compositional shift in the population might appear as a behavioral change among those remaining. However, column (2) of Appendix Table A7 shows that our estimates are unchanged if we restrict our analysis to people who remain in the same location for at least three months. This restriction is feasible because we can approximate each subscriber's home location based on the locations from which they place mobile phone calls (Chi et al., 2020)). Thus, the results are not driven by selective migration.

Second, we consider the possibility that changes in religious adherence are caused by coercion from religious extremists. For instance, the presence of the Taliban and other armed insurgents likely increases public displays of religiosity. This dynamic would, if anything, bias our estimates toward zero, since Taliban presence should raise, not reduce, observed religious adherence. Nonetheless, when we include a proxy for Taliban control in Column (8) of Table A8, both the magnitude and precision of the main estimate remains unchanged.[42]

Finally, we consider whether the decline in religious adherence could reflect broader reductions in economic activity rather than changes in belief or practice. Prior research indicates that violence depresses local economic outcomes (Abadie and Gardeazabal, 2003; Blumenstock et al., 2024; Herskowitz et al., 2025). However, if the effect were purely economic, we would expect the opposite sign: deteriorating economic conditions typically increase religiosity (cf. Azzi and Ehrenberg, 1975). Indeed, our second case study (Section 5) shows that

[42] Direct measures of Taliban control are only available after 2015, beyond our violence observation window. However, following Wright (2024), we proxy Taliban presence in our sample period using surveyors' ability to enter a district, which captures de facto Taliban control. Specifically, we use measures from the Afghan Center for Socio-Economic and Opinion Research (ACSOR) to construct a binary indicator of whether the surveyors found the district to be totally inaccessible or accessible only by men. When we incorporate this variable into column (8) we also include a dummy variable for missing values in this measure. We find that incorporating this proxy does not affect the precision or magnitude of the coefficient on insurgent violence.

adverse economic shocks increase the Maghrib Dip in Afghanistan. In contrast, here we find that insurgent violence reduces it. This divergence suggests that the results documented in this section are not driven by the economic consequences of conflict but rather reflect a distinct behavioral response to religiously motivated violence.

5 Using the Maghrib Dip Measure to Study How Climate Shocks Shape Religious Adherence

Our second case study explores how climate shocks affect religious adherence. We focus on climate shocks in the form of droughts, which have been increasing in frequency and severity since 1950 (Climate Security Expert Network, 2019), and which can dramatically reduce agricultural yields.[43] These shocks have profound economic consequences: in 2017, agriculture accounted for 23% of GDP and served as a source of income for 62% of the population (Muradi and Boz, 2018).

While the adverse effects of climate shocks on the Afghan economy are well-documented, (cf. UNEP, 2016; Kochhar and Knippenberg, 2023), the relationship between economic adversity and religiosity is conceptually ambiguous. On the one hand, economic hardship may weaken religious adherence. If people turn to religion with the expectation that God will insure them against economic shocks (Auriol et al., 2020, 2021a), then experiencing adverse events may weaken faith and reduce religious practices. Moreover, income loss may also reduce available time or resources for religious activities (Buser, 2015). Under these interpretations, negative income shocks should lower religious adherence.

On the other hand, there are several reasons why worsening economic conditions might cause an increase in religious adherence. First, negative income shocks may lower the opportunity cost of time, and thus facilitate participation in religious activities (Azzi and

[43] Average temperatures in Afghanistan have risen by 1.8°C since 1950 (Climate Security Expert Network, 2019). Two main drought mechanisms operate: (i) rainfall shortages, which primarily affect rainfed regions and have become more frequent in recent decades (UNEP, 2016); and (ii) reduced winter snowfall, which especially affects downstream areas irrigated by streams and rivers that originate in the Hindu Kush mountains (UNEP, 2016). Wheat, Afghanistan's dominant crop, is vulnerable to both. In 2017, wheat covered one-third of all arable land (2.3 million hectares), compared to 0.33, 0.27, 0.22, 0.15, and 0.12 million hectares for opium poppy, fruit, barley, maize, and rice, respectively (Muradi and Boz, 2018; UNODC, 2021).

Ehrenberg, 1975). Second, religious participation can act as informal insurance, if stronger adherence religious norms helps secure resources and support from religious social networks (Dehejia, DeLeire, and Luttmer, 2007; Chen, 2010; Ager and Ciccone, 2018; Auriol et al., 2020).[44] Third, lower income security may strengthen religious beliefs, as people turn to religion when they either experience hardship or expect negative outcomes. Classical secularization theories posit that religious belief originates in fear and ignorance (Hume, 1757; Freud, 1927; Marx, 1970), implying that modernization and rising incomes will reduce religiosity (Wesley, 1760; Weber, 1905).[45] This line of reasoning suggests that adversity may increase adherence, if adverse events promote interdependence psychology (Henrich, 2020; Winkler, 2021) and through the use of religions as a psychological coping mechanism (Bentzen, 2019, 2021).

Although our empirical analysis cannot fully distinguish among these mechanisms, we present evidence below suggesting that economic conditions mediate how climate shocks influence religious behavior. We also explore the role of opportunity cost, social insurance and coping channels as a part of this account.

5.1 Empirical Strategy

Our empirical strategy estimates the impact of quasi-random climate shocks on the Maghrib dip measure of religious adherence.

Measuring climate shocks

We measure drought using the Standardized Precipitation-Evapotranspiration Index (SPEI), developed by Vicente-Serrano, Beguería, and López-Moreno (2010). This index helps capture the fact that the impact of rainfall on agriculture depends not just on the amount of

[44]The extent to which we should expect to observe this response is theoretically ambiguous under some models that conceptualize religion as a club good. For example, when adverse shocks occur, highly religious individuals may raise religious prohibitions to make it more costly for less religious individuals to enter the religious club (Berman, 2000). This exclusionary dynamic may discourage some non-members from entering and being able to acquire the club good of social insurance (Iannaccone, 1992).

[45]Conversely, some theoretical work suggests that economic development could stimulate religious revival if it leaves aspirations unfulfilled (Carvalho, 2009; Binzel and Carvalho, 2017), or if competition across denominations increases participation (McBride, 2010).

precipitation, but also on the soil's ability to retain water. This is determined by *potential evapotranspiration*, which is a function of other weather inputs including temperature, pressure, sunshine exposure, and wind speed. SPEI incorporates these other inputs into its measurement, calculating water deficit (or surplus) by subtracting potential evapotranspiration from precipitation. Empirically, SPEI has been shown to outperform other drought metrics in predicting crop yields (Vicente-Serrano, Beguería, and López-Moreno, 2010), and can also predict other outcomes such as conflict (Harari and La Ferrara, 2018).

Our main analysis uses a measure of SPEI that is defined for each 10 km x 10 km grid cell, for each month. This spatial and temporal resolution corresponds to the underlying ERA-5 Land reanalysis data, which provide high-quality estimates of weather and energy cycles (Muñoz-Sabater et al., 2021). SPEI is expressed as the standardized deviation of a 12-month moving average from its long-run mean (1981–2020 baseline).[46] Positive SPEI values indicate more precipitation relative to the historical mean (which is generally more favorable to agriculture), whereas negative values indicate less precipitation relative to the historical mean. Appendix Figure A6 maps SPEI in Afghanistan. The top panel shows the average across our entire sample period; the bottom panel shows SPEI in 2018, a year of severe drought.

For certain analyses, we also construct growing-season averages of SPEI (December–April), which corresponds to the primary cropping season for the most important crops in Afghanistan including wheat, the single most important crop, which is grown in all provinces (Tiwari et al., 2020). We then relate growing-season SPEI to religious adherence across three periods: the growing season itself, the harvest season (May–July), and the post-harvest season (August–September).

To examine whether the effects of drought operate through agricultural channels, we also analyze how growing season SPEI affects yearly agricultural output. Since there are no granular (sub-province) data for agricultural production in Afghanistan, we proxy for output using a satellite-based vegetation index, the Enhanced Vegetation Index (EVI). We follow

[46]SPEI can be constructed over different timescales — most commonly 6 months, 9 months, and 12 months. We focus on 12-month SPEI, which best captures cumulative hydrological stress from both rainfall shortages and snowmelt deficits (see discussion in footnote 43). Results for 6- and 9-month timescales, available on request, are qualitatively similar.

Asher and Novosad (2020) by subtracting the early growing season value (in December) from the maximum growing season value in log terms, an approach which controls for differences in non-crop vegetation growth over this period.

Econometric Specification

Our main specification estimates the relationship between climate shocks and religious adherence at the monthly grid-cell level.[47] We then estimate the following panel fixed-effects model:

$$d_{gm} = \alpha_g + \theta_m + \beta SPEI_{gm} + \varepsilon_{gm} \tag{3}$$

where d_{gm} denotes the Maghrib dip in grid cell g and month m; $SPEI_{gm}$ denotes the SPEI; α_g are grid-cell fixed effects; and θ_m are month fixed effects. In some specifications, we wish to test whether climate impacts differ by location type, such as croplands and pastoral areas. To assess heterogeneity by land use, we estimate:

$$d_{gm} = \alpha_g + \theta_m + \beta \mathrm{SPEI}_{gm} + \gamma\big(\mathrm{SPEI}_{gm} * \mathrm{AG}_g\big) + \rho\big(\mathrm{SPEI}_{gm} * \mathrm{OTH}_g\big) + \varepsilon_{gm} \tag{4}$$

where AG_g is the fraction of the grid cell classified as agricultural or pastoral land (i.e., rainfed cropland, irrigated cropland, and rangeland), based on land type data from the Food and Agriculture Organization (FAO, 2021) from 2010 (a year preceding our sample period). OTH_g is the fraction of other land types (forest, fruit trees and vineyards, barren areas, water bodies and marshland). The coefficient γ captures the differential sensitivity of religious adherence to precipitation shocks in agricultural regions relative to urban or non-agricultural areas. When estimating Equations (3) and (4), our main specifications cluster standard errors at the grid-cell level; in robustness tests, we also show results clustered at the district level. Appendix Table A5 summarizes descriptive statistics for all main variables, while Appendix Table A6 provides details for variables used in robustness analyses.

[47] To compute adherence for each 10km x 10km grid cell in each month, we calculate the total outgoing call volume across all towers in that grid cell in that month, during the 30-minute windows immediately pre- and post-Maghrib. Following Equation (1), we then calculate the dip as the volume before Maghrib minus the volume after Maghrib, divided by the average volume before and after.

5.2 Results: Climate and Religious Adherence

Table 2 provides our estimates of the effect of climate shocks on religious adherence. Column (1) indicates a significant negative relationship between SPEI and the Maghrib dip outcome. In other words, climate conditions more favorable to agriculture reduce religious adherence; conversely, drought conditions increase adherence.

To gauge the magnitude of these effects, we use the same benchmarking approach as in our violence application: We compare the effect of SPEI on the Maghrib dip to the effect of being in a predominantly Pashtun area. A moderate drought corresponds to a -1.3 SD fall in SPEI (Chen et al., 2023). The coefficient in column (1) implies that a change in SPEI of this magnitude increases religious adherence by approximately 18% as much as being in a Pashtun-dominated grid cell.[48] For a major drought, such as the one that afflicted Afghanistan in 2018 (depicted in Appendix Figure A6-Panel B), SPEI falls by roughly 1.6 SD. The estimate in column (1) suggests that a SPEI drop of this magnitude increases religious adherence by 22% of the Pashtun effect.

Robustness Checks In Table A10 we verify that this estimate is robust to all of the same checks undertaken with the violence results in Table A8: constructing the Maghrib dip using alternative functional forms and window lengths, and adding controls for call volume and the lagged dependent variable. We also show that the results remain almost identical when we cluster the standard errors at the district level, to account for the possibility that the errors may be correlated across grid cells within a district.

In Table A11, we additionally verify that the results do not depend on the sample, using the same tests as in the violence application, Table A9. This includes dropping districts with sizable Shia populations, excluding days during Ramadan, and removing the sparsest locations. We also present two additional checks. First, we show that urban areas do not drive the results: the estimates remain unchanged when we drop major urban centers such as Kabul.[49] This is reassuring since we expect precipitation conditions to exert the largest

[48] Multiplying the coefficient by the change in SPEI (-.67 x -1.3) implies that the Maghrib dip rises by .87. Column (2) of Table A4 shows that being in a Plurality Pashtun grid cell increases the Maghrib dip by 4.90. Scaling .87 by 4.90 yields the implied increase of 18%.

[49] We define a grid cell as urban if more than 5% of the cell constitutes built-up area, as defined by land cover data from the Food and Agriculture Organization. Approximately 19% of our grid cells are considered

Table 2: Climate and Religious Adherence

	Maghrib Dip		Agricultural Growth	
	(1)	(2)	(3)	(4)
SPEI	–0.672***	0.994		
	(0.199)	(1.010)		
SPEI x Rainfed Cropland		–2.790**		
		(1.279)		
SPEI x Irrigated Cropland		–1.776		
		(1.416)		
SPEI x Rangeland		–1.313		
		(1.028)		
Growing Season SPEI			0.203***	0.140
			(0.015)	(0.152)
Growing Season SPEI x Rainfed Cropland				0.359**
				(0.166)
Growing Season SPEI x Irrigated Cropland				0.130
				(0.173)
Growing Season SPEI x Rangeland				–0.114
				(0.149)
Observations	37496	37306	4212	4191
Grid Cell Fixed Effects	Y	Y	Y	Y
Month Fixed Effects	Y	Y		
Year Fixed Effects			Y	Y
Controls - Other Land Types		Y		Y

Notes: Each column is a separate regression. In columns (1)-(2): One observation is included for each month for each 10km X 10km grid cell; and the dependent variable is the Maghrib dip measure of religious adherence. The Maghrib dip is regressed on the monthly SPEI in column (1) and its interaction with the fraction of the grid cell containing rainfed and irrigated cropland, and rangeland in column (2). Both regressions include grid cell and month fixed effects. In columns (3)-(4): One observation is included for each year for each grid cell; and the dependent variable is the (log) difference in the Enhanced Vegetation Index (EVI) between the maximum and the beginning of the growing season, which is December. This transformation of EVI is regressed on the growing season SPEI in column (3), as well as its interaction with the fraction of the grid cell containing rainfed and irrigated cropland, and rangeland (in column 4). These two regressions include grid cell and year fixed effects. The "Controls - Other Land Types" refers to interactions of SPEI in column (2) and growing season SPEI in column (4), with the fraction of the grid cell containing forest cover, fruit trees and vineyards, barren areas, water and marshland (with the omitted category being built-up urban areas). Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

effects on economic conditions in rural areas. Second, we verify that dropping districts that fell under Taliban control does not alter the results.[50] This check rules out the possibility that negative SPEI shocks increased religious adherence solely because adherence was coerced by the Taliban.

Interpretation

Why do climate shocks increase religious adherence? By disaggregating our analysis spatially, we find evidence that climate conditions affect religiosity at least in part through economic channels. In particular, Column (2) of Table 2 shows that the negative effects of SPEI on the Maghrib dip are driven by locations that contain more cropland. The interaction coefficient is largest and most precisely estimated for areas with greater shares of rainfed croplands, which are also the areas where drought conditions most severely harm economic production.[51] This pattern is reinforced in the remaining columns of Table 2, which examine how SPEI during the growing season — the period when precipitation matters the most for agricultural yields — affects agricultural output annually. Consistent with prior work (Schlenker and Lobell, 2010; Lobell, Schlenker, and Costa-Roberts, 2011), SPEI exerts a positive effect on output in Afghanistan (Column (3)), especially in areas with more rainfed croplands (Column (4)). The coefficient in Column (3) implies that a moderate growing season drought is associated with a 26% decrease in vegetation growth, while a severe growing season SPEI shock is associated with a 33% decrease. Since the religious response is largest in areas where SPEI also most strongly affects economic output, this suggests that economic factors mediate the relationship between climate and religious adherence.

We also speculate as to *why* economic hardship might affect religious practices, examining the different mechanisms discussed at the beginning of Section 5 (opportunity costs, social insurance, and psychological coping). Although we do not have definitive evidence in favor of a single economic channel, we find suggestive evidence that opportunity costs and social

urban under this definition.

[50] Data on direct measures of Taliban control are only available from PiX (Protected Internet Exchange, 2023) for 2015-2020. Therefore, we remove the districts that experienced any Taliban control between 2015-2020 from all years of our data, and re-run the specifications for the 2013-2020 period.

[51] For example, the coefficient on SPEI X Rainfed Cropland implies that moving from the mean to 90th percentile of the rainfed cropland distribution increases the effect of a moderate drought from 7% to 32% of the effect of being in a Pashtun-dominated area.

insurance are unlikely to be major factors in our institutional context; instead, the pattern of results is more consistent with the coping channel.

If social insurance considerations were driving the religious response to climate shocks, and a primary reason for religious adherence was to publicly conform to social norms, we would not expect climate shocks to have much influence on private behavior that is less easily observed by the social network. However, as we observe in column (1) of Appendix Table A12, climate shocks also cause people to reduce shortcode calls — which are much less publicly visible. The implied effects are, if anything, qualitatively larger than with regular calls.[52] These effects on more private behavior imply that publicly visible motivations, including social insurance, cannot be the sole reason why climate shocks increase the Maghrib dip.[53]

To explore the opportunity cost mechanism, we disaggregate our analysis over the wheat cropping cycle. Here, we observe that the Maghrib dip is generally *largest* during the harvest season, which already suggests that the opportunity cost of time is not a major determinant of adherence in Afghanistan, since agricultural labor is most intensive during harvest.[54] We also check whether the effects of climate shocks are greatest during the harvest season, which is when the need for labor is greatest and opportunity costs are highest. Table 3 presents these results, by calculating the growing-season SPEI for each grid cell-year, and then estimating its impact on the Maghrib dip separately in each agricultural season. Different columns correspond to different sets of control variables: columns (2)-(3), (5)-(6), and (8)-(9) control for SPEI during the harvest and post-harvest seasons; columns (4)-(9) also control for the Maghrib dip in the previous 12 months (since growing season SPEI could directly affect growing season religiosity and thus influence religiosity in subsequent seasons); and columns (7)-(9) drop the days that fall within Ramadan, a period that overlaps primarily with the

[52]A moderate SPEI shock would imply a 27% effect while a severe SPEI shock would imply a 33% effect (using column (4) from Table A4 for benchmarking purposes.)

[53]This result contrasts with Chen (2010), which links social insurance to changes in religious adherence (measured through Koranic study) during Indonesia's financial crisis. Key contextual differences may explain the divergence. Afghanistan is one of the most religious countries in the world; and adherence to prayer is a widely observed norm. Thus, while Koranic study may represent a threshold for access to club goods in Indonesia, prayer adherence may not represent such a threshold in Afghanistan. Additionally, club goods provision is highly centralized in the Afghan context (e.g., by extremist organizations such as the Taliban). As such, prayer may not suffice as a screen for club goods provided by organizations in Afghanistan.

[54]For example, after removing Ramadan days, which coincide with the harvest period, the Maghrib dip is 12.8, 26.4, and 10.3 in the growing, harvest, and post-harvest seasons, respectively.

harvest season. Across specifications, we observe no effects during the harvest period. By contrast, the fact that religious adherence is most responsive during the growing and post-harvest seasons is consistent with the idea that people turn to religion when they expect or experience negative outcomes (i.e., the secularization hypothesis). For example, during the growing season, people may find consolation through prayer, or seek divine intervention (e.g., for rain), while in the post-harvest season they respond to the realized income loss by seeking psychological comfort.

To explore whether psychological coping might lead people to increase religious adherence after climate shocks, we look for heterogeneity in response by the type of individual affected by the shock. For this analysis, we leverage the massive amount of data available in order to construct a measure of "baseline" religiosity for each mobile subscriber in the dataset, during the first few years for which we have data (2013-2015).[55] We then test whether the response to climate shocks varies by baseline religiosity.

Specifically, we construct a measure of baseline adherence by aggregating each subscriber's activity in the 30 minutes before and after Maghrib during 2013-2015. The first two columns of Table A13 test whether individuals who are more religious at baseline react differently to SPEI shocks that occur between 2016-2020. This analysis uses data from approximately 8.5 million unique subscribers, with separate observations for each individual-quarter. We include individual subscriber fixed effects (as well as grid cell and quarter fixed effects) to isolate within-individual changes in religiosity that occur in response to climate shocks experienced by the individual. Results in Table A13 indicate that individuals who are more religiously adherent at baseline become even more adherent in response to adverse climate shocks. This heterogeneity by baseline religiosity holds whether 'more religious' is defined as above-median religiosity (column (1)) or by religiosity tercile (column (2)). As a further test of robustness, we construct an alternative measure of baseline religiosity that nets out the effect of SPEI shocks in the baseline period; results in columns (3) and (4) re-

[55] As discussed in Section 3.3, most subscribers make only a few calls each day, so high-frequency measures of an individual subscriber's religiosity (at the daily, weekly and monthly levels) are very imprecise. For this reason, most of our analysis relies on aggregating the Maghrib dip across subscribers at small geographic units (i.e., grid cells), at the monthly level. To construct a (baseline) measure of religious adherence for each subscriber, we instead aggregate each subscriber's activity over a 33-month period spanning 2013-2015.

main qualitatively unchanged.[56] The findings from Table A13 are consistent with the coping mechanism: individuals who are religiously observant at baseline are more likely to turn to religion to cope with negative income shocks.[57]

Alternative Accounts

Thus far, our results suggest that climate shocks affect religious adherence as people look to religion to cope with the expectation and experience of adverse economic shocks. Before concluding, we consider and present evidence against several alternative accounts, including changes in mood, liquidity constraints, out-migration and drug crop production.

First, a number of papers have suggested that weather conditions affect mood (Cunningham, 1979; Sanders and Brizzolara, 1982; Eagles, 1994; Denissen et al., 2008; Hannak et al., 2012). If mood also determines religious adherence, our main results in column (1) of Table 2 may reflect changes in mood rather than changes in economic conditions. However, it is difficult to reconcile this explanation with the specific patterns of heterogeneity observed in column (2), which indicate that the effects of climate are greatest in regions most economically dependent on rainfall. (Of course, the mood response to rainfall may be greater among those who are economically dependent on rainfall, but such a narrative is consistent with our interpretation that economic channels determine the response).

[56]This second, two-stage approach is designed to address the concern that the baseline religiosity measure in columns (1)-(2) could reflect the effect of SPEI shocks in the baseline period (2013-2015), and that those shocks may be correlated with SPEI shocks during the estimation period (2016-2020). In the first stage, we regress each subscriber's quarterly Maghrib dip on SPEI shocks in the home grid cell-quarter over 2013-2015, controlling for grid cell and quarter fixed effects. The residuals from this regression (averaged over all baseline quarters for each subscriber) measure the individual's baseline religious adherence net of baseline SPEI shocks. Columns (3)-(4) use bootstrapped standard errors (clustered by grid cell) to account for the use of a generated regressor. Although these standard errors are larger, the coefficients are nearly identical in magnitude to those in columns (1) and (2). Columns (3)-(4) have fewer observations due to missing SPEI data in some grid cells during 2013-2015.

[57]In the first case study on the effect of violence on adherence, we do not conduct a similar analysis of heterogeneity, since the ISAF violence data only overlaps with our mobile phone CDR during 2013-2014.

Table 3: Climate and Religious Adherence by Agricultural Season

	Maghrib Dip in			*Maghrib Dip in*			*Maghrib Dip in*		
	(1) Growing Season	(2) Harvest Season	(3) Post-harvest Season	(4) Growing Season	(5) Harvest Season	(6) Post-harvest Season	(7) Growing Season	(8) Harvest Season	(9) Post-harvest Season
Growing Season SPEI	–0.732***	0.594	–0.532	–0.628**	0.598	–0.865**	–0.669**	0.346	–0.821**
	(0.281)	(0.479)	(0.341)	(0.307)	(0.534)	(0.381)	(0.306)	(0.521)	(0.379)
Observations	3251	3251	3251	2815	2815	2815	2808	2808	2808
Grid Cell Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Control for own season SPEI		Y	Y		Y	Y		Y	Y
Control for Prev. Maghrib Dip				Y	Y	Y	Y	Y	Y
Dropping Ramadan days							Y	Y	Y

Notes: Each column is a regression of the Maghrib dip during an agricultural season (growing, harvest, or post-harvest) on SPEI during the growing season. Seasons are defined based on the wheat crop calendar: growing season is December-April, harvest season is May-July, and post-harvest season is August-September. The "Control for own season SPEI" controls for Harvest season SPEI in columns (2) (5) and (8); and for Post-harvest season SPEI in columns (3) (6) and (9). The "Control for Prev. Maghrib Dip" controls for the average Maghrib dip over the previous 12 months in columns (4)-(9). One observation is included for each year for each 10 km x 10 km grid cell. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Second, if droughts create liquidity constraints, it is possible that call volumes fall because people cannot afford to make as many phone calls. However, our measure of the Maghrib dip is a relative one (based on changes in calls over a within-day window), so a general decrease in call volume – if evenly distributed throughout the day – should not affect the Maghrib dip measure of religious adherence. Nonetheless, to directly examine this account we regress the change in (log) daily call volume on SPEI. Column (2) of Appendix Table A12 shows a small, insignificant coefficient, that is *negative* in sign. This indicates that favorable rainfall does not increase call activity overall, and that drought conditions do not meaningfully suppress total call volume in a way that could generate spurious Maghrib dips. Thus, we do not see evidence that more favorable rainfall conditions increase overall call activity.

Relatedly, adverse shocks may prevent individuals from making any calls at all, leading them to stop appearing in the CDR data. In that case, these compositional changes in the sample could affect our results. Thus, column (3) restricts the sample in each month to the set of subscribers who have made a call in each of the previous three months, to create a rolling sample of constant users. The coefficient remains unchanged, indicating that selective exit from the sample is not driving our results.

In column (4) of Appendix Table A12, as in our violence application, we again consider the possibility that out-migration may affect our results. For example, if the least religious leave in response to droughts, this could lead us to over-estimate the effect of SPEI shocks. However, restricting the sample to those who had the same district home location over the previous three months does not affect the estimates. This suggests that climate-induced migration does not meaningfully bias our estimates of the Maghrib dip.

We also directly address the role of opium poppies, the drug crop used to manufacture heroin. Since poppies are more drought-resistant than wheat, this raises the possibility that adverse climate shocks may lead to increased poppy cultivation, which in turn may lead to the increased presence of armed groups involved in drug trafficking – i.e., the Taliban. The increased presence of the Taliban could then serve as an alternate channel affecting religious adherence. As discussed above, Appendix Table A11 shows that our effects are not driven by areas subject to Taliban control – a finding which casts doubt on this alternative channel. We also undertake two additional tests to more directly address the role of poppy, utilizing district-year level data on poppy cultivation from the UNODC (2021).[58] In columns (1) and (2) of Appendix Table A14, we estimate a grid cell-month level specification in which we regress land cultivated with poppy on SPEI, controlling for grid cell and month fixed effects. We do not find evidence that SPEI significantly affects opium cultivation. In columns (3) and (4), we re-estimate Equation (3) while controlling for poppy cultivation.[59] Our main coefficient remains effectively unchanged, indicating that variation in drug crop cultivation is unlikely to drive the observed effects on religious adherence.

Finally, we consider the possibility that conflict may serve as a channel through which adverse economic shocks increase religious adherence. Yet, this seems unlikely for the following reason. Past work has shown that adverse rainfall shocks increase violent conflict.[60] And, our first case study shows that greater conflict leads to lower religious adherence. Yet, here we find that adverse economic shocks lead to *greater* religious adherence, the opposite of the conflict effect. This suggests that conflict is unlikely to be the channel behind this observed effect.

6 Conclusion

In this paper, we develop a new measure of religious adherence using anonymized mobile phone transaction records, and use it to address consequential questions about how conflict and climate shocks shape religious behavior in an Islamic society. Our measure tracks the decrease in phone calls during the Maghrib prayer window and interprets this "Maghrib dip" as an indication of religious adherence.

This measure has several advantages: it is based on revealed behavior; it can be collected at the scale of entire countries at low cost; it can be analyzed individually and at various levels of aggregation (over time and space); and it can capture religious activity even in circumstances, such as active conflict, where conventional survey-based measures of religios-

[58] While this is the best available data on poppy cultivation in Afghanistan, almost 41% of the observations are missing. We therefore present results that linearly interpolate this outcome, as well as results based on the IHS transformation, which is preferable to the logarithm given the prevalence of zeroes.

[59] In these specifications, to prevent missing values in the poppy variable from reducing the number of observations, we fill these missing values with an arbitrary number (0) and add a control variable indicating that missing values have been filled in this way.

[60] A complete survey of this literature beyond the scope of this paper but see Hsiang, Burke, and Miguel (2013) and Burke et al. (2024) for two recent meta-analyses.

ity are infeasible to collect. At the same time, as discussed in Section 3.4, the measure has important limitations. In particular, it requires access to mobile operator data, and it captures a specific behavior rather than the richer sentiments documented through qualitative interviews or well-designed surveys. We therefore view the Maghrib dip measure as a complement to more traditional data sources, particularly in research designs that exploit its spatial and temporal granularity.

Our empirical analysis illustrates how this measure can shed light on two questions that would be extremely difficult to address with existing measures of religiosity in Afghanistan. In the first case study, we find that Taliban attacks reduce religious observance, whereas unrealized attacks and state-led attacks have no comparable effect — providing placebo tests that reinforce a causal interpretation of the effect of Taliban violence on religious adherence. In the second case study, we find that adverse climate shocks increase religious observance, especially in areas dependent on rainfed agriculture, where precipitation shocks are most economically consequential. In both applications, we show that it is not just public behaviors (such as interpersonal phone calls) that fall during the Maghrib window; rather, more private phone-based activity (such as calls to shortcodes) also decrease in response to both insurgent violence and economic adversity. This pattern suggests that private motivations —– not merely outward-facing social considerations —– play an important role in shaping religious responses to these types of shocks.

The fact that we observe opposite effects in our two applications highlights how different shocks can influence religious adherence in distinct ways. In particular, we observe that shocks directly related to religion, such as violence perpetrated by Islamist insurgents, can lead people to turn people away from religious observance. In contrast, purely economic shocks can instead lead people to turn toward religion.

While our empirical focus is on using the Maghrib dip to study two specific applications in Afghanistan, we expect that the approach could be adapted to a wider range of empirical settings. Most straightforward would be to use the Maghrib Dip measure to address other questions related to religious adherence in similarly devout Muslim societies — for example, to study the relationship between religious adherence and other socio-economic factors (such as schooling, science and technological advancements) and institutional factors (such as corruption and the nature of local governance). In settings where the population is less uniformly adherent, we expect that the measure would still capture changes in adherence to Muslim norms, but there may be added nuance to interpreting those changes (for instance, to determine if changes in adherence are driven by changes in the intensity of adherence of a fixed population, or by a compositional change in who is observant).

More speculatively, we can imagine extensions of this approach to settings much farther afield. Our approach relies on the simple insight that aggregate patterns of technology use (and dis-use) can provide a new, quantitative perspective on religious adherence over time and space. Thus, it is plausible that the approach could be adapted to other religions that have customs that may shift technology use at specific times — such as Sandhyavandanam rituals in Hinduism (performed at dawn, noon, and dusk), or Sabbath practices by Orthodox Jews. And while we focus on mobile phone transactions because cell phones are the most widely used digital technology in Afghanistan, in other contexts, other sources of unobtrusively collected digital data – such as social media posts, internet routing and traffic data, or financial transaction records – might be more suitable or easy to obtain. In sum, we hope this effort can help inspire new and diverse approaches to studying the causes and consequences of religion.

References

Abadie, Alberto and Javier Gardeazabal. 2003. "The Economic Costs of Conflict: A Case Study of the Basque Country." *American Economic Review* 93 (1):113–132. URL `https://www.aeaweb.org/articles?id=10.1257/000282803321455188`.

Afghan Analysts Network. 2025. "Living a Mullah's Life (1): The changing role and socio-economic status of Afghanistan's village clerics." Tech. rep., Afghan Analysts Network. URL `https://www.afghanistan-analysts.org/en/reports/political-landscape/living-a-mullahs-life-1-the-changing-role-and-socio-economic-status-of-afghanistans-village-clerics/`.

Ager, Philipp and Antonio Ciccone. 2018. "Agricultural Risk and the Spread of Religious Communities." *Journal of the European Economic Association* 16 (4):1021–1068.

Aiken, Emily, Suzanne Bellue, Dean Karlan, Christopher R. Udry, and Joshua E. Blumenstock. 2022. "Machine Learning and Phone Data Can Improve Targeting of Humanitarian Aid." *Nature* :1–7URL `https://www.nature.com/articles/s41586-022-04484-9`. Publisher: Nature Publishing Group.

Allport, Gordon W. and J. Michael Ross. 1967. "Personal Religious Orientation and Prejudice." *Journal of Personality and Social Psychology* 5 (4):432–443.

Asher, Sam and Paul Novosad. 2020. "Rural Roads and Local Economic Development." *American Economic Review* 110 (3):797–823.

Atkin, David, Eve Colson-Sihra, and Moses Shayo. 2021. "How Do We Choose Our Identity? A Revealed Preference Approach Using Food Consumption." *Journal of Political Economy* 129 (4):1193–1251.

Auriol, Emmanuelle, Diego Delissaint, Maleke Fourati, Josepa Miquel-Florensa, and Paul Seabright. 2021a. "Betting on the Lord: Lotteries and Religiosity in Haiti." *World Development* 144:105441.

———. 2021b. "Trust in the Image of God: Links Between Religiosity and Reciprocity in Haiti." *Economics of Transition and Institutional Change* 29 (1):3–34.

Auriol, Emmanuelle, Julie Lassébie, Amma Panin, Eva Raiber, and Paul Seabright. 2020. "God Insures Those Who Pay? Formal Insurance and Religious Offerings in Ghana." *The Quarterly Journal of Economics* 135 (4):1799–1848.

Azzi, Corry and Ronald Ehrenberg. 1975. "Household Allocation of Time and Church Attendance." *Journal of Political Economy* 83 (1):27–56.

Bahal, Girish, Sriya Iyer, Kishen Shastry, and Anand Shrivastava. 2023. "Religion, Covid-19 and Mental Health." *European Economic Review* 160:104621.

Barfield, Thomas J. 2022. *Afghanistan: A Cultural and Political History*. Princeton University Press.

Barro, Robert J. and Rachel M. McCleary. 2003. "Religion and Economic Growth across Countries." *American Sociological Review* 68 (5):760–781. URL `http://www.jstor.org/stable/1519761`.

———. 2019. *The Wealth of Religions: The Political Economy of Believing and Belonging.* Princeton University Press.

Bazzi, Samuel, Masyhur Hilmy, and Benjamin Marx. 2020. "Religion, Education, and the State." Working Paper 27073, National Bureau of Economic Research. URL `https://www.nber.org/papers/w27073`.

Bazzi, Samuel, Gabriel Koehler-Derrick, and Benjamin Marx. 2020. "The Institutional Foundations of Religious Politics: Evidence from Indonesia." *The Quarterly Journal of Economics* 135 (2):845–911.

Becker, Sascha O., Jared Rubin, and Ludger Woessmann. 2021. "Religion in Economic History: A Survey." In *The Handbook of Historical Economics*, edited by Alberto Bisin and Giovanni Federico. Academic Press, 585–639.

———. 2024. "Religion and Growth." *Journal of Economic Literature* 62 (3):1094–1142.

Becker, Sascha O. and Ludger Woessmann. 2009. "Was Weber Wrong? A Human Capital Theory of Protestant Economic History." *The Quarterly Journal of Economics* 124 (2):531–596.

Bénabou, Roland, Davide Ticchi, and Andrea Vindigni. 2022. "Forbidden Fruits: The Political Economy of Science, Religion, and Growth." *The Review of Economic Studies* 89 (4):1785–1832.

Bentzen, Jeanet Sinding. 2019. "Acts of God? Religiosity and Natural Disasters Across Subnational World Districts." *The Economic Journal* 129 (622):2295–2321.

———. 2021. "In Crisis, We Pray: Religiosity and the COVID-19 Pandemic." *Journal of Economic Behavior & Organization* 192:541–583.

Berman, Eli. 2000. "Sect, Subsidy, and Sacrifice: An Economist's View of Ultra-Orthodox Jews." *The Quarterly Journal of Economics* 115 (3):905–953.

———. 2003. "Hamas, Taliban and the Jewish Underground: An Economist's View of Radical Religious Militias." Working Paper 10004, National Bureau of Economic Research. URL `https://www.nber.org/papers/w10004`.

———. 2011. *Radical, Religious, and Violent: The New Economics of Terrorism.* MIT press.

Berman, Eli, Michael Callen, Joseph H Felter, and Jacob N Shapiro. 2011. "Do working men rebel? Insurgency and unemployment in Afghanistan, Iraq, and the Philippines." *Journal of Conflict Resolution* 55 (4):496–528.

Binzel, Christine and Jean-Paul Carvalho. 2017. "Education, Social Mobility and Religious Movements: The Islamic Revival in Egypt." *The Economic Journal* 127 (607):2553–2580.

Blaydes, Lisa and Rachel M. Gillum. 2013. "Religiosity-of-Interviewer Effects: Assessing the Impact of Veiled Enumerators on Survey Response in Egypt." *Politics and Religion* 6 (3):459–482.

Blondel, Vincent D, Markus Esch, Connie Chan, Fabrice Clérot, Pierre Deville, Etienne Huens, Frédéric Morlot, Zbigniew Smoreda, and Cezary Ziemlicki. 2012. "Data for Development: The D4D Challenge on Mobile Phone Data." *arXiv preprint arXiv:1210.0137* .

Blumenstock, Joshua. 2018. "Don't Forget People in the Use of Big Data for Development." *Nature* 561 (7722):170–172. URL `https://doi.org/10.1038/d41586-018-06215-5`.

Blumenstock, Joshua, Michael Callen, Tarek Ghani, and Robert Gonzalez. 2024. "Violence and Financial Decisions: Evidence from Mobile Money in Afghanistan." *The Review of Economics and Statistics* :1–45.

Bottan, Nicolas L. and Ricardo Perez-Truglia. 2015. "Losing My Religion: The Effects of Religious Scandals on Religious Participation and Charitable Giving." *Journal of Public Economics* 129:106–119.

Brenner, Philip S. 2011. "Exceptional Behavior or Exceptional Identity? Overreporting of Church Attendance in the US." *Public Opinion Quarterly* 75 (1):19–41.

———. 2014. "Testing the Veracity of Self-Reported Religious Practice in the Muslim World." *Social Forces* 92 (3):1009–1037.

Brenner, Philip S. and John DeLamater. 2016. "Lies, Damned Lies, and Survey Self-reports? Identity as a Cause of Measurement Bias." *Social Psychology Quarterly* 79 (4):333–354.

Bryan, Gharad, James J. Choi, and Dean Karlan. 2021. "Randomizing Religion: The Impact of Protestant Evangelism on Economic Outcomes." *The Quarterly Journal of Economics* 136 (1):293–380.

Bryant-Davis, Thema and Eunice C Wong. 2013. "Faith to Move Mountains: Religious Coping, Spirituality, and Interpersonal Trauma Recovery." *Am Psychol.* 68:675–684.

Burke, Marshall, Joel Ferguson, Solomon M. Hsiang, and Edward Miguel. 2024. "New Evidence on the Economics of Climate and Conflict." Working Paper 33040, National Bureau of Economic Research. URL `https://www.nber.org/papers/w33040`.

Bursztyn, Leonardo, Michael Callen, Bruno Ferman, Saad Gulzar, Ali Hasanain, and Noam Yuchtman. 2020. "Political Identity: Experimental Evidence on Anti-Americanism in Pakistan." *Journal of the European Economic Association* 18 (5):2532–2560.

Bursztyn, Leonardo, Georgy Egorov, and Robert Jensen. 2019. "Cool to be Smart or Smart to be Cool? Understanding Peer Pressure in Education." *The Review of Economic Studies* 86 (4):1487–1526.

Bursztyn, Leonardo and Robert Jensen. 2015. "How Does Peer Pressure Affect Educational Investments?" *The Quarterly Journal of Economics* 130 (3):1329–1367.

———. 2017. "Social Image and Economic Behavior in the Field: Identifying, Understanding, and Shaping Social Pressure." *Annual Review of Economics* 9 (1):131–153.

Buser, Thomas. 2015. "The Effect of Income on Religiousness." *American Economic Journal: Applied Economics* 7 (3):178–95.

Butinda, Lewis Dunia, Aimable Amani Lameke, Nathan Nunn, Max Posch, and Raúl Sánchez de la Sierra. 2023. "On the Importance of African Traditional Religion for Economic Behavior." Working Paper 31430, National Bureau of Economic Research. URL `https://www.nber.org/papers/w31430`.

Callen, Michael, Mohammad Isaqzadeh, James D. Long, and Charles Sprenger. 2014. "Violence and Risk Preference: Experimental Evidence from Afghanistan." *American Economic Review* 104 (1):123–148.

Campante, Filipe and David Yanagizawa-Drott. 2015. "Doe Religion Affect Economic Growth and Happiness? Evidence from Ramadan." *The Quarterly Journal of Economics* 130 (2):615–658.

Cantoni, Davide. 2015. "The Economic Effects of the Protestant Reformation: Testing the Weber Hypothesis in the German Lands." *Journal of the European Economic Association* 13 (4):561–598.

Cantoni, Davide, Jeremiah Dittmar, and Noam Yuchtman. 2018. "Religious Competition and Reallocation: The Political Economy of Secularization in the Protestant Reformation." *The Quarterly Journal of Economics* 133 (4):2037–2096.

Carvalho, Jean-Paul. 2009. "A Theory of the Islamic Revival." Economics Series Working Papers 424, University of Oxford, Department of Economics.

———. 2013. "Veiling." *The Quarterly Journal of Economics* 128 (1):337–370.

———. 2019. "Religious Clubs: The Strategic Role of Religious Identity." In *Advances in the Economics of Religion*, edited by Jean-Paul Carvalho, Sriya Iyer, and Jared Rubin. Palgrave Macmillan, 25–41.

Cavalcanti, Tiago, Sriya Iyer, Christopher Rauh, Christian Roerig, and Maryam Vaziri. 2022. "A City of God: Afterlife Beliefs and Job Support in Brazil." Cambridge Working Papers in Economics 2268.

Central Asian Cultural Intelligence for Military Operations. . "Tajiks in Afghanistan." `https://info.publicintelligence.net/MCIA-AfghanCultures/Tajik.pdf`. Accessed: 2023-04-14.

Cesur, Resul, Travis Freidman, and Joseph J. Sabia. 2020. "War, Traumatic Health Shocks, and Religiosity." *Journal of Economic Behavior & Organization* 179:475–502.

Chaney, Eric. 2013. "Revolt on the Nile: Economic Shocks, Religion, and Political Power." *Econometrica* 81 (5):2033–2053.

———. 2016. "Religion and the Rise and Fall of Islamic Science." *Working Paper* .

———. 2019. "Religion, Political Power and Human Capital Formation: Evidence from Islamic History." In *Advances in the Economics of Religion*, edited by Jean-Paul Carvalho, Sriya Iyer, and Jared Rubin. Palgrave Macmillan, 437–448.

Chaudhary, Latika and Jared Rubin. 2011. "Reading, Writing, and Religion: Institutions and Human Capital Formation." *Journal of Comparative Economics* 39 (1):17–33.

———. 2016. "Religious Identity and the Provision of Public Goods: Evidence from the Indian Princely States." *Journal of Comparative Economics* 44 (3):461–483.

Chen, Daniel L. 2010. "Club Goods and Group Identity: Evidence from Islamic Resurgence During the Indonesian Financial Crisis." *Journal of Political Economy* 118 (2):300–354.

Chen, Yun, David Penton, Karim Fazlul, Santosh Aryal, Shahriar Wahid, Peter Taylor, and Susan M Cuddy. 2023. "Characterisation of Meteorological Drought at Sub-Catchment Scale in Afghanistan Using Station-Observed Climate Data." *PLOS ONE* 18.

Chi, Guanghua, Fengyang Lin, Guangqing Chi, and Joshua Blumenstock. 2020. "A General Approach to Detecting Migration Events in Digital Trace Data." *PLOS ONE* 15 (10):e0239408. URL `https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0239408`. Publisher: Public Library of Science.

Cinnirella, Francesco, Alireza Naghavi, and Giovanni Prarolo. 2023. "Islam and Human Capital in Historical Spain." *Journal of Economic Growth* 28 (2):225–257.

Climate Security Expert Network. 2019. "Climate-Fragility Risk Factsheet: Afghanistan." URL `https://climate-security-expert-network.org/sites/climate-security-expert-network.com/files/documents/csen_climate_fragility_factsheet_-_afghanistan.pdf`.

Clingingsmith, David, Asim Ijaz Khwaja, and Michael Kremer. 2009. "Estimating the Impact of the Hajj: Religion and Tolerance in Islam's Global Gathering." *The Quarterly Journal of Economics* 124 (3):1133–1170.

Condra, Luke N, James D Long, Andrew C Shaver, and Austin L Wright. 2018. "The logic of insurgent electoral violence." *American Economic Review* 108 (11):3199–3231.

Condra, Luke N. and Jacob N. Shapiro. 2012. "Who Takes the Blame? The Strategic Effects of Collateral Damage." *American Journal of Political Science* 56 (1):167–187.

Costa, Francisco, Angelo Marcantonio, and Rudi Rocha. 2019. "Stop Suffering! Economic Downturns and Pentecostal Upsurge." *Journal of the European Economic Association* .

Cunningham, Michael R. 1979. "Weather, Mood, and Helping Behavior: Quasi Experiments with the Sunshine Samaritan." *Journal of Personality and Social Psychology* 37 (11):1947.

de Montjoye, Yves-Alexandre, Sébastien Gambs, Vincent Blondel, Geoffrey Canright, Nicolas de Cordes, Sébastien Deletaille, Kenth Engø-Monsen, Manuel Garcia-Herranz, Jake Kendall, Cameron Kerry et al. 2018. "On the Privacy-Conscientious Use of Mobile Phone Data." *Scientific Data* 5 (1):1–6.

Dehejia, Rajeev, Thomas DeLeire, and Erzo F.P. Luttmer. 2007. "Insuring Consumption and Happiness Through Religious Organizations." *Journal of Public Economics* 91 (1-2):259–279.

Dell, Melissa and Pablo Querubin. 2018. "Nation Building Through Foreign Intervention: Evidence from Discontinuities in Military Strategies." *Quarterly Journal of Economics* 133 (2):701–764.

Denissen, Jaap J. A., Ligaya Butalid, Lars Penke, and Marcel A. G. Van Aken. 2008. "The Effects of Weather on Daily Mood: A Multilevel Approach." *Emotion* 8 (5):662.

Eagles, John M. 1994. "The Relationship Between Mood and Daily Hours of Sunlight in Rapid Cycling Bipolar Illness." *Biological Psychiatry* .

Esteban, Joan, Gilat Levy, and Laura Mayoral. 2018. "Liberté, Égalité… Religiosité." *Journal of Public Economics* 164:241–253.

———. 2019. "Personal Liberties, Religiosity, and Effort." *European Economic Review* 120:103320.

FAO. 2021. "Aggregated Land Cover Database of the Islamic Republic of Afghanistan (2010)." URL `https://data.apps.fao.org/map/catalog/srv/eng/catalog.search?id=1289#/metadata/1dd35e22-bd51-4c4d-bf0c-546baababe74`.

Freud, Sigmund. 1927. *The Future of an Illusion.* Broadview Press.

Fruehwirth, Jane Cooley, Sriya Iyer, and Anwen Zhang. 2019. "Religion and Depression in Adolescence." *Journal of Political Economy* 127:1178–1209.

Gentilini, Ugo, Mohamed Almenfi, Ian Orton, and Pamela Dale. 2020. "Social Protection and Jobs Responses to COVID-19: A Real-Time Review of Country Measures." *World Bank Policy Brief* URL `https://openknowledge.worldbank.org/handle/10986/33635`.

Gonzalez, Robert M. 2021. "Cell Phone Access and Election Fraud: Evidence from a Spatial Regression Discontinuity Design in Afghanistan." *American Economic Journal: Applied Economics* 13 (2):1–51. URL `https://www.aeaweb.org/articles?id=10.1257/app.20190443`.

Grosfeld, Irena, Etienne Madinier, Seyhun Orcan Sakalli, and Ekaterina Zhuravskaya. 2024. "Independent Media, Propaganda, and Religiosity: Evidence from Poland." *American Economic Journal: Applied Economics* 16 (4):361–403.

Gruber, Jonathan. 2004. "Pay or Pray? The Impact of Charitable Subsidies on Religious Attendance." *Journal of Public Economics* 88 (12):2635–2655.

Gruber, Jonathan and Daniel M. Hungerman. 2008. "The Church Versus the Mall: What Happens When Religion Faces Increased Secular Competition?*." *The Quarterly Journal of Economics* 123 (2):831–862. URL https://doi.org/10.1162/qjec.2008.123.2.831.

Hadaway, C Kirk, Penny Long Marler, and Mark Chaves. 1993. "What the Polls Don't Show: A Closer Look at US Church Attendance." *American Sociological Review* :741–752.

———. 1998. "Overreporting Church Attendance in America: Evidence That Demands the Same Verdict." *American Sociological Review* 63 (1):122–130.

Hanna, Rema, Gabriel Kreindler, and Benjamin A. Olken. 2017. "Citywide Effects of High-Occupancy Vehicle Restrictions: Evidence from "Three-in-One" in Jakarta." *Science* 357 (6346):89–93.

Hannak, Aniko, Eric Anderson, Lisa Feldman Barrett, Sune Lehmann, Alan Mislove, and Mirek Riedewald. 2012. "Tweetin'in the Rain: Exploring Societal-Scale Effects of Weather on Mood." In *Proceedings of the International AAAI Conference on Web and Social Media*, vol. 6. 479–482.

Harari, Mariaflavia and Eliana La Ferrara. 2018. "Conflict, Climate, and Cells: a Disaggregated Analysis." *Review of Economics and Statistics* 100 (4):594–608.

Henrich, Joseph. 2020. *The WEIRDest People in the World: How the West Became Psychologically Peculiar and Particularly Prosperous*. Penguin UK.

Henrich, Joseph, Michal Bauer, Alessandra Cassar, Julie Chytilová, and Benjamin Grant Purzycki. 2019. "War Increases Religiosity." *Nature Human Behaviour* 3 (2):129–135.

Herskowitz, S., Tarek Ghani, J. Blumenstock, E. Kapstein, T. Scherer, and O. Toomet. 2025. "Insecurity and Firm Displacement: Evidence from Afghan Corporate Phone Records." *American Economic Journal: Economic Policy* URL https://www.semanticscholar.org/paper/%E2%80%9CHow-Do-Firms-Respond-to-Insecurity-Evidence-from-Blumenstock-Ghani/77623ab91302fed2292ac9fc5ccec31dedfbf505.

Hsiang, Solomon M., Marshall Burke, and Edward Miguel. 2013. "Quantifying the Influence of Climate on Human Conflict." *Science* 341.

Hume, David. 1757. *Four Dissertations: I. The Natural History of Religion. II. Of the Passions. III. Of Tragedy. IV. Of the Standard of Taste*. 32. A. Millar.

Iannaccone, Laurence R. 1992. "Sacrifice and Stigma: Reducing Free-riding in Cults, Communes, and Other Collectives." *Journal of Political Economy* 100 (2):271–291.

———. 1998. "Introduction to the Economics of Religion." *Journal of Economic Literature* 36 (3):1465–1495.

Isaqzadeh, Mohammad. 2024. "Religious Traditions and Coping With War and Displacement: Evidence from a Field Experiment with Afghan Refugees."

Iyer, Sriya. 2016. "The New Economics of Religion." *Journal of Economic Literature* 54 (2):395–441.

Iyer, Sriya, Shaun Larcom, Jaimin Shah, and Po-Wen She. 2025. "Do Religious People Cope Better in a Crisis? Evidence from the UK Pandemic Lockdowns." *Journal of Economic Behavior & Organization* 237:107136.

Iyer, Sriya and Melvyn Weeks. 2020. "Social Interactions, Ethnicity, Religion, and Fertility in Kenya." *Journal of Demographic Economics* 86 (3):329–365.

Joshua Project. 2023. "Afghan Tajik in Afghanistan." `https://joshuaproject.net/people_groups/14372/AF`. Accessed: 2023-04-14.

Juergensmeyer, Mark. 2017. *Terror in the mind of God: The global rise of religious violence*, vol. 13. Univ of California Press.

Kochhar, Nishtha and Erwin Willem Yvonnick Leon Knippenberg. 2023. "Droughts and Welfare in Afghanistan." Policy Research Working Paper WPS 10272, World Bank Group. URL `http://documents.worldbank.org/curated/en/099419201092321423`.

Kohli, Nitin, Emily Aiken, and Joshua E. Blumenstock. 2024. "Privacy guarantees for personal mobility data in humanitarian response." *Scientific Reports* 14 (1):28565. URL `https://www.nature.com/articles/s41598-024-79561-2`. Publisher: Nature Publishing Group.

Kuran, Timur. 1995. *Private truths, public lies: The social consequences of preference falsification*. Harvard University Press.

———. 2018. "Islam and Economic Performance: Historical and Contemporary Links." *Journal of Economic Literature* 56 (4):1292–1359.

Le Rossignol, Etienne, Sara Lowes, and Nathan Nunn. 2024. "The Social Consequences of Traditional Religion in Contemporary Africa." Working Paper 29695, National Bureau of Economic Research. URL `https://www.nber.org/papers/w29695`.

Levy, Gilat. 2019. "The Intelligent Design of Religious Beliefs." In *Advances in the Economics of Religion*, edited by Jean-Paul Carvalho, Sriya Iyer, and Jared Rubin. Palgrave Macmillan, 73–88.

Levy, Gilat and Ronny Razin. 2012. "Religious Beliefs, Religious Participation, and Cooperation." *American Economic Journal: Microeconomics* 4 (3):121–151.

———. 2014. "Rituals or Good Works: Social Signaling in Religious Organizations." *Journal of the European Economic Association* 12 (5):1317–1360.

Litz, Brett T, Nathan Stein, Eileen Delaney, Leslie Lebowitz, William P Nash, Caroline Silva, and Shira Maguen. 2009. "Moral injury and moral repair in war veterans: A preliminary model and intervention strategy." *Clinical psychology review* 29 (8):695–706.

Livny, Avital. 2021. "Can Religiosity be Sensed with Satellite Data? An Assessment of Luminosity during Ramadan in Turkey." *Public Opinion Quarterly* 85 (S1):371–398.

Lobell, David B, Wolfram Schlenker, and Justin Costa-Roberts. 2011. "Climate Trends and Global Crop Production Since 1980." *Science* 333 (6042):616–620.

Lu, Xin, Linus Bengtsson, and Petter Holme. 2012. "Predictability of Population Displacement After the 2010 Haiti Earthquake." *Proceedings of the National Academy of Sciences* 109 (29):11576–11581.

Mahmood, Rafat and Michael Jetter. 2023. "Gone with the Wind: The Consequences of US Drone Strikes in Pakistan." *Economic Journal* 133 (650):787–811.

Marx, Karl. 1970. *Critique of Hegel's Philosophy of Right*. Cambridge University Press.

Mayer, Jonathan, Patrick Mutchler, and John C. Mitchell. 2016. "Evaluating the Privacy Properties of Telephone Metadata." *Proceedings of the National Academy of Sciences* 113 (20):5536–5541.

McBride, Michael. 2007. "Club Mormon: Free-Riders, Monitoring, and Exclusion in the LDS Church." *Rationality and Society* 19 (4):395–424.

———. 2010. "Religious Market Competition in a Richer World." *Economica* 77 (305):148–171.

McCleary, Rachel M. and Robert J. Barro. 2006. "Religion and Economy." *Journal of Economic Perspectives* 20 (2):49–72.

Michalopoulos, Stelios, Alireza Naghavi, and Giovanni Prarolo. 2016. "Islam, Inequality and Pre-Industrial Comparative Development." *Journal of Development Economics* 120:86–98.

Mill, Wladislaw, Tobias Ebert, Jana B Berkessel, Thorsteinn Jonsson, Sune Lehmann, and Jochen E Gebauer. 2024. "War Causes Religiosity: Gravestone Evidence from the Vietnam Draft Lottery." *SocArXiv* .

Milusheva, Sveta, Anat Lewin, Tania Begazo Gomez, Dunstan Matekenya, and Kyla Reid. 2021. "Challenges and Opportunities in Accessing Mobile Phone Data for COVID-19 Response in Developing Countries." *Data & Policy* 3.

Montero, Eduardo and Dean Yang. 2022. "Religious Festivals and Economic Development: Evidence from the Timing of Mexican Saint Day Festivals." *American Economic Review* 112 (10):3176–3214.

Muñoz-Sabater, Joaquín, Emanuel Dutra, Anna Agustí-Panareda, Clément Albergel, Gabriele Arduini, Gianpaolo Balsamo, Souhail Boussetta, Margarita Choulga, Shaun Harrigan, Hans Hersbach, Brecht Martens, Diego G. Miralles, María Piles, Nemesio J. Rodríguez-Fernández, Ervin Zsoter, Carlo Buontempo, and Jean-Noël Thépaut. 2021. "ERA5-Land: A State-of-the-Art Global Reanalysis Dataset for Land Applications." *Earth System Science Data* 13 (9):4349–4383. URL `https://essd.copernicus.org/articles/13/4349/2021/`. Publisher: Copernicus GmbH.

Muradi, Ahmad Jawid and Ismet Boz. 2018. "The Contribution of Agriculture Sector in the Economy of Afghanistan." *International Journal of Scientific Research and Management* 6 (10):750–755.

Naghavi, Alireza. 2019. "Islam, Trade, and Innovation." In *Advances in the Economics of Religion*, edited by Jean-Paul Carvalho, Sriya Iyer, and Jared Rubin, International Economic Association Series. Palgrave Macmillan, 449–460.

Oliver, Nuria, Bruno Lepri, Harald Sterly, Renaud Lambiotte, Sébastien Deletaille, Marco De Nadai, Emmanuel Letouzé, Albert Ali Salah, Richard Benjamins, Ciro Cattuto et al. 2020. "Mobile Phone Data for Informing Public Health Actions Across the COVID-19 Pandemic Life Cycle." *Science Advances* 6 (23):eabc0764.

Pargament, Kenneth I., Bruce W. Smith, Harold G. Keonig, and Lisa Perez. 1998. "Patterns of Positive and Negative Religious Coping with Major Life Stressors." *Journal for the Scientific Study of Religion* 37:710–724.

Pew Research Center. 2021. "Measuring Religion in Pew Research Center's American Trends Panel: Self-Administered Surveys Indicate That Americans Attend Religious Services Less Often than Previously Estimated." Tech. rep., Pew Research Center. URL `http://www.jstor.org/stable/resrep63329`.

Pew-Templeton Global Religious Futures. 2022. "Global Religious Futures Project." URL `https://www.pewresearch.org/religion/2022/12/21/key-findings-from-the-global-religious-futures-project/`.

Pope, Devin G. 2024. "Religious Worship Attendance in America: Evidence from Cellphone Data." Working Paper 32334, National Bureau of Economic Research. URL `http://www.nber.org/papers/w32334`.

Protected Internet Exchange. 2023. "Areas of Control in Afghanistan." `https://pixtoday.net`. Accessed: 2023-10-01.

Rubin, Jared. 2017. *Rulers, Religion, and Riches: Why the West Got Rich and the Middle East Did Not*. Cambridge University Press.

———. 2022. "Religious Legitimacy and Long-Run Economic Growth in the Middle East." In *The Oxford Handbook of Politics in Muslim Societies*, edited by Melani Cammett and Pauline Jones. Oxford Academic.

———. 2024. "Religion and Cliometric Analysis." In *Handbook of Cliometrics*, edited by Claude Diebolt and Michael Haupert. Springer, 3rd ed., 1055–1074.

Sanders, Jeffrey L and Mary S Brizzolara. 1982. "Relationships Between Weather and Mood." *Journal of General Psychology* .

Schlenker, Wolfram and David B Lobell. 2010. "Robust Negative Impacts of Climate Change on African Agriculture." *Environmental Research Letters* 5 (1):014010.

Scott, James C. 1985. "Weapons of the weak: Everyday forms of peasant resistance." *Yale University Press* .

Seabright, Paul. 2024. *The Divine Economy: How Religions Compete for Wealth, Power, and People*. Princeton, NJ: Princeton University Press.

Sosis, Richard and W. Penn Handwerker. 2011. "Psalms and Coping with Uncertainty: Religious Israeli Women's Responses to the 2006 Lebanon War." *American Anthropologist* 113:40–55.

Tai, Xiao Hui, Shikhar Mehra, and Joshua E. Blumenstock. 2022. "Mobile Phone Data Reveal the Effects of Violence on Internal Displacement in Afghanistan." *Nature Human Behavior* .

Tiwari, Varun, Mir A Matin, Faisal M Qamer, Walter Lee Ellenburg, Birendra Bajracharya, Krishna Vadrevu, Begum Rabeya Rushi, and Waheedullah Yusafi. 2020. "Wheat Area Mapping in Afghanistan Based on Optical and SAR Time-Series Images in Google Earth Engine Cloud Environment." *Frontiers in Environmental Science* 8:77.

Tourangeau, Roger and Ting Yan. 2007. "Sensitive questions in surveys." *Psychological bulletin* 133 (5):859.

UNEP. 2016. "Climate Change in Afghanistan: What Does It Mean for Rural Livelihoods and Food Security?" URL `https://wedocs.unep.org/20.500.11822/22424`.

United Nations, Global Working Group on Big Data for Official Statistics. 2019. *Handbook on the Use of Mobile Phone Data for Official Statistics*. 9. UN.

UNODC. 2021. "Afghanistan Opium Survey 2019." Tech. rep. URL `https://www.unodc.org/documents/crop-monitoring/Afghanistan/20210217_report_with_cover_for_web_small.pdf`.

Vail, Kenneth E 3rd, Zachary K Rothschild, Dave R Weise, Sheldon Solomon, Tom Pyszczynski, and Jeff Greenberg. 2010. "A Terror Management Analysis of the Psychological Function of Religion." *Pers Soc Psychol Rev.* 14:84–94.

Vicente-Serrano, Sergio M, Santiago Beguería, and Juan I López-Moreno. 2010. "A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index." *Journal of Climate* 23 (7):1696–1718.

Weber, Max. 1905. "The Protestant Ethic and the Spirit of Capitalism." *New York: Scribners* .

Wesley, John. 1760. "The Use of Money, a Sermon on Luke." *Sermons on Several Occasions* :127–144.

Winkler, Max. 2021. "Do Disasters Affect the Tightness of Social Norms."

World Bank. 2021. "Mobile Cellular Subscriptions (Per 100 People) - Afghanistan." URL `https://data.worldbank.org/indicator/IT.CEL.SETS.P2?locations=AF`.

Wright, Austin. 2024. "Territorial Control." URL `https://www.austinlwright.com/territorial-control`. Seminar Slides.

Zussman, Asaf. 2014. "The Effect of Political Violence on Religiosity." *Journal of Economic Behavior & Organization* 104:64–83.

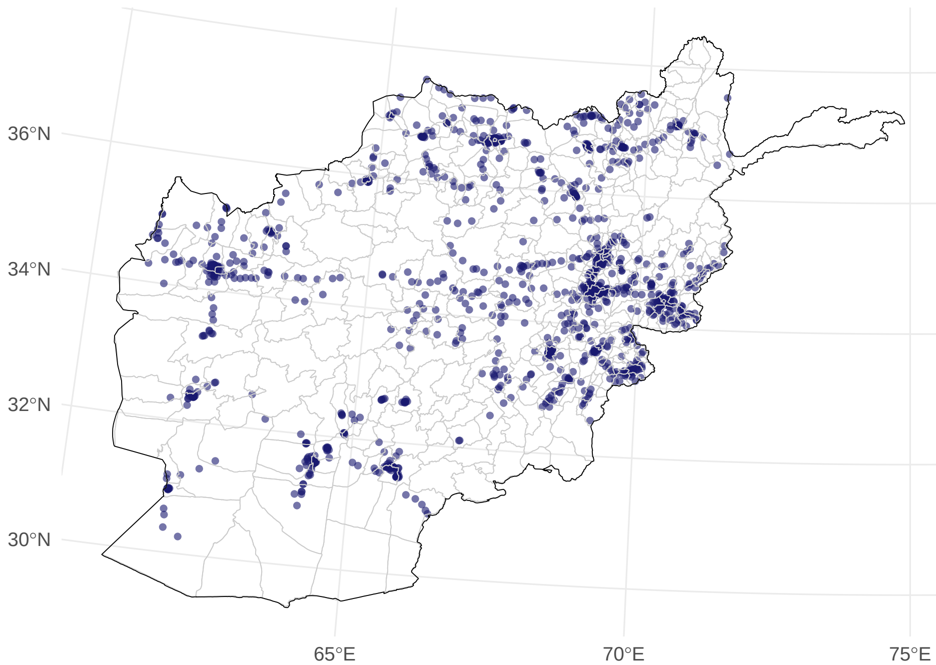
Appendices

A Appendix figures and tables

Figure A1: Poster Prohibiting Cell Phone Use

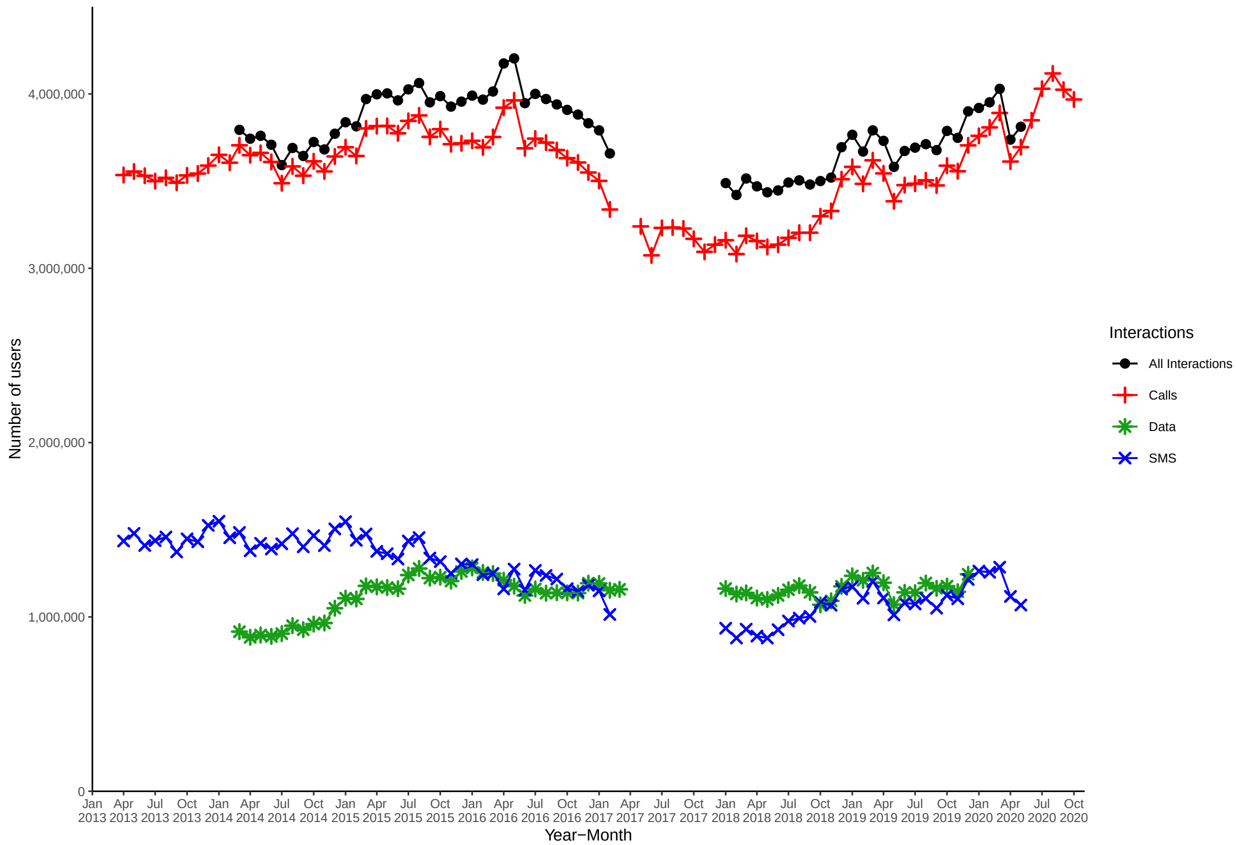
Notes: Poster found in Hounslow Muslim Centre. See here.

Figure A2: Cellphone Towers in our Sample



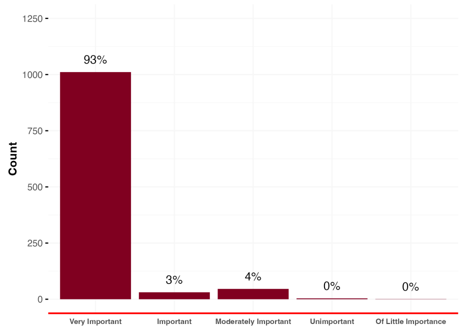
Notes: This figure shows the location of the cellphone towers in our sample, along with district boundaries in grey.

Figure A3: The Number of Cell Phone Users over Time

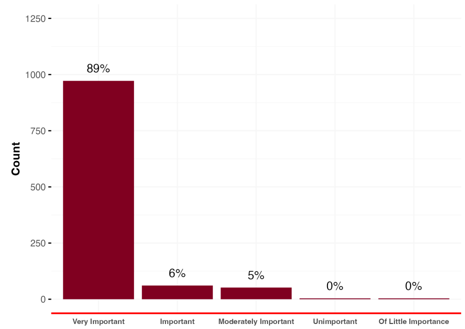


Notes: This figure plots the number of mobile phone users in each month of our data. The total number of users is shown for every month for which we have data for every type of user (phone calls, Data, SMS).

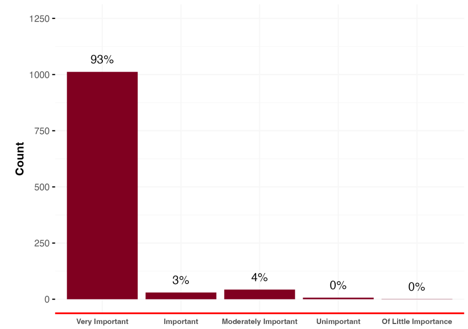
Figure A4: Survey Responses on Religiosity Questions



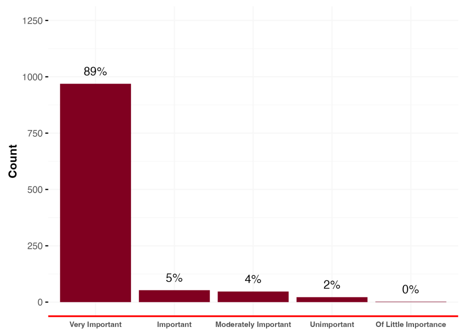
(a) Fasting During Ramadan



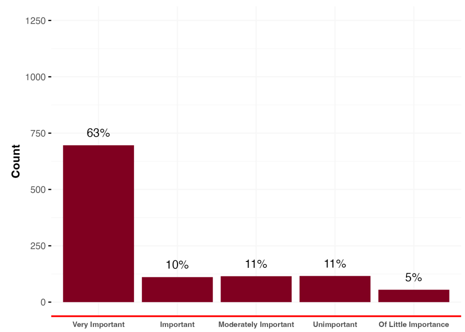
(b) Giving Zakat



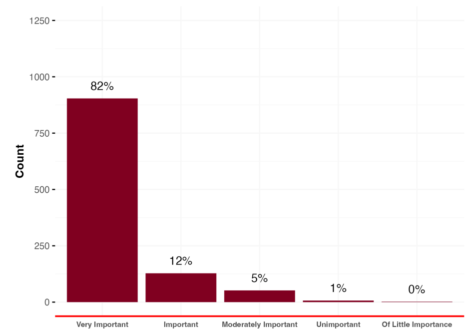
(c) Namaz 5 Times a Day



(d) No Alcohol



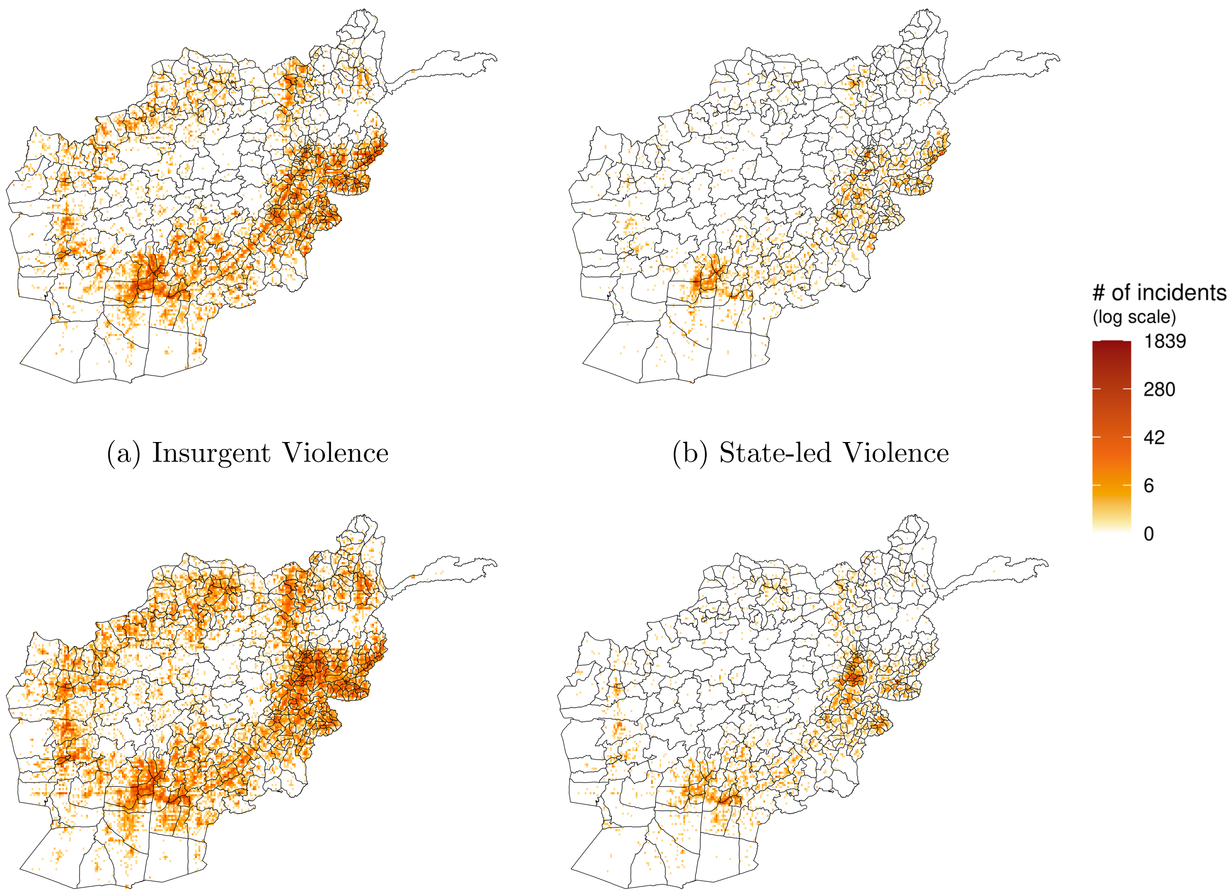
(e) No Music



(f) Reading Quran Daily

Notes: This figure presents responses to the question "How important are the following practices to you?". Responses include "Very important", "Important", "Moderately important", "Unimportant" and "Of little importance".

Figure A5: ISAF Incidents in Afghanistan



(a) Insurgent Violence

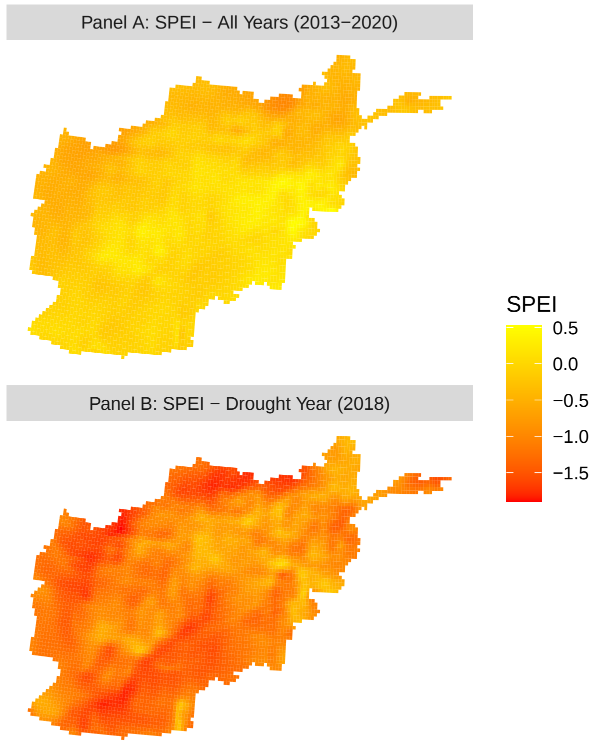
(b) State-led Violence

(c) Other Insurgent Activity

(d) Other State-led Activity

Notes: Maps show the location of different types of incidents recorded by the International Security Assistance Force (ISAF) in Afghanistan between 2013-2014. The four categories are (a) insurgent violence, (b) state-led violence, (c) other insurgent activities, and (d) other state-led activities. See footnote 36 for details on these event types. Event counts are aggregated for each 0.05°grid cell. District boundaries are shown in black.

Figure A6: SPEI Measures in Afghanistan



Notes: This figure maps the SPEI measures calculated over the 12 month timescale. Panel A shows the average over the entire sample period. Panel B shows the measures for 2018, a year in which much of Afghanistan experienced a major drought.

Table A1: Comparing the Maghrib Dip in Calls to Shortcodes vs. Standard Numbers

	Maghrib Dip	
	Grid Cell	District
	(1)	(2)
Shortcode Transaction Type (Indicator)	–10.410***	–10.545***
	(0.293)	(0.350)
Observations	74954	42108
Mean Non-shortcode Maghrib Dip	15.7	16.4
Grid Cell Fixed Effects	Y	
Month Fixed Effects	Y	Y
District Fixed Effects		Y

Notes: This table examines if the measured Maghrib dip differs statistically based on the transaction type (shortcode calls versus non-shortcode calls). The Maghrib dip is regressed on a indicator of whether the measure uses shortcode calls (versus non-shortcode calls). Column (1) is a grid cell-month level regression which incorporates grid cell and month fixed effects; standard errors, shown in parentheses, are clustered on grid cell. Column (2) is a district-month level regression which uses district and month fixed effects; standard errors, shown in parentheses, are clustered on district. *p<.10, ** p<.05, *** p<.01.

Table A2: The Maghrib Dip and Survey Measures of Religiosity

	Maghrib Dip	
	(1)	(2)
Survey Religiosity Index	3.135	3.783**
	(1.913)	(1.923)
Standardized components:		
Reading the Quran Daily	3.813**	4.383***
	(1.678)	(1.685)
Observing Namaz 5 Times per Day	0.882	1.414
	(1.448)	(1.457)
No Alcohol	3.398*	3.866*
	(2.030)	(2.027)
No Music	3.343*	3.363*
	(1.990)	(2.011)
Fasting during Ramadan	0.980	1.577
	(1.481)	(1.496)
Giving Zakat	0.572	1.077
	(1.446)	(1.468)
Observations	1092	1092
Mean of Dependent Variable	12.94	12.94
District Fixed Effects	Y	Y
Demographic Controls		Y

Notes: This table examines correlations between the Maghrib dip measure of religious adherence and religious practices self-reported in a household survey. One observation is included for each surveyed individual. Individuals were surveyed in October 2015, so we calculate their Maghrib dip measure using 2015 and 2016 call data. In the top row, the independent variable is an index of responses to survey questions that ask about the importance of six different Islamic religious practices. To construct the index, we convert the responses for each religious practice into an indicator variable (equal to one if the respondent reports the practice is "very important" or "important"), standardize these indicators, and take their average. In the remaining rows, the independent variables are each of the standardized components that comprise the index. All regressions include district fixed effects. Column (2) includes demographic controls for: number of men in their household, number of women in their household, number of children in their household, and an indicator for whether the respondent is of the Hazara ethnic group. Robust standard errors shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A3: The Maghrib Dip and Demographic Characteristics of Survey Respondents

	Maghrib Dip
	(1)
Age	0.265*
	(0.143)
Rural	3.724
	(7.804)
Can Read and Write	2.978
	(4.161)
Owns Agricultural Land	12.33**
	(5.609)
Pashtun	13.39**
	(5.677)
Observations	1043
Mean of Dependent Variable	13.30
District Fixed Effects	Y
Hazara Ethnicity Control	Y

Notes: This table examines correlations between the Maghrib dip measure of religious adherence and demographic characteristics of survey respondents. Since individuals were surveyed in October 2015, we calculate the Maghrib dip calculated using call data over 2015-2016. We regress this Maghrib dip measure on the demographic characteristics shown in the rows of the table. This includes age measured in years; whether the respondent resides in a rural location, can read and write, owns agricultural land and is a member of the Pashtun ethnic group. The regression also includes district fixed effects, and a control for whether the respondent is a member of the Hazara ethnic group. One observation is included for each surveyed individual. Robust standard errors shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A4: Ethnicity and the Maghrib Dip

	Maghrib Dip (All Calls)		Maghrib Dip (Shortcode Calls)	
	District	Grid Cell	District	Grid Cell
	(1)	(2)	(3)	(4)
Plurality Pashto Speaking	4.754***	4.903***	3.838**	5.552***
	(1.062)	(0.957)	(1.602)	(1.505)
Observations	288	595	288	595
Province Fixed Effects	Y	Y	Y	Y
Plurality Hazara Control	Y	Y	Y	Y

Notes: We proxy ethnicity by language spoken in each village. To define the plurality language spoken in each unit (district or grid cell) we aggregate village-level data from 2012 to either district level or grid cell level, restricting to villages within 10km of a cell tower. There are 128 plurality Pashto speaking districts; of the remaining 160 districts, 113 are plurality Dari speaking, 24 Uzbek, 11 Turkmen, 5 Pashai, 4 Balochi, 2 Nuristani, and 1 Hazaragi. Each column is a separate regression. The Maghrib dip is calculated using all calls in columns (1)-(2) and shortcode calls in columns (3)-(4). Columns (1) and (3) are district level regressions in which the district's average Maghrib Dip over 2013-2020 is regressed on an indicator of whether the largest number of villages in the district are plurality Pashto-speaking (while controlling for an indicator of whether the largest number of villages in the district are plurality Hazaragi-speaking). Columns (2) and (4) are grid cell level regressions in which the grid's average Maghrib Dip over 2013-2020 is regressed on an indicator of whether the largest number of villages in the grid are plurality Pashto-speaking (while controlling for an indicator of whether the largest number of villages in the grid are plurality Hazaragi-speaking). All regressions include province fixed effects. Robust standard errors shown in parentheses. *p<.10, **p<.05, *** p<.01.

Table A5: Summary Statistics of Main Variables

	Mean (1)	SD (2)	Min (3)	Max (4)	Obs (5)
A. Variables at District-Month level					
Maghrib Dip	13.006	16.482	–133.907	200.000	4705
Violent Insurgent Events	5.939	12.291	0.000	192.000	4705
Other Insurgent Events	12.254	23.638	0.000	511.000	4705
State-led Violence	0.911	4.391	0.000	99.000	4705
Other State-led Activity	1.145	3.740	0.000	97.000	4705
B. Variables at Grid Cell-Month Level					
Maghrib Dip	15.117	20.910	–200.000	200.000	37496
SPEI	–0.180	0.847	–2.774	2.702	37496
C. Variables at Grid Cell-Year Level					
EVI Max - December	6.292	0.943	–0.736	8.173	4213
Growing Season SPEI	–0.242	0.755	–2.384	1.476	4213
Maghrib Dip in Growing Season	12.728	13.102	–200.000	144.667	3330
Maghrib Dip in Harvest Season	26.443	16.711	–159.788	200.000	3330
Maghrib Dip in Post-harvest Season	10.349	15.419	–200.000	200.000	3330
D. Variables at Grid Cell-Level					
Fraction Rainfed Cropland	0.098	0.191	0.000	0.944	610
Fraction Irrigated Cropland	0.203	0.229	0.000	0.933	610
Fraction Rangeland	0.411	0.306	0.000	0.995	610
Fraction Land Type Aggregated Control	0.260	0.255	0.000	1.000	610
Fraction Built-up	0.029	0.057	0.000	0.608	610

Table A6: Summary Statistics of Additional Variables

	Mean (1)	SD (2)	Min (3)	Max (4)	Obs (5)
A. Variables at Individual Level (In Survey)					
Survey Religiosity Index	0.002	0.831	–3.780	0.299	1092
Reading the Quran Daily	0.944	0.230	0.000	1.000	1092
Observing Namaz 5 Times per Day	0.953	0.211	0.000	1.000	1092
No Alcohol	0.935	0.247	0.000	1.000	1092
No Music	0.738	0.440	0.000	1.000	1092
Fasting during Ramadan	0.953	0.211	0.000	1.000	1092
Giving Zakat	0.945	0.228	0.000	1.000	1092
Age	39.577	14.049	16.000	87.000	1092
Rural	0.495	0.500	0.000	1.000	1092
Read and Write	0.620	0.486	0.000	1.000	1043
Own Agricultural Land	0.245	0.431	0.000	1.000	1092
Pashtun	0.177	0.382	0.000	1.000	1092
B. Variables at District-Month Level					
Maghrib Dip (Shortcode)	1.244	26.451	–200.000	200.000	4705
Maghrib Dip (Constant Home Location)	13.017	16.961	–122.197	200.000	4488
Maghrib Dip (25 min)	16.081	17.200	–123.348	200.000	4705
Maghrib Dip (35 min)	9.468	15.974	–140.197	200.000	4705
Maghrib Dip (40 min)	6.841	15.819	–143.066	200.000	4705
Maghrib Dip - Before Denom.	11.279	12.586	–100.000	100.000	4704
Maghrib Dip - IHS	2.504	1.760	–5.590	5.991	4705
IHS(Call Volume)	13.164	1.554	6.349	18.553	4705
Taliban Control (ACSOR)	0.151	0.359	0.000	1.000	3982
Missing Indicator: Taliban Control (ACSOR)	0.154	0.361	0.000	1.000	4705
C. Variables at Grid Cell-Month Level					
Maghrib Dip (Shortcode)	5.277	36.402	–200.000	200.000	37475
Maghrib Dip (25 min)	17.507	21.134	–200.000	200.000	37496
Maghrib Dip (35 min)	12.049	20.753	–200.000	200.000	37496
Maghrib Dip (40 min)	9.645	20.864	–200.000	200.000	37496
Maghrib Dip - Before Denom.	12.801	15.677	–100.000	100.000	37471
Maghrib Dip - IHS	2.562	2.079	–5.991	5.991	37496
IHS(Call Volume)	12.336	1.737	0.881	17.961	37496
D. Variables at District Level					
Plurality Pashto	0.457	0.499	0.000	1.000	396
Plurality Dari	0.389	0.488	0.000	1.000	396
Plurality Neither Dari nor Pashto	0.154	0.361	0.000	1.000	396
District Experienced Any Taliban Control between 2015-2020 (PiX)	0.213	0.410	0.000	1.000	389
E. Variables at Individual-Quarter Level (in CDR)					
Maghrib Dip	10.198	100.014	–200.000	200.000	78419140
SPEI	–0.268	0.861	–2.538	2.033	78419140
E. Variables at District-Year Level					
Poppy - IHS	3.695	3.457	0.000	10.911	1114
Interpolated Poppy - IHS	3.824	3.267	0.000	10.911	1299

Table A7: Addressing Accounts of how Violence affects Religious Adherence

	Maghrib Dip (2013-2014)	
Sample:	Shortcode Calls	Non-Movers
	(1)	(2)
Insurgent Violence	–0.112**	–0.068**
	(0.047)	(0.034)
Observations	4703	4486
District Fixed Effects	Y	Y
Month Fixed Effects	Y	Y
Controls for Other Insurgent Activity and State-led Actions	Y	Y

Notes: In column (1), we restrict to shortcode calls when defining the Maghrib dip. In column (2), we restrict to individuals who have not changed their home location in the past 3 months. We define home location as the district where a caller has made the most calls in a given month. Controls for State-led Actions include the variables "State-led Violence" and "Other State-led Activity". Standard errors clustered on district shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A8: Insurgent Violence and Religious Adherence: Robustness to Additional Controls and Alternate Dip Measures

	Maghrib Dip (2013-2014)							
	(1) (Main)	(2) (Main)	(3) (25 min)	(4) (35 min)	(5) (40 min)	(6) (Before Denom.)	(7) (IHS)	(8) (Main)
Insurgent Violence	–0.073***	–0.081***	–0.054**	–0.072**	–0.066**	–0.076***	–0.013***	–0.072**
	(0.028)	(0.030)	(0.027)	(0.028)	(0.029)	(0.025)	(0.004)	(0.028)
Maghrib $\text{Dip}_{\text{t-1}}$	0.037							
	(0.044)							
IHS(Total Volume)		–2.723*						
		(1.578)						
Taliban Control								–0.530
								(0.899)
Observations	4468	4703	4703	4703	4703	4702	4703	4703
District Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Month Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Controls for Other Insurgent Activity & State-led Actions	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Column (1) controls for the Maghrib dip in the previous month. Column (2) controls for the inverse hyperbolic sine (IHS) transform of the average daily call volume in a month. Columns (3)-(5) construct the outcome by considering the change in call volume 25, 35, and 40 minutes before and after the start of Maghrib, respectively. In column (6), the Maghrib dip is constructed by scaling the change in call volume 30 minutes before and after by the volume 30 minutes before. In column (7), the dependent variable is the IHS transform of the ratio of call volume in the 30 minutes before Maghrib over the average call volume in 30 minutes before and after. Column (8) controls for Taliban control, based on a binary indicator for whether the survey firm (ACSOR) could access the district to conduct the survey (1 if a district was coded as "Totally inaccessible" or "No women – only men can work there"; 0 otherwise), as well as a dummy variable for missing values of Taliban control. Each regression is at the district-month level, using data from April 2013 to December 2014. Controls for State-led Actions include the variables "State-led Violence" and "Other State-led Activity". Standard errors, clustered by district, are shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A9: Insurgent Violence and Religious Adherence: Robustness to Various Samples

	Maghrib Dip (2013-2014)			
Sample:	Non-Ramadan Days	Non-Hazara Districts	# Users (Top 95%)	Call Volume (Top 95%)
	(1)	(2)	(3)	(4)
Insurgent Violence	–0.078***	–0.091***	–0.074***	–0.072**
	(0.027)	(0.032)	(0.028)	(0.028)
Observations	4603	4693	4511	4514
District Fixed Effects	Y	Y	Y	Y
Month Fixed Effects	Y	Y	Y	Y
Controls for Other Insurgent Activity and State-led Actions	Y	Y	Y	Y

Notes: Column (1) excludes Ramadan days. Column (2) excludes districts in which at least 5% of villages speak primarily Hazaragi. Column (3) excludes the 5% of districts that have the fewest number of active mobile phone subscribers over 2013-2014. Column (4) excludes the 5% of districts with the lowest call volume over 2013-2014. Controls for State-led Actions include the variables "State-led Violence" and "Other State-led Activity". Standard errors clustered on district shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A10: Climate and Religious Adherence: Robustness to Additional Controls & Alternate Dip Measures

	Maghrib Dip							
	(1) (Before Denom.)	(2) (IHS)	(3) (25 min)	(4) (35 min)	(5) (40 min)	(6) (Main)	(7) (Main)	(8) (Main)
SPEI	–0.518***	–0.036**	–0.608***	–0.684***	–0.688***	–0.484***	–0.579***	–0.672***
	(0.137)	(0.016)	(0.188)	(0.212)	(0.230)	(0.148)	(0.195)	(0.201)
Maghrib Dip_{t-1}						0.189***		
						(0.031)		
IHS(Total Volume)							–2.038***	
							(0.356)	
Observations	37470	37496	37496	37496	37496	35362	37496	37496
Grid Cell Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Month Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Clustering on	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	Grid Cell	District

Notes: In column (1), the Maghrib dip is constructed by scaling the change in call volume 30 minutes before and after by the volume 30 minutes before. In column (2), we take the Inverse hyperbolic sine (IHS) transform of the ratio of call volume in the 30 minutes before over the average call volume in the before and after periods. In columns (3)-(5), we construct the Maghrib dip measure by considering the change in all volume 25, 35, and 40 minutes before and after the start of Maghrib, respectively. Column (6) controls for the Maghrib dip in the previous month. Column (7) controls for the IHS transform of the average daily call volume in a month. In column (8), standard errors are clustered on district, as opposed to on grid. In columns (1)-(7), standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A11: Climate and Religious Adherence: Robustness to Various Samples

	Maghrib Dip					
Sample:	Non-Hazara Districts	Non-Ramadan Days	Users (Top 95%)	Call Volume (Top 95%)	Non-Urban Areas	Non-Taliban Districts
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI	–0.705***	–0.523***	–0.632***	–0.563***	–0.726***	–0.753***
	(0.203)	(0.195)	(0.197)	(0.191)	(0.233)	(0.220)
Observations	36590	37381	36273	36444	30920	33518
Grid Cell Fixed Effects	Y	Y	Y	Y	Y	Y
Month Fixed Effects	Y	Y	Y	Y	Y	Y

Notes: In column (1), we drop grids in which at least 5% of villages speak Hazaragi. In column (2), we drop Ramadan days. In column (3), we drop the sparsest 5% of grids, defining sparsity based on the number of mobile phone users within the grid cell over 2013-2020. In column (4), we drop the bottom 5% of grids in terms of 2013-2020 call volume. In column (5), we drop the urban areas defined as those in which the fraction of the grid cell with "built up" area exceeds 5%. In column (6), we drop districts under Taliban control, which is directly measured in the PiX data for the 2015-2020 period. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A12: Climate and Religious Adherence: Addressing Alternate Accounts

	Maghrib Dip	IHS(Call Volume)	Maghrib Dip	
	Shortcode	Full Sample	In Sample Continuously	Non-Movers
	(1)	(2)	(3)	(4)
SPEI	–1.002***	–0.007	–0.709***	–0.641***
	(0.342)	(0.009)	(0.212)	(0.205)
Observations	37475	37496	37141	37138
Grid Cell Fixed Effects	Y	Y	Y	Y
Month Fixed Effects	Y	Y	Y	Y

Notes: In column (1), the dependent variable is the Maghrib dip restricted to shortcode calls. In column (2), the outcome is the IHS transform of the average daily call volume in a month in a grid cell. In columns (3) and (4), the dependent variable is the Maghrib dip across different sample restrictions. In column (3), we restrict the sample to callers who have made at least 1 call in each of the past 3 months. In column (4), in each month, we restrict the sample to users who have only made calls from the same home location over the previous 3 months. We define home location as the district where a caller has made the most calls in a given month. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A13: Climate and Religious Adherence: Heterogeneity by Initial Religiosity

	Maghrib Dip (2016–2020)			
Baseline religious adherence:	Average		Residual	
	(1)	(2)	(3)	(4)
SPEI	-0.151	-0.125	-0.149	-0.141
	(0.136)	(0.139)	(0.211)	(0.212)
SPEI × Above Median Baseline Religious Adherence	-0.127***		-0.128*	
	(0.042)		(0.077)	
SPEI × Tercile 2 Baseline Religious Adherence		-0.043		-0.032
		(0.052)		(0.066)
SPEI × Tercile 3 Baseline Religious Adherence		-0.230***		-0.188*
		(0.057)		(0.100)
Observations	78419140	78419140	78404045	78404045
Individual FE	Y	Y	Y	Y
Grid Cell FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y

Notes: Each column is a separate regression. One observation is included for each individual-quarter between 2016 to 2020. SPEI is calculated for each quarter in each individual's home grid, where home is defined as the grid from which they made the most calls in that quarter. The regressions in this table examine heterogeneity by baseline religious adherence. In columns (1) and (2), baseline religious adherence is defined based on the Maghrib dip calculated by aggregating call volumes in the 30-minute windows before and after Maghrib, for all 33 months during the baseline period (spanning 2013-2015). Columns (3) and (4) use a two-stage approach to calculate baseline religiosity as the residual after accounting for SPEI shocks (and grid and quarter fixed effects) during the baseline period (see text for details). The table shows that adverse climate shocks (measured by SPEI) are associated with a larger increase in religious adherence for those who are initially more religiously adherent. Standard errors clustered on grid cell are shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A14: Climate and Religious Adherence: Role of Poppy Cultivation

	IHS(Poppy)	IHS(Interpolated Poppy)	Maghrib Dip	
	(1)	(2)	(3)	(4)
SPEI	–0.004	0.009	–0.668***	–0.675***
	(0.052)	(0.045)	(0.200)	(0.201)
Observations	20711	24360	37496	37496
Grid Cell Fixed Effects	Y	Y	Y	Y
Month Fixed Effects	Y	Y	Y	Y
Controls – IHS(Poppy)			Y	
Controls – IHS(Int. Poppy)				Y

Notes: In column (1), the dependent variable is the IHS transform of hectares of land cultivated with poppy. In column (2), the dependent variable is the IHS transform of linearly interpolated poppy cultivation. In columns (3) and (4), the dependent variable is the Maghrib dip, and we control for the IHS transform of the poppy cultivation and the IHS transform of linearly interpolated poppy cultivation, respectively. The poppy cultivation variable is a the district-year level. Regressions are at the grid cell-month level, with standard errors clustered on grid cell shown in parentheses. In columns (3) and (4), missing values of the poppy control variable are filled in by an arbitrary number (zero) and an additional control variable is included indicating if missing values have been filled in this way. *p<.10, ** p<.05, *** p<.01.