# Measuring Religion from Behavior: Violence, Economic 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 determinants of religious practice in Afghanistan. We find that religious adherence decreases after violent attacks by Islamist insurgents but increases in response to climate-driven economic shocks. This approach creates new avenues for studying religious behavior in contexts where traditional measures of religion are unavailable or unreliable.

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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 what drives people to be religious and to adhere to religious practices.

In this study, we develop a new method for measuring 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 new measure to shed light on how insurgent violence and economic adversity shape religiosity in Afghanistan. This empirical analysis is uniquely enabled by the new 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 drops 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 also Figure A1.

"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 tracks the timing of sunset perfectly.

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: 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 motivations (e.g., Iannaccone, 1992; Berman, 2000; McBride, 2007; Chen, 2010; Berman, 2011; Levy and Razin, 2012; Carvalho, 2013; Levy and Razin, 2014; Carvalho, 2019; Levy, 2019; Iyer and Weeks, 2020; Cavalcanti et al., 2022; Seabright, 2024). However, an advantage of our data is that we can observe several different types of transactions that vary in the extent to which they can be publicly

observed. 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.

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 from which our data originate, and 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).[2] 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). However, much less is known about what happens when violence is perpetrated in the name of religion, by one group against others who share the same religion. Such violence may instead lead to backlash against religion, particularly if it is destructive.

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 records to tens of thousands of geo-coded violent events over 2013-2014, and estimate the impact of violence on the Maghrib dip at the district-month level, conditioning on 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

[2]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, Larcom, and She, 2024).

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.

In our second case study, we explore how economic adversity affects religious behavior. Prior work highlights the ambiguity of this relationship. On the one hand, adverse 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).

Our empirical analysis examines the impact of quasi-random climate shocks, measured using the Standard Evapotranspiration Index (SPEI) (Vicente-Serrano, Beguería, and López-Moreno, 2010; Harari and La Ferrara, 2018), on religious adherence, measured using the Maghrib dip in mobile phone transactions. Our analysis is based on a panel fixed-effects specification defined at the level of 10 km x 10 km grid cells, since that is the native resolution of SPEI weather data. We find that adverse climate conditions significantly *increase* religious adherence. We further find that the effects are strongest in rainfed croplands that do not have access to irrigation, which are precisely the areas where the economic consequences of drought are the greatest. Relatedly, when we disaggregate the effects of climate by season, we find that climate shocks during the growing season exert the strongest effects on religious adherence during the growing and post-harvest seasons, but exert no effect during the harvest season itself. We interpret the lack of harvest season effects as evidence that the opportunity cost of time is not the primary mechanism linking climate and religious adherence. By contrast, the growing season response is consistent with individuals praying for divine intervention when shocks hit, and the post-harvest effect suggests people may pray to cope with the income shock.

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, which 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 often arise when surveys are used to elicit self-reports of religious practices (cf. Hadaway, Marler, and Chaves, 1993; Brenner, 2014).[3] It also 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). The measure also has several attractive empirical properties. It can be observed at very high frequency for individuals subscribers, or aggregated over arbitrarily granular units of space and time. In turn, this granularity can facilitate econometric analyses (such as our case studies) that would be quite difficult to undertake with traditional data. Finally, unlike any other passive measure of religious adherence, the Maghrib dip makes it possible to separately observe religious behaviors across a spectrum ranging from very public behaviors (such as talking on the phone), which likely reflect a degree of social and external pressures, to more private behaviors (such as using internet data) that are more likely to reflect intrinsic motivations.

[3] 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.

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 work is the first to find a negative relationship between insurgent violence and religious adherence. This finding also contains an important implication about religious extremism: it suggests that violence may not necessarily be strategically advantageous 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),[4] 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 from monthly climate data, 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 clearly demonstrates 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.

In developing our new measure of religious adherence we hope to foster even more 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).

More broadly, we also see our work as relating to the literature that has examined the economic consequences of religion.[5] Recent empirical work in this area has examined the

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

[5] 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 (2015); 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);

consequences of particular institutional features of religion, such as the Hajj (Clingingsmith, Khwaja, and Kremer, 2009), Ramadan (Campante and Yanagizawa-Drott, 2015), religious holidays (Montero and Yang, 2021), and programs aimed at promoting Protestant theology (Bryan, Choi, and Karlan, 2021). These papers present important advances; we hope that expanding the data sources and methods use to measure religious behavior can help advance the study of religion in economics, where it is a relatively new, but burgeoning field of work (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 necessary background about prayer norms under Islam, with a particular focus on how they relate to the daily Maghrib prayer window.

**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 today, apps on mobile phones also alert Muslims when the prayer window opens. The prayers are only considered valid if they are completed before the window closes.

Generally, prayers do not have to be undertaken at a particular location, such as at the mosque. For men, there is an extra prayer on Fridays (the Jummah prayer) that has to be done in congregation (for which men typically attend mosque). However, other prayers can be done individually and in private. In Afghanistan, women do not typically pray in the mosque. Thus, much prayer activity takes place in private settings.

Becker, Rubin, and Woessmann (2024); Le Rossignol, Lowes, and Nunn (2024); Rubin (2024).

A large body of religious texts and rulings have established that talking during prayer time invalidates the prayer. For example, *The Book of Prayer (Kitab Al-Salaat)* makes this point explicitly by drawing on hadiths — records of the sayings of Muhammad, which serve as a major source of religious law and moral guidance, second in authority only to the Quran. Chapter 51 of the *The Book of Prayer*, entitled "Forbiddance of talking in Prayer and Abbrogation of what was once Possible", draws on several such hadiths from Sahih Islam, a series of books authored circa 840 A.D., which illustrate how silence during prayer came to be the norm.[6] For example, Book 4, Number 1098 provides the following narrative:

> 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.

Another hadith in Book 4, Number 1101 states:

> 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 errand] for which I sent you? I could not talk with you for the fact that I was engaged in prayer.

The principle of not talking during prayer has also been reinforced by a series of fatwas, which are legal rulings regarding elements of Sharia law.[7] For example, one fatwa (Majmu' al-Fatawa 12/93) by renowned Islamic theologian Ibn Taymiyyah, found:

> 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) ruled:

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

[6] A translation of Chapter 51 can also be found here: `https://www.iium.edu.my/deed/hadith/muslim/004a_smt.html`.

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

To summarize, talking during prayer, whether on the phone or otherwise, is strictly prohibited. As a consequence, mosques around the world today display signs indicating cell phone use is not permitted. See Appendix Figure A1 for one example.

**The Maghrib Prayer Window** Much of our analysis focuses on the Maghrib ("sunset") prayer window, the fourth daily prayer window, which begins after sunset. Under Sunni Islam, which is the branch practiced by 90% of Afghans, the Maghrib window opens precisely at sunset and must be completed by dusk.[8] While "dusk" is not clearly defined, many Muslims advocate completing the prayer before darkness sets in by starting the prayer within 15 minutes of the prayer window opening. It is in fact considered "Makruh" (disliked or offensive) to delay the start of the Maghrib prayer past this point without a reason.[9]

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 at a time when most individuals 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 across the country and changes with the seasons, so that the prayer window doesn't consistently overlap with other fixed activities of the day (such as the end of the workday or rush hour in urban areas).[10]

# 3 Measuring Religious Adherence with Mobile Phone Metadata

The first contribution of this paper is to develop and validate a measure of religious adherence derived from anonymous mobile phone transaction logs. This builds on a substantial body of

[8]The Maghrib window is different under Shia Islam. It starts 5 to 15 minutes later, and is also long, as it is merged with the Isha prayer window. Thus, we should not observe sharp changes in call volume over the Sunni Maghrib prayer window in heavily Shia areas – a point which we discuss explicitly in Section 3 below.

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

[10]We use a Python library (called `prayertimes`) that calculates Sunni prayer times. See `http://praytimes.org/calculation`.

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). 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 more than 400% (Pope, 2024). In Muslim societies, prayer observance is also frequently over-reported, particular for women and for those who self-identify as more religious (Brenner, 2014).[11]

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 reduction in calls that occurs during the Maghrib prayer window, relative to the volume of calls immediately before Maghrib, as an indication of the religious adherence of the underlying population. This section introduces the mobile phone data in more detail, formally defines the Maghrib dip measure, and provides visual intuition and quantitative validation using two traditional sources of data.

## 3.1 Mobile Phone Metadata (Call Detail Records)

Mobile phones are a frequent 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 that occurred on one of Afghanistan's largest mobile phone networks during the eight-year period from 2013 to 2020. These transaction logs cover 6.5-8 million unique phone numbers each year (out of a total population of 39 million), who collectively made 22.6 billion calls over this period. Geographically, the phone company operates 1739 cell phone towers that are spread across 292 of Afghanistan's 398 districts (Appendix Figure A2). In general, tower density is proportional to population density, and the number of subscribers in a district is highly correlated (Pearson $\rho = 0.94$) with the total population of the district (Tai, Mehra, and Blumenstock, 2022).

[11] 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.

The specific data we use are 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. Since we also have the geographic coordinates of each tower, we can roughly locate the person making the phone call at the time of the call (to within a few hundred meters in urban areas and a few kilometers in rural areas). There is no tower identifier associated with the receiving party, which means we can only locate the calling party in outgoing calls. For this reason, our analysis focuses on outgoing calls, though we also provide supporting results using other types of mobile network activity.[12]

**Data Access and Data Privacy** While most of our analysis involves aggregated data, and while the CDR are metadata and do not capture the *content* of individual communications, the raw data are nonetheless confidential and sensitive (Mayer, Mutchler, and Mitchell, 2016). To protect the privacy of individual subscribers, our analysis and data management plan were reviewed and approved by the U.C. Berkeley Committee for the Protection of Human Subjects (protocols #2018-03-10929 and #2016-10-9212). This includes strict data security protocols 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), and Oliver et al. (2020) discuss these and other privacy considerations that arise in the use of mobile phone data. Such data have historically been a challenge for researchers to access; in recent years they have grown increasingly common 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 re-

[12]Outgoing calls are also more complete. We observe all outgoing calls placed by users on this operator's network, whether the calls are made to others on the same network or other networks. In contrast, we only observe an incoming call to a user on this network if it comes from another user on the same network. We do not observe calls between subscribers of other networks.

sponse (Lu, Bengtsson, and Holme, 2012), and transport planning (Hanna, Kreindler, and Olken, 2017).

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

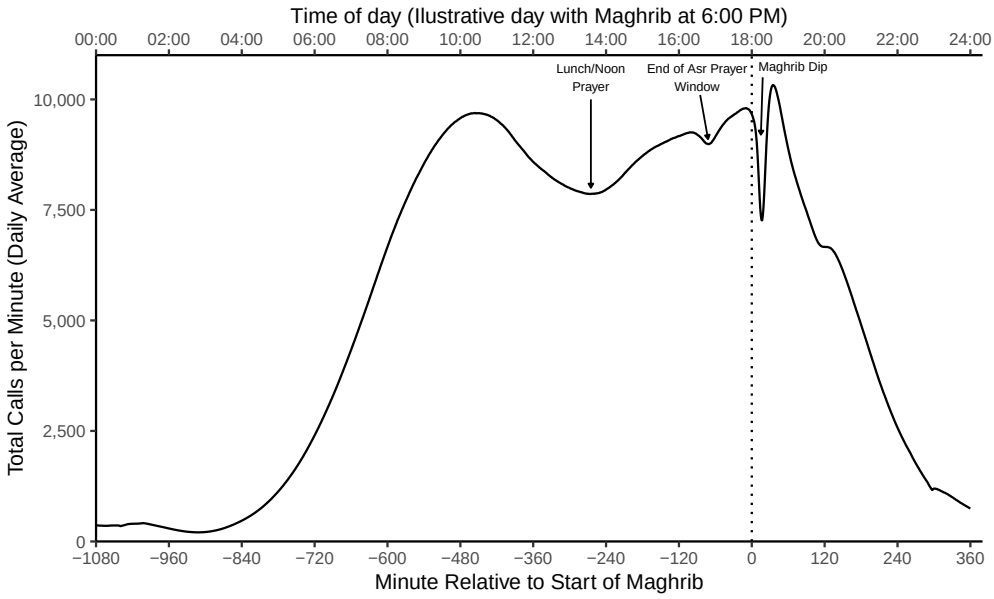
Our measure of local religious adherence quantifies the extent to which outgoing call volume drops during the Maghrib prayer window. To provide intuition for this approach, Figure 1 shows total country wide call volume in each minute relative to the start of Maghrib, averaged across all days in our 2013-2020 sample. In the top axis, we also show the time of day for an illustrative day in which sunset (and the start of the Maghrib prayer window) occurs at 6 pm.

Figure 1 shows several interesting features of call activity and religious observance. First, call volumes are low at night when most people are sleeping; volume starts to increase as people awaken. In the illustrative day, call volumes reach a peak around 9:00 - 11:00 am, then decrease until reaching a local minimum around 13:00 (1 pm). This lull likely reflects a combination of people eating over the lunch hour and people undertaking the noon prayer. Call volumes increase again in the afternoon, although there is a small dip around 17:00 (5 pm), which likely corresponds to the end of the Asr prayer window.

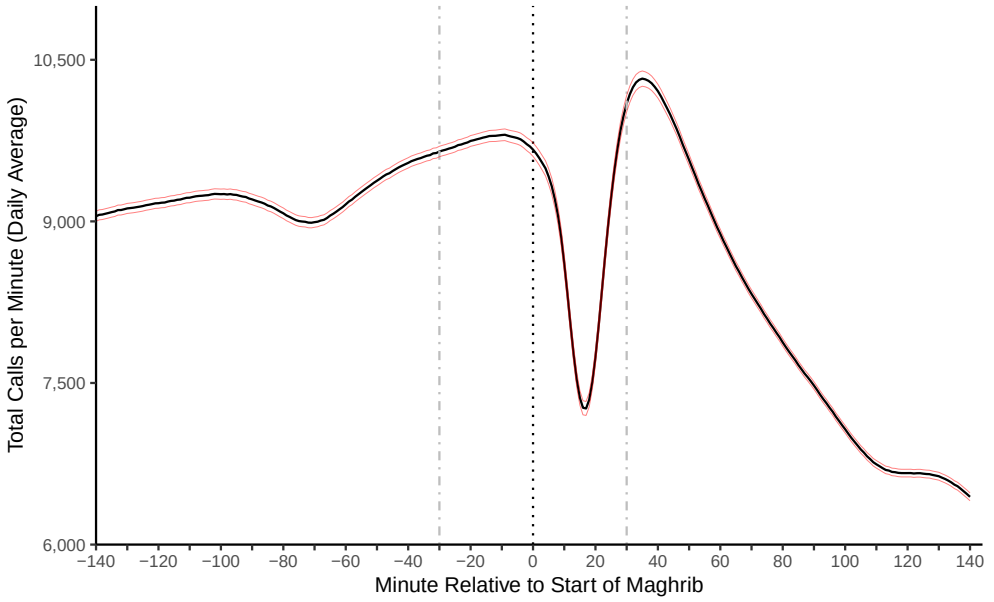
Immediately after the Maghrib prayer window opens (the solid vertical line), there is a sharp decrease in call volume. We refer to this drop as the "Maghrib dip," as it captures the idea that call volumes fall as people complete the Maghrib prayer. The Maghrib dip can be seen more clearly in the enlargement in Figure 1b, which displays the period 140 minutes before and after sunset. The lowest point in the dip occurs 17 minutes after the start of the prayer window, when call volume per minute is approximately 25% lower than at the starting point of the window.[13] Beyond the 17-minute mark, call volumes increase and reach the pre-Maghrib level around 30 minutes after. Thereafter, call volumes fall again until people go to bed for the night.

[13]The extent 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%.

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). For illustrative purposes, in the top figure, we also show an example 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 it takes approximately 15 minutes to complete the prayer itself, we focus on the difference in call volume 30 minutes before and 30 minutes after the start of Maghrib in our main specification. We scale this difference by the average call volume of the before and after periods ($\text{CallVolume}^{Avg(Before,After)}$), to avoid omitting cases where the call volume before Maghrib is zero. In robustness analysis, we confirm that our results also hold for other reasonable time frames, including 25-minute and 40-minute windows around the start of Maghrib.[14] 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 take a closer look at this issue, Figure 2 shows how call volume varies both by the time of day and by the day of the year. As can be seen in Figure 2a, call volumes begin to increase with sunrise, as people wake up and begin their daily activities. The timing of sunset varies between 17:00 and 19:30 over the course of the year. The light band undulating in a wave pattern just after sunset is the Maghrib dip. When sunset occurs later in summer months like August, the Maghrib dip occurs later; conversely, when sunset occurs earlier in winter months like January, the Maghrib dip also appears earlier. This confirms 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 are the holy months of Ramadan. Annual observance of Ramadan is another of the five pillars of Islam, and Muslims observe

[14] Our main analysis uses the 30-minute window because smaller windows miss some of the fall in call volume that occurs as a part of the dip; larger windows capture the fall in call volumes unrelated to prayer, as people wind down phone call activity for the night. See Figure 1b.

the religious holiday through fasting, prayer, and reflection. The figure shows that Ramadan corresponds to lower overall call activity and larger Maghrib dips, indicating higher religious observance during these periods. Figures 2a and 2b also clearly show the reduction in phone activity that occurs around the noon prayer and lunchtime. The vertical striations in Figure 2a are enlarged in Figure 2b to reveal a consistent reduction in mobile phone activity on Fridays, the holiest day of the week in Islam (and also a weekend day in Afghanistan). On these days, 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. This longer observance period corresponds to a more sustained fall in call volume visible in the middle of Fridays.

Finally, Figure 2 also contains useful information about other types of non-religious activities. For example, we observe a sharp increase in calls on October 26, 2015 (the dark vertical patch in the top panel). This corresponds to the Hindu Kush earthquake, which struck Afghanistan at 13:39. In addition, there are some periods with completely white patches where there is no call volume whatsoever. These typically correspond to tower outages, when cell phone towers shut down – a point we return to 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."[15] On the other hand, there are a range of more social, extrinsic considerations that lead people to observe religious norms. For instance, 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

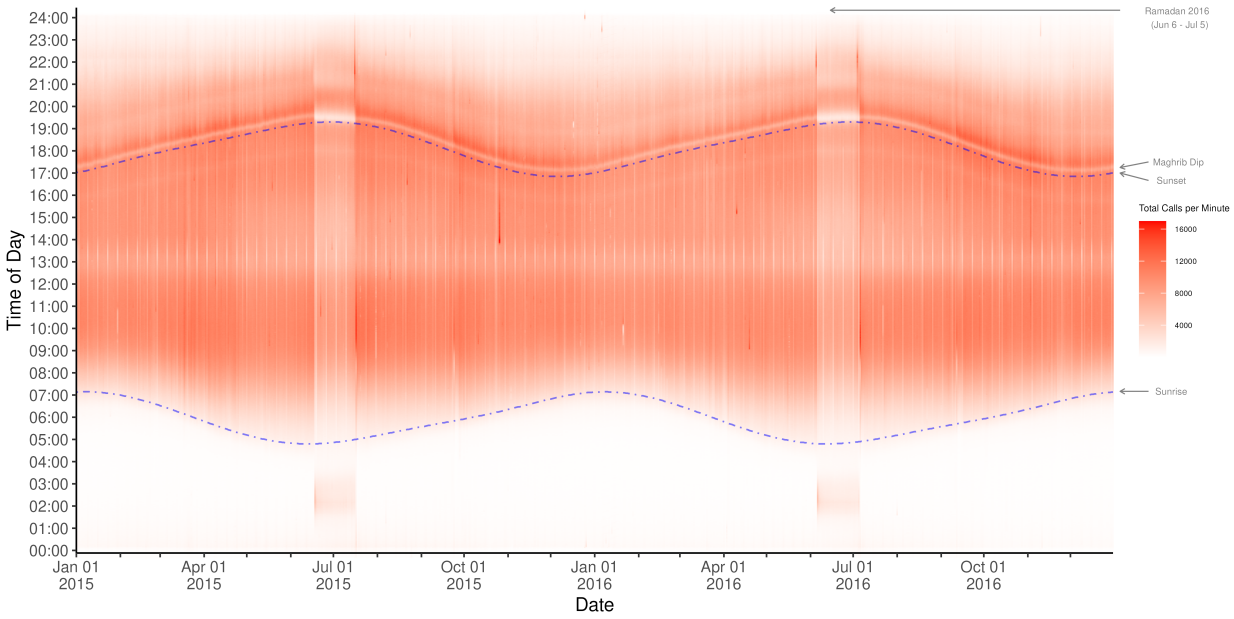
[15] Allport and Ross (1967) contrasts these intrinsic motivations with extrinsic motivations: "Persons with [an extrinsic] orientation are disposed to use religion for their own ends...Extrinsic value is always instrumental and utilitarian. Persons with this orientation may find religion useful in a 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."

hours during Ramadan). However, even in the absence of mandates, individuals may engage in religious practices out of a desire to conform or to foster a sense of belonging.[16] Closely related, religious observance can offer instrumental benefits. These may be 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).

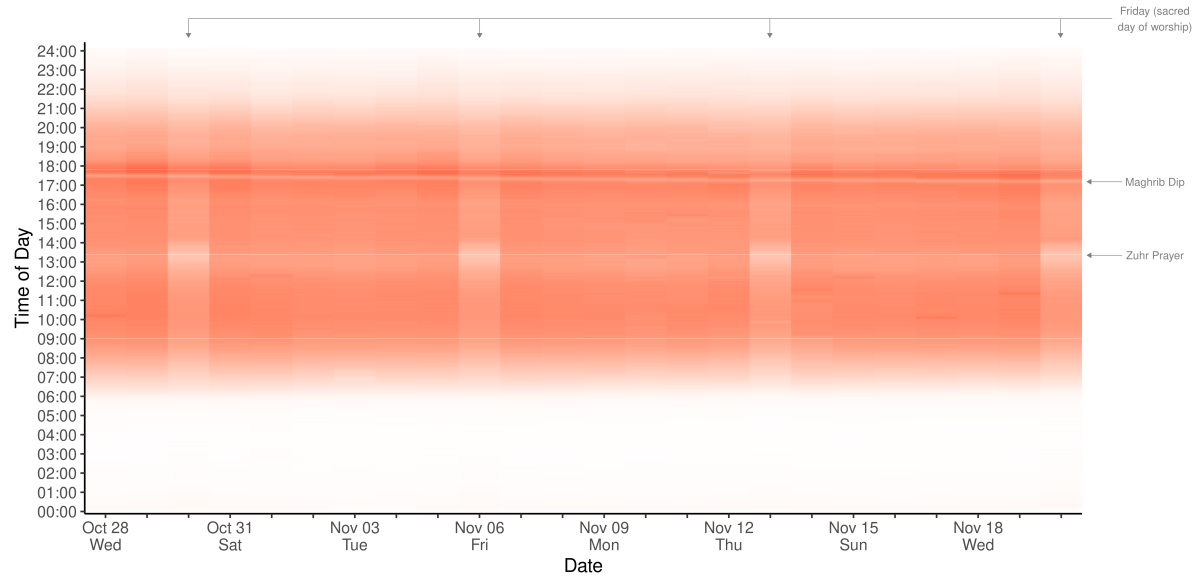
The nuanced nature of religious behavior highlights several key methodological considerations in the measurement of religious adherence. First, revealed preferences of religious activity are likely to be more accurate than self-reports, given the consistent finding of overreporting across religions, countries, and over several decades. Second and related, it is helpful if the measure is "incidental" in the sense that the subject does not realize the behavior of interest in the observation. Also termed "unobtrusive," "indirect," or "passive" in the literature, 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. Both approaches provide compelling examples of incidental and revealed preference measures of religiosity. Third, when the focus is on individual decisions — reflecting personal preferences and beliefs — it is important that the measure reveals behavior at the individual level. Fourth, it may be useful for the measure to distinguish between decisions driven by extrinsic versus intrinsic motivations. Finally, and more practically, surveys often face limitations in spatial and temporal coverage, particularly in conflict zones (Livny, 2021).

[16]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).

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.

To the best of our knowledge, the Maghrib dip is the only measure of religious adherence that simultaneously addresses all of these considerations: it is passively collected; it can be analyzed individually and at various levels of aggregation (in space and time); it is available in locations and time periods of instability and when other political, institutional and economic conditions make it infeasible to embark on data collection through surveys; and it can be constructed from different types of behavior that vary in the degree to which they are publicly observed, which can indicate whether adherence is driven by entirely social considerations.

**More and less private Maghrib dips** In particular, our dataset contains four different types of phone-based transactions that vary in their social observability. In addition to phone calls, the three other types of transactions 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 access to emergency or information services — many of which are handled by automated systems; (b) data packet transfers, which facilitate internet use; and (c) text messages.

Appendix Figure A3 shows how the average volume per minute varies during the period around the Maghrib prayer window for these three additional transaction types. The general pattern of activity is different for these types of transactions than it is for phone calls: for instance, text and data transaction volumes rise into the late evening, whereas call volume falls. However, despite these differences, there is a pronounced dip in transaction volume across all transaction types after the start of Maghrib. Between the peak volume prior to Maghrib and the minimum volume in the 30 minutes after Maghrib, shortcode 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 by social observability alone. However, the fact that the reduction in voice calls is larger than the drop in less observable transactions suggests that extrinsic considerations do influence the Magrhib dips we observe.[17] In our context, likely consider-

[17]For instance, the average volume of calls that are not to shortcode numbers is 12% lower during the 30 minutes after Maghrib than the 30 minutes before Maghrib. In contrast, the average volume of calls

ations 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. To summarize: the fact that people are more likely to reduce their most observable behaviors (i.e., standard phone calls) implies that extrinsic factors do influence the Maghrib dip; however, the reduction in even the most private transactions suggests that intrinsic motivations also play a role.[18]

While all four types of transactions in our data reveal a dip, we focus our analysis on phone calls, with a few checks performed on shortcode calls, specifically, for four reasons. First, phone calls are by far the most common and representative form of communication in Afghanistan. For instance, Appendix Figure A4 shows that while, on average, 95% of unique monthly subscribers place phone calls, only 32% send text messages, and only 29% use data.[19] Second, whereas each phone call is associated with a specific cell phone tower, which we use to roughly locate people when they place calls, no geographic information is included in the logs of SMS activity. We can approximately infer the location from which a text message was sent based on recent calls made by that same subscriber, but this process introduces measurement error.[20] Third, a great deal of mobile data use does not require the active involvement of the subscriber, and thus may not be as appropriate for inferring the

to shortcode numbers is 5% lower in the 30 minutes after Maghrib than in the 30 minutes before. (This average percent fall differs from the peak to minimum fall of 20% reported in the preceding paragraph, as the average percent fall is calculated using the average call volume over *all* 30 minutes before Maghrib and after Maghrib.) As we show in Appendix Table A1, the difference in dips between shortcode calls 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 variable for whether the measure was constructed using calls to shortcode numbers (versus other, standard numbers), controlling for location and time fixed effects.

[18]More precise quantitative decomposition, while attractive at first blush, 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, usage of text messages and data is also much less common than voice and shortcode calls.

[19]These numbers are influenced by the country's low adult literacy rate (43%), and the relatively low rate of smartphone penetration. For such reasons, we expect that inferences based on SMS and data use would be less representative of the broader Afghan population.

[20]Specifically, to construct Appendix Figure A3c, 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 the SMS transactions could be interpolated using a phone call that was made in the same hour; 47% had to be interpolated based on calls made in the day; while 37% had to be interpolated based only on a call that was made in the same month.

focus of the subscriber's attention. For instance, emails and other apps update regularly in the background. Moreover, data use is 'lumpy' since a single action (such as downloading an image) often requires the transmission of multiple data packets, which appears as multiple consecutive transactions in the transaction logs.[21] Thus, a user could hit download prior to the Maghrib window and data transactions could appear after the window is already open. Finally, although a large fraction (72%) of mobile phone subscribers make shortcode calls at some point during the year, the total volume of shortcode calls is quite small, comprising just 3% of all phone calls.

**Addressing Tower Outages** Cell phone towers in Afghanistan have outage periods. This can occur because of ongoing maintenance or unexpected technical difficulties at a cell phone tower, or because the Taliban would sometimes order the operator to turn off towers at night.[22] If these tower outages overlap with the Maghrib dip, it could distort our measure. For example, if an outage happened to occur over a time period that overlapped with the 30 minutes after (before) the start of Maghrib, this would lead to an overestimate (underestimate) of how much call volumes fall owing to religious adherence. To address this, we identify all potentially problematic outages, defined as 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 systematically remove all tower-days that contain these outages.

## 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. In this section, we validate the Maghrib dip measure using two different approaches. The first approach compares self-reports of religiosity from a subset of individuals to the Maghrib dip we observe for those same individuals. The second approach examines the correlation between regionally-aggregated measures of the Maghrib dip and other regional datasets that we expect to reflect religious adherence.

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

[22] For example, see: `https://www.wsj.com/articles/SB10001424052748704117304575137541465235972`.

**Validation Using Surveys** Ideally, we would like to validate the Maghrib dip using a large, nation-wide survey that measures religiosity regularly over time and space. However, no such data exist: While there have been a few national surveys in Afghanistan in the past decade, none examine religiosity, and most are fielded irregularly.[23]

Instead, we compare survey-based measures of religiosity to phone-based measures of the Maghrib dip for respondents to a small household survey (approximately 1090 individuals). This survey, conducted in the provinces of Parwan and Kabul in 2015 (Blumenstock et al., 2024), was not focused on religious beliefs, but did include a series of questions about the importance of six different religious practices, including: fasting during Ramadan, giving Zakat (Islamic charity), namaz (prayer) 5 times a day, not drinking alcohol, not listening to music; and reading the Quran daily. Important to our analysis, the survey also requested informed consent to link survey responses to mobile phone records obtained from the mobile phone company, to which we have access.

The distribution of survey responses, shown in Appendix Figure A5, highlights the fact that almost every respondent indicated that every religious practice was important or very important to them. Thus, while the responses likely contain some signal, they also highlight another challenge in using surveys to measure religiosity, particularly in contexts such as Afghanistan: We cannot know whether people actually observe the practices that they report are important to them. Afghanistan is among the most religiously observant societies in the world (Pew-Templeton Global Religious Futures, 2022), and such observance is deeply embedded in historical norms which trace back centuries (Barfield, 2022). As such, it is possible that responses to questions regarding religiosity could be subject to social desirability bias.

Nonetheless, we find evidence of a clear correlation between self-reported religious practices and our measure of the Maghrib dip. To measure this correlation, we first calculate a religiosity index for each individual: For each of the six survey questions, we group together the values 'important' and 'very important', standardize this indicator, and then take the average of these six indicators.[24] We also create an individual-level measure of the Maghrib

[23]Nationally representative surveys include the Afghan National Quarterly Assessment Research (ANQAR), the Survey of the Afghan People, and the National Risk and Vulnerability Assessment (NRVA).

[24]The results are not dependent on this grouping and look similar if we instead generate an indicator that

dip using Equation (1), calculated using data from a 48-month period around the time of the survey.[25] 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).

In Table A2, we regress the individual Maghrib dip on survey measures of religiosity, controlling for district fixed effects in the first column and additionally controlling for household demographic characteristics in the second column. The top row examines the correlation with the Survey Religiosity Index. The coefficient in Column (2) indicates that a one standard deviation (SD) increase in the index is associated with a 27% increase in the Maghrib dip ($p < 0.04$).[26] The other rows of the table present analogous regressions with the individual questions comprising the index, which suggest 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.

**Validation using district-level correlations** Our second validation exercise examines the correlation, at the district level, between the Maghrib dip measure and 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 generate its Z-score, subtracting out the nation-wide mean and dividing by the standard deviation, which gives us the measure in standard deviation units. Figure 3 maps this measure, displaying where religious adherence is above and below the nation-wide average.

The map shows dark clusters in the South and the East, indicating that the reduction in call volume during Maghrib is greater in these areas than in the rest of the country. These

takes on the value one for 'very important' and zero for the other responses, 'important', 'a little important' and 'unimportant'.

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

[26]The coefficient shows that a one SD increase in the survey index increases the Maghrib dip by 3.45, which represents a 27% increase above 12.94, the mean of the Maghrib dip measure in this regression.

are the areas where the Pashto-speaking Pashtun ethnic group is concentrated. To make this point explicit, the map uses a yellow boundary to demarcate the districts in which the Pashto speakers are dominant.[27]

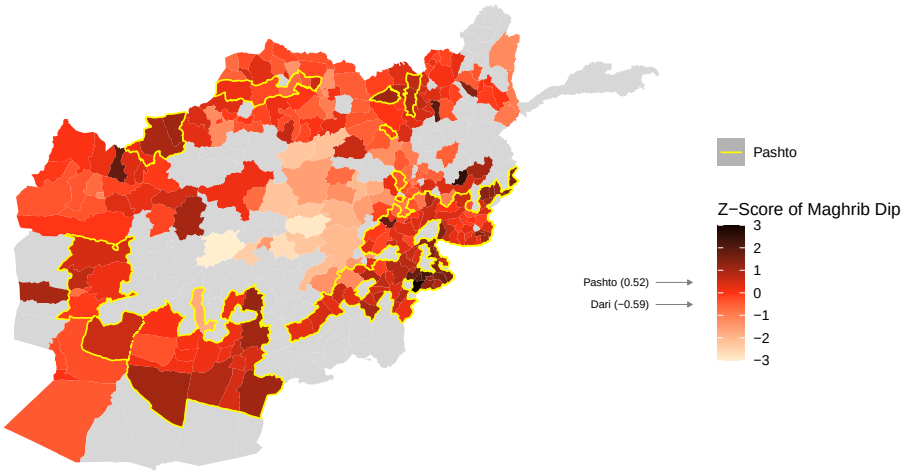
Pashto-speaking districts on average display a relatively high Maghrib dip (0.52 SD above the national average). This points to the validity of our measure since the Pashtun, who dominate the ranks of the Taliban (Central Asian Cultural Intelligence for Military Operations), are widely regarded as having high levels of religious conservatism, even within the highly religious setting of Afghanistan (Barfield, 2022). In regard to religious adherence, the Pashtun are often contrasted with Dari-speakers (such as the Tajik ethnic group), who have traditionally favored a less strict version of Sharia law and are generally less religiously adherent. Relatedly, Tajik women have also generally enjoyed more rights (Joshua Project, 2023). Dari-speakers are concentrated in the center and Northwestern parts of Afghanistan, which is also the lightest region shown in the map.[28]

To further corroborate these visual results, in column (1) of Table A3, we present district-level regressions, which regress 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 (while 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, relative to districts in which other ethnic groups constitute the plurality. We repeat this exercise with grid-cell level regressions in column (2). The significant coefficients in both columns further helps to validate our measure.

[27]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. Specifically, we focus on the villages in the 10 km radii around each cell phone tower in our CDR sample and identify the fraction of the villages for which each ethnic group (defined as speakers of a specific language) constitutes the majority; we then average this fraction over towers in a district to identify the largest, or dominant ethnic group among these districts.

[28]The central areas are also home to the Hazaragi-speaking Hazara ethnic group, who are Shia Muslim. For the Shia, the Maghrib window starts later and is merged with the Isha window (which lasts all night long). Therefore we do not expect to see a Maghrib dip with this group. However, the Hazara constitute a relatively small fraction of the population; indeed there is only 1 district in which they constitute the majority ethnicity. This corresponds to the fact that Afghanistan is close to 90% Sunni.

Figure 3: 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.

**Summary of the Maghrib dip measure** Thus far in the paper, we have presented a behavioral measure of religious adherence. The measure leverages mobile phone metadata to gauge 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 to different geographic units, such as provinces, districts, villages, or grid cells of various sizes; and which exists at different frequencies, such as years, months, weeks or even days. It can therefore serve as a high-frequency metric of religious behavior in small communities and allows us to answer social science research questions that require temporal and spatial variation in religious adherence.

# 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, scholarship points to a number of reasons why violence may 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). Moreover, experiencing violence may reshape preferences in ways that lead to greater religiosity. For example, a heightened preference for certainty, as observed in Callen et al. (2014), could lead to a stronger inclination toward the stability and promises of an afterlife offered by Islam. Experiencing violence could also manifest in increased religious devotion as a source of comfort (Bentzen, 2019, 2021; Isaqzadeh, 2024). And, this may be particularly relevant for explaining why those who participate in combat display greater religiosity later in life (Cesur, Freidman, and Sabia, 2020; Mill et al., 2024). Finally, conflict between two religious groups could increase religious adherence by reinforcing group cleavages and identities (Zussman, 2014; Atkin, Colson-Sihra, and Shayo, 2021).

On the other hand, if violence is religiously motivated, but imposes casualties on members of the same religious group, this could produce provoke backlash. This idea has received less attention, but is highly germane to many Islamic countries experiencing conflict over the past few decades. As a case in point, the conflict in Afghanistan was deeply tied to religion: the Taliban sought to establish a strict Sharia-based order, while the US-backed Afghan Republic aimed to build a more secular, yet still Islamic, state. In that regard, violence carried out by Islamist groups aiming to enforce a strict interpretation of Sharia could potentially reduce support for these ideologies and corresponding adherence to religious practices. Along these lines, Condra and Shapiro (2012) provide evidence that civilian casualties perpetrated by insurgents leads to a backlash, particularly in communities with weaker religious ties to insurgent groups.

## 4.1 Empirical Strategy

Our granular data provide a unique opportunity to determine how violence shapes religious behavior. We use detailed violence data to distinguish between insurgent violence and other types of wartime activities, and our granular Maghrib dip measure to see how religious adherence changes in response to these different types of incidents.

### Measuring Violence in Afghanistan

By 2013, the beginning of our study period, Afghanistan had suffered over three decades of nearly continuous conflict. This period began with the military coup of the communist People's Democratic Party of Afghanistan in 1978 and the subsequent Soviet invasion in 1979. Violence in the timeframe covered by our data reached levels not seen since the bloody civil war after the Soviet exit in 1989 and prior to the Taliban takeover in 1996. During our observation window, from April 2013 to the end of 2014, violence in Afghanistan increased, with frequent Taliban attacks, IED incidents, and targeted assassinations. This period, coinciding with the planned withdrawal of international forces at the end of 2014, saw the Taliban groups intensifying their efforts, leading to substantial casualties for both Afghan National Security Forces (ANSF) and civilians.

For the 2013-2014 period, we have precisely geocoded data on violence to complement our CDR records. These data come from incident records of the International Security Assistance Force (ISAF), a multilateral military body present since December 2001.[29] In addition to geocodes at five–decimal digit precision (accurate to within one meter at the equator), these data capture all types of violence reported to the ISAF, and provide information on the type of incident that occurred. Although the time span of the ISAF data restrict our analysis to the first two years for which we have CDR, nonetheless a total of 95,231 incidents are identified during our observation window in regions that overlap with the CDR data.

We separate incidents into four categories. First, we define 'Insurgent Violence' to include 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

[29]The dataset we use is accessible here: `https://github.com/knapply/data4ds4da/blob/master/data/sigacts_afghanistan_df.rda`

war, and assassination). Second, we define 'Other Insurgent Activity' to include a collection of threats, unexploded IEDs, mines, and explosives, as well as a range of other activities undertaken by these groups.[30] Although the ISAF data do not explicitly list the groups carrying out insurgent attacks, most of these attacks were carried out by the Taliban. In the third category we group together violent incidents initiated by state-led forces (primarily ISAF, but also the Afghan army and police). This 'State-led Violence category' includes escalation of force, direct fire, close air support, and indirect fire. Last, we define 'Other State-led Activity' to include 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 A6 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 $m$; $\text{Insurgent Violence}_{d,m}$ and $\text{State-led Violence}_{d,m}$ denote the number violent incidents initiated by insurgents and state forces, respectively; $\text{Other Insurgent Activity}_{d,m}$ and $\text{Other State-led Activity}_{d,m}$ are other types of incidents initiated by insurgents and state forces, respectively; and $\alpha_d$ and $\theta_m$ are district and month fixed effects. $\varepsilon_{d,m}$ is an idiosyncratic error term that we cluster on district.

Appendix Table A4 presents descriptive statistics of the key variables that are used in our

[30] Specifically, threats 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 checkpoint, corruption, smuggling, theft, demonstration, narcotics, surveillance, terrorist tactics and procedures, terrorist recruitment, defecting, assault, terrorist training, arson, counterfeiting, sabotage.

analysis and which appear in the main tables. Appendix Table A5 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), and using the Maghrib dip (calculated from all phone calls) as the dependent variable. Column (1) indicates that insurgent violence reduces the Maghrib dip. In other words, violence perpetrated by religious extremist groups lowers religious adherence. While specification (2) includes location and time fixed effects, the estimates may still be endogenous if changes in religiosity lead to more (or less) violence. In particular, if violence were caused by religiosity, estimates in column (1) would under-state the extent to which violence reduces religiosity. To further gauge this, column (2) incorporates two monthly leads in insurgent violence. The coefficients on the lead terms are both small and statistically insignificant, suggesting that greater religious adherence today does not correspond to greater violence in future months. This suggests that the estimates are not driven by third factors that simultaneously predict religious adherence and rising violence.

In the two remaining columns of Table 1, we turn toward understanding potential mechanisms. If exposure to violence produces backlash because people observe its destructive effects, we should only see this response when attacks are realized. Column (3) corroborates this: other insurgent activities (such as threats of attacks, or attacks that are not actualized) do not lead to significant changes in the Maghrib dip. This null effect also suggests that the estimate on insurgent violence is not driven by omitted factors correlated with war escalation and lower religious adherence. If that were the case, we should also see effects of other war-related insurgent activity.

In addition, if people reduce religious adherence specifically when violence is perpetrated in the name of religion, then violence initiated by the state should not produce similar responses. To examine this idea, we introduce state-led violence and other war activities into column (4). This analysis is less precise because, of the four categories, state-led violence has the fewest (4,285) incidents. However, we observe that neither incidents of state-led violence (nor other military activities) significantly reduce the Maghrib dip.

Notably, the coefficient on Insurgent Violence remains similar with the addition of controls for these other types of violence and wartime activities. Since the Maghrib dip is measured in units that do not have a natural interpretation, we provide intuition for the magnitude of this effect by comparing changes associated with Insurgent violence to changes associated with other factors that also affect religious adherence. In particular, we compare the effect in column (4) of Table 1 (-.072) to changes in the Maghrib dip associated with being in a predominantly Pashtun area (Table A3). This benchmarking implies the following: Going 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 21% as much as going from a district that is plurality Pashtun to a district which has a different plurality ethnic group.[31]

**Robustness** In this section, we assess the robustness of our results to alternative econometric specifications, changes in the way we define our key variables, and to the sample used in our analysis. For these checks, we focus on our preferred estimate from Table 1, which incorporates all four measures of war activity (i.e., column (4)).

Table A6 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, in column (1), we control for a one-period lag of the measure. In column (2), we control for the total daily call volume, which accounts for time-varying factors related to population and network size. Incorporating this variable helps address a potential concern that the magnitude of the dip may be affected by total call volume in the location, including in the pre-Maghrib window. We find that our results are unchanged with these additional controls.

Columns (3)-(5) of Table A6 show that the effects also remain qualitatively unchanged if the Maghrib dip measures changes in call volume over different time windows, including 25-, 35-, and 40-minute intervals around the start of the prayer window, instead of the 30-minute interval used in our main specification. In column (6), we scale the change in call

[31]Multiplying the coefficient by the change in violent incidents (-.07 x 12) implies that the Maghrib dip would fall by -.84. Column (1) of Table A3 shows that being in a Plurality Pashtun district changes the Maghrib dip by 4.75. Scaling -.84 by 4.75 yields the implied effect of 21%.

Table 1: Insurgent Violence and Religious Adherence

| | Maghrib Dip | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Insurgent Violence | –0.078*** | –0.058** | –0.072*** | –0.072** |
| | (0.029) | (0.029) | (0.028) | (0.028) |
| Insurgent Violence Lead1 | | –0.028 | | |
| | | (0.034) | | |
| Insurgent Violence Lead2 | | –0.015 | | |
| | | (0.025) | | |
| Other Insurgent Activity | | | –0.012 | –0.015 |
| | | | (0.014) | (0.015) |
| State-led Violence | | | | –0.021 |
| | | | | (0.048) |
| Other State-led Activity | | | | 0.053 |
| | | | | (0.053) |
| Observations | 4703 | 4153 | 4703 | 4703 |
| District Fixed Effects | Y | Y | Y | Y |
| Month Fixed Effects | 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 two monthly leads of insurgent violence. Column (3) controls for other insurgent activity incidents. Column (4) additionally incorporates state-led violence and other types of war-related activity undertaken by state-led forces. All regressions include district and month fixed effects. Standard errors clustered on district shown in parentheses. *p<.10, ** p<.05, *** p<.01.

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)). In column (7), we take the inverse hyperbolic sine (IHS) transform of the ratio of the call volume in the 30 minutes before over call volume in the before and after periods, to better account for potential outliers. We find that the results are robust across these specifications.

In Appendix Table A7, we consider a series of sample restrictions to further stress test the results. As religious adherence is much larger during Ramadan (see Figure 2), column (1) reconstructs our baseline Maghrib dip measure (using all types of phone calls), but dropping Ramadan days. We again find the results unchanged, which suggests that violence does not simply lower adherence on account of religious responses during the holiest months. Since the Shia Maghrib prayer window differs from the Sunni window, column (2) verifies that our results hold when we drop districts that have a sizable Shia population, as proxied by the presence of villages in which the Hazara constitute the majority ethnic group.[32] Finally, to verify that sparsity in cell phone usage does not affect our results, we find that dropping the 5% most sparse districts based on the number of users (column 3) and call volume (column 4) does not change our results.

**Interpretation** Taken together, the results above indicate that people reduce their religious adherence when violence is carried out by religious extremist organizations. This finding highlights the idea that religiously motivated violence could lead to a backlash against religious observation, if violence is carried out in a setting where civilians share the same religion as the perpetrators. This aligns with other examples of religious backlash in response to harmful actions carried out by religious actors — such as sex scandals in the Catholic Church exposed by the media (Grosfeld et al., 2024). In that regard, our findings are consistent with the broader idea that religious actors may lose support from the population if their actions are perceived to be costly to society.

[32]Specifically 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 if we drop districts in which even 1% of the villages are majority Hazara, and also districts in which 10% of the settlements are Hazara.

**Alternative Accounts** We briefly consider several alternative accounts for the observed effect of violence on religious adherence. First, we test whether our results are impacted by people moving in response to violence. This is a concern if, for example, religious individuals moved out of districts in response to insurgent violence, and we misinterpreted a compositional change in the population as a change in religious adherence of the people who stayed behind. However, the first column of Appendix Table A8 shows that our estimates unchanged if we restrict our analysis to people who remain in the same location for at least three months. (This is possible because it is possible to infer the approximate home location of each subscriber based on the locations from which the place mobile phone calls (Chi et al., 2020)).

Next, we explore whether the increase in adherence induced by violence is driven entirely by outward-facing religious adherence, or if it also reflects changes in private religious adherence. Specifically, column (2) of Appendix Table A8 examines the effect of violence on a version of the Maghrib dip constructed from shortcode calls, a more private type of mobile phone activity (see Section 3.2). We see exactly the same pattern of results. In fact, the implied effect size is qualitatively larger than the baseline effect on the Maghrib dip calculated using all calls. Moving from the median to the 90th percentile of insurgent violence leads to an effect 41% as large as the Pashtun effect (when we benchmark against the coefficient in Column (3) of Table A3). This suggests that the impact of insurgent violence is not just about changing outwardly observable religious behavior, but reflects changes in private behavior.

Related, we consider the more extreme possibility that changes in religious adherence are caused by coercion from religious extremists. In particular, it is likely that our measure of violence is correlated with the presence of armed insurgents like the Taliban, whose presence likely increases publicly observed religious adherence. Note, however, that this dynamic would lead us to *under*-estimate the negative effect of violence on religious adherence; our results suggest that adherence decreases in response to violence, whereas Taliban presence is likely to increase adherence. In results available on request, we control for a proxy measure of Taliban presence, and find that both the precision and magnitude of our main estimates

are unaffected.[33]

One final possibility is that changes in religious adherence are not driven by changes in religious beliefs, but rather are due to the fact that violence reduces overall economic activity (Abadie and Gardeazabal, 2003; Blumenstock et al., 2024; Herskowitz et al., 2025). However, the most likely account would suggest a relationship opposite to the one we find. In particular, worse economic conditions generally lead to an *increase* in religious adherence (cf. Azzi and Ehrenberg, 1975); indeed, our second case study (Section 5) provides robust evidence that economic shocks increase the Maghrib Dip in Afghanistan. Yet, here we find the opposite result: greater insurgent violence lowers religious adherence. This suggests that the results documented in this section are not driven by the effects of violence on economic activity.

# 5 Using the Maghrib Dip Measure to Study How Economic Adversity Shapes Religious Adherence

Our second set of results explores how economic hardship affects religious adherence. As noted in Section 1, this effect is conceptually ambiguous, both in direction and in mechanism.

On the one hand, there are several reasons why adverse economic shocks might cause an increase in religious adherence. Negative income shocks may lower the opportunity cost of participating in religious activities through time use considerations (Azzi and Ehrenberg, 1975). Alternatively, individuals may adhere more to religious practices for social insurance purposes, if displaying 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).[34] Finally, lower income security may lead to stronger religious beliefs, if

[33]Direct measures of Taliban control are only available after 2015, subsequent to our violence observation window. However, we conduct a robustness check leveraging the approach of (Wright, 2024), which uses an enumerator's ability to enter a district as a measure of whether it is effectively under Taliban control. Since this measure is available for our observation window, when we control for it in our preferred specification, we find that both the precision and magnitude of the estimates are unaffected.

[34]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). These higher prohibitions may discourage some non-members from entering

people turn to religion when they either experience or expect negative outcomes. For example the secularization hypothesis suggests that religious belief has its roots in fear and ignorance (Hume, 1757; Freud, 1927; Marx, 1970), and therefore, modernity and rising incomes will weaken religiosity (Wesley, 1760; Weber, 1905).[35] This could occur if adverse events promote interdependence psychology (Henrich, 2020; Winkler, 2021) or if turning to God helps people cope psychologically (Bentzen, 2019, 2021).

On the other hand, 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 test and weaken their faith, leading them to moderate their religious beliefs and practices. Additionally, lower income may also reduce time available to participate in religious activity (Buser, 2015). Under these views, an adverse income shock might be expected to lower religious adherence.

## 5.1 Empirical Strategy

To adjudicate between these alternative hypotheses, our empirical strategy estimates the impact of quasi-random economic shocks on religious adherence in Afghanistan. We focus on climate shocks, and link data on climatic conditions with the Maghrib dip measure of religious adherence.

### Climate shocks

Agriculture is an important sector of the Afghan economy, constituting 23% of the GDP and serving as a source of income for 62% of the population in 2017 (Muradi and Boz, 2018). 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.[36]

and being able to acquire the club good of social insurance (Iannaccone, 1992).

[35] On the other hand, theoretical work suggests that economic development could stimulate religious revival if it leaves aspirations unfulfilled (Carvalho, 2009; Binzel and Carvalho, 2017); and may also produce countervailing effects on religious participation by promoting competition across denominations (McBride, 2010).

[36] Average temperatures in Afghanistan have risen by 1.8°C since 1950 (Climate Security Expert Network, 2019). There are two main types of droughts: the most severe droughts affecting rainfed areas are caused by a lack of rainfall, a risk that has increased throughout the country over the past 30 years (UNEP, 2016). A

We measure drought using the Standardized Precipitation - Evapotranspiration Index (SPEI), developed by Vicente-Serrano, Beguería, and López-Moreno (2010). This measure helps capture the fact that the impact of rainfall on agriculture depends not just on the amount of 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. In jointly considering these various factors, SPEI has been shown to perform better than other indices in predicting crop yields (Vicente-Serrano, Beguería, and López-Moreno, 2010), and has also been found to 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 is determined by 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 in standard deviations of the 12-month moving average from the historical mean (calculated over the years 1981-2020).[37] Positive values of SPEI indicate more precipitation relative to the historical mean (which is generally more favorable to agriculture), while negative values indicate less precipitation relative to the historical mean. Appendix Figure A7 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 some specifications, we also calculate the SPEI of the growing season, defined as the average SPEI over December-April, the major growing season for the most important crops in Afghanistan – including wheat, the single most important crop, which is grown in

second drought risk is caused by reduced winter snowfall, which especially affects downstream areas irrigated by streams and rivers originating in the Hindu Kush mountains (UNEP, 2016). Wheat is vulnerable to both types of drought, and is by far the single most important crop. In 2017, it covered a third of arable land and was cultivated in every province. While wheat covered 2.3 million hectares, opium poppies, fruits, barley, maize, and rice – which are the next largest crop categories – covered .33, .27, .22, .15, and .12 million hectares, respectively (Muradi and Boz, 2018; UNODC, 2021).

[37] SPEI can be constructed over different timescales, the most common of which are 6 months, 9 months, and 12 months. We focus on the 12-month timescales, which best captures snowmelt drought (see discussion in footnote 36), but results for 6- and 9-month timescales, available on request, are qualitatively similar.

all provinces (Tiwari et al., 2020). We analyze how growing season SPEI affects religious adherence during growing season, as well as harvest season (spanning May-July) and the post-harvest season (spanning August-September).

We also analyze how growing season SPEI affects yearly agricultural output. Since there are no granular (subprovince) data for agricultural production in Afghanistan, we proxy for output using a satellite-based vegetation index, the Enhanced Vegetation Index (EVI). We follow 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**

To examine the relationship between climate shocks and religious adherence, we calculate the Maghrib dip for each 10km x 10km grid cell, separately for each month.[38] We then estimate the following panel fixed-effects model:

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

where $d_{gm}$ is the Maghrib dip in grid cell $g$ and month $m$; $SPEI_{gm}$ denotes the SPEI; $\alpha_g$ are grid-cell fixed effects; and $\theta_m$ are month fixed effects. In some specifications, we wish to test whether climate impacts differ for different types of locations, such as croplands and pastoral areas. For this analysis, we use data on land types from the Food and Agriculture Organization (FAO, 2021), measured in 2010 (a year preceding our sample period). To study this heterogeneity, we estimate:

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

where $AG_g$ is the fraction of the grid cell engaged in the agricultural activities that vary in the degree of their rain sensitivity (i.e., rainfed and irrigated croplands, and rangelands)

[38] To do so, we calculate each tower's total outgoing call volume on each day during the 30-minute windows immediately pre- and post-Maghrib, as in Equation (1). We then calculate the average daily call volume during these periods for each tower, by averaging across all days in the month. Finally, we take the mean of these (average daily) call volumes across all towers in each grid cell, separately for each month.

and $OTH_g$ is the fraction of other land types (forest, fruit trees and vineyards, barren areas, water bodies and marshland). Here, our estimates of $\gamma$ capture the differential effect of precipitation conditions on croplands and rangelands relative to built-up (urban) 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 A4 also presents descriptive statistics of the key variables appearing in the main tables from this application, while Appendix Table A5 summarizes additional variables used for robustness checks.

## 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, we find that 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 utilized 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.[39] For a major drought, such as the one that afflicted Afghanistan in 2018 (depicted in Appendix Figure A7-Panel B), SPEI typically falls by roughly 1.6 SD. The estimate in column (1) suggests that a SPEI drop of this magnitude increases religious adherence by 22% as much as the Pashtun effect.

**Robustness Checks** In Table A9 we verify that this estimate is robust to all of the same checks undertaken with the violence results in Table A6: constructing the Maghrib dip measure using different functional forms and over different windows of time; as well as controlling for call volume and the lag dependent variable. We also show that the results

[39]Multiplying the coefficient by the change in SPEI (-.67 x -1.3) implies that the Maghrib dip rises by .87. Column (2) of Table A3 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%.

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.

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 in a district.

In Table A10 we additionally verify that the results do not depend on the sample, using the same tests as in the violence application, Table A7. This includes dropping districts with sizable Shia populations, days during Ramadan, and the sparsest locations. We also present two additional checks. We show that the urban areas do not drive the results, which remain unchanged when we drop major urban centers such as Kabul from the sample.[40] This is reassuring since we expect precipitation conditions to exert the largest effects on economic conditions in rural areas. In addition, we verify that dropping districts that fell under Taliban control does not alter the results.[41] This check rules out the idea that negative SPEI shocks led to increased religious adherence solely because it 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 and rangeland. The coefficient is qualitatively the largest and most precisely estimated for areas containing greater shares of rainfed croplands.[42] These are also the areas where drought conditions are also most likely to harm economic production. This can be seen 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

[40] 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 urban under this definition.

[41] Data on direct measures of Taliban control are only available from 2015-2020, from the PiX data source (Protected Internet Exchange, 2023). 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.

[42] 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.

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 in this measure. Since the religious response is largest in areas where SPEI also exerts the largest effects on 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 insurance are unlikely to be major factors in our institutional context; rather, 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 A11, 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.[43] These effects on private religious adherence suggest that outward-facing, public motivations such as social insurance cannot be the sole reason why climate shocks increase the Maghrib dip.[44]

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

[43] A moderate SPEI shock would imply a 27% effect while a severe SPEI shock would imply a 33% effect (using column (4) from Table A3 for benchmarking purposes.)

[44] 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 religious 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.

of adherence in Afghanistan, since agricultural labor is most intensive during harvest.[45] We also check whether the effects of climate shocks are greatest during the harvest season, which is when there is the greatest need for labor, and when opportunity costs are likely 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 harvest season, when religiosity is also especially high. Comparing these columns, 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 instance, during growing season, people may cope with drought conditions through prayer as a form of consolation, or to seek divine intervention (i.e., to pray for rain). In the post-harvest seasons, income has already been realized: the religious response post-harvest (to pre-harvest SPEI) is consistent with individuals turning to religion as a means of coping with the negative experience of the realized income shock.

To explore whether psychological coping might lead people to increase religious adherence after economic 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 religiosity for each mobile subscriber in the dataset, during a baseline period (2013-2015).[46] In Table A12, we then ask whether individuals who are more religious at baseline react differently to SPEI shocks during a 2016-2020 estimation window.

[45] 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.

[46] 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 at small geographic units (i.e., grid cells), at the monthly level. However, to construct a (baseline) measure of religious adherence for each subscriber, we instead aggregate each subscriber's activity in the 30-minute intervals immediately before and after Maghrib, over a 33-month period (2013-2015).

This analysis uses data from 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 A12 indicate that individuals who are more religiously adherent at baseline become even more adherent in response to adverse economic shocks. This heterogeneity by baseline religiosity holds whether 'more religious' is defined as above-median religiosity (in column (1)), or by religiosity tercile (column (2)). These findings are consistent with the coping mechanism: they suggest that those who are religiously observant in the first place might be the ones who further turn to religion as means of coping in response to negative income shocks.

**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).

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 may 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 A11 shows a small, insignificant coefficient, that is *negative* in sign. 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, in column (3), for each month, we restrict our sample to the set of users who have made a call in each of the previous three months, which creates a rolling sample of constant users. We again find the results unchanged upon imposing this restriction.

In column (4) of Appendix Table A11, 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 to an over-estimate. However, restricting the sample to those who had the same district home location over the previous three months does not affect the estimates. Thus, compositional changes stemming from migration are unlikely to be driving our estimates.

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 A10 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).[47] In columns (1) and

[47]While this is the best available data on poppy cultivation in Afghanistan, almost 41% of the observations

(2) of Appendix Table A13, 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.[48] Our main coefficient of interest is unchanged, which suggests that 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.[49] 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, which 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 economic 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 new measure confers several benefits: it is based on revealed preferences; it can be collected at the scale of entire countries at relatively low cost; it can be analyzed individually and at various levels of aggregation (over time and space); and it can provide a window into religious behavior under circumstances, such as active conflict, when other measures of religiosity are typically infeasible to collect. In addition, the measure can be constructed from behaviors that vary in their observability, which in turn can help shed light on whether adherence is driven by entirely social motivations.

We demonstrate the potential of this new measure through two applications. In the first

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.

[48] 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.

[49] 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.

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 link between Taliban violence and religious adherence. In the second case study, we show that adverse climate shocks increase religious observance, particularly in areas with rainfed agriculture, where climate conditions are especially economically consequential.

In both applications, we find that it is not just publicly observable 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 suggests that private motivations play an important role in shaping how religious adherence changes in response 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 to people to turn toward religion.

While our empirical focus is on using the Maghrib dip to study two specific applications in Afghanistan, we believe that the same approach could be applied in several other areas — 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). And while we focus on mobile phone transactions because cell phones are the most widely used digital technology in Afghanistan, in other contexts, social media or other digital trace datasets might be more suitable or easy to obtain. 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, we expect that similar fine-grained measures of religious adherence could facilitate the study of religion in other Muslim countries, and could also be potentially extended into environments with different religious norms, such as Sabbath observance by Orthodox Jews. More broadly, we hope this effort can help inspire new and diverse approaches to studying the causes and consequences of religion.

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# Appendices

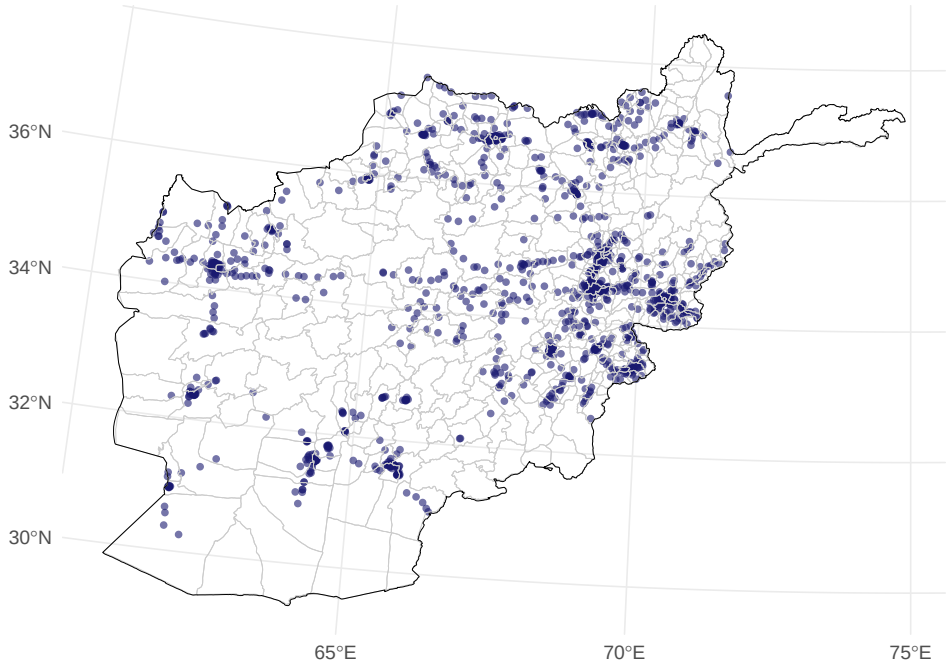
## A Appendix figures and tables

Figure A1: Poster Prohibiting Cell Phone Use



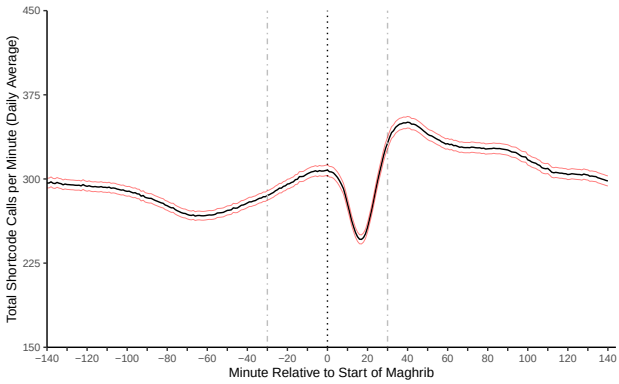

*Notes:* Poster found in Hounslow Muslim Centre. See here.

Figure A2: Cellphone Towers in our Sample

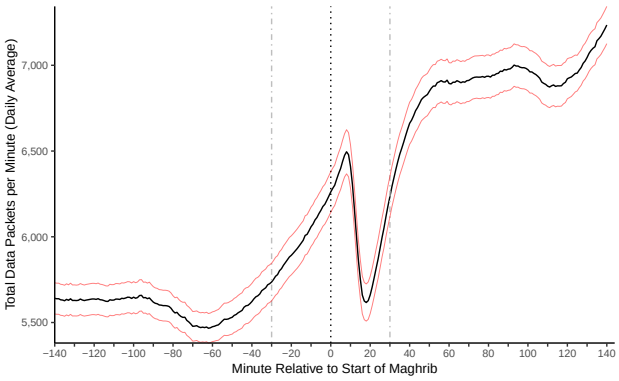



*Notes:* This figure shows the location of the cellphone towers in our sample, along with district boundaries in grey.

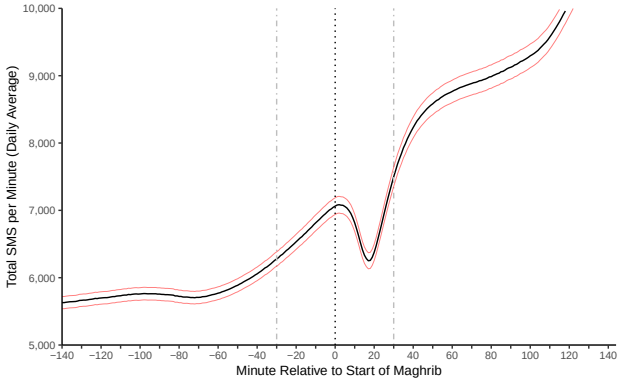
Figure A3: Shortcode Call, Data and SMS Volume around the Maghrib Window




(a) Shortcode Calls



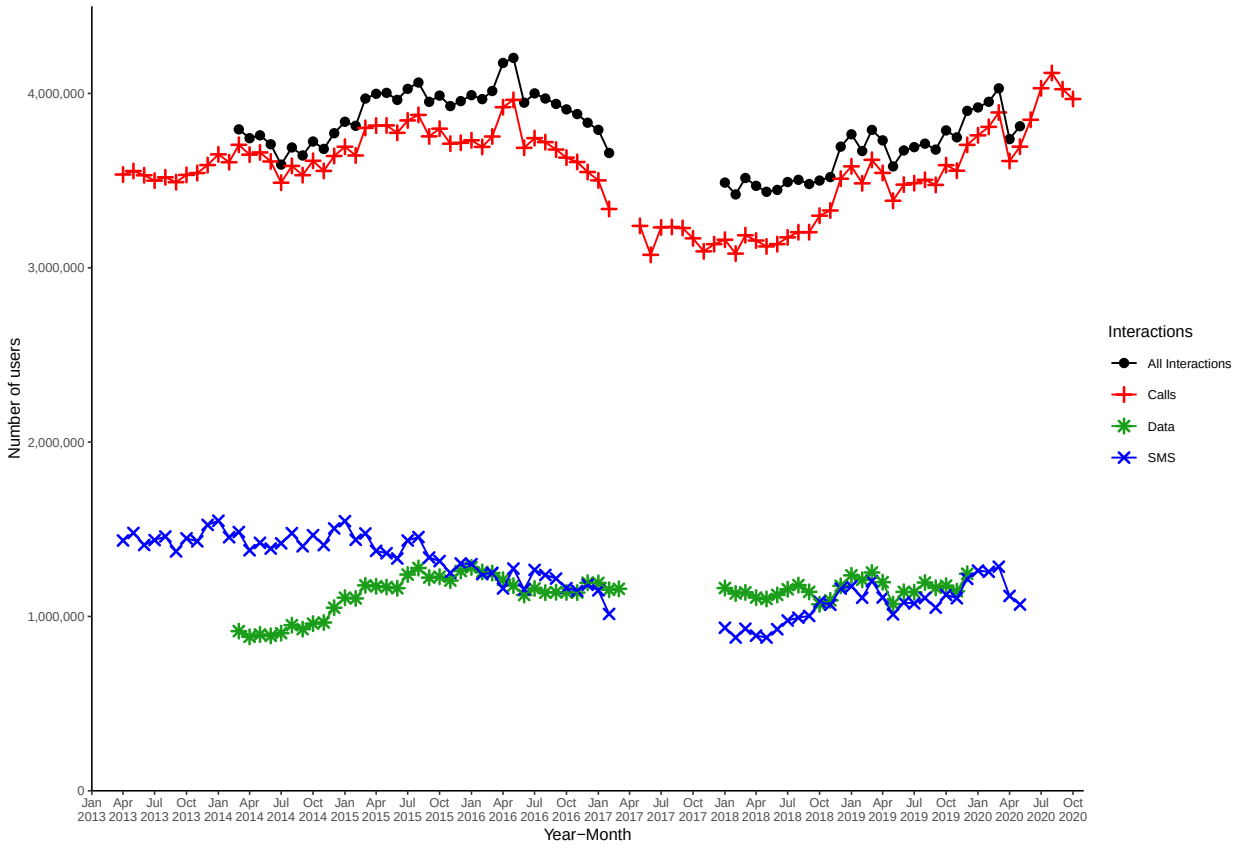

(b) Data Transactions




(c) Text Messages

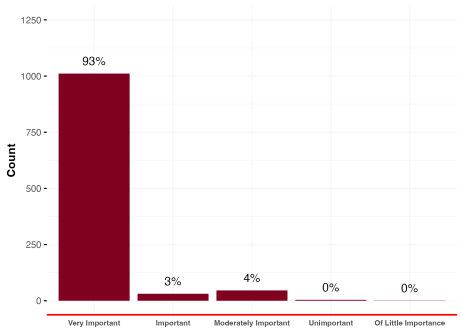
*Notes:* Panel A plots the average number of shortcode calls in each minute defined relative to the start of Maghrib, zooming in on the 140 minutes before and after the start of the prayer window. Panel B plots the average number of data packets transacted in each of these minutes. Panel C plots the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

Figure A4: The Number of Cell Phone Users over Time

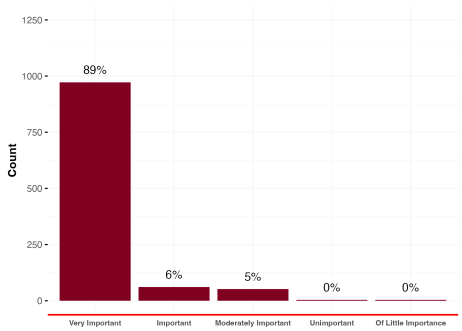



*Notes:* This figure plots the number of mobile phone users in each month of our data. The total number of users is shown for every month for which we have data for every type of user (phone calls, Data, SMS).

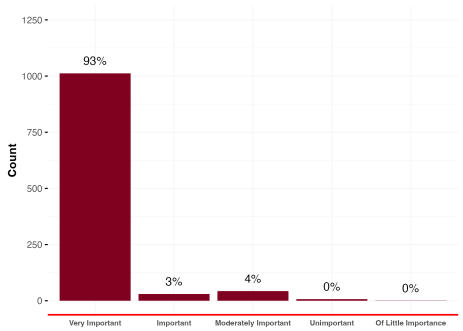
Figure A5: Survey Responses on Religiosity Questions



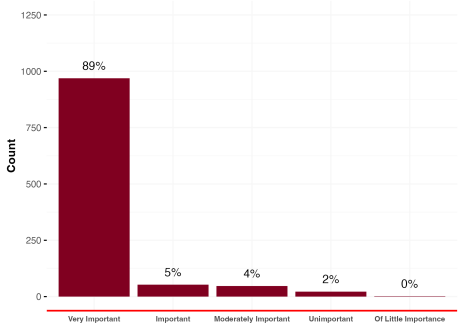

(a) Fasting During Ramadan



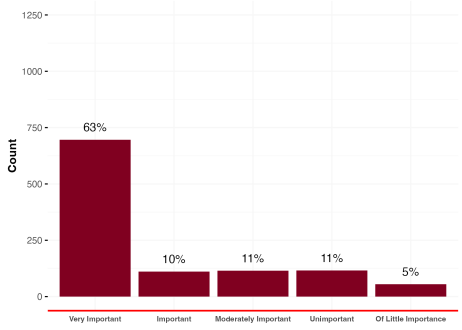

(b) Giving Zakat



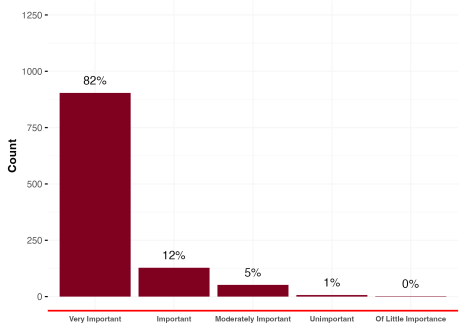

(c) Namaz 5 Times a Day




(d) No Alcohol



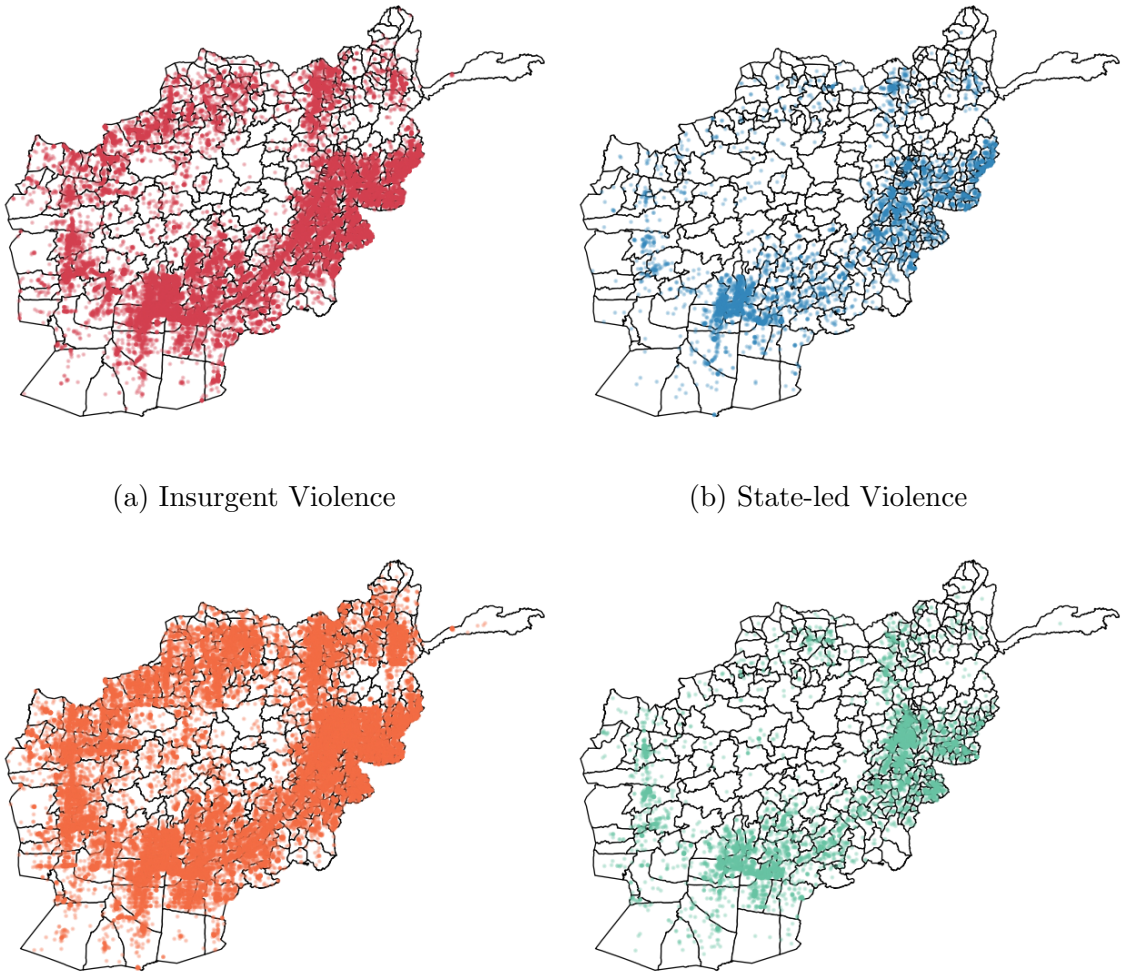

(e) No Music




(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 A6: ISAF Incidents in Afghanistan



(a) Insurgent Violence

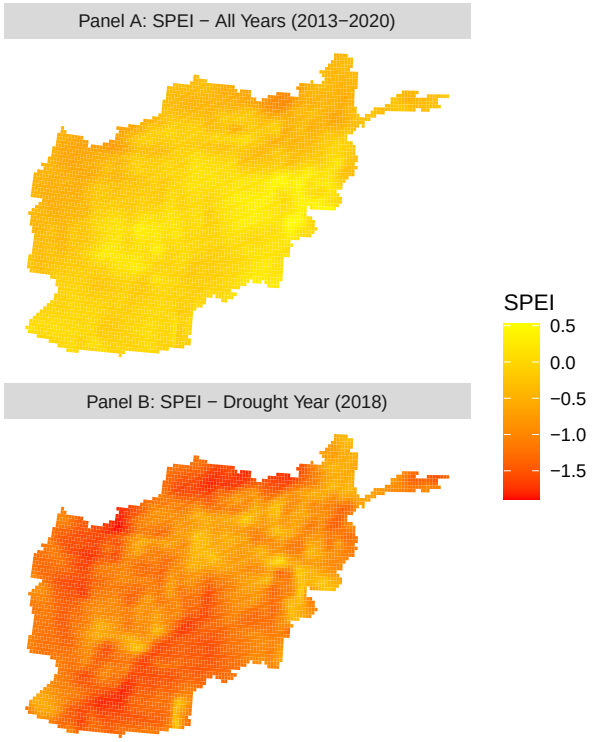
(b) State-led Violence

(c) Other Insurgent Activity

(d) Other State-led Activity

*Notes:* This map shows the location of incidents from the International Security Assistance Force (ISAF) in Afghanistan, over 2013-2014. The four categories are (a) insurgent violence (b) state-led violence (c) other insurgent activities (d) other state-led activities. District boundaries are shown in black.

Figure A7: 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 observability of 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 | 2.962* | 3.446** |
| | (1.648) | (1.656) |
| *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 | 1092.00 | 1092.00 |
| Mean of Dependent Variable | 12.94 | 12.94 |
| District Fixed Effects | Y | Y |
| Demographic Controls | | Y |

*Notes:* Each row is a different regression where the dependent variable is the Maghrib dip measure of religious adherence. 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. 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 the survey respondent: 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. One observation is included for each surveyed individual. Robust standard errors shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A3: 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 A4: 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 A5: 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 |
| **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 |
| **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 |
| **E. Variables at Individual-Quarter Level (in CDR)** | | | | | |
| Maghrib Dip | 9.966 | 100.014 | –200.000 | 200.000 | 78,419,140 |
| SPEI | –0.268 | 0.861 | –2.538 | 2.033 | 78,419,140 |
| **F. 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 A6: 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) |
| Insurgent Violence | –0.073*** | –0.081*** | –0.054** | –0.072** | –0.066** | –0.076*** | –0.013*** |
| | (0.028) | (0.030) | (0.027) | (0.028) | (0.029) | (0.025) | (0.004) |
| Maghrib $Dip_{t-1}$ | 0.037 | | | | | | |
| | (0.044) | | | | | | |
| IHS(Total Volume) | | –2.723* | | | | | |
| | | (1.578) | | | | | |
| Observations | 4468 | 4703 | 4703 | 4703 | 4703 | 4702 | 4703 |
| District Fixed Effects | Y | Y | Y | Y | Y | Y | Y |
| Month Fixed Effects | Y | Y | Y | Y | Y | Y | Y |
| Other Insurgent Activity and State-led Controls | Y | Y | Y | Y | Y | Y | Y |

*Notes:* Column (1) controls for the Maghrib dip in the previous month. Column (2) controls for the IHS transform of the average daily call volume in a month. 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. 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), 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. Each regression is at the district-month level, and the overlapping period in which we have both violence and CDR is April 2013 to December 2014. Standard errors clustered on district shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A7: Insurgent Violence and Religious Adherence: Robustness to Various Samples

| *Sample:* | Maghrib Dip (2013-2014) | | | |
|---|---|---|---|---|
| | Non-Ramadan Days | Non-Hazara Districts | No. 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 |
| Other Insurgent Activity and State-led Controls | Y | Y | Y | Y |

*Notes:* In column (1), we drop Ramadan days; in column (2) we drop districts in which at least 5% of villages speak primarily Hazaragi; in column (3), we drop the sparsest 5% of districts, defining sparsity based on the number of mobile phone users within the district over 2013-2014; in column (4), we drop the bottom 5% of districts in terms of 2013-2014 call volume. Standard errors clustered on district shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A8: Violence and Religious Adherence: Addressing Alternate Accounts

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

*Notes:* In column (1), 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. In column (2), we restrict to shortcode calls when defining the Maghrib dip. Standard errors clustered on district shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A9: 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 A10: 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 area exceeds 5%. In column (6), we drop districts under Taliban control. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A11: 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 A12: Climate and Religious Adherence: Heterogeneity by Initial Religiosity

| | Maghrib Dip (2016-2020) | |
|---|---|---|
| | (1) | (2) |
| *Variables* | | |
| SPEI | -0.151 | -0.125 |
| | (0.136) | (0.139) |
| SPEI x Above Median Baseline Religious Adherence | -0.127*** | |
| | (0.042) | |
| SPEI x Tercile 2 Baseline Religious Adherence | | -0.043 |
| | | (0.052) |
| SPEI x Tercile 3 Baseline Religious Adherence | | -0.230*** |
| | | (0.057) |
| Observations | 78,419,140 | 78,419,140 |
| Individual FE | Y | Y |
| Grid Cell FE | Y | Y |
| Quarter FE | Y | Y |

*Notes:* Each column is a separate regression. One observation is included for each individual-quarter over 2016 to 2020. SPEI is calculated separately for each quarter in the the individual's home grid, defined as the grid where they made the most calls in that quarter. The regressions in column (1) and (2) examine heterogeneity by baseline religiosity. Baseline religiosity 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). Column (1) includes an interaction of SPEI with above median baseline religiosity. Column (2) includes interactions of SPEI with terciles of baseline religiosity. 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 A13: 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.