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

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March 12, 2023

Abstract

Religious adherence has been hard to study in part because it is hard to measure. We develop a new measure of religious adherence, which is granular in both time and space, using anonymized mobile phone transaction records. After validating the measure with traditional data, we show how it can shed light on the nature of religious adherence in Islamic societies. Exploiting random variation in climate, we find that as economic conditions in Afghanistan worsen, people become more religiously observant. The effects are most pronounced in areas where droughts have the biggest economic consequences, such as croplands without access to irrigation.

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

Keywords: Religion, Mobile Phones, Big Data, Climate, Economic Shocks

*We thank Sendhil Mullainathan, Benjamin Marx, Emine Deniz, Eli Berman, and seminar participants at Bocconi, Harvard, ITAM, Berkeley, Stanford, Montreal, Georgetown/World Bank, Northwestern and the IOG-BFI conference for helpful comments and feedback. We also thank Carolina Bernal, Claire Fan, Smriti Ganapathi, Cristina Mac Gregor Vanegas, Gonzalo Moromizato, Purushottam Mohanty and Vishwanath Emani Venkata for excellent research assistance. We additionally thank Karim Khoja, Jacob N. Shapiro, and Dr. Mohammad Najeeb Azizi for their help in negotiating data access with the Afghanistan Telecommunications Regulatory Authority. We gratefully acknowledge financial support from the Kevin Xu Initiative on Science, Technology, and Inequality at the Harris School of Public Policy, as well as the Development Impact Lab.

†Callen's primary contribution to this paper was in facilitating access to the phone data used for the analysis.

1 Introduction

Religion plays a fundamental role in human society. Religions shape cultural norms and values, influence social group organization, and define the contours of political and economic power (Becker, Rubin, and Woessmann, 2021; Berman, 2000). These dynamics underscore the importance of understanding what drives people to be religious and to adhere to religious practices.

Yet, religious adherence has been hard to study in part because it is hard to measure. The vast majority of studies focusing on religion in economics have relied on survey-based measures. And while we have learned much from these approaches, (Iannaccone, 1998; McCleary and Barro, 2006), surveys have several drawbacks. There are many circumstances – such as in insecure or violent environments – where it is infeasible to collect such data. In addition, surveys tend to be fielded infrequently, with sparse geographic coverage; and, typically rely on stated rather than revealed preferences.

In this paper, we present a new approach to measuring religious adherence and illustrate its potential by using it to study the economic determinants of religiosity in Afghanistan. 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 the amount of non-prayer activity observed during the prescribed prayer window can provide an indication of the religious adherence of the population.

Our paper has two main parts, one methodological and the other applied. In the first part, we implement and validate this measurement approach using anonymized mobile phone data from one of Afghanistan's largest mobile phone operators. In this context, we measure religious adherence based on the extent to which call volume drops during the evening Maghrib prayer window. The relevance of this measure relies on the strong Islamic norm that talking to others – including on the phone – is widely considered to invalidate prayer.[1] The Maghrib prayer window is well-suited to this task because it is short and well-defined,

[1] This norm is laid out explicitly in a series of religious texts and rulings, including sayings of Muhammad collated in the *Book of Prayers*.

and because it occurs during a time when people are awake and otherwise active.

To provide intuition for this new measure, we first show that there is a substantial decrease in call volume immediately following the start of the Maghrib window. This analysis leverages data from nearly 10 million unique phone users, who collectively make 22 billion phone calls over the 8-year period for which we have data (2013-2020). We find that across the country, on average, call volumes drop by roughly 25% about 15 minutes into the Maghrib prayer window. We refer to this decrease as the "Maghrib dip."

A critical feature of the Maghrib prayer window is that it begins exactly at sunset, which varies by season and by geographic region. Since the mobile phone metadata are recorded every second by thousands of unique cell towers throughout the country, we can measure the magnitude of the Maghrib dip in very fine-grained geographic regions, for every day over the course of the year. By disaggregating in this way, we show that the Maghrib dip tracks the timing of sunset perfectly. For example, when sunset occurs later in the summer months, the dip also occurs later, immediately after sunset. This timing allows us to separate reductions in call activity caused by Maghrib from reductions related to the end of the workday, rush hour, and other events that do not vary over time and space.

After developing this intuition for the Maghrib dip, we validate it as a measure of religious adherence using two different approaches. First, 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., 2022). Thus, for each individual, we have a survey-based index of religiosity (based on how they rank the importance of several religious practices such as praying 5 times a day) as well as a measure of their Maghrib dip based on when they are active on their mobile phone. We find that these two variables are strongly correlated: A one standard deviation increase in the survey religiosity index is associated with a 44% increase in the Maghrib dip.

Second, we show that geographic variation in the Maghrib dip across Afghanistan correlates with existing data related to religious norms. Of course, no traditional dataset provides the same spatial or temporal granularity as our measure based on mobile phone use, but when we aggregate our measure to match the resolution of traditional data, expected patterns emerge. For example, the Maghrib dip is largest in areas taken over by the Taliban, which strictly – and at times violently – enforced religious norms. Regression analysis also confirms that there is a strong correlation between these two factors (significant at the 1% level). This provides further support for the idea that larger falls in call volume over the Maghrib prayer window reflect greater religious adherence.

The Maghrib dip measure that we develop likely reflects two different aspects of religious adherence: a private component motivated by internal factors such as piety; and a more social, outward-facing component, motivated by a desire to abide by prevailing social norms. Most existing, traditional measures of religiosity reflect a similar dual composition, and as with those measures, we cannot empirically decompose the Maghrib dip into private versus social components. However, by analyzing specific types of private phone activity, we argue that the Maghrib dip is unlikely to solely reflect social considerations. In particular, we show that data transactions and text messages display a similar decrease in volume during the Maghrib prayer window. Likewise, we find that calls to shortcodes, which are used to contact customer care, manage account balances, and call information and emergency services, similarly fall during Maghrib. If social considerations alone led people to refrain from making calls during this period, we would not expect to see such large dips in internet use, text messages, and shortcodes, which others are less able to observe. Relatedly, the observed dip in shortcode calls, where the recipient is typically unknown to the caller, also helps rule out the concern that people stop calling not because they intend to pray but because they anticipate their peers are praying and therefore unavailable to take phone calls.[2] Taken together, this evidence indicates that our measure of religiosity successfully captures the private aspect (along with the social aspect).

In the second major part of the paper, we use this new measure to study the effects of economic adversity on religious adherence. This empirical example is meant to illustrate the

[2]Our main analysis uses call volume as the basis for the Maghrib dip since calls are, by far, the most common and representative form of phone-based communication in Afghanistan. Phone calls also provide a more precise measure of activity since (i) a great deal of mobile data use occurs in the background, without the active involvement of the user; and (ii) there is no geographic information associated with the text messages in our dataset, whereas we observe the location of the nearest cell tower for each outgoing call.

potential of the measure, and also to shed light on an important and conceptually ambiguous question. On the one hand, adverse economic shocks may *lower* religious adherence by testing people's faith, particularly if faith goes hand-in-hand with the expectation that God can protect against these types of shocks (Auriol et al., 2020). Or, lower income may also reduce time available to participate in religious activity (Buser, 2015).

On the other hand, economic shocks may *increase* religious adherence by lowering the opportunity cost of participating in religious activities (Azzi and Ehrenberg, 1975). Or, they may spur individuals to turn to religious clubs to seek social insurance (Chen, 2010), if they are not deterred when clubs raise the costs of entry in the wake of adverse shocks (Berman, 2000; Iannaccone, 1992). Finally, adherence may rise if people turn to religion when they experience or expect negative shocks (Freud, 1927; Hume, 1757; Marx, 1970; Weber, 1905; Wesley, 1760) — if religion, for instance, helps them psychologically cope with adversity (Bentzen, 2019, 2021), or if social norms tighten more generally in response to negative shocks (Henrich, 2020; Winkler, 2021).

Given this theoretical ambiguity, we empirically study the relationship between economic adversity and religion in the context of Afghanistan by examining the effect of quasi-random climate shocks on religious adherence. Such shocks have had stark consequences for Afghanistan's agricultural sector, as rising temperatures have caused more frequent and severe droughts over the past four decades (Climate Security Expert Network, 2019). We measure droughts using the Standard Evapotranspiration Index (SPEI) (Vicente-Serrano, Beguería, and López-Moreno, 2010), a carefully-validated indicator that incorporates information about rainfall, temperature and other weather inputs (Harari and La Ferrara, 2018). Our econometric specification uses a panel fixed-effects model to link data on droughts to data on religious adherence at the level of 10km x 10km grid cells, for each month between 2013 and 2020.

We find that adverse climate conditions significantly *increase* religious adherence. To give some intuition for the magnitude of the observed effects, we find that a change in SPEI equivalent to that of a major drought increases religious adherence by 18% as much as the change that occurs when the Taliban take control of a district.

We also present several pieces of evidence which suggest that climate shocks influence religiosity through their economic impact. In particular, we show that the effects of climate on adherence are concentrated in areas that are most sensitive to droughts, such as cropland and pastoral areas. We further find that the effects are strongest in *rainfed* croplands that do not have access to irrigation, which are precisely the areas where we expect the economic consequences of drought to be most severe. 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, and have no statistically significant 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.

Our paper makes two distinct types of contributions. First, we contribute to the study of religion in the social sciences by developing a novel measure of religious adherence. This measure is rooted in observing what people do, rather than what they say, and thus complements measures of religious behavior that rely on self-reports.[3]

Our measure complements existing survey-based measures by making it possible to measure religious behavior in contexts where surveys may be infeasible to conduct, such as contexts beset by violent conflict. Indeed, we expect our measure to be relevant to any Islamic context in which people use mobile phones. It is also versatile in the sense that it can be used to study a range of substantive questions. A major advantage is that the measure can both span a country and also be disaggregated into arbitrarily fine spatial and temporal units. By contrast, survey-based measures of religiosity are typically either only representative at the national level or limited to very specific regions. Thus, we expect this measure to be especially useful for studying questions that require both spatial and temporal variation in religious adherence.

Second, our empirical analysis provides new evidence that people become more reli-

[3]Our approach also engages with a broader literature that explores how new sources of 'big' data can be used to measure social and economic behavior – including wealth and poverty (Blumenstock, 2018b; Blumenstock, Cadamuro, and On, 2015; Jean et al., 2016), GDP (Henderson, Storeygard, and Weil, 2012), credit-worthiness (Björkegren and Grissen, 2018), and unemployment (Toole et al., 2015).

giously observant as economic conditions worsen. This finding builds on a literature that has examined the relationship between income and religiosity, both across countries (McCleary and Barro, 2006) and within countries (Chen, 2010).[4] Our findings also fit into a broader literature on the economic determinants of religiosity, which has examined factors such as agricultural risk (Ager and Ciccone, 2018),[5] schooling (Bazzi, Hilmy, and Marx, 2020), charity (Gruber, 2004), group ties (Berman, 2000) and Islamic institutions (Bazzi, Koehler-Derrick, and Marx, 2020). It is also in the spirit of Atkin, Colson-Sihra, and Shayo (2021), which uses the consumption of taboo goods from surveys as a measure of religious identity; Bentzen (2021), which uses Google searches for "prayer" as a measure of prayer intensity; and Livny (2021), which uses brighter night light during Ramadan as a measure of religiosity.[6] In related work, Augenblick et al. (2016) also uses financial levers to conduct an incentivized elicitation of religious beliefs.

Finally, our paper relates to the literature examining the economic consequences of religion (Barro and McCleary, 2003; Becker and Woessmann, 2009; Bénabou, Ticchi, and Vindigni, 2022; Bottan and Perez-Truglia, 2015; Cantoni, 2015; Cantoni, Dittmar, and Yuchtman, 2018; Gruber, 2004; Gruber and Hungerman, 2008; Kuran, 2018). Recent work in this area has examined the 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 expect that additional, broader measures of religious behavior can generate even

[4]McCleary and Barro (2006) find that countries with higher income per capita have lower levels of religiosity, based on measures such as church and mosque attendance from the World Values Survey. Chen (2010) finds that the Indonesian financial crisis intensified Islamic religious adherence, as reflected in measures such as Koranic study. Similarly, Costa, Marcantonio, and Rocha (2019) show that economic downturns in Brazil led to increased Pentecostal affiliation. On the other hand, Buser (2015) finds that cash transfers in Ecuador led to increased church attendance, as reported in household surveys. We build on this past work by examining the impact of high-frequency shocks at the monthly level and utilizing our revealed preferences measure of religious adherence.

[5]Ager and Ciccone (2018) examine how rainfall risk affected church participation in U.S. communities over the 19th and 20th centuries. Their work hones in on the risk aspect of rainfall, while controlling for its potential consequence for income, by examining the variance in rainfall, while conditioning on agricultural output.

[6]This highly creative measure is best suited as a measure of religiosity in contexts where Ramadan does not shift other social and economic activity into night hours — a shift that would also intensify night-time luminosity but be unrelated to religiosity.

further insight into how religion shapes societal outcomes.

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 the Maghrib Dip measure to examine how climate shocks affect religious adherence. Section 5 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.

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.[7] 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.[8] 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.

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 that begins after sunset. Under Sunni Islam, which is the branch practiced by 90% of Afghans, the Maghrib window opens precisely

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

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

at sunset and must be completed by dusk.[9] 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.[10]

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).[11]

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. The key insight behind this measure is that – as discussed in detail in Section 2 – Islamic religious norms forbid talking during the Maghrib prayer window, the timing of which is very precisely specified. We, therefore, interpret the reduction in calls that occur 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 used to construct our measure, formally defines the measure, and provides visual intuition and quantitative validation using two traditional sources of data.

[9] 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.

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

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

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 7.5-9 million unique phone numbers each year (out of a total population of 39 million), who collectively made 22 billion calls over this period. Geographically, the phone company operates 1730 cell phone towers that are spread across 286 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).

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]

In most of the analysis that follows, we aggregate mobile phone activity geographically – either at the level of the cell phone tower, a spatial grid cell, or an administrative unit – by aggregating call traffic from towers located within each unit. We generally avoid working

[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.

with individual-level CDR data for two reasons. First, as we discuss in greater detail below, aggregating data over multiple individuals helps limit potential privacy risks to individuals who did not provide informed consent. Second, since much of our analysis relies on high-frequency measures of religious adherence, aggregating over multiple individuals helps reduce sparsity in the data.

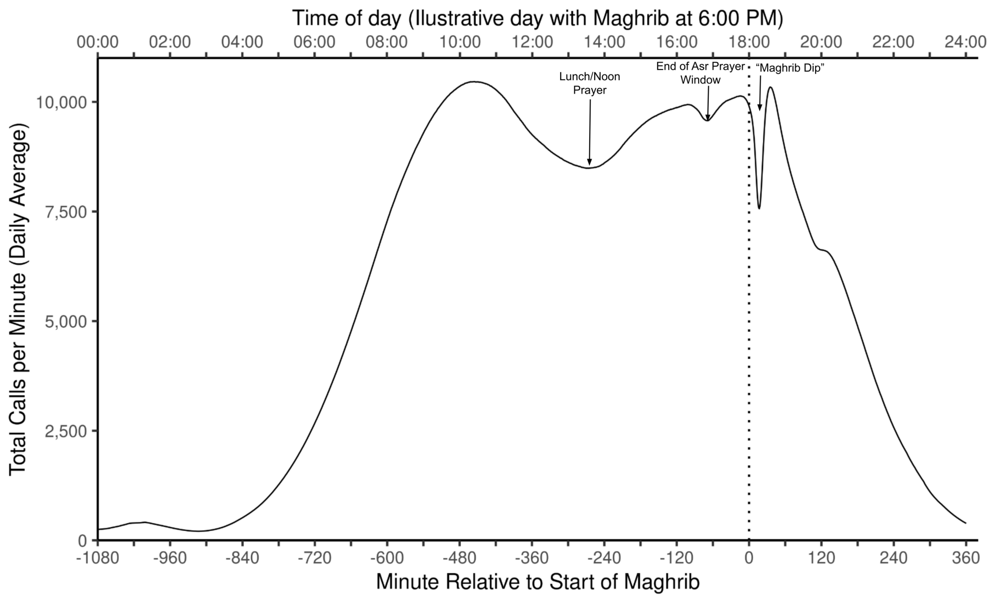
Data Access and Data Privacy While the CDR are metadata and do not capture the *content* of individual communications, the raw data are nonetheless confidential and sensitive (Mayer, Mutchler, and Mitchell, 2016). To protect the privacy of individual subscribers, our analysis and data management plan were reviewed and approved by the U.C. Berkeley Committee for the Protection of Human Subjects. 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. In addition, and as discussed above, our primary analysis is performed on data that are aggregated across a large number of transactions. The only exception is one of the validation exercises described in Section 3.3, but for this population, we obtained informed consent to use their CDR for research purposes.

More broadly, de Montjoye et al. (2018), Blumenstock (2018a), and Oliver et al. (2020) discuss these and other considerations that arise in the privacy-conscientious 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. Aiken et al., 2022; Gentilini et al., 2020), public health interventions (Milusheva et al., 2021), disaster response (Lu, Bengtsson, and Holme, 2012), and transport planning (Hanna, Kreindler, and Olken, 2017).

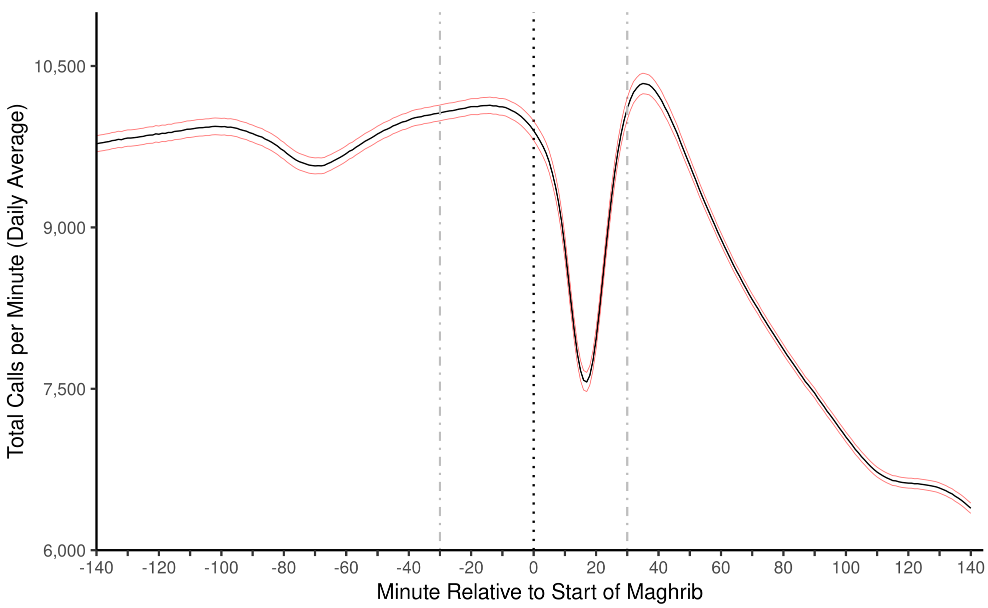
3.2 The 'Maghrib Dip' as a Measure of Religious Adherence

Our measure of local religious adherence quantifies the extent to which outgoing call volume drops during the Maghrib prayer window. To provide intuition for this approach, Figure 1 shows total call volume per minute across the entire country of Afghanistan, for each minute relative to the start of Maghrib (shown in the bottom x-axis of the figure). 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: 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 line indicates the start of Maghrib; dashed grey lines on the bottom figure mark 30 minutes before and after Maghrib; and red lines show the 99% confidence intervals.

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 example 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 dashed 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 24% 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.

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

$$\text{MaghribDip} = \frac{\text{CallVolume}^{Before} - \text{CallVolume}^{After}}{\text{CallVolume}^{Before}} \tag{1}$$

Since it takes approximately 15 minutes to complete the prayer itself, we focus on the 30 minutes before and 30 minutes after the start of Maghrib in our main specification. However, in robustness analysis, we confirm that our results hold for other reasonable time frames, including 25-minute and 40-minute windows around the start of Maghrib.[14] We also show robustness to alternative methods for quantifying the dip, such as scaling (1) by a different

[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 2%; the second quartile of 19%; the third quartile of 31%; and the fourth quartile of 50%.

[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.

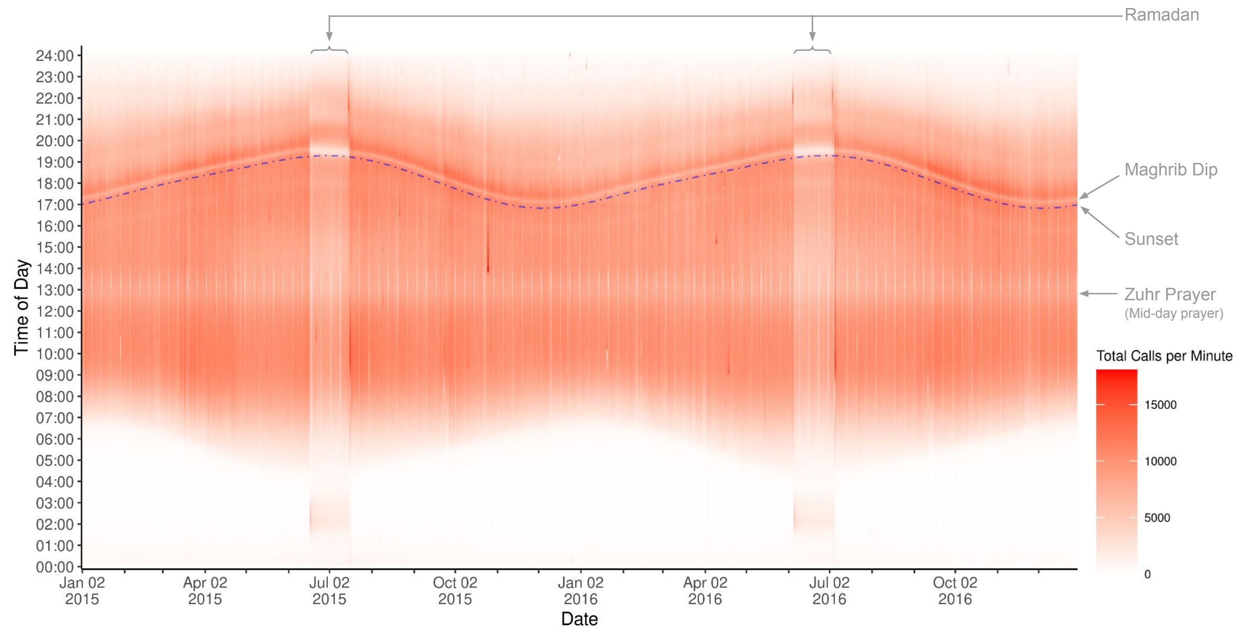
denominator – see Section 4.2.

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, the timing of sunset (dashed blue line) varies over the course of the year from between 17:00 and 19:30. 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.

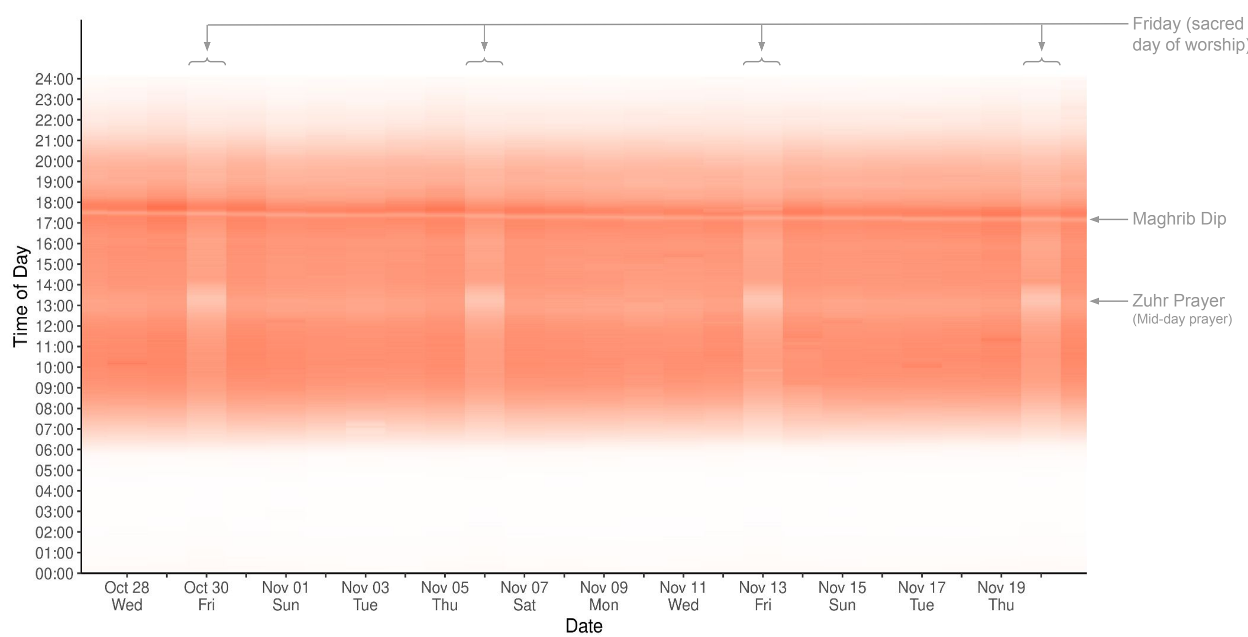
Figure 2a displays other interesting signatures of Islamic religious observance. For instance, the two light vertical bands around June-July are the holy months of Ramadan. Annual observance of Ramadan is another of the five pillars of Islam, and Muslims observe the religious holiday through fasting,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

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 line in the top figure demarcates the start of sunset.

Social and Private Components of Religious Adherence We interpret the Maghrib dip as a measure of religious adherence but do not claim that it necessarily reflects religious beliefs. This is because publicly-observed religious adherence may occur for two distinct reasons. On the one hand, it could be due to intrinsic motivations such as religious piety (as well as private factors such as the opportunity cost of time). On the other hand, it might be driven by more social, extrinsic considerations related to the desire to abide by social norms. In other words, some people may refrain from making phone calls and talking to others over this period because they are reciting prayers and are intrinsically pious; others may refrain because that is the prevailing social norm during prayer time. We note that the dual presence of private and public motives affects most measures of religious adherence, and is not unique to our Maghrib dip measure. For example, observed church attendance may be motivated by some people who attend because they wish to pray, while others may go because that is what people in their community do on a Sunday.

While we can't easily quantitatively decompose the Maghrib dip in outbound phone calls into private versus social components, there is considerable evidence that suggests that the decrease in activity is not driven solely by social considerations. Specifically, we test whether there is a corresponding Maghrib dip in other less social and less observable types of mobile phone activity. Appendix Figure A3 shows average call volume per minute for three additional transaction types: (a) shortcode calls, which are special numbers set up by companies and public agencies so that subscribers can contact customer care, manage accounts (for services like airtime top-up, bill payments, and mobile money transactions), and reach emergency and information services; (b) data packet transfers, which facilitate internet use; and (c) text message communications.[15] 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, Appendix Figure A3 shows a pronounced Maghrib dip across all transaction types: shortcode volume falls by 18%, data volume falls by 13%, and SMS volume falls by 10%, and all reach minima approximately 17 minutes into the Maghrib window. The

[15] Note that none of these volumes are directly comparable with one another, since phone calls are different units than text messages, and both are distinct from data packets.

fact that these dips exist suggests that social considerations alone are not driving the fall in call volume over the Maghrib window. While calls are more public (i.e., people can hear you talking on the phone), texts are more private (as only the person you text will know you are engaged in texting). This is even more true for internet use, which is easy to hide, and shortcode calls, which are often to automated systems or to service representatives who are unknown to the caller.

The Maghrib dip in shortcode calls (Figure A3a) also helps limit a more specific concern that individuals may refrain from making calls not because they intend to pray during the Maghrib window, but because they expect that their peers are praying and therefore unavailable to answer phone calls during this time. This "reflection" issue is likely to most affect people who are not religious themselves but who are part of a religious social network. However, given that shortcode calls are generally to large organizations and often involve automated responses, they should be much less impacted by considerations of peer behavior.[16]

While shortcodes, text messages, and mobile data all exhibit decreased volume during Maghrib, our main analysis focuses on call volume 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 93.76% of unique subscribers place phone calls, only 31.96% send text messages, and only 28.48% use data.[17] 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.[18] Third,

[16]In Afghanistan, shortcode calls are quite common: each year, 63% of unique subscribers, on average, place one or more shortcode calls.

[17]Relatively low SMS use may not be surprising in light of the country's low adult literacy rate (43%). Use of mobile data is likely limited by 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.

[18]Specifically, to construct Appendix Figure A3, 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; 43.6% had to be interpolated based on calls made in the day; while 34.1% had to be interpolated based only on a call that was made in the same month.

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 focus of the subscriber's attention. For instance, emails and other apps update regularly in the background – this can be seen in the hourly upticks in Appendix Figure A3. Moreover, data use is often '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.[19] Thus, a user could hit download prior to the Maghrib window and data transactions could appear after the window is already open. For these reasons, data use is not as well suited for our measure, which attempts to track pro-active use of the phone. Finally, although a large fraction of mobile phone subscribers makes shortcode calls at some point during the year, the total volume of shortcode calls is quite small, comprising just 3.4% of our phone data. In sum, we believe total phone call volume is the most reliable and accurate type of phone transaction to use for measuring religious adherence.

Addressing Tower Outages Cell phone towers in Afghanistan have periods of downtime. If these tower outages overlap with the Maghrib dip, it could distort our measure. For example, if an outage happened to occur in 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 type of 'technical' outage, we identify all tower-days in which there were 60 minutes of zero call volume around either side of the Maghrib window and remove these days from the data. In Afghanistan, some towers also experience regular 'night' outages, since the Taliban would sometimes require the operator to turn off towers at night in areas under Taliban control.[20] To address this type of night outage, we remove all tower-days in which there were zero calls placed between 21:00 (9 pm) and 03:00 (3 am).[21] In sum, we generate our Maghrib dip measure by comparing aggregate call volume before and after the start of Maghrib – after removing any tower-days with night or technical outages.

[19] For instance, in a random sample of 30,000 unique users in our data, 64.5% of the data transactions occur within 5 seconds of each other and 75% occur within one minute of each other.

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

[21] We consider this to be a relatively conservative window. For example, consider the case in which the Taliban allowed towers to turn back on at 05:00 (5 am) after shutting the tower down at night. If we defined an outage as zero call volume over a larger window (i.e., between 21:00 (9 pm) to 06:00 (6 am)) we would miss classifying this incident as a night outage.

3.3 Validating the CDR-Based Measure of Religious Adherence

Up until this point, we have argued that the Maghrib dip might 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 the self-reported religiosity of a subset of individuals to the Maghrib dip computed 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.

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.[22]

Instead, we compare survey-based measures of religiosity to phone-based measures of the Maghrib dip for respondents to a small household survey (approximately 1050 individuals). This survey, conducted in the provinces of Parwan and Kabul in 2015 (Blumenstock et al., 2022), 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 an inherent challenge in using surveys to measure religiosity: We cannot know whether people actually observe the practices that they report are important to them.

Nonetheless, we find evidence of a strong correlation between self-reported religious prac-

[22] 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).

tices 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.[23] We also create an individual-level measure of the Maghrib dip using Equation (1), calculated using data from a 48-month period around the time of the survey.[24] 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 the top row of Table 1, we regress the individual level Maghrib dip measure on the survey religiosity index, including district fixed effects (for Parwan and Kabul). The coefficient indicates that a one standard deviation (SD) increase in the index is associated with a 44% increase in the Maghrib dip measure ($p < 0.04$).[25] The other rows of the table present analogous regressions with the individual questions comprising the index, which suggest that the correlation is strongest for the component "Reading the Quran Daily". While "Observing Namaz (Prayer) 5 Times a Day" and "Not Drinking Alcohol" are also significant, the others are positively correlated but the correlation is not statistically significant.

Given the non-linearity in survey responses, Panel A of Appendix Table A1 uses an ordinal logit instead of a linear model. In this alternate specification, we regress each of the raw survey responses on the Maghrib dip measure. Appendix Table A1 also demonstrates a clear correlation between the survey responses and the Maghrib dip measure. Although the strength of some correlations differ from those observed in Table 1, these results also show that the strongest correlation exists for "Reading the Quran Daily".[26]

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

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

[25]The coefficient shows that a one SD increase in the survey index increases the Maghrib dip by 3.42, which represents a 44% increase above 7.85, the mean of the Maghrib dip measure in this regression.

[26]When using the ordinal logit model, we are unable to aggregate the survey responses into an index (since the aggregate itself would not be an ordered variable). Therefore in Panel B we again present OLS results, this time with the survey measures as the dependent variable. The index in the final column demonstrates the power gains from aggregating various outcomes.

Table 1: The Maghrib Dip and Survey Measures of Religiosity

	Maghrib Dip	
	Coef. (Std. Error)	N
Survey Religiosity Index	3.420**	1,041
	(1.675)	
Standardized components:		
Reading the Quran Daily	3.647***	1,041
	(1.405)	
Observing Namaz 5 times per day	2.266*	1,041
	(1.356)	
No Alcohol	2.397*	1,041
	(1.414)	
No Music	2.010	1,041
	(1.427)	
Fasting During Ramadan	2.194	1,041
	(1.413)	
Giving Zakat	1.918	1,041
	(1.350)	
District fixed effects?	Y	

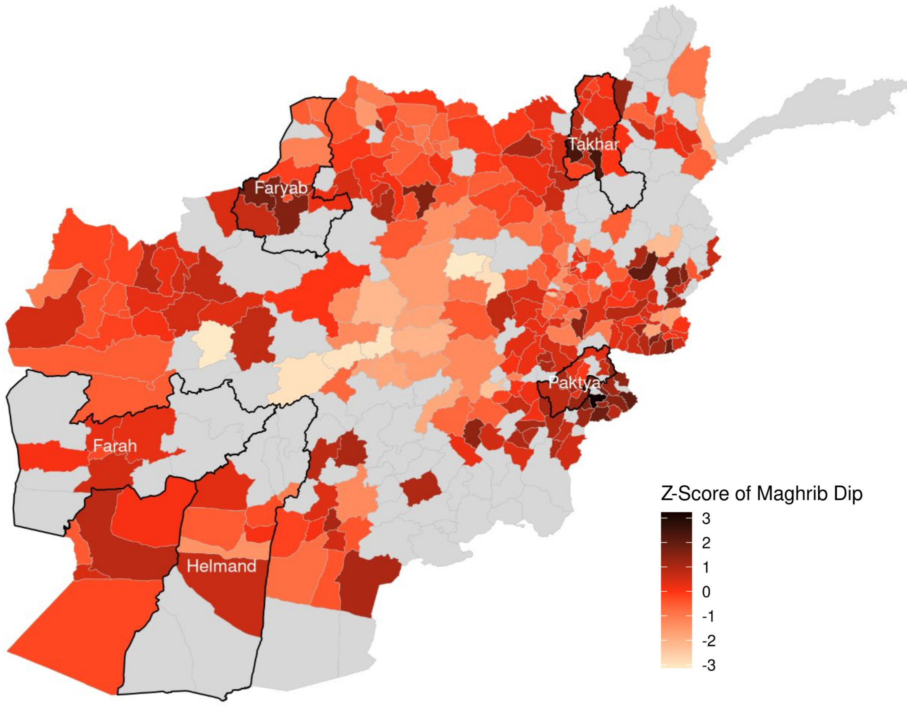
Notes: Each row is a different regression where the dependent variable is the Maghrib dip measure of religious adherence. The mean of this variable is 7.85 in all the regressions in this table. In the top row the independent variable is an index of responses to survey questions that ask about the importance 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. One observation is included for each surveyed individual. Robust standard errors shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Taken together, these results suggest that people who believe that Islamic religious practices are important 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 data on 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.

Figure 3 shows that many of the more religiously adherent provinces – such as Farah, Helmand, Faryab, Takhar and Paktya which are outlined in the map – were under Taliban control during this period. Since the Taliban strictly and often violently enforced religious norms, we expect these areas to display higher levels of religious adherence.

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 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. Provinces mentioned in the text are labeled with white lettering, and boundaries are outlined with a thick black line.

We test this visual intuition empirically, by measuring how the Maghrib dip varies when a region falls under Taliban control.[27] While the available data on Taliban control lacks the spatial and temporal granularity of our mobile phone data, it indicates, for every three months over 2015-2020, which districts were under Taliban control (defined as the district center being under the armed group's control) and which districts were instead contested, at risk of incursion by the Taliban, or fully under government control.

Among the districts in our CDR sample, 11 are cases in which the Taliban consolidated control – i.e., where the district remained consistently under Taliban's control after its initial

[27]We obtain data on Taliban control from a U.S. Government Information System called the Protected Internet Exchange (see `https://pixtoday.net`), which compiled sensitive information about conditions on the ground in Afghanistan for U.S. and Allied civilian and military personnel. These data are available starting August 2015, and span to the end of the period of our CDR sample period, October 2020.

takeover. Another 23 districts instead oscillated between the Taliban taking and losing control, fluctuating in their control status.

To examine how Taliban control shapes religiosity, in columns 1-4 of Appendix Table A2 we pool together the 11 consolidated districts with those that were never taken over by the Taliban, and regress the Maghrib dip on an indicator of when the armed group took control in these consolidated districts. These specifications progressively incorporate district and month fixed effects.

The table confirms the visual evidence presented in Figure 3. Column (4), for example, indicates that Taliban control corresponds to a .23 standard deviation increase in the Maghrib dip measure (significant at the 1% level). This significant relationship continues to hold in the next four columns when we additionally add in the oscillating districts, and control for their effect with an indicator that equals one for all periods after the first time the Taliban temporarily gained control of these districts. Oscillating districts appear to have a weaker, less robust relationship with the Maghrib dip measure. The pattern of results in Table A2 is consistent with the idea that the Taliban enforce religious norms where they consolidate control. More generally, the fact that the Maghrib dip is larger when the Taliban takes consistent control of an area helps validate the Maghrib dip as a measure of religious adherence.

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. Thus, it can 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 Economic Adversity Shapes Religious Adherence

Our second set of results illustrates how the Maghrib dip measure can be used to study consequential social and economic questions. Specifically, we investigate the impacts of economic hardship on religious adherence.

As noted in Section 1, the nature of this effect is conceptually ambiguous. There are several reasons why adverse economic shocks might cause an increase in religious adherence. First, negative income shocks may lower the opportunity cost of participating in religious activities through time use considerations (Azzi and Ehrenberg, 1975). Second, individuals may adhere more to religious practices for social insurance purposes, if displaying religious norms helps secure resources and support from their religious social network (Chen, 2010). Third, lower income security may lead to stronger religious beliefs, if people turn to religion when they either experience or expect negative outcomes. This could be for psychological reasons – i.e., if turning to God helps individuals cope (Bentzen, 2019, 2021), or if adverse events promote interdependence psychology (Henrich, 2020) or otherwise serve to strengthen social and religious norms (Winkler, 2021). This notion relates to the broader secularization hypothesis, which suggests that religious belief has its roots in fear and – more extremely – ignorance (Freud, 1927; Hume, 1757; Marx, 1970); thus the secularization hypothesis predicts that rising incomes and modernity will weaken religious belief while falling incomes will strengthen it (Weber, 1905; Wesley, 1760).

On the other hand, if people turn to religion with the expectation that God will insure them against economic shocks (Auriol et al., 2020), then experiencing adverse events may test and weaken their faith, leading them to moderate their religious beliefs and practices. Or, 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.

4.1 Empirical Strategy

Our empirical strategy is designed to estimate 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. This section provides background on how climate conditions affect the Afghan agricultural sector, describes how we measure climate shocks, and presents our estimation strategy.

Droughts and the agricultural sector in Afghanistan

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). Wheat 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).

Climate shocks have had stark implications for Afghanistan's agricultural sector. Temperatures have risen by 1.8°C since 1950, raising the frequency and severity of droughts (Climate Security Expert Network, 2019). There are two types of droughts which affect Afghanistan: 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 second drought risk is caused by reduced winter snowfall in the Hindu Kush mountains, which especially affects downstream irrigated areas through its impact on streams and rivers. However, this type of drought is more localized to areas dependent on the tributaries of the Hindu Kush mountains (UNEP, 2016).

Measuring droughts

We measure drought using the Standardized Precipitation - Evapotranspiration Index (SPEI), developed by Vicente-Serrano, Beguería, and López-Moreno (2010). The key idea behind the drought index is that the impact of rainfall on agriculture will depend not just on the amount of precipitation, but also on the soil's ability to retain water. This is determined by *poten-*

tial 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 performs better than other indices in predicting crop yields (Vicente-Serrano, Beguería, and López-Moreno, 2010), and has also been found to have predictive power on other outcomes such as conflict (Harari and La Ferrara, 2018).

The weather inputs we use are based on ERA-5 Land reanalysis data, which provide high-quality estimates of weather and energy cycles (Muñoz-Sabater et al., 2021). These inputs come in native units of 10 km x 10 km grid cells, which then serve as the geographic units of our analysis. The SPEI measures are expressed as standard deviations from the historical mean (calculated over the years 1981-2020). 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.

Since drought conditions in the current period are a function of precipitation conditions in the current and past periods, SPEI is constructed using moving averages over different timescales. We construct SPEI over three different timescales: 6 months, 9 months and 12 months. The 6-month timescale reflects short- and medium-run climate conditions over the course of an agricultural season.[28] The 9-month and 12-month timescales reflect longer-run conditions, and are also better suited for capturing snowmelt drought. In the analysis below, we analyze the impact of SPEI measured over all three timescales.[29]

Appendix Figure A6 maps the SPEI measures in Afghanistan. The top panel shows the average for our entire sample period. The bottom panel shows the same for 2018 – a year in which there was a particularly severe drought in the country.

Econometric Specification

To examine the relationship between climate shocks and religious adherence, we first measure the Maghrib dip in outgoing calls for each 10km x 10km grid cell (the native resolution of the

[28] For example, the growing season for wheat, Afghanistan's largest crop, stretches from December to April.

[29] We interchangeably reference these measures using one of two conventions – i.e., SPEI (6 months) or SPEI-6.

SPEI data), separately for each month.[30] We then estimate the following panel fixed-effects model:

$$d_{gm} = \alpha_g + \theta_m + \beta SPEI_{gm}^T + \varepsilon_{gm} \tag{2}$$

where d_{gm} is the Maghrib dip in grid cell g and month m; α_g are grid-cell fixed effects; θ_m are month fixed effects; and $SPEI^T$ is the SPEI measure for one of T timescales (6-, 9-, or 12-month). In Equation (2), β is the coefficient of interest, which indicates how precipitation conditions relate to religious adherence.

In some specifications, we wish to test whether precipitation conditions have differential effects in grid cells with agricultural activities 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 which directly precedes our sample period). To study this heterogeneity, we estimate:

$$d_{gm} = \alpha_g + \theta_m + \beta \mathrm{SPEI}_{gm}^T + \gamma\big(\mathrm{SPEI}_{gm}^T * \mathrm{AG}_g\big) + \rho\big(\mathrm{SPEI}_{gm}^T * \mathrm{OTH}_g\big) + \varepsilon_{gm} \tag{3}$$

where AG_g is the fraction of the grid cell engaged in the most rain-sensitive agricultural activities (i.e., rangeland and croplands in some specifications, and rainfed and irrigated croplands in others) and OTH_g is the fraction of other land types (forest, fruit trees and vineyards, barren areas, water bodies and marshland). Since we control for the interaction of SPEI with these other land types, our estimates of γ capture the differential effect of precipitation conditions on croplands and rangelands relative to built-up (urban) areas. When estimating Equations (2) and (3), we cluster the standard errors at the grid-cell level in our main specifications, and at the district level in further robustness tests.

Appendix Table A3 presents descriptive statistics of the key variables that are used in our analysis and which appear in the main tables. Appendix Table A4 summarizes additional variables that are used for robustness checks later in the paper.

[30] To do so, we calculate each tower's total call volume on each day during the 30-minute windows immediately pre- and post-Mahghrib, 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, to compute the Maghrib dip at the grid cell month level we take the mean of these (average daily) call volumes across all towers that are in each grid cell, separately for each month.

4.2 Results

This section presents our findings on the impact of climate shocks on religious adherence. We first show the empirical results, then provide a large number of robustness tests, then conclude with a discussion of the possible mechanisms underlying the observed effects.

Main Results

Table 2 provides our estimates of the effect of climate shocks, measured at three different timescales, on religious adherence. The coefficients indicate that there is a significant negative relationship between all three measures of 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.

Table 2: Climate and Religious Adherence

	Maghrib Dip		
	(1)	(2)	(3)
SPEI (6 months)	-0.290***		
	(0.100)		
SPEI (9 months)		-0.353***	
		(0.114)	
SPEI (12 months)			-0.342***
			(0.126)
Obs.	35579	35579	35579
Grid cell fixed effects?	Y	Y	Y
Month fixed effects?	Y	Y	Y

Notes: Each column is a regression of the Maghrib dip measure of religious adherence on different versions of the Standardized Precipitation-Evapotranspiration Index (SPEI). Positive values of the Maghrib dip indicate more religious adherence; positive values of SPEI indicate more precipitation relative to the historical mean. (Negative coefficients indicate favorable precipitation reduces religious adherence). One observation is included for each month for each 10km X 10km grid cell. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Since the Maghrib dip is measured in units that do not have a natural interpretation, we provide intuition for the magnitude of these effects by comparing changes associated with SPEI to changes associated with other factors that also affect religious adherence. In particular, we compare the results in Table 2 to changes in the Maghrib dip associated with the Taliban consolidating control over a district. First, we consider the effect of a one SD fall in SPEI-9 (-.86), which corresponds to a moderate-sized drought. The coefficient in column (2) tells us that a fall of this magnitude increases religious adherence by 10% as much as when the Taliban take ocontrol of an area.[31] Second, we consider the effect of a major drought, such as the one that afflicted Afghanistan in 2018 (depicted in Appendix Figure A6 and described in Section 4.1). To do so, we calculate the average SPEI-9 for the bottom third of the grid cell-months that were most drought-affected in 2018 – i.e., that ranked lowest in terms of SPEI-9 values that year. We find these grid cell-months to have a mean SPEI-9 value of -1.64. The coefficient in column (2) implies that a change in SPEI-9 of this magnitude increases religious adherence by approximately 18% as much as the Taliban effect.

Robustness Checks

Our main results in Table 1 remain qualitatively unchanged when subjected to a number of different robustness checks. First, Appendix Table A5 shows that the results are robust to measuring changes in call volume over different time windows, including 25-, 35-, and 40-minute intervals around the start of the Maghrib window. Appendix Table A6 additionally shows that the results are unchanged when the Maghrib dip is constructed in a variety of alternative ways. In the first three columns of this table, we scale the change in call volume 30 minutes before and after Maghrib using the average call volume over this entire one-hour period (rather than just the 30 minutes before, as in Equation (1)). In the remaining columns, we take the inverse hyperbolic sine (IHS) transform of the ratio of the call volume in the 30 minutes before over 30 minutes after Maghrib, to better account for potential outliers. We find that the results are robust across these specifications.

Next, in Appendix Table A7, we incorporate additional controls that may affect our mea-

[31]The coefficient multiplied by a one SD fall in SPEI (-.353 x -.86) implies that the Maghrib dip would increase by .31. As shown in both columns (2) and (4) of Appendix Table A2, when the Taliban take control of an area, the Maghrib dip increases by 3.2. Scaling .31 by 3.2 indicates that the one SD SPEI effect is 10% as large as the Taliban effect.

surement of the Maghrib dip outcome. Since religious adherence may be serially correlated, in columns 1-3 we control for a one-period lag of the measure. In columns 4-6, we control for the total daily call volume, which accounts for time-varying factors related to population and network size. Incorporating this control also addresses the concern that the magnitude of the dip may be mechanically related to the extent of call volume in the location, including in the pre-Maghrib period. We find our results unchanged with these additional controls.

To further explore if variation in the density of mobile phone users across towers affects our results, Appendix Table A8 examines robustness across samples that vary in the number of subscribers (in columns 1-3) and call volume (in columns 4-6). Specifically, we calculate the total number of subscribers and total call volume for each grid cell over 2013-2015 (the beginning of our sample period), and drop the 5%, 10%, and 25% most sparse grid cells based on these two measures. We then estimate Equation (1) over 2016-2020. We find that the results remain unchanged across these specifications, which verifies that sparsity in some towers does not affect our estimates.[32]

In Appendix Table A9, we show robustness to other changes in the sample. Major urban centers such as Kabul may differ from other locations in a number of ways, including the density of mobile phone users, as well as factors such as the underlying levels of religious adherence. To verify that the results are not driven by these types of locations, we drop urban areas and find the results unchanged (columns 1-3).[33] Since the Shia Maghrib prayer window differs from the Sunni window, in columns 4-6 we additionally verify that our results continue to hold when we drop districts that have sizable Shia populations as proxied by the presence of villages in which the Hazara constitute the majority ethnic group.[34]

We also check whether precipitation shocks lead to changes in religious behavior only in locations where the Taliban are in control and thus able to enforce strict religious norms. To examine this, columns 7-9 of Appendix Table A9 drops districts that fell under Taliban

[32] These checks look the same if we instead calculate the sparsity on the basis of other periods (e.g., if we define sparsity based on the 2013-2014 period, and examine effects over 2015-2020.)

[33] We define areas as urban if more than 5% of the grid cell constitutes built-up area based on land cover data from the Food and Agriculture Organization. Approximately 19% of our grid cells are considered urban under this definition.

[34] 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.

over 2015-2020.[35] We find that our coefficients remain unchanged in the sub-sample of non-Taliban areas. This suggests that increases in religious adherence arising from economic shocks are a broader phenomenon beyond coerced adherence to religious norms. In addition, this suggests that drought does not lead to greater religious adherence solely because those facing economic hardship signal greater religiosity in order to gain social assistance from religious authorities – a point to which we return in the next sub-section.

Finally, in Appendix Table A10, we consider an alternative approach to inference: We cluster the standard errors at the district level, which accounts for the possibility that the errors may be correlated across grid cells within a district. We again find our results unchanged.

Why Do Climate Shocks Increase Religious Adherence?

The analysis presented above indicates that climate shocks lead to an increase in religious adherence. In this section, we examine the potential mechanisms underlying this effect. Our leading conjecture is that climate affects religiosity through economic channels; in other words, climate shocks have negative economic impacts, which in turn lead people to become more religiously adherent. Here, we present evidence in support of this conjecture, attempt to disentangle the different economic mechanisms that might be at play, and then discuss potential alternative accounts for our results.

The Economic Channel Important evidence in support of the economic channel comes from our analysis of spatial heterogeneity in how climate affects religious adherence. In particular, Table 3 disaggregates the main effects of climate by land cultivation type. In the odd-numbered columns, we observe that the negative effects of climate are concentrated in locations where droughts are most likely to harm economic production – namely, cropland areas where droughts can reduce agricultural output, and rangeland areas, where droughts can affect pastoralism through factors such as the availability of water and feed. For example, the coefficient on SPEI (9 months) X Cropland implies that moving from the 10th to 90th percentile of the cropland distribution increases the effect of the major drought in 2018

[35] Specifically, 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.

from 2% to 58% of the effect of being under Taliban control. The even-numbered columns of Table 3 drill down further by disaggregating cropland areas into rainfed areas (which are most susceptible to rainfall shocks) and irrigated lands (which are more resilient to drought). Here, we observe again that the effects of climate shocks are most pronounced in the agricultural areas that are most dependent on rainfall.

We also find direct evidence that climate shocks – in general, and especially in rainfall-dependent agricultural areas – reduce agricultural output. The climate-output relationship has been extensively documented in prior work (for two recent examples, see Schlenker and Lobell (2010) and Lobell, Schlenker, and Costa-Roberts (2011)) and is not our primary focus. Rather, we view it as a specification test of sorts, to help ensure that our climate models are capturing variation that meaningfully impacts economic production, and to confirm the intuition behind the economic channel by verifying that climate-induced changes in religiosity correspond (spatially) to climate-induced changes in economic output. Thus, Appendix Tables A11 and A12 replicate the analysis in Tables 2 and 3, using a measure of agricultural output as the dependent variable. Since no granular (sub-province) data exist for agricultural production in Afghanistan, we proxy for output using a satellite-based vegetation index, the Enhanced Vegetation Index (EVI), measured over the primary growing season.[36] As expected, the three different measures of SPEI all significantly affect satellite-measured vegetation (Appendix Table A11), and these effects specifically are concentrated in rainfed croplands (Appendix Table A12).

The preceding results are consistent with the interpretation that the economic consequences of drought play a role in increasing religious adherence, but also beg the question, *why* does economic hardship lead to greater adherence? We consider three distinct conceptual reasons. First, economic shocks could lower the opportunity cost of time. In particular, when realized income is lower (and when there is less agricultural work to be done), people may engage more in religious activities based on a lower value of time (Azzi and Ehrenberg, 1975).[37] Second, social insurance may play a role. Religious organizations can play a critical

[36] Specifically, we adapt the approach of Asher and Novosad (2020): we subtract out the early growing season value (in December) from the maximum growing season value, which controls for differences in non-crop vegetation. December - April corresponds to the major growing season for most important crops in Afghanistan, including wheat, the country's single most important crop (Tiwari et al., 2020).

[37] The opportunity cost of time could also increase during drought, if labor can be used to compensate for

Table 3: Climate and Religious Adherence by Land Type

	Maghrib Dip					
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI (6 months)	0.741	0.509				
	(0.456)	(0.460)				
SPEI (6 months) x Cropland	-1.251**	-				
	(0.580)	-				
SPEI (6 months) x Rainfed Cropland	-	-1.379**				
	-	(0.587)				
SPEI (6 months) x Irrigated Cropland	-	-0.777				
	-	(0.633)				
SPEI (6 months) x Rangeland	-0.869*	-0.607				
	(0.500)	(0.517)				
SPEI (9 months)			0.926*	0.603		
			(0.536)	(0.533)		
SPEI (9 months) x Cropland			-1.553**	-		
			(0.671)	-		
SPEI (9 months) x Rainfed Cropland			-	-1.761***		
			-	(0.673)		
SPEI (9 months) x Irrigated Cropland			-	-0.892		
			-	(0.721)		
SPEI (9 months) x Rangeland			-1.278**	-0.912		
			(0.574)	(0.585)		
SPEI (12 months)					1.195**	0.748
					(0.595)	(0.577)
SPEI (12 months) x Cropland					-1.946***	-
					(0.743)	-
SPEI (12 months) x Rainfed Cropland					-	-2.271***
					-	(0.732)
SPEI (12 months) x Irrigated Cropland					-	-1.033
					-	(0.781)
SPEI (12 months) x Rangeland					-1.571**	-1.068*
					(0.625)	(0.622)
Obs.	35466	35466	35466	35466	35466	35466
Grid cell fixed effects?	Y	Y	Y	Y	Y	Y
Month fixed effects?	Y	Y	Y	Y	Y	Y
Controls – Other land types?	Y	Y	Y	Y	Y	Y

Notes: Each column is a regression of the Maghrib dip measure of religious adherence on different versions of the Standardized Precipitation-Evapotranspiration Index (SPEI) and the interactions of the SPEI measures with the fraction of the grid cell containing cropland and rangeland (in columns 1, 3, and 5) or containing rainfed cropland, irrigated cropland, and rangeland (in columns 2, 4, and 6). Controls for other land types include interactions of the SPEI measures with the fraction of the grid cell containing forest cover, fruit trees and vineyards, barren areas, water bodies, and marshland. The omitted category is built-up (urban) areas. Positive values of the Maghrib dip indicate more religious adherence; positive values of SPEI indicate more precipitation relative to the historical mean. (Negative coefficients on SPEI interacted with an area indicate favorable precipitation reduces religious adherence more in these areas relative to urban areas). One observation is included for each month for each 10km X 10km grid cell. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

role in facilitating social insurance (Ager and Ciccone, 2018; Auriol et al., 2020; Chen, 2010; Dehejia, DeLeire, and Luttmer, 2007); thus when people experience an adverse shock, they may wish to send a public signal that they are religious in order to secure material resources from these religious groups (Chen, 2010).[38] Third, the secularization idea – that humans turn to religion in response to emotions such as fear (Freud, 1927; Hume, 1757) – may also be at play.[39] In particular, people may become more adherent when they experience or expect negative outcomes (Marx, 1970; Weber, 1905; Wesley, 1760), or, conversely, become less adherent when things go well.

Although we are not able to present definitive evidence in favor of a single economic channel, we provide suggestive evidence indicating that the opportunity cost mechanism and social insurance motivations are unlikely to be major factors in our institutional context. Our main evidence against opportunity costs comes from disaggregating our analysis according to the cropping cycle of Afghanistan. For this analysis, we focus on the wheat harvest, since wheat is Afghanistan's most dominant crop and is grown in every province. When we disaggregate by season, we find that the Maghrib dip itself – irrespective of climate shocks – is generally *largest* during the harvest season compared to the other two seasons.[40] Since agricultural labor is most intensive during the harvest period, the fact that people are, if anything, more adherent during harvest suggests that the opportunity cost of time is not a major determinant of adherence in Afghanistan.

More pointedly, we find in Table 4 that adverse climate shocks during the growing season (December-April) – which is the period where SPEI matters most for agricultural yield

lower rainfall.

[38]As with the opportunity cost of time, the extent to which we should expect to observe this type of response is theoretically ambiguous. For example, if the club has achieved a separating equilibrium between low and high religious types, high types (who are club members) will anticipate potential free-riding by low types (who are not members), and seek to maintain separation. When adverse shocks occur, club members may increase the entry cost for non-members by, for instance, increasing religious prohibitions or expected sacrifices (Berman, 2000). Subsequently, non-members may or may not choose to enter, depending on their utility gains from acquiring the club good (i.e., social insurance) and their utility losses from adhering to more costly religious norms (Iannaccone, 1992). Thus, higher prohibitions in the wake of shocks may discourage non-members from attempting to enter the club by signaling religiosity.

[39]Psychologically, this mechanism might arise if religion serves as a means of coping with fear (Bentzen, 2019, 2021); or, as evolutionary psychologists hold, because humans have evolved in a way that leads to tighter norms (such as religiosity) in response to adverse shocks (Henrich, 2020; Winkler, 2021).

[40]For example, after removing Ramadan, the Maghrib dip is 10.4, 10.7, and 8.2 in the growing, harvest, and post-harvest seasons, respectively.

– increase religious adherence during both the growing and *post*-harvest seasons (August-September), but have no effect on adherence during the harvest season (May-July).[41] The pattern of results in Table 4 is difficult to reconcile with the opportunity cost mechanism. In particular, if religious adherence responded mainly to time use considerations, we would expect larger effects during harvest, when growing season SPEI creates the greatest variation in how much work there is to be completed. Instead, 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 bad weather 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 the potential for social insurance considerations to be driving the religious response to climate shocks, we consider an additional test. In particular, if individuals adhere to religious norms solely in order to send a public signal to their social insurance network, then we would not expect climate shocks to have much influence on private behavior that is less easily observed by the social network. To test this intuition, we replicate the analysis in Table 2 using only shortcode calls to measure the Maghrib dip. As discussed in Section 3.2, most shortcode interactions are either automated or conducted with a representative who is unknown to the caller. Thus, in principle, individuals could continue to make these calls without damaging their prospects of acquiring social insurance.

[41] Table 4 uses the 9-month measure of SPEI, but results are unchanged when using 6-month or 12-month SPEI (Appendix Table A13). All specifications are run at the grid cell-year level, and include grid cell and year fixed effects. Different columns correspond to different sets of control variables: columns 2-3 control for SPEI during the harvest and post-harvest seasons; columns 4-6 also control for the Maghrib dip in the previous 9 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 the holy month of Ramadan, since religious adherence is particularly high during this period, and since Ramadan overlaps primarily with the harvest season.

Table 4: Climate and Religious Adherence by Agricultural Season

	Maghrib Dip in:			*Maghrib Dip in:*			*Maghrib Dip in:*		
	Growing Season	Harvest Season	Post-harvest Season	Growing Season	Harvest Season	Post-harvest Season	Growing Season	Harvest Season	Post-harvest Season
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Growing Season SPEI (9 mo)	-0.398*	0.122	-0.467*	-0.535**	0.259	-0.741***	-0.567***	-0.004	-0.737***
	(0.222)	(0.234)	(0.240)	(0.210)	(0.245)	(0.269)	(0.210)	(0.276)	(0.278)
Obs.	3118	3118	3118	2673	2673	2673	2667	2667	2667
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 (9 mo)?	-	Y	Y	-	Y	Y	-	Y	Y
Control for Maghrib Dip – Prev. 9 mo?				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-9 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. Columns 1-3 control for SPEI in the harvest and post-harvest seasons. Columns 4-6 also control for the average Maghrib dip over the previous 9 months. Columns 7-9 drop Ramadan days that fall within each season. 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.

Results in Appendix Table A14, estimated using only shortcode calls (which comprise just 3.4% of all calls), are qualitatively similar to the results based on all outgoing calls in Table 2. Benchmarking the effects in Appendix Table A14 against the reduction in shortcode calls when the Taliban take over a district, we find that a one SD drop in SPEI-9 increases (private) religious adherence by 13% as much as Taliban control – an effect roughly similar to the 10% effect found in Table 2. These results suggest that when adverse shocks occur, individuals become more religiously adherent, even lowering phone calls during the Maghrib prayer window that others in their social circles cannot observe. These effects on private religious adherence suggest that outward-facing, public motivations such as social insurance cannot be the sole driver of our estimated effects.[42]

In summary, in this section we find evidence that climate shocks affect religious adherence through their economic impact on agricultural production. The estimated effects are largest in areas where precipitation can harm agricultural output, such as rainfed croplands. The effects of growing season climate conditions are also largest in both the growing season (when people may pray for divine intervention) and the season after the harvest (when incomes are realized). These results are consistent with the idea that economic adversity shapes religious behavior as individuals turn to religion to cope with adverse 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, drug crop production, and the role of

[42] While superficially this result differs from Chen (2010), who finds that social insurance can help explain changes in religious adherence after the Indonesian financial crisis, there are many contextual differences. For instance, we examine adherence to the Maghrib prayer norm, a core requirement of Islam, in one of the most religious countries in the world. In contrast, Chen (2010) examines Koranic study, a religious activity that extends beyond the basic prayer norm, in a country that is less religious than Afghanistan. It is possible that Koranic study in Indonesia crosses a threshold of devotion required for entry into religious networks, while adherence to the prayer norm does not cross the required threshold for access to religious clubs and hence the club good of social insurance in Afghanistan. Relatedly, social insurance may be allocated by the Taliban in Afghanistan, but allocated in a more decentralized manner by community members in Indonesia; and compliance to the prayer norm may be particularly insufficient for access to club goods like social insurance if it is allocated by extremist groups like the Taliban.

violent conflict.

First, a number of papers have suggested that weather conditions affect mood (Cunningham, 1979; Denissen et al., 2008; Eagles, 1994; Hannak et al., 2012; Sanders and Brizzolara, 1982). If mood also determines religious adherence, our main results (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 Table 3, 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).

Second, if droughts create liquidity constraints, it is possible that call volumes may fall because people cannot afford to make 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 the SPEI measures. Appendix Table A15 shows that the coefficients are negative (and significant for SPEI-6 and SPEI-9), indicating that call volumes are, if anything, *larger* when economic conditions are less favorable. Thus, we do not see evidence that adverse shocks lower overall call activity.

Third, if drought conditions cause substantial out-migration, we might be concerned that compositional effects in who stays and who leaves may affect our results. For example, if those who leave are less religious, we might overestimate effects on religious adherence. A nice feature of the cell phone data is that we can use the number of unique subscribers (i.e., those making phone calls) as a rough proxy for the number of individuals residing in an area. Because some users may be transient (i.e., make phone calls while traveling through a location), we separately consider (i) the number of users in an area; and (ii) the number of users who have made at least five phone calls over the past month in an area, which we consider to be a more reliable indicator of the number of residents. Appendix Table A16 indicates that we do not see consistent evidence that SPEI affects migration. There is a weak relationship between the number of subscribers and SPEI-12, specifically, but this effect is not significant when we consider the more robust measure. Thus, compositional changes stemming from migration are unlikely to be driving our estimates.

Next, we 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 A9 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-level data on poppy cultivation from the UNODC (2021).[43] In Appendix Table A17, we estimate a district-level specification in which we regress the poppy outcome on SPEI, controlling for district and month fixed effects. We do not observe any significant effects, which suggests that the SPEI measures do not lead to increased opium cultivation. In Appendix Table A18, we then re-estimate Equation (2) but additionally control for poppy.[44] Incorporating this control also does not alter the estimates in any way. Although the data on poppy cultivation may well be noisy, these additional tests suggest that increased poppy cultivation is unlikely to drive the observed effects on religious adherence.

Finally, we consider the role of conflict. Several studies find that rainfall shocks (Miguel, Satyanath, and Sergenti, 2004; Sarsons, 2015) and other climate shocks (Couttenier and Soubeyran, 2014; Eberle, Rohner, and Thoenig, 2020; Harari and La Ferrara, 2018; McGuirk and Nunn, 2020) lead to violent conflict.[45] Conflict, in turn, may affect religiosity (Henrich et al., 2019). This creates the possibility that conflict could serve as another channel behind our findings. To test this possibility, we utilize geo-coded data on conflict events from

[43]While this is the best available data on poppy cultivation in Afghanistan, a great deal of observations (approximately 41%) 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.

[44]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.

[45]These studies estimate effects of different magnitudes and posit different mechanisms, and the strength of the relationship has been the subject of academic debate. See Burke, Hsiang, and Miguel (2015) for a review and meta-analysis and Buhaug et al. (2014) and Ciccone (2011) for commentary.

UCDP/PRIO to create indicators of whether a grid cell experienced any conflict event over two periods: 2003-2012 (the period preceding our sample period); and 2003-2020 (which covers both the pre- and sample periods).[46] Appendix Table A19 presents results showing the relationship between SPEI and religiosity, separately for grid cells that did and did not experience conflict during these two time periods. If conflict were driving the relationship, we would expect to observe stronger effects in locations that experienced conflict. Instead, we observe that the effects are larger and statistically significant in the grid cells without conflict (i.e., the left side of the table); and smaller and statistically insignificant in the locations that did experience conflict (i.e., the right side of the table).[47] These estimates indicate that adverse climate conditions lead to especially pronounced increases in religious behavior in locations that did not experience conflict. Overall, these results suggest that the effects of climate shocks on religious adherence are not mediated by conflict.

5 Conclusion

In this paper, we develop a new measure of religious adherence using anonymized mobile phone transaction records, and use it to address an important question about the economic determinants of religiosity. 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 circumvents many of the limitations of existing survey-based measures of religious practice: It is based on revealed rather than stated preferences; it can be collected at the scale of entire countries at relatively low cost; and it can provide granular measures of religious adherence in both time (e.g., monthly) and space (e.g., sub-district).

[46] We use the 2021 version of the UCDP/PRIO Armed Conflict Dataset (Sundberg and Melander, 2013), an event-based data source that tracks violent events on the basis of news sources. We generate conflict measures starting in 2003, the first year that the dataset tracks events involving the Taliban as an armed group, which demarcates the phase of conflict that is most relevant for our study period.

[47] A challenge with this approach is that the UCDP/PRIO data only provide the precise location for 42% of conflict events. It is thus possible that some grid cells that we regard as having "No Confirmed Conflict" may have actually experienced conflict over this period. To address this potential concern around false negatives, we also test whether *districts* with confirmed conflict have stronger effects than districts without confirmed conflict – which allows us to include 79% of the events for which at least the district location is known. When splitting the sample by this definition, we continue to find that the effects in the "No Confirmed Conflict" districts are, if anything, larger than the effects in "Confirmed Conflict" districts. These additional results are available upon request.

We demonstrate the power of the new measure by studying how economic adversity has shaped religious behavior in Afghanistan. This analysis exploits random variation in weather over time at the level of 10 km x 10 km grid cells, and estimates the causal effect of climate shocks on religious adherence. We show that droughts intensify religious observance: When economic conditions worsen, people become more adherent.

The mobile phone data can also provide unique insight into *why* economic adversity increases religiosity. In particular, we find that it is not just publicly observable behaviors (such as inter-personal phone calls) that fall during the Maghrib window; rather, more private phone-based activity (such as calls to automated shortcodes) also display a similar drop. And, when economic shocks occur, this more private measure of religious adherence likewise increases – suggesting that people are not becoming more adherent just to appear more religious to others, but that private motivations play an important role in shaping how they respond to adversity.

While the focus of our empirical analysis is on religiosity in Afghanistan, this general framework may be relevant to a wide range of contexts where anonymized digital transaction logs can be obtained. 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. We expect that similar fine-grained measures of religious adherence could facilitate the study of religion in other Muslim countries, as well as in environments with different religious norms, such as Sabbath observance by Orthodox Jews. And while we focus on mobile phone transactions because cell phones are the most widely used digital technology in Afghanistan, in other contexts, social media or other 'digital trace' datasets might be more suitable or easy to obtain. Our study documents how the Maghrib Dip measure can provide insight into religious adherence in Afghanistan; we hope this effort can help inspire new and diverse approaches to studying the causes and consequences of religion worldwide.

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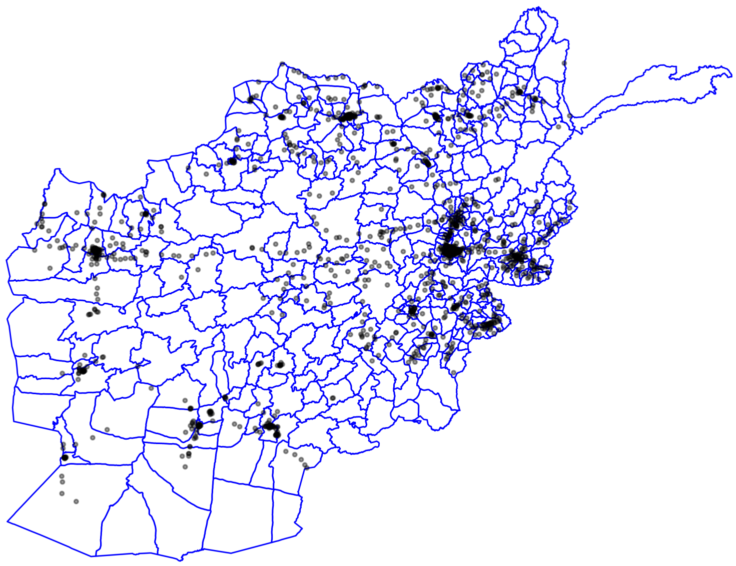
Appendices

A Appendix figures and tables

Figure A1: Poster Prohibiting Cell Phone Use

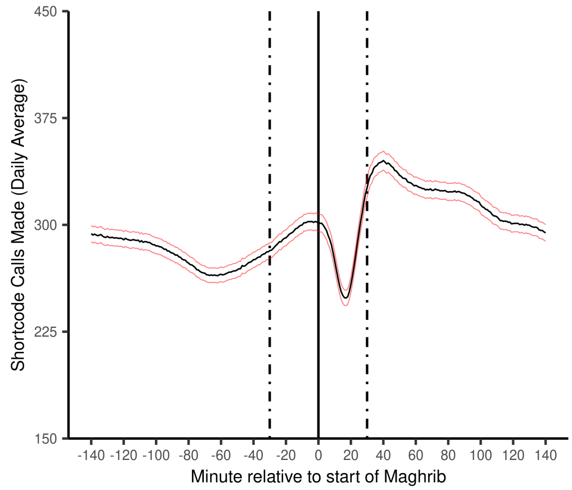
Notes: Poster found in Hounslow Muslim Centre. See here.

Figure A2: Cellphone Towers in our Sample



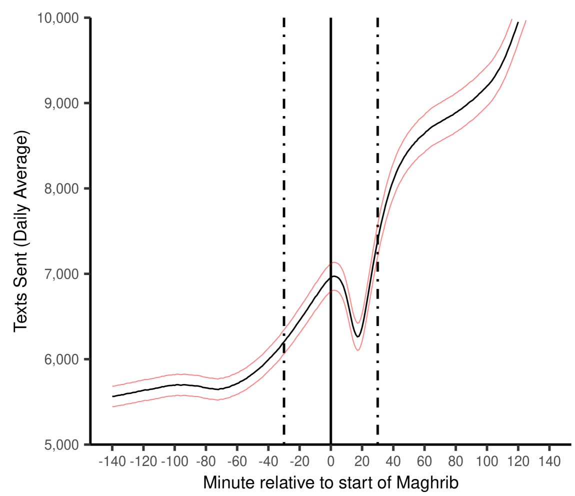
Notes: This figure shows the location of the cellphone towers in our sample, along with district boundaries in blue.

Figure A3: Text Messages, Mobile Data transactions and Shortcode Calls around the Maghrib Window



(a) Shortcode Calls

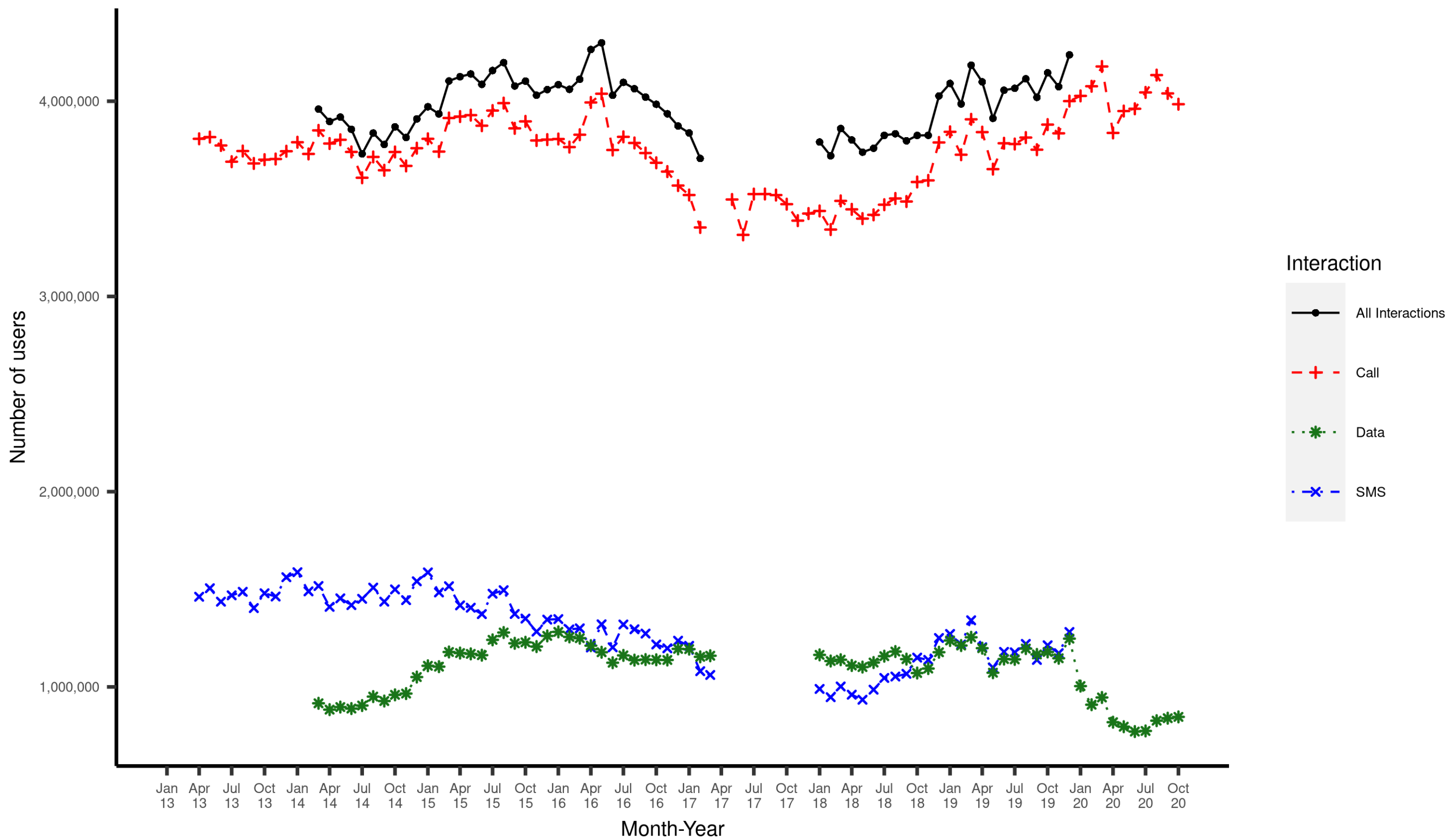
(b) Data Transactions



(c) Text Messages

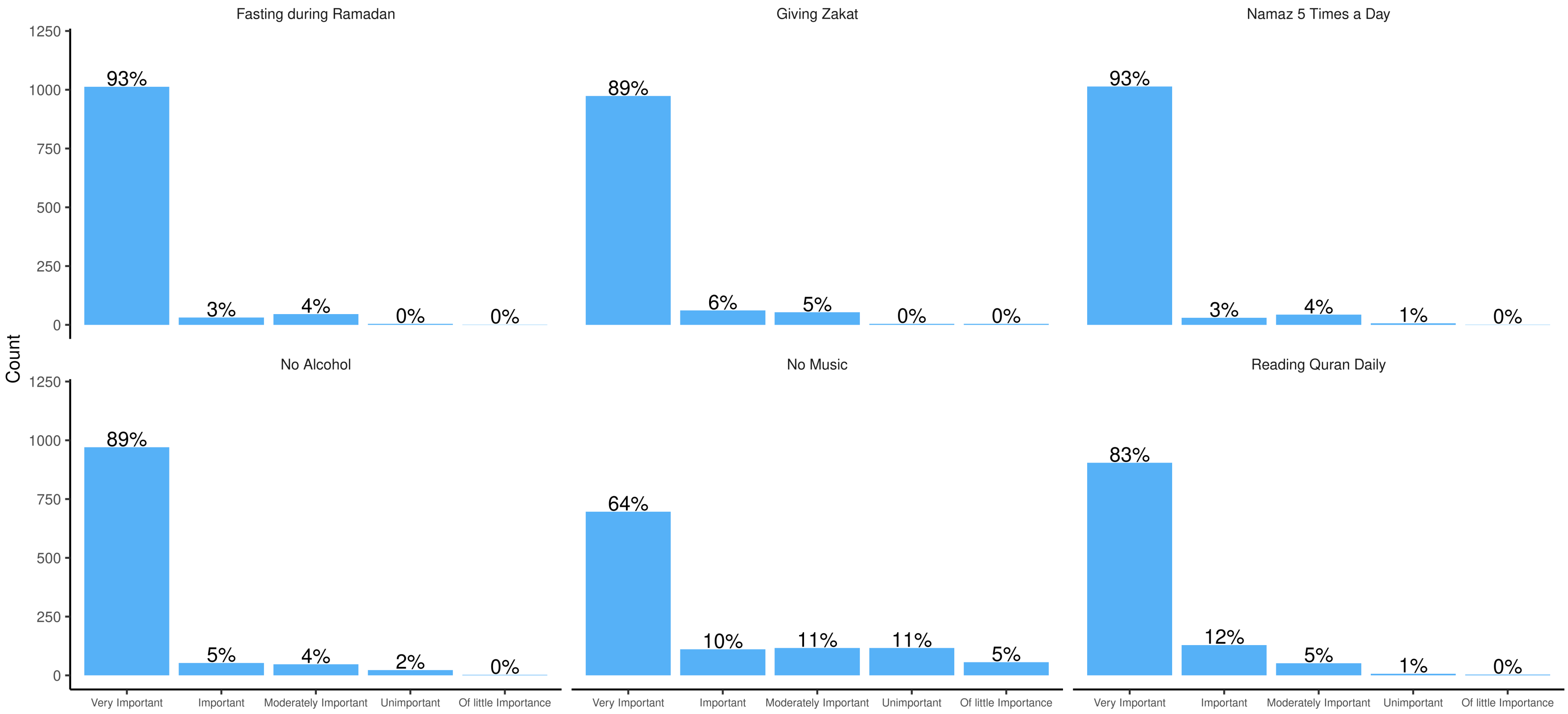
Notes: Panel A plots the average number of calls to shortcode numbers in each minute defined relative to the start of Maghrib, zooming in on the 140 minutes before and after the start of the prayer window. Panel B plots the average number of data packets transacted in each of these minutes. Panel C plots 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



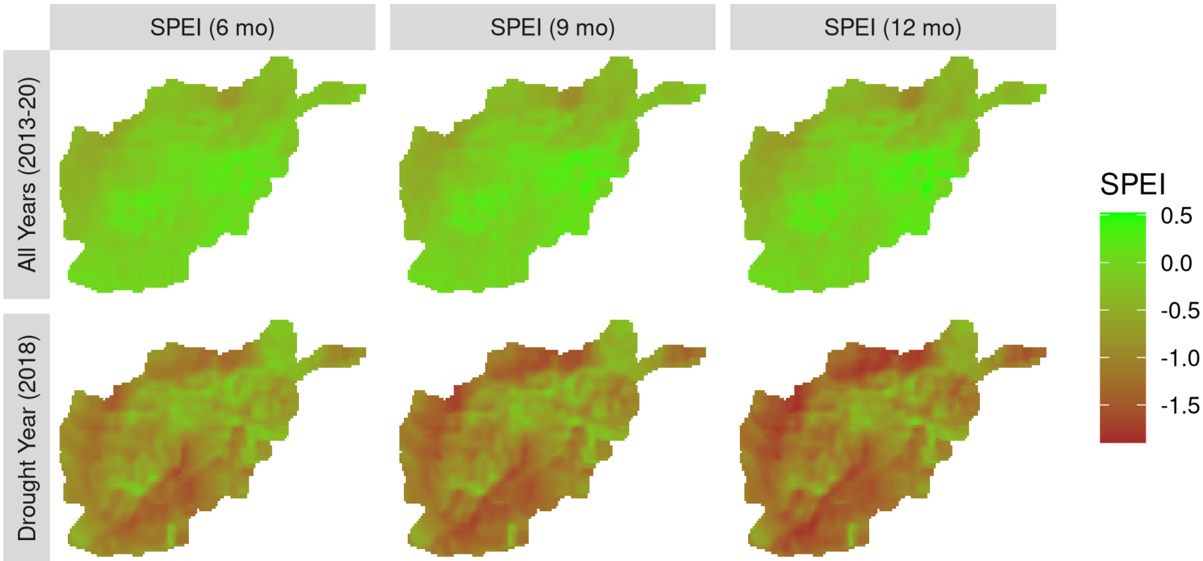
Notes: This figure plots the number of mobile phone users in each month of our data. The total number of users is shown for every month for which we have data for every type of user (phone, text and data).

Figure A5: Survey Responses on Religiosity Questions



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: SPEI Measures in Afghanistan



Notes: This figure maps the SPEI measures calculated over the 6, 9 and 12 month timescales. The top row shows the average over the entire sample period. The bottom row shows the measures for 2018, a year in which much of Afghanistan experienced a major drought.

Table A1: The Maghrib Dip and Survey Measures of Religiosity: Alternate Specifications

	Reading the Quran Daily	Observing Namaz 5 times per day	No Alcohol	No Music	Fasting during Ramadan	Giving Zakat	Survey Religiosity Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A: Ordinal Logit			
Maghrib Dip	0.005***	0.003	0.002	0.002	0.005*	0.002	-
	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)	-
				Panel B: OLS			
Maghrib Dip	0.002**	0.001	0.001*	0.001	0.001	0.001	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs.	1041	1041	1041	1041	1041	1041	1041
District fixed effects?	Y	Y	Y	Y	Y	Y	Y

Notes: Each column presents a different regression. Panel A presents Ordinal Logit regressions in which the dependent variables are response to questions that ask "How important are the following practices to you?" and responses are coded as "5=Very important", "4=Important", "3=Moderately important", "2=Unimportant" and "1=Of little importance". Panel B presents OLS regressions in which the responses of 4 and 5 have been grouped together into an indicator, and converted to Z-scores. The dependent variable in columns 1-6 are these Z-scores, while the dependent variable in column 7 is the mean effect index formed using these Z-scores. All regressions include district fixed effects. Robust standard errors shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A2: The Correlation between Taliban Control and the Maghrib Dip

	Maghrib Dip (Z-score)	Maghrib Dip	Maghrib Dip (Z-score)	Maghrib Dip	Maghrib Dip (Z-score)	Maghrib Dip	Maghrib Dip (Z-score)	Maghrib Dip
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Taliban Control	0.317***	4.347***	0.233***	3.202***	0.317***	4.347***	0.236***	3.238***
	(0.075)	(1.025)	(0.068)	(0.940)	(0.075)	(1.025)	(0.068)	(0.937)
Oscillating Control					0.145***	1.996***	-0.057	-0.782
					(0.054)	(0.742)	(0.048)	(0.663)
Obs.	13383	13383	13383	13383	14350	14350	14350	14350
District fixed effects?	Y	Y	Y	Y	Y	Y	Y	Y
Month fixed effects?			Y	Y			Y	Y
Oscillating districts included?					Y	Y	Y	Y

Notes: Each column presents a different regression. One observation is included for each month for each district. The dependent variable in odd-numbered columns is the standardized Maghrib Dip measure. The dependent variable in even-numbered columns is the un-standardized Maghrib Dip measure. "Taliban Control" equals one after a district falls under Taliban control, for the districts that remain consistently under Taliban control for the duration of the sample period. "Oscillating Control" equals one after the first period in which the Taliban take control of a district, for the districts that subsequently oscillate in and out of Taliban control. Standard errors clustered at district level in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A3: Summary Statistics of Main Variables

	Mean	Sd	Min	Max	Obs.
	(1)	(2)	(3)	(4)	(5)
A. Variables at grid-cell month level					
Maghrib Dip	12.081	14.688	-89.513	100.000	35579
SPEI (6 month timescale)	-0.138	0.887	-2.788	2.327	35579
SPEI (9 month timescale)	-0.145	0.858	-2.693	2.214	35579
SPEI (12 month timescale)	-0.150	0.846	-2.793	2.313	35579
B. Variables at individual level					
Survey Religiosity Index	-0.004	0.849	-3.794	0.297	1041
Reading the Quran Daily	0.943	0.231	0.000	1.000	1041
Observing Namaz 5 times per day	0.951	0.216	0.000	1.000	1041
No Alcohol	0.935	0.247	0.000	1.000	1041
No Music	0.743	0.437	0.000	1.000	1041
Fasting during Ramadan	0.951	0.216	0.000	1.000	1041
Giving Zakat	0.944	0.229	0.000	1.000	1041
C. Variables at grid-cell level					
Fraction Cropland	0.297	0.260	0.000	0.955	595
Fraction Rainfed Cropland	0.096	0.190	0.000	0.944	595
Fraction Irrigated Cropland	0.201	0.227	0.000	0.933	595
Fraction Rangeland	0.415	0.306	0.000	0.995	595
Fraction Barren	0.172	0.230	0.000	1.000	595
Fraction Marshes	0.010	0.035	0.000	0.416	595
Fraction Water Bodies	0.027	0.045	0.000	0.456	595
Fraction Forest	0.037	0.121	0.000	0.871	595
Fraction Fruit Trees	0.013	0.033	0.000	0.367	595
Fraction Built-up	0.029	0.057	0.000	0.608	595

Table A4: Summary Statistics of Additional Variables

	Mean	Sd	Min	Max	Obs.
	(1)	(2)	(3)	(4)	(5)
A. Variables at grid-cell month level					
Maghrib Dip (25 min)	14.087	14.843	-87.238	100.000	35572
Maghrib Dip (35 min)	9.427	14.575	-87.272	100.000	35579
Maghrib Dip (40 min)	7.092	14.869	-100.000	100.000	35587
Maghrib Dip - Ave. Denom.	14.205	18.158	-197.654	200.000	35579
Maghrib Dip - IHS	99.197	15.005	0.590	458.507	35572
Daily Call Volume	5546	5337	5	47613	35579
No. of unique subscribers	31752	75959	16	891481	35579
No. of unique subscribers - Robust	150201	44977	2	567285	35579
B. Variables at grid-cell year level					
EVI Max - December	6.287	0.941	-0.736	8.173	4133
Growing Season SPEI (6 months)	-0.143	0.624	-1.983	1.284	4133
Growing Season SPEI (9 months)	-0.191	0.698	-2.204	1.391	4133
Growing Season SPEI (12 months)	-0.239	0.755	-2.384	1.476	4133
Maghrib Dip in Growing Season	10.339	9.337	-89.513	62.264	3118
Maghrib Dip in Harvest Season	21.080	11.103	-42.330	81.512	3118
Maghrib Dip in Post-harvest Season	8.337	11.202	-89.513	62.500	3118
C. Variables at district month level					
Taliban Control	0.030	0.171	0.000	1.000	14350
D. Variables at district year level					
Poppy - IHS	3.596	3.443	0.000	10.911	1332
Interpolated Poppy - IHS	3.726	3.271	0.000	10.911	1534
E. Variables at grid-cell level					
Confirmed Conflict (2003-2012)	0.440	0.497	0.000	1.000	598
Confirmed Conflict (2003-2020)	0.657	0.475	0.000	1.000	598

Table A5: Alternate Time Windows for the Maghrib Dip

	Maghrib Dip (25 min)			Maghrib Dip (35 min)			Maghrib Dip (40 min)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SPEI (6 months)	-0.208**			-0.299***			-0.299***		
	(0.094)			(0.107)			(0.115)		
SPEI (9 months)		-0.258**			-0.356***			-0.348***	
		(0.105)			(0.122)			(0.132)	
SPEI (12 months)			-0.234**			-0.346**			-0.339**
			(0.116)			(0.136)			(0.146)
Obs.	35572	35572	35572	35583	35583	35583	35587	35587	35587
Grid cell fixed effects?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month fixed effects?	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Columns 1-3 construct the Maghrib dip measure by considering the change in all volume 25 minutes before and after the start of Maghrib. Columns 4-6 construct the measure by considering the change in call volume in the 35 minutes before and after the start of Maghrib. Columns 7-9 construct the measure by considering the change in call volume in the 40 minutes before and after the start of Maghrib. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A6: Additional Functional Forms for the Maghrib Dip

	Maghrib Dip – Ave. Den.			Maghrib Dip – IHS		
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI (6 months)	-0.325**			-0.287***		
	(0.136)			(0.106)		
SPEI (9 months)		-0.408***			-0.357***	
		(0.151)			(0.120)	
SPEI (12 months)			-0.420**			-0.359***
			(0.164)			(0.130)
Obs.	35590	35590	35590	35583	35583	35583
Grid cell fixed effects?	Y	Y	Y	Y	Y	Y
Month fixed effects?	Y	Y	Y	Y	Y	Y

Notes: In columns 1-3, the Maghrib dip is constructed by scaling the change in call volume 30 minutes before and after Maghrib using the average call volume over the entire one hour period around the start of the prayer window. In columns 4-6 the Maghrib dip is constructed by IHS transforming the ratio of the call volumes 30 minutes before and after the start of the window. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A7: Robustness to Additional Controls

	Maghrib Dip					
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI (6 months)	-0.223***			-0.307***		
	(0.082)			(0.100)		
SPEI (9 months)		-0.258***			-0.367***	
		(0.093)			(0.114)	
SPEI (12 months)			-0.238**			-0.351***
			(0.102)			(0.126)
Maghrib $\text{Dip}_{t\text{-}1}$	0.268***	0.267***	0.268***			
	(0.023)	(0.023)	(0.023)			
Obs.	33607	33607	33607	35579	35579	35579
Grid cell fixed effects?	Y	Y	Y	Y	Y	Y
Month fixed effects?	Y	Y	Y	Y	Y	Y
Control - daily call volume?				Y	Y	Y

Notes: Columns 1-3 control for the Maghrib dip in the previous month. Columns 4-6 control for the average daily call volume in a month. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A8: Robustness When Dropping Sparsely Populated Grid Cells

Dependent variable:	Maghrib Dip (2016-2020)					
Sparsity based on:	Number of Users			Call Volume		
Percent of grid cells dropped:	5	10	25	5	10	25
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI (6 months)	-0.298**	-0.326***	-0.353***	-0.298**	-0.325***	-0.363***
	(0.119)	(0.122)	(0.128)	(0.120)	(0.123)	(0.128)
SPEI (9 months)	-0.374***	-0.395***	-0.422***	-0.368***	-0.391***	-0.415***
	(0.131)	(0.135)	(0.139)	(0.133)	(0.135)	(0.137)
SPEI (12 months)	-0.373***	-0.398***	-0.438***	-0.364**	-0.398***	-0.408***
	(0.143)	(0.147)	(0.151)	(0.144)	(0.147)	(0.146)
Obs.	17941	17085	14365	17876	16971	14181
Grid cell fixed effects?	Y	Y	Y	Y	Y	Y
Month fixed effects?	Y	Y	Y	Y	Y	Y

Notes: Each cell is a regression of the Maghrib dip on the SPEI measure displayed in each row, over the 2016-2020 period. In columns 1-3, we drop the sparsest 5, 10, and 25 percent of grid cells, respectively, defining sparsity based on the number of mobile phone users within the grid cell over 2013-2015. In columns 4-6 we drop the sparsest 5, 10, and 25 percent of grid cells, respectively, defining sparsity based on call volumes within the grid cell over 2013-2015. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A9: Robustness across Various Samples

	Maghrib Dip								
Sample:	*No Urban Areas*			*No Hazara Districts*			*No Taliban Districts*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SPEI (6 months)	-0.318***			-0.270***			-0.353***		
	(0.118)			(0.095)			(0.110)		
SPEI (9 months)		-0.398***			-0.329***			-0.436***	
		(0.135)			(0.110)			(0.127)	
SPEI (12 months)			-0.391***			-0.320**			-0.427***
			(0.148)			(0.124)			(0.140)
Obs.	28939	28939	28939	34659	34659	34659	31682	31682	31682
Grid cell fixed effects?	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month fixed effects?	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: Columns 1-3 drop the urban areas defined as those in which the fraction of the grid cell with "built up" area exceeds 5%. Columns 4-6 drop districts in which at least 5% of the villages are majority Hazara. Columns 7-9 drop the districts which had Taliban control. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A10: Alternative Approach to Clustering Standard Errors

	Maghrib Dip		
	(1)	(2)	(3)
SPEI (6 months)	-0.290**		
	(0.114)		
SPEI (9 months)		-0.353***	
		(0.126)	
SPEI (12 months)			-0.342**
			(0.136)
Obs.	35579	35579	35579
Grid cell fixed effects?	Y	Y	Y
Month fixed effects?	Y	Y	Y

Notes: Standard errors, clustered at the district level, shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A11: Climate and Agricultural Growth

	EVI Max - December		
	(1)	(2)	(3)
Grow. SPEI (6 months)	0.231***		
	(0.018)		
Grow. SPEI (9 months)		0.214***	
		(0.016)	
Grow. SPEI (12 months)			0.200***
			(0.015)
Obs.	4133	4133	4133
Grid cell fixed effects?	Y	Y	Y
Year fixed effects?	Y	Y	Y

Notes: The dependent variable is the (log) difference in vegetation between the maximum of the growing season and the beginning of the growing season (in December). Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A12: Climate, Cropland and Agricultural Growth

	EVI Max - December					
	(1)	(2)	(3)	(4)	(5)	(6)
Grow. SPEI (6 months)	0.020	0.175				
	(0.186)	(0.172)				
Grow. SPEI (6 months) x Cropland	0.500**	-				
	(0.203)	-				
Grow. SPEI (6 months) x Rainfed Cropland	-	0.526***				
	-	(0.191)				
Grow. SPEI (6 months) x Irrigated Cropland	-	0.215				
	-	(0.201)				
Grow. SPEI (6 months) x Rangeland	-0.076	-0.249				
	(0.183)	(0.169)				
Grow. SPEI (9 months)			0.046	0.157		
			(0.166)	(0.156)		
Grow. SPEI (9 months) x Cropland			0.411**	-		
			(0.181)	-		
Grow. SPEI (9 months) x Rainfed Cropland			-	0.423**		
			-	(0.172)		
Grow. SPEI (9 months) x Irrigated Cropland			-	0.206		
			-	(0.180)		
Grow. SPEI (9 months) x Rangeland			-0.040	-0.164		
			(0.163)	(0.153)		
Grow. SPEI (12 months)					0.061	0.145
					(0.149)	(0.142)
Grow. SPEI (12 months) x Cropland					0.358**	-
					(0.162)	-
Grow. SPEI (12 months) x Rainfed Cropland					-	0.367**
					-	(0.157)
Grow. SPEI (12 months) x Irrigated Cropland					-	0.202
					-	(0.164)
Grow. SPEI (12 months) x Rangeland					-0.023	-0.116
					(0.147)	(0.139)
Obs.	4112	4112	4112	4112	4112	4112
Grid cell fixed effects?	Y	Y	Y	Y	Y	Y
Year fixed effects?	Y	Y	Y	Y	Y	Y
Controls – Other land types?	Y	Y	Y	Y	Y	Y

Notes: The dependent variable is the (log) difference in vegetation between the maximum of the growing season and the beginning of the growing season (in December). Each column is a regression of this vegetation variable on different versions of the Standardized Precipitation-Evapotranspiration Index (SPEI) and the interactions of the SPEI measures with the fraction of the grid cell containing cropland and rangeland (in columns 1, 3, and 5) or containing rainfed cropland, irrigated cropland and rangeland (in columns 2, 4, and 6). Controls for other land types include the interactions of the SPEI measures with the fraction of the grid cell with forest cover, fruit trees and vineyards, barren areas, water and marshland. The omitted category is built-up (urban) areas. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A13: Climate and Religious Adherence by Agricultural Seasons Using other SPEI Timescales

	Maghrib Dip in:			*Maghrib Dip in:*			*Maghrib Dip in:*		
	Growing Season	Harvest Season	Post-harvest Season	Growing Season	Harvest Season	Post-harvest Season	Growing Season	Harvest Season	Post-harvest Season
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: *Growing Season SPEI 6 months*								
Growing Season SPEI (6 mo)	-0.412*	0.027	-0.469*	-0.456**	0.150	-0.968***	-0.550**	-0.322	-0.924***
	(0.239)	(0.247)	(0.269)	(0.221)	(0.261)	(0.290)	(0.226)	(0.295)	(0.295)
Obs.	3118	3118	3118	2661	2661	2661	2655	2655	2655
	Panel B: *Growing Season SPEI 12 months*								
Growing Season SPEI (12 mo)	-0.381*	0.233	-0.427*	-0.485**	0.337	-0.648**	-0.524**	0.187	-0.656**
	(0.218)	(0.239)	(0.237)	(0.209)	(0.257)	(0.276)	(0.215)	(0.296)	(0.282)
Obs.	3118	3118	3118	2685	2685	2685	2681	2681	2681
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 Maghrib Dip – Prev. months?				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 (6-month timescale in Panel A and 12-month timescale in Panel B). 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. Columns 1-3 control for SPEI in the harvest and post-harvest seasons. Columns 4-6 also control for the average Maghrib dip over the previous 6 months in Panel A and 12 months in Panel B. Columns 7-9 drop Ramadan days that fall within each season. 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.

Table A14: Climate and Religious Adherence Measured using Shortcode Calls

	Maghrib Dip (Shortcode Calls)		
	(1)	(2)	(3)
SPEI (6 months)	-0.523*		
	(0.288)		
SPEI (9 months)		-0.571**	
		(0.286)	
SPEI (12 months)			-0.555*
			(0.300)
Obs.	35344	35344	35344
Grid cell fixed effects?	Y	Y	Y
Month fixed effects?	Y	Y	Y

Notes: The outcome is the Maghrib dip measure based on shortcode calls (i.e. calls to numbers set up by companies and public agencies, for reasons such as providing customer care, facilitating automated top-up and mobile money transactions, as well as providing emergency and information services). Each column is a regression of this Maghrib dip measure of religious adherence on different versions of the Standardized Precipitation-Evapotranspiration Index (SPEI). Positive values of the Maghrib dip indicate more religious adherence; positive values of SPEI indicate more precipitation relative to the historical mean. (Negative coefficients indicate favorable precipitation reduces religious adherence). One observation is included for each month for each 10km X 10km grid cell. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A15: Addressing the Role of Liquidity Constraints

	Log(daily call volume)		
	(1)	(2)	(3)
SPEI (6 months)	-0.014**		
	(0.006)		
SPEI (9 months)		-0.014*	
		(0.008)	
SPEI (12 months)			-0.014
			(0.009)
Obs.	35590	35590	35590
Grid cell fixed effects?	Y	Y	Y
Month fixed effects?	Y	Y	Y

Notes: The outcome is the log of the average daily call volume in a month. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A16: Addressing the Role of Migration

	No. of Unique Subscribers			No. of Unique Subscribers - Robust		
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI (6 months)	146.050			66.562		
	(132.336)			(80.389)		
SPEI (9 months)		197.968			93.336	
		(147.315)			(89.898)	
SPEI (12 months)			286.982*			143.462
			(163.750)			(100.957)
Obs.	35579	35579	35579	35579	35579	35579
Mean Dependent Variable	31752	31752	31752	15021	15021	15021
Grid cell fixed effects?	Y	Y	Y	Y	Y	Y
Month fixed effects?	Y	Y	Y	Y	Y	Y

Notes: In columns 1-3 the dependent variable is the number of users that have made phone calls over the past month. In columns 4-6 the dependent variable is the number of users that have made at least five phone calls during the past month. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A17: Climate and Poppy Cultivation

	IHS(Poppy)			IHS(Interpolated Poppy)		
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI (6 months)	0.004			0.008		
	(0.025)			(0.023)		
SPEI (9 months)		0.006			0.012	
		(0.030)			(0.028)	
SPEI (12 months)			0.013			0.019
			(0.034)			(0.032)
Obs.	15984	15984	15984	18408	18408	18408
District fixed effects?	Y	Y	Y	Y	Y	Y
Month fixed effects?	Y	Y	Y	Y	Y	Y

Notes: This table presents regressions estimated at the district-month level. In Cols 1-3 the dependent variable is the IHS of hectares of land cultivated with poppy. In cols 4-6, the dependent variable is the IHS of poppy cultivation, linearly interpolated. Standard errors clustered on district shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A18: Controlling for Poppy Cultivation

	Maghrib Dip					
	(1)	(2)	(3)	(4)	(5)	(6)
SPEI (6 months)	-0.287***			-0.293***		
	(0.099)			(0.100)		
SPEI (9 months)		-0.350***			-0.357***	
		(0.114)			(0.114)	
SPEI (12 months)			-0.338***			-0.346***
			(0.126)			(0.126)
Obs.	35579	35579	35579	35579	35579	35579
Grid cell fixed effects?	Y	Y	Y	Y	Y	Y
Month fixed effects?	Y	Y	Y	Y	Y	Y
Controls – IHS(Poppy)?	Y	Y	Y			
Controls – IHS(Int. Poppy)?				Y	Y	Y

Notes: Cols 1-3 control for district-level poppy cultivation. Cols 4-6 control for district-level poppy cultivation that has been linearly interpolated. In all specifications 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. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.

Table A19: Addressing the Role of Conflict

Dependent variable:	Maghrib Dip (2013-2020)					
Sample:	*No Confirmed Conflict*			*Confirmed Conflict*		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: *Sample based on conflict over 2003-2012*					
SPEI (6 months)	-0.531***			-0.092		
	(0.162)			(0.112)		
SPEI (9 months)		-0.575***			-0.154	
		(0.190)			(0.126)	
SPEI (12 months)			-0.535**			-0.152
			(0.214)			(0.138)
Obs.	18176	18176	18176	17403	17403	17403
	Panel B: *Sample based on conflict over 2003-2020*					
SPEI (6 months)	-0.711***			-0.128		
	(0.244)			(0.103)		
SPEI (9 months)		-0.779***			-0.181	
		(0.262)			(0.123)	
SPEI (12 months)			-0.726***			-0.184
			(0.268)			(0.143)
Obs.	10067	10067	10067	25512	25512	25512
Grid cell fixed effects?	Y	Y	Y	Y	Y	Y
Month fixed effects?	Y	Y	Y	Y	Y	Y

Notes: In both panels, across all columns, the dependent variable is the Maghrib dip, measured in each grid cell month over 2013-2020. The sample in columns 1-3 is comprised of grid cells that did not experience any conflict events — over 2003-2012 in Panel A, and over 2003-2020 in Panel B. The sample in columns 4-6 is comprised of grid cells that experienced at least one conflict event — over 2003-2012 in Panel A, and over 2003-2020 in Panel B. Standard errors clustered on grid cell shown in parentheses. *p<.10, ** p<.05, *** p<.01.