Dynamics of Conflict and Revolution in Iraq and Tunisia

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To Mum, Dad, and Georgia

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Abstract

This thesis is formed of three articles. Stand-alone pieces in their own right, they are nonetheless united by an interest in the endogenous dynamics of conflict and mass mobilization in the Middle East and North Africa (MENA). The first article investigates identity dynamics in the face of conflict threat using a natural experiment in Iraq after the fall of Mosul to the Islamic State of Iraq and al-Sham (ISIS). Relying on a theoretical synthesis of propositions from both social psychology and political sociology, I show that war can be generative of common intergroup identities when organizational structures exist to enable interethnic cooperation. The second two papers investigate mobilization dynamics during the 2011 Tunisian Revolution. The first article proceeds from the claim that current approaches to the study of democratic mobilization suffer from a basic conceptual problem. Revolution often does not begin as revolutionary—demands are generated in the context of contention as new constituencies are incorporated into a developing protest wave. As a result, cross-sectional analysis is too blunt an instrument to understand what are fundamentally time-dependent dynamics. Using original event data as well as survey data from Tunisia, I show that the correlates of both protest occurrence and participation shift dramatically over the twenty-nine day period of the Revolution. This processual character, I go on to detail, is shared by multiple historical instances of mass mobilization. Against this backdrop, I argue for a reconceptualization of revolution as process. This reconceptualization entails respecifying the object of explanation. Here, coalition formation during episodes of mass contention becomes a key explanandum. I conclude by advancing one analytically tractable mechanism that inheres in this process—brokerage—and propose that this lay behind some of the association between organizational density and democratic transition. In the third paper, I again use event data from the twenty-nine days of the Tunisian Revolution. I couple these data with social media data from Twitter, and am able to leverage information on the medium of protest reportage (Facebook versus non-Facebook) to gain insights into the effect of online information exposure on protest diffusion. I find that, despite the translocal affordances of new information and communications technologies (ICTs), protest has an overlooked parochial dimension. Online information exposure leads to protest diffusion, but the strength of the signal diminishes significantly with distance. Further, I find little evidence of online platforms being used for coordination. I bolster this finding with evidence from a qualitative coding of some 10,000 tweets as well as field interviews. I find that "attributions of similarity" and physical copresence remain crucial both to how information online is interpreted and to how signals of willingness are communicated.

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Introduction

This thesis is formed of three articles and focuses on two events: the fall of Mosul to the Islamic State of Iraq and al-Sham in June, 2014, and the Tunisian Revolution of 2010-2011. Instead of rehearsing each article in its abstract, this introductory section is intended as insight into the theoretical and methodological motivations informing the three articles contained in the thesis. While these articles are to be read as stand-alone pieces of research, they naturally share several orienting theoretical assumptions. I sketch these out first. The methods I have chosen to employ are, in good measure, informed by these theoretical predicates. These I discuss in a second half.

If we are to judge events by their outcomes, revolutions only become revolutions once the fate of incumbents is sealed. The temptation is then to regard such outcomes as inevitabilities. In reality, revolutionaries—even the card-carrying among them—do not know they are revolutionaries at the time. In order to study such events, then, we need to put ourselves, through what Marc Bloch referred to as "that bold exercise of the mind," in the position of the participant before any outcomes are known—that is, we need to read history forward (Bloch [1954] 2004, 103).

Through this exercise we begin to see that the carrying classes of revolution are rarely

the card-carrying among them. If popular insurrection results in the democratic transfer of power, this does not mean that it was impelled by democrats. The post-hoc narratives assigned to revolutionary episodes should not stop us from probing beneath this surface rendering to the complex concatenations of multiple conflicts that constitute the very material of mass upheaval. Does this complexity imperil the positivist project? Not necessarily. I show in Paper Two of this thesis that, by recognizing this complexity, we can begin to disentangle its knotted threads. And we can achieve this using systematic statistical techniques. What we see as a result is that the object of explanation requires redefinition. If revolution, and its contemporary corollary in democratic transition, cannot be conceptualized as unitary events or outcomes, we can nonetheless identify generalizable causal mechanisms that inhere *within* the process of mass protest. One such mechanism, I discuss in Paper Two, is brokerage. This single, analytically tractable mechanism, brings us closer to understanding the complex dynamics of contention. It helps us identify what is common to revolutionary upheaval—the coming together of multiple social sites in loose coalitions of common cause. And it points to one mechanism that likely lay beneath some of the discovered association between organizational density and democratization as a whole.

In this search for mechanisms I have taken lessons from the contentious politics scholarship (McAdam et al. 2001a). I nonetheless have tried to discipline my approach; rather than enumerating mechanisms at each stage of a causal narrative, I have enlisted the help of singular mechanisms to explain what I deem to be the foremost object of explanation. The reader will also detect beneath these propositions the influence of another literature in the study of conflict. Kalyvas (2006), in his *Logics of Violence*, made the appeal for a disaggregated approach to the study of civil war that recognized such events as sites of mul-

tiple conflicts, which can only with difficulty be arrayed along the apparent master cleavage driving the outbreak of violence: "the game of record is not the game on the ground" (5). It is through this disaggregated approach, he found, that we are able nonetheless to identify what is analytically scaleable in the complexity of civil war, and to see this complexity as "a matter of essence rather than noise" (365). An attention to the microlevel implications of macrolevel theory must also be brought to bear on the study of mobilization for democracy. Mass mobilization cannot be elided with democratization, and nor can it be understood as a unitary phenomenon. It is by pulling it apart as a phenomenon that the formation of protest coalitions emerges as a key explanandum, and one that is amenable to a systematic analytical approach.

Flowing from an ontology of mass phenomena as aggregations of microlevel conflicts is an attention to endogeneity. This concern is shared across all three papers. In Paper Two I demonstrate that democratic demands may emerge endogenously, as new constituencies are incorporated into the unfolding protest wave and collective identities are shaped and reshaped. In Paper One, I demonstrate that identity, rather than being exogenous to the onset of war, is profoundly shaped by the contingencies of conflict outbreak and the alliances that are mobilized in its immediate aftermath (cf. Kalyvas and Kocher 2007). Here, I also take lessons from the laboratory-level findings of the social psychology literature but aim to test their population validity in a real-world setting: Iraq after the fall of Mosul to ISIS. A conceptualization of mass uprisings as recursive processes of information exposure is central to Paper Three wherein I demonstrate that, despite the translocal reach of new ICTs, the local continues to inhere in dynamics of protest diffusion in important ways.

As a heuristic tool, protest event catalogues, have proved central to the research contained

in this thesis. An example of their use that most impressed this author is to be found in the early work of Charles Tilly and James Rule on the revolutionary events of 1830 in France (Tilly and Rule 1973). Noting that the task of the historian is to select what is most salient in an event of historical importance, the authors meditate on this process, and ask: "how do we choose what to cull and what to save?" (1973, 1). They conclude that "seeing dramatic events as *the* essence of revolution automatically diverts attention from other events and processes of great importance" and propose instead that "we want to push these outstanding events back into the crowd of conflicts which surround them" (1973, 2). This crowd of conflicts only emerges through the exercise of building event catalogues. In Paper One, I built an event catalogue of tribal mobilization events, with accompanying event details, in order to illuminate this instance of interethnic cooperation within a conflict episode that all too often was described as revolt of Iraqi Sunnis against their exclusionary Shi'i conationals. The contribution of event catalogues to Papers Two and Three is even larger. Through building these day-by-day, and sometimes hour-by-hour, accounts of revolutionary uprisings we begin to see the diversity of grievances and contentious forms that lay beneath such moments of revolutionary upheaval. This method relates back, then, to theory: it is by recreating these episodes from the date of their onset that we are able to place ourselves in the position of the participant or onlooker and peer forward into what is not yet known.

Given their unpredictability, studying events such as those I choose to study in this thesis requires an ecumenical approach to source material. We do not have at our disposal the periodically deployed survey instruments of the demographic sciences or the exit-polls readied in advance by the psephologist. Even if we were able to hold a referendum on the preferences of the revolutionary crowd, this would likely be inadequate. As one notable

observer of revolutionary tumult put it: "consultations of the people are carried out at a single moment... [whereas] the difference in level and mood of the different layers of the people is overcome in action" (Trotsky [1932] 2008, 748).

In light of this, I have chosen to assemble a broad range of data and source material in this thesis, ranging from more conventional survey data, to event data, documentary evidence, digital and print archives, online messageboards and Twitter data, as well as two periods of fieldwork in several regions of Tunisia and over forty interviews. Arabic-language source material has formed the bulk of these data, and these, along with interviews, have helped shine a light on the categories of action used by participants themselves (versus those the analyst chooses to assign). One example is the the notion of *ta'ṭīr*, a word that captures the brokering role of organizations in tying together social sites and producing joint meaning—something I unpack in the concluding section of Paper Two. New frontiers in the use of "digital trace" data have prompted me to look into the possibilities of reconstructing the information to which individuals were exposed at the time of their communication. These data are "always-on" (Salganik 2018), giving the researcher a handle on unpredictable events that previously was unavailable. That said, I have made efforts to combine these data, most obviously in Paper Three, with inferences gleaned from the field. While digital trace data provide invaluable insight into the intensity and content of online communication, they do not tell us how this information was perceived, interpreted, and acted upon by individuals on the ground. It is this question that provides the motivation for the final paper of this thesis.

In sum, the research contained in this thesis builds from a central overarching proposition: that the character and consequences of events are decided in the context of action. In the

source material I have compiled, and techniques I employ, I have aimed to excavate this context. It is by looking inside events to their internal dynamics, I hope to show, that we are able to understand them.

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Chapter 1

Paper One

Sect, Nation, and Identity after the Fall of Mosul: Evidence from a Natural Experiment

Abstract

How does war affect group identity? Does common threat unite ethnic groups behind the nation? What explains subethnic heterogeneity in identity responses? Experimental scholarship on conflict and intergroup identity relies on laboratory settings; identifying real-world variation is hindered by the difficulties of conducting social inquiry in wartime. I address this gap by exploiting a unique source of exogenous variation—the fall of Mosul to the Islamic State of Iraq and al-Sham (ISIS)—during the fieldwork for a nationally representative survey in Iraq. I find systematic differences in the identity responses of Sunni and Shi'i Iraqis. While Shi'is cleave to the nation, Sunnis mobilize behind an Arab identity. In tribal areas, however, Sunnis rally behind the nation. Findings are explained with reference to prior attachment and achieved cooperation. Excluded groups are less likely to identify with the nation; but where organization enables interethnic cooperation, wartime mobilization generates national loyalty.

1 Introduction

War has long been central to the scholarly study of identity. Early sociological work on conflict, while recognizing its capacity for destruction, saw in it too the germ of cohesion. The nation state represented the preeminent social group, and one that was born of war: "France owes the consciousness of its national unity to its fight against the English, and only the Moorish war made the Spanish regions into one people" (Simmel 1955, 69). Recognizing the centrality of groups to conflict dynamics, laboratory-level research in social psychology has sought to unpick the cognitive underpinnings of group formation (Brewer 1979; Tajfel and Turner 1979), cooperation (Sherif 1966), and common identification (Gaertner and Dovidio 2000). Empirically arbitrating these findings in situations of real-world conflict is normally not possible. The population validity of arguments from social psychology therefore remains an open question. Do groups unite in the face of common threat? What explains subgroup response heterogeneity? And how can we answer these questions outside of the laboratory?

Iraq after the fall of Mosul to ISIS provides us with a unique test case for understanding the identity consequences war, as well as the capacity of common threat to unite previously disunited groups.[1] This sudden, and wholly unexpected, event precipitated a wave of popular enlistment that saw Sunnis and Shi'is mobilize in common against the ISIS-led assault. In the ethnically exclusive political context of post-2003 Iraq, such cooperation between Iraq's

[1]I elect to use 'ISIS' since, at the time of the fall of Mosul, ISIS had not yet transferred their franchise to the more expansive 'Islamic State', which occurred on June 29. In what follows, I will refer on occasion to Sunnis rather than Sunni Arabs and to Shi'is rather than Shi'i Arabs. I am aware that both Sunni Kurds and (Faili) Shi'i Kurds are Iraqis but not Arabs. In the analyses that follow, however, I focus solely on non-Kurdish regions and will thus refer to both sects using this shortened qualifier. The principal cleavage among Arab Iraqi communities is that between Sunni and Shi'i Iraqis. In referring to this as an "ethnic" division, I follow Horowitz (1985) in understanding "religious" or "sectarian" identities as subsets of ethnicity (see also Wimmer 2008).

marginalized Sunni population and Shi'i-dominated government forces had never before been witnessed.

Identifying the effects of this event at the individual level is made possible by a nationally representative survey of Iraqis that was in the field when Mosul fell to ISIS. Relying on this natural experiment, I employ a mixture of empirical strategies to test hypotheses relevant to threat and intergroup identity formation. These I derive from a theoretical synthesis of the social psychology and political sociology literature, arguing that identity responses are a function of *prior attachment* to the state and *achieved cooperation* between groups. A first basic insight predicts that when individuals have low levels of prior attachment to the state, they are unlikely to seek psychological refuge in a national identity under threat. Crucially, however, this theory predicts that the effects of low prior attachment may be overcome by the experience of cooperation. When cooperation between groups is secured, a common superordinate (national) identity may result.

Support for this theory comes first from a series of multilevel designs and matching strategies used to test for differences between treatment (post-Mosul) and control (pre-Mosul) groups. I find that Sunnis—a group with low prior attachment to the state—are significantly less likely to rally behind the nation after Mosul's fall. However, consistent with theoretical expectations, in areas with a high density of clan ties, where there were tribal mobilization structures enabling of interethnic cooperation, the fall of Mosul saw Sunnis rally strongly behind the nation. In a final section, I address questions of exposure heterogeneity using instrumental variable and causal mediation analysis, and identify one cognitive pathway mediating responses. Excluded groups, who have low levels of attachment to the state, are also more likely to perceive threat in local (versus national) terms, and

this differential in threat perception significantly mediates observed intergroup differences in identification.

The importance of this contribution stems from its highly unusual basis in a real-world setting. The findings thus represent a rare test of theoretical predictions drawn almost exclusively from the laboratory. Ethnically marginalized groups are unlikely to rally behind the nation under threat. But when interethnic cooperation is secured—through abeyant organization—common intergroup alliances conduce to national loyalty: war can make the state, but organization precedes war.

2 The fall of Mosul to ISIS

On June 6 2014, ISIS launched an unexpected attack on Mosul from bases across the Syrian border. With a population of over 1.5 million, Mosul was Iraq's second-largest city. In just four days, a band of 1,300 roving fighters, carrying small arms, had overcome the combined forces of approximately 60,000 Iraqi army and police (Cockburn 2015). While ISIS had been a long-term presence in Anbar province, in the southwest of Iraq, few, if anyone, had expected a campaign on Iraq's northern second city. Until June 10, the severity of the assault on Mosul and its likely outcomes had also been difficult to discern. National newspapers contained small reports of clashes in Nineweh Province, but the seizure of Mosul by ISIS was a barely considered prospect.[2] Google Trends data provide a window onto this. While there were slight increases between June 6 and June 9, it was only after June 10 that search interest, and news interest, in Iraq for ISIS "*dā'ish*" (داعش) and Mosul *"al-mūṣil"* (الموصل)

[2]Front pages of Iraqi national newspapers on June 9 and June 10 can be found in Appendix Figure A11.

spiked (see Figure 1).[3] A manual count of articles in *al-Mada* newspaper mentioning Da'ish or Mosul (Figure 1) over the dates of the survey data analysed below points to the same trend: it is only after June 10 that article numbers show a pronounced increase.[4] The fall of Mosul, in other words, was both sudden and unexpected.

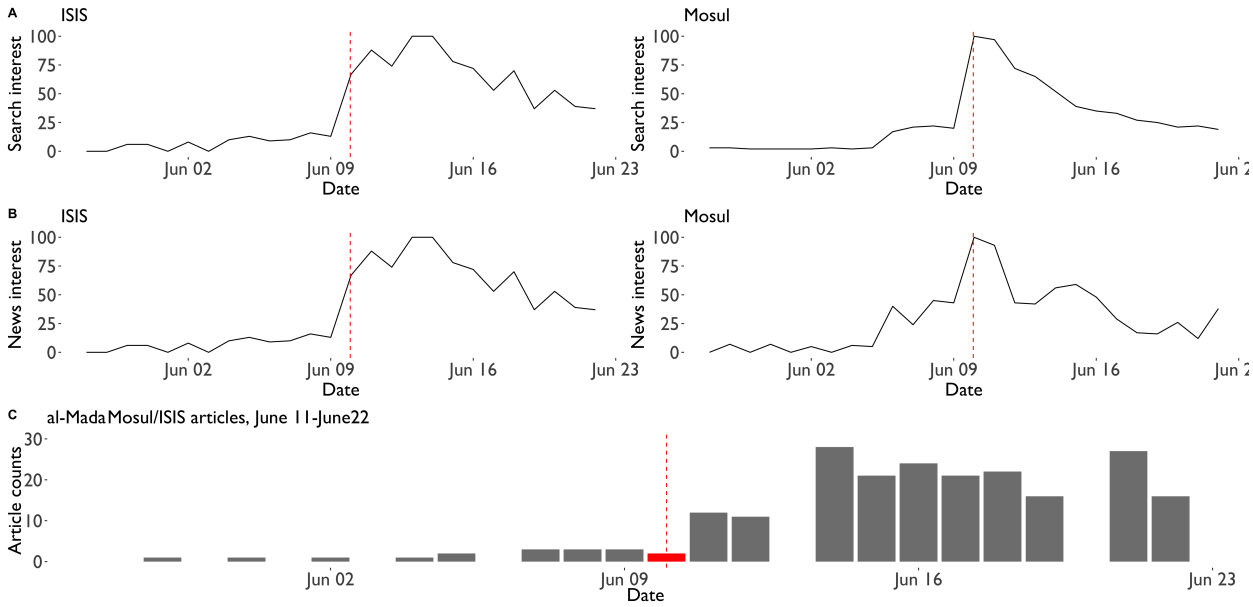


Figure 1: Google Trends and *al-Mada* data for Iraq from the period May 28 2014-June 22 2014. The vertical red lines indicate June 10 and the fall of Mosul. **A**: Search volume for "dā'ish" and "al-mūṣil"; **B**: News interest for "dā'ish" and "al-mūṣil"; **C**: *Al-Mada* article counts.

These were extraordinary and unprecedented events. If previously Sunni jihadist forces had threatened Iraqi national security, it was through unconventional warfare, attacking Western forces or Shi'i targets with sporadic "terrorist-" and "guerrilla-" style tactics (Kalyvas 2015). By stark contrast, the fall of Mosul to ISIS, and subsequent territorial gains,

[3]Search interest is a calculated as number of searches for keywords denominated by total searches. This is then indexed on 1-100 scale and, for each keyword, or combination, and normalized relative to the location and date range specified (here, Iraq and the date range of the survey). Thus, a value of 100 represents the day, within the specified location and date range, on which search concentration was at its peak, relative to other days in the same location. Search language and news interest language is Arabic; location is set to Iraq. For further information, see `https://medium.com/google-news-lab/what-is-google-trends-data-and-what-does-it-mean-b48f07342ee8`.

[4]*Al-Mada* does not publish on Fridays (the first day of the weekend in Iraq), hence the zero counts on these days.

took the form of more conventional organized warfare and represented an existential threat to Iraqi territorial integrity, even casting into doubt the continued existence of Iraq as a nation.

Immediately following the fall of Mosul, Iraq's political and religious elites made urgent appeals for unity, the formation of a national unity government, and recruitment of a popular civilian defence force. On June 11, Iraq's foremost Shi'i religious leader, Ayatollah Ali al-Sistani also called on all able Iraqi citizens to join the Iraqi security forces. His fatwa was absent any sectarian language, and was even qualified with an addendum on June 12 stating that it represented a nationalist appeal to all Iraqis, encouraging voluntary recruitment to the Iraqi security forces rather than any sectarian militia. Despite this, Iraq's Prime Minister, Nouri al-Maliki, exploited the fatwa to formalize the mobilization of Iraq's Shi'i militias under the banner of the Popular Mobilization Forces (PMF) (Mansour and Jabar 2017, 7). Previously a loose assemblage of nonstate, progovernment, forces used by Maliki to fight ISIS before the fall of Mosul, his efforts were to legitimize the subsumption of these militias into the state forces fighting ISIS.[5]

Civilian mobilization was not the sole preserve of Shi'i Iraqis, however. In a speech on June 10, Maliki made appeals across ethnosectarian lines by explicitly calling on (Sunni) Iraqi tribes to volunteer to fight. On June 13, Saad Maan, spokesperson for the Iraqi Interior Ministry, announced plans for the formal remobilization of "*Sahwat*" organizations to defend Baghdad. The *Sahwa* (Awakening) was the name given to the mobilization of Sunni tribal forces alongside the U.S. army from 2006-2007 to fight against al-Qai'da in Iraq (AQI). In the

[5]The seven original militias comprised: the Badr Organization; Asaib Ahl al-Haq; Kata'ib Hezbollah; Kata'ib Sayyid al-Shuahada; Harakat Hezbollah al-Nujaba; Kata'ib al-Imam Ali; and Kata'ib Jund al-Imam.

twelve days following the fall of Mosul (the period covered by the survey analysed below), Sunni tribal forces would mobilize alongside the Iraqi security forces, PMF, and sometimes Kurdish Peshmerga, in all of Ba'quba, Hamrine, Miqdadiyah, Udhaim (Diyala province); Hawija (Kirkuk province); Qadisiyyah, Tal Afar (Nineweh province) Alam, al-Mu'tasim, Dhuluiya, Dujail, Tikrit, and Tuz Khurmatu (Salah ad-Din province).[6] Figure 2 displays the locations of reported tribal mobilizations.

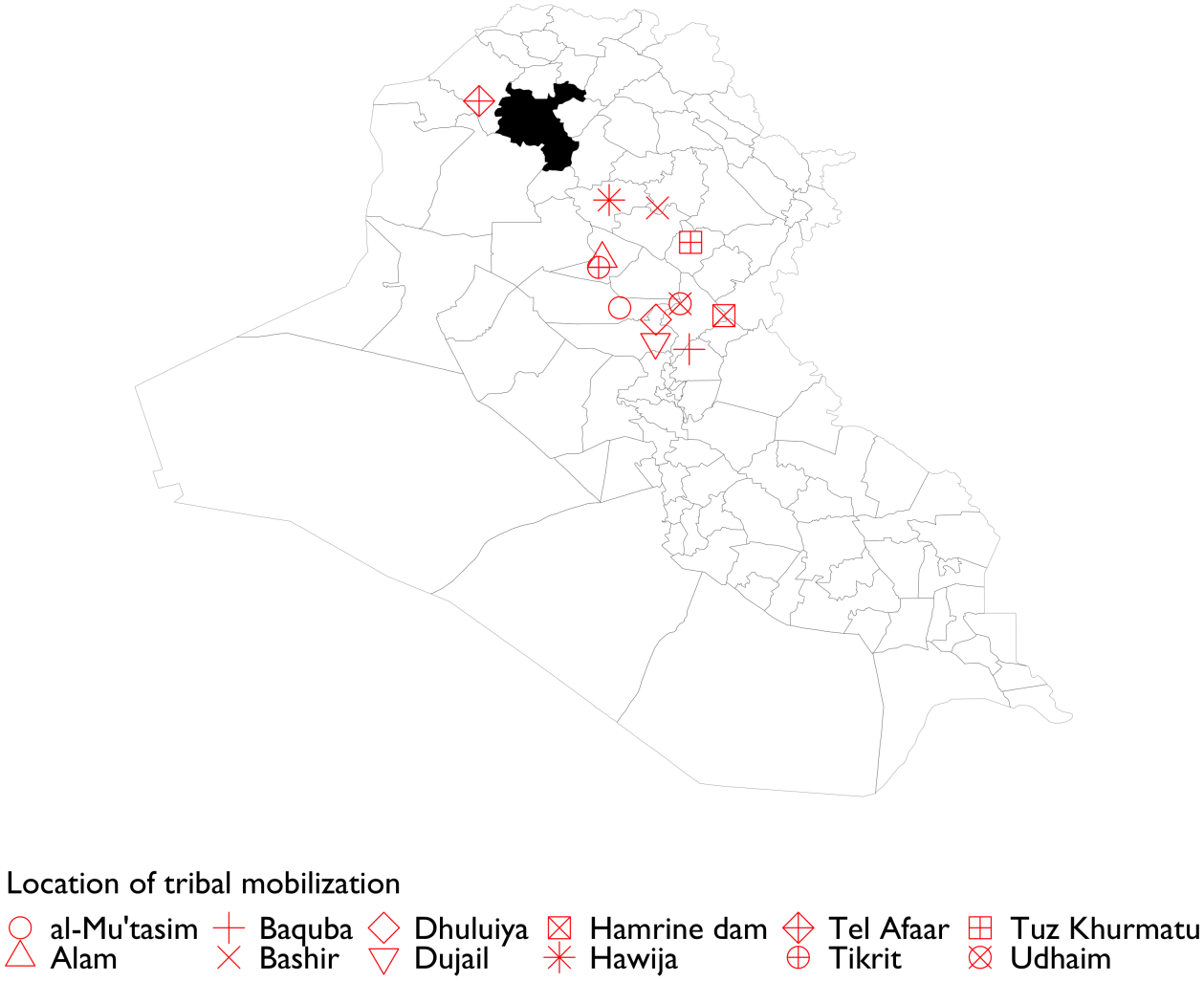


Figure 2: Tribal mobilization events, June 11–June 22, 2014. Mosul filled black.

[6]Reports of tribal mobilizations were compiled through online searches of several Iraqi newspapers, including: *al-Mada*; *al-Mashriq*; *Azzaman*; *Alsumaria News*; and *Shafaaq News*, several of which were found in Iraq military messageboards. See e.g., `http://iraqimilitary.org/forums/viewtopic.php?f=9&t=2037&start=75&sid=2ca26cd2415cd60a4a9a888108790c97`, last accessed: September 14, 2019.

This pattern of tribal mobilization would continue over the coming months.[7] Such military cooperation between Sunni tribes and Iraqi security forces did not predate the fall of Mosul and was in no way a given. Rather, in the months and years preceding the seizure of Mosul by ISIS, tribal groupings had participated in protracted, and sometimes violent, protest against the Shi'i-dominated, and ethnically exclusive, Maliki-led regime (ISW 2013). The *Sahwat*, for their part, had been consistently marginalized in the years following the defeat of AQI and US withdrawal (Benraad 2011; Gerges 2016). In short, the mobilization of these tribal groups alongside Iraqi security forces was a result not of preexisting ties of allegiance, but of the severity of threat posed by ISIS and the concomitant reorientation of primary loyalties that this seemingly generated.

Observers at the time were keenly aware of the transformative potential of Mosul's fall for sectarian relations in Iraq. Writing on June 15, Hisham al-Hashimi, a prominent commentator on Iraqi internal affairs and Islamist politics, argued that the fall of Mosul to ISIS was not an unqualified ill. Rather, it had succeeded in reigniting a much needed "nationalist spirit" (*rūḥ waṭaniyya*), he wrote, asserting that the fight against ISIS was not a sectarian battle between Iraq's Sunni and Shi'i communities, but a resistance campaign in which "all the people of Iraq could participate" (see al-Mada 15/06/2014 p. 16). Accompanying the article was a cartoon by Maytham Radhi depicting two (Sunni and Shi'i) militiamen reconciling their differences under the heading "Thank you Da'ish" (see Figure 3).

In sum, the fall of Mosul—a wholly unforeseen event—occasioned a crisis of national security and represented a threat to the territorial integrity of Iraq. The immediate aftermath

[7] In the remainder of June, and through July, clashes between Sunni tribal forces and ISIS were reported in all of Haditha, Ramadi (Anbar province), al-Jazeera, Khamis, Miqdadiyah, Sadia, Sansal, Udhaim (Diyala province), Hawija, Rashad, Taza (Kirkuk province), Amerli, Dhuluiya, Mishak, and Zowiya (Salah ad-Din province) (ISW 2014).

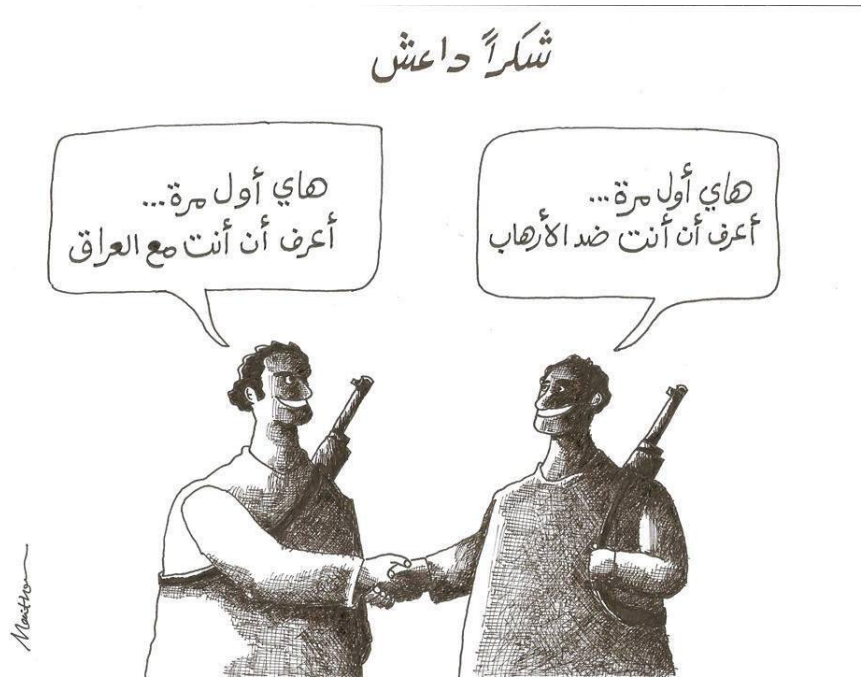


Figure 3: Cartoon by Maytham Radhi published in *al-Mada* newspaper 15/06/2014, p.16. Image taken from `https://twitter.com/zaidbenjamin/status/477952087024992256?lang=en` (last accessed: 25/10/2017). The right-hand side darker-skinned (Shi'i) figure is saying: "Now, for the first time, I know you're against terrorism", while the left-hand side (Sunni) figure is saying: "Now, for the first time, I know you're with Iraq".

saw calls for national mobilization and explicit appeals for national unity against a force that was seen as a foreign and terrorist threat. Most strikingly, we witness mobilization across ethnosectarian lines, with Sunni tribal communities rallying alongside Iraqi security forces and Shi'i militias. What were the identity consequences of these events and how should we theorize them?

3 Theorizing identity in war

A central premise of this paper is that *identification* with a social group is subject to situational change given the variable salience of group identities. This basic insight is shared across literatures in sociology, social and political psychology, anthropology, and economics

(Moerman 1965; Stets and Burke 2000; Akerlof and Kranton 2000; Brubaker and Cooper 2000). An understanding of identity as a dynamic, shifting construct subject to situational redefinition, and exhibiting inter- and intra-group heterogeneity, has come to dominate the theoretical literature on conflict (e.g., Brubaker 2004, 2009; Hale 2004; Abdelal et al. 2006; Kalyvas 2006, 2008; Kalyvas and Kocher 2007; Wimmer 2008, 2013). Despite these theoretical insights, there remains little systematic empirical work investigating the identity consequences of war. Instead, owing to the dangers of conducting social inquiry in conflict settings, the scholarship that does exist relies on post-war surveys to gauge longer-term effects of war, or threat of war, on social and political identities (Balcells 2012; Dyrstad 2012; Gibler et al. 2012; Lupu and Peisakhin 2017) or investigates the identity consequences of elections and exposure to violence short of war (Eifert et al. 2010; Gutiérrez-Romero 2014).[8] As a result, the extent to which identity attachments precede or are produced by war remains a subject of central and ongoing theoretical interest in the study of conflict (Kalyvas 2008; Denny and Walter 2014).

An understanding of war as generative of national identity has a long history in comparative macrosciology. Smith (1981, 389) argues explicitly that war be treated as "the independent variable and one of the chief forces shaping various aspects of ethnicity". "In a crisis, in the heat of battle," he writes, "old divisions are laid aside, and the nationalist

[8]Balcells (2012), as well as Lupu and Peisakhin (2017)), use specialized post-war surveys to assess the intergenerational transmission of political identities. Dyrstad (2012) uses before and after surveys in Bosnia wherein the time lag to assess the effect of the war 'treatment' is considerable (eight years), while Gibler and colleagues (2012) use cross-national survey data combined with Correlates of War data wherein territorial threat is coded as a dichotomous measure of military dispute occurrence in the five years prior to the survey being fielded. A cognate literature examines the longer-term consequences of war for prosociality and (intergroup) cooperation (Blattman and Miguel 2010; Bauer et al. 2016; Mironova and Whitt 2016). To the author's knowledge, this article represents the first time identity shifts have been captured using a natural experimental design in contexts of domestic conflict, providing a far stronger identification tool.

dream of ethnic fraternity becomes a momentary reality. It is war itself which creates any sense of belonging and community" (1981, 389) . For Tilly, the prosecution of war gave rise to early nation building: "war made the state, and the state made war" (Tilly and Rule 1975, 42, see also Tilly 1990; Mann 1986; Malešević 2010). The bellicist theory of state formation has been carried forward by later scholars arguing for its application to internal as well as external wars (Slater 2010; Rodríguez-Franco 2016). Explanations for this phenomenon have operated at the elite and institutional levels, leaving the microlevel mechanisms underlying these macrolevel predictions largely unspecified (Gibler, 2010).

In order to pinpoint these mechanisms, I take lessons first from social psychology and second from political science and sociology. An acknowledged shortcoming of much of the social psychology literature on identity is its reliance on laboratory settings and inherent problems of population validity (Brewer 1996, 2000). By noting commonalities between disciplines, we are better able to see how laboratory-level observations might scale to "real-world" contexts. The resulting theoretical synthesis comes in two parts. First, I demonstrate that both literatures point to *prior attachments* to a given collectivity as predictive of identity responses in the face of threat. Unless a common intergroup identity is available before conflict outbreak, a common rallying response is unlikely. Second, I argue that threat is itself subject to contextual variance on the basis of *achieved cooperation*. When groups do cooperate—or form alliances—this cooperation can conduce to national identification even in the absence of strong prior attachments. The potential for cooperation, I argue, is a function of the availability of cross-cutting (or cross-ethnic) organizational ties. In a final section, I propose one cognitive causal pathway through which differential identity responses may be produced. While the literature emphasizes instrumental security-seeking motives to

explain identity loyalties, these instrumental considerations can be understood as causally prior to threat perception. When threat is commonly perceived as a threat involving the entire nation—or as "sociotropic"—individuals are more likely to rally behind a common national identity.

3.1 Prior attachments and identification

A body of research in social psychology, under the heading of *optimal distinctiveness theory* (ODT), provides us with an orienting theoritical framework for understanding intergroup identity dynamics. This perspective, taken from evolutionary psychology, sees ethnocentric attachments as founded on "expectations of cooperation and security" within such groups (Brewer 1999, 433). Ingroups are thus defined as "bounded communities of mutual obligation and trust" (Brewer 2000, 122). But the crucial claim made by this literature is that psychological attachment to a group precedes ingroup positivity (Brewer 2007). Why does this matter? The importance of this argument is most obvious in contexts of threat. ODT predicts that ingroup solidarity will increase in the face of threat as individuals derive "expectations of security and cooperation" from ingroup identification (Brewer 2007, 732). But for that ingroup to combine elements of formerly distinct groups, i.e., for intra- to become intergroup solidarity, a common ("superordinate") identity must precede the emergence of this threat (Brewer 2000). Translated to a national context, this theory would then predict that, for groups to rally behind a common national identity (a common national ingroup), members of these groups must possess some prior attachment to this collectivity. Prior attachments, in other words, precondition identity responses under conditions of threat.

This concern with prior attachments, while operating largely outside of social psychology, is common to much literature in conflict studies and public opinion research. Early theoretical work on conflict and cohesion, building on the work of Coser (1956), cites "prior solidarity" as a key determinant of intergroup cohesion, and common identification, in the wake of conflict outbreak (Stein 1976, 145). National rallying effects are also conditional on prior group attachments. Scholarship examining the effects of the 9/11 US terror attacks, for example, finds that African Americans, who on average have lower levels of trust in government, were less likely to trade off civil liberties and less likely to report increased trust in the government in the aftermath of this event (Davis and Silver 2004; Perrin and Smolek 2009). This finding has received wider validation in experimental and observational studies of threat and identification: where individuals lack prior trust in, and attachment to, the given (national) collectivity, threat is markedly less likely to induce individuals to defend institutions of state or rally behind the nation (Kay et al. 2009; Gorman and Seguin 2018).

Ethnic exclusion is among the most powerful determinants of weak attachment to the nation (Green 2018; Wimmer 2018). In contexts of ethnic exclusion, then, we should expect the excluded group to place less trust in state institutions and be less likely to identify with a national collectivity. The survey analysed below asks respondents to rate, on a four-point scale, the level of trust they place in various state institutions. I plot below (Figure 4) the mean responses of Sunni and Shi'i Iraqis prior to the fall of Mosul, as well as the proportion identifying with the nation for each group.[9]

[9]The question asks: "I'm going to name a number of institutions. For each one, please tell me how much trust you have in them.: "Government (Council of Ministers)"; "The elected council of representatives (the parliament)"; "The armed forces (the army)." Options include: "(1) No trust at all; (2) Not very much trust; (3) Quite a lot of trust; (4) A great deal of trust". As below, respondents in Kurdish districts are excluded. No other controls are included.

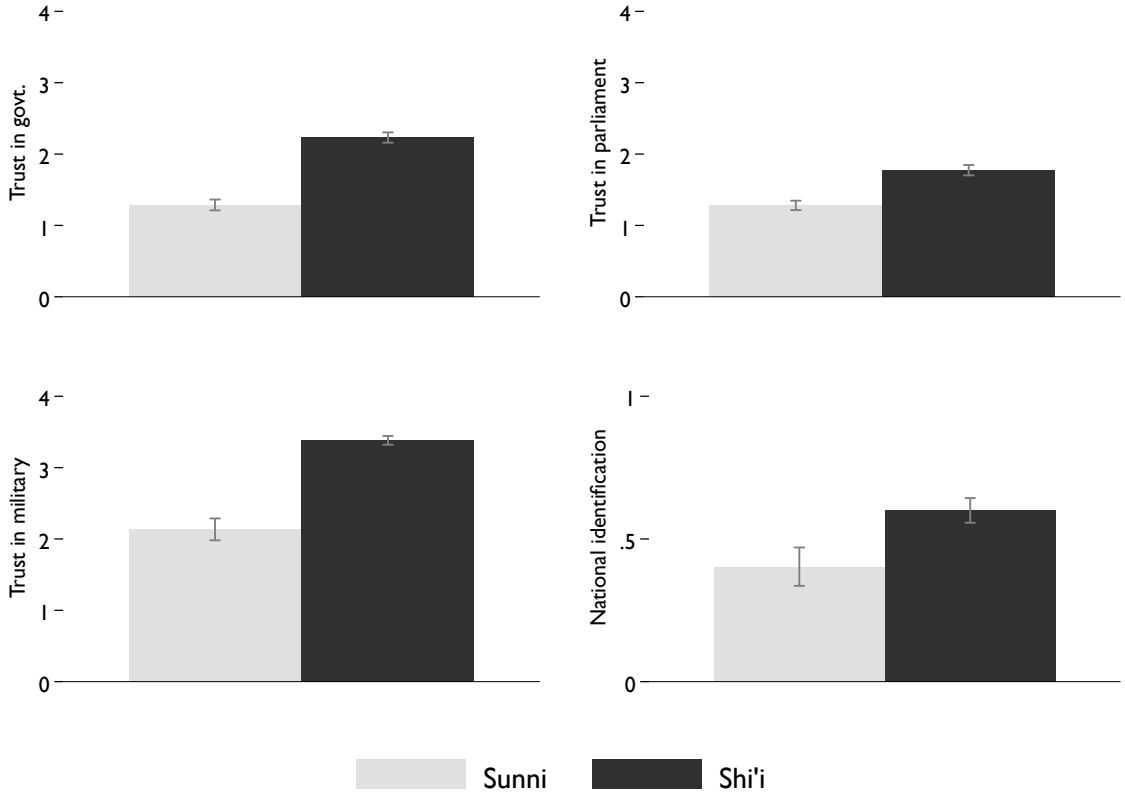


Figure 4: Trust in state institutions and national identification before the fall of Mosul by sect.

The political field in Iraq at this time was defined by the exclusion of minority Sunni communities from the post-2003 Iraqi state (see Allawi 2007; Cordesman 2008; ICG 2014; Gerges 2016). As should be clear from Figure 4, trust in state instutions is consistently and significantly reduced among Sunnis relative to their Shi'i counterparts. Furthermore, a full twenty percentage points more Shi'is identify with the nation compared with Sunni Iraqis (60% versus 40%). Under conditions of threat, the theoretical framework outlined above proposes that responsive national identification will be shaped by these prior attachments. A first hypothesis thus follows: ***H1****: groups with low prior attachment to the state are less likely to rally behind the nation.*

To where, then, do excluded groups turn when threatened? Recent work by Gorman

and Seguin (2018) finds that marginalized constituencies tend to emphasize expansive, even global, identities compared to their included, or less marginalized, conationals. This finding is conditional, however, on the marginalized group perceiving "global actors" as potential sources of security. The survey analysed below includes separate questions asking respondents whether they view the USA, Russia, and China as sources of stability or instability. Before the fall of Mosul, 82% of Sunnis saw the USA as a source of instability. The majority of Sunni respondents (57% and 54% respectively) saw Russia and China, two other key global actors, as not affecting their country.[10] The survey does not contain a question probing attachment to "world society" and so we cannot test the specific claims of Gorman and Seguin (2018). It nonetheless seems unlikely, given Sunnis' appraisal of major world superpowers, that they would identify as "world citizens."

The survey does, however, offer respondents a more expansive, and still border-crossing, "Arab" identity category. Prior to 2003, Sunni state domination and a pronounced (pan-)Arabism comingled in Iraq, with the salience of Arabism in Iraq's Sunni communities often couched in anti-Shi'i and anti-Iranian terms (see Dawisha 1999; Wimmer 2002; Nakash 2006; Haddad 2011). Further, "[i]n the post-2003 environment," writes Haddad, "many Sunnis anchored their identity in the Arab world that was seen as their only ally against what they regarded as a political order that excluded them and was dominated by Iranian influence" (2011, 167; see also Allawi 2007; Tripp 2010). Examining the survey data, before Mosul's fall, nearly three times the proportion of Sunnis (19%) compared with Shi'is (7%) identified as primarily Arab. Given reduced trust and attachment to the nation, and the availability of

[10]The precise wording of the question was as follows: "Do you think any of these countries (or institutions) poses factor of stability or instability to your country?: USA". Options included : "Factor of instability"; "Does not affect my country"; "Factor of stability"; "Don't know."

a more expansive identity dimension for Sunnis, we may thus expect that threat will provoke border-crossing identification: ***H2****: excluded groups will cleave to expansive (non-national) identity dimensions.*

3.2 Cooperation and identification

When can common threat bring groups closer together? Recall that ODT argues identity attachments precede ingroup solidarity. This insight is key and runs counter to experimental social psychology and sociology arguing that common goals conduce to intergroup cooperation and common identity (e.g., Sherif 1966; Simmel 1904; Sumner 1906). In fact, interdependence has the capacity to exacerbate intergroup distances by making "salient the absence of mutual trust" and the possibility of "exploited cooperation" (Brewer 2007, 734). Asymmetries in interdependence, in other words, create the possibility of exploitation, rendering salient intergroup distinctions and exacerbating identity cleavages. Here, ODT shares much with the civil conflict literature on ethnic exclusion, which similarly sees the power asymmetries inherent to ethnically exclusionary settings as detrimental to nation-building and cooperation in times of crisis (Stein 1976; Wimmer 2018).

A crucial qualification to this model has yet to be mentioned, however. Additional experimental research found that once cooperation is achieved between groups, intergroup biases may be overcome (Deschamps and Brown 1983; Brewer 2000. These findings motivated later research on "common ingroup identity" formation, which points to the importance of actually experienced cooperation for transforming "perceptions of group boundaries from "us" and "them" to a more inclusive "we"" (Gaertner et al. 1993, see also Brewer 1996,

2000; Gaertner and Dovidio 2000; Riek et al. 2010). One way of achieving such cooperation is through the assignment of cross-cutting categorizations (Marcus-Newhall et al. 1993; Crisp and Hewstone 1999; Crisp et al. 2006).[11]

While operating largely outside of this theoretical framework, research in political science has similarly underscored the capacity of common (national) identification to overcome ingroup favouritism (Transue 2007; Dunning and Harrison 2010; Robinson 2016). What is more, conflict studies and historical sociology share an emphasis on cross-cutting ties. Stein (1976) cites the internal organization of groups as central to their ability to mount a common response in the face of threat. For his part, Kalyvas (2008) demonstrates that the likelihood a given ethnic grouping, or subgrouping, will engage in cross-ethnic defensive mobilization with incumbents is heightened by "organizational demand" and, specifically, the presence of cross-cutting organizational resources enabling of interethnic or intergroup cooperation (see also Fearon and Laitin 1996).

After the fall of Mosul, interethnic cooperation was achieved when Sunni tribal groups mobilized in numerous regions alongside the Iraqi security forces and PMF. Absent the experimental manipulation afforded by a laboratory setting, we can exploit such contextual affordances to test whether the experience of cooperation impinged on identity loyalties. This example of intergroup cooperation relied on the remobilization of abeyant tribal mobilization groups that had continued to exist after the *Sahwa*. The availability of collaborationist structures that facilitated the common cooperative inclusion of ethnic counterparts, we can hypothesize, helped overcome intergroup bias and conduced to common national identifica-

[11] (Brewer, 1999, Appendix A) discusses explicitly the parallels between social psychology research on cross-cutting ties and large literature in anthropology, political science, and sociology.

tion: ***H3****: the experience of intergroup cooperation leads to common national identification.*

3.3 Threat perception and identification

Prior attachments, as well as organizational means to achieve intergroup cooperation, are thus expected to shape identity loyalties in situations of threat. To explain this link, scholars from various disciplines have pointed to security-seeking mechanisms. When faced with threat, individuals exposed to danger will identify with the category most likely to provide "access to security-granting institutions" (Gorman and Seguin 2018, see also Posner 2007; Wimmer 2013). Even in ethnically heterogeneous settings, this institution is most ofen the nation (Gibler et al. 2012; Sambanis and Shayo 2013). In the absence of prior attachment, groups may "seek security elsewhere in the face of threat" and identify with categories that are more expansive than the nation as they (Gorman and Seguin, 2018, 713). ODT shares this emphasis on "security motives", arguing that threatened individuals will turn to a salient ingroup for psychological security (Brewer 1991, 2007).[12]

Importantly, security motives are, in turn, related to the way in which a given threat is perceived. And this threat perception plays an important mediating function when it comes to identity responses (Stephan et al. 2002; Brewer 2007).[13]. Research on rallying effects and prejudice finds that attitudinal change is principally mediated by a perception of sociotropic threat; i.e., as a threat to the entire national collectivity (Davis and Silver 2004; Sniderman et al. 2004; Huddy et al. 2005; Gibson 2006). In contexts of insecurity, threat perception exhibits important heterogeneity. Those who report lower levels of trust in government

[12]It is important to distinguish these claims from so-called *positive distinctiveness theory* (see e.g., Turner 1985), which sees ingroup favouritism as driven by self-enhacement rather than security motivations.

[13]Notably, a focus on threat perception was also central to earlier sociological work on conflict and cohesion (Coser 1956)

are more likely to perceive threat in personal ("egocentric"), rather than sociotropic, terms (Davis and Silver 2004). In other words, whether or not threat is perceived as a threat to an imagined national community is conditional on prior attachment to that collectivity.

In making this observation, I do not discount the instrumental dimensions of identity loyalties. Prior attachment to a national identity may well be reduced if one judges a national collectivity incapable of providing security. Diminished national identity attachments, in turn, make it less likely that an external threat will prime, or make salient, a national identity (Rousseau and Garcia-Retamero 2007). This is not, however, solely because individuals will instrumentally seek security in identification with alternative security-granting institutions. It is additionally on the basis of prior attachment that individuals will perceive the subjective nature of the threat differently (Rouhana and Fiske 1995; Rousseau and Garcia-Retamero 2007). Security-seeking orientations, in other words, may be causally prior to threat perception. A final hypothesis thus emerges ***H4****: intergroup identity responses are mediated by differential threat perception.*

4 Data and method

The principal data source I use to test these hypotheses is a nationally representative survey of Iraq conducted as part of the Arab Transformations Project.[14] The survey was in the field over the period May 28 2014-June 22 2014. The fall of Mosul to ISIS occurred on June 10. The number of survey respondents by day is shown in Figure 5. As should be clear, the fall of Mosul to ISIS essentially bisects the respondents into relatively equal before and

[14]For detailed information on this survey see the Appendix.

after groups. Overall, 13 of Iraq's 19 governorates, and 36 of its 104 districts were included in the sample. The survey coverage, both before and after Mosul, is displayed in Figure 6. Fourteen districts were surveyed before the fall of Mosul (did not receive the treatment), while thirteen districts were surveyed after the fall of Mosul (received the treatment), and ten districts were surveyed both before and after the fall of Mosul (received both treatment and control).[15]

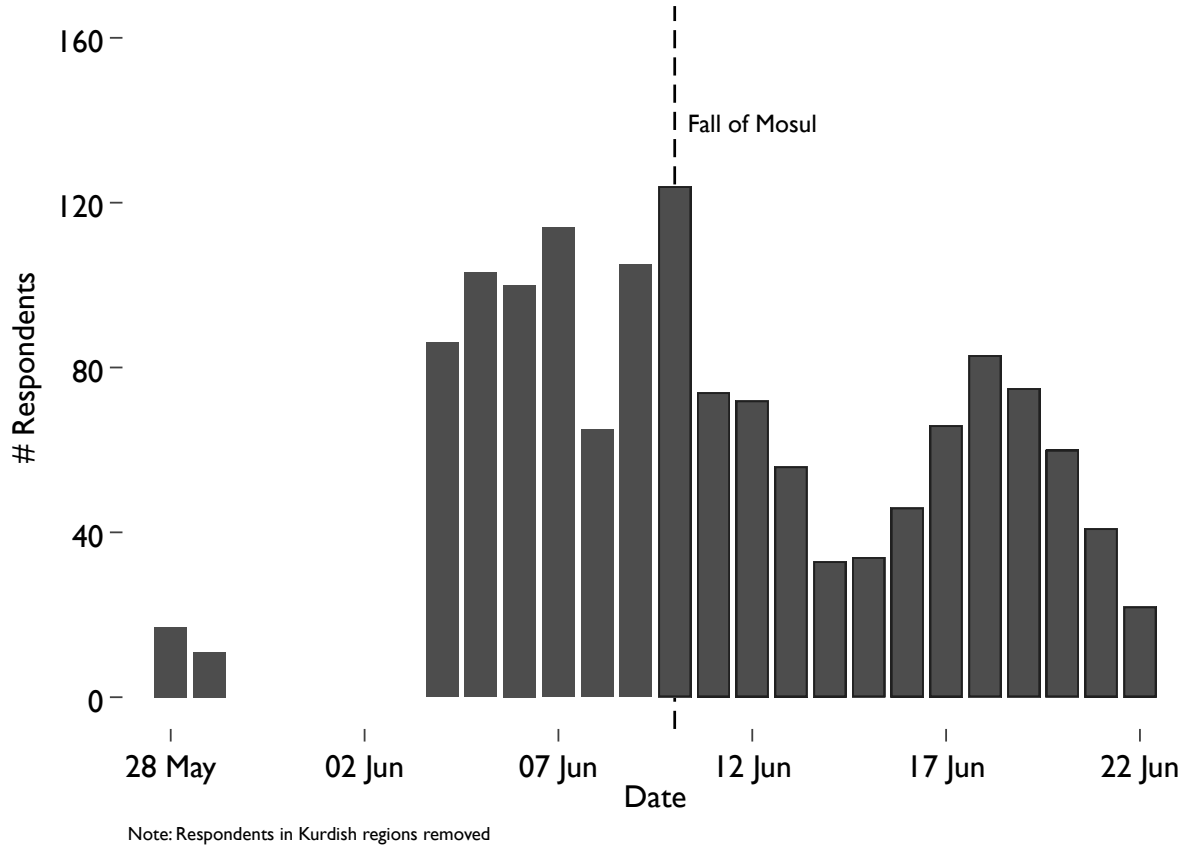


Figure 5: Respondents before and after the fall of Mosul. Number of respondents interviewed before the fall of Mosul: 709 (210 Sunni; 499 Shi'i). Number of respondents interviewed after the fall of Mosul: 628 (273 Sunni; 355 Shi'i)

The principal dependent variable is coded as a binary response to the question: "If

[15]See Appendix for full details of districts surveyed.

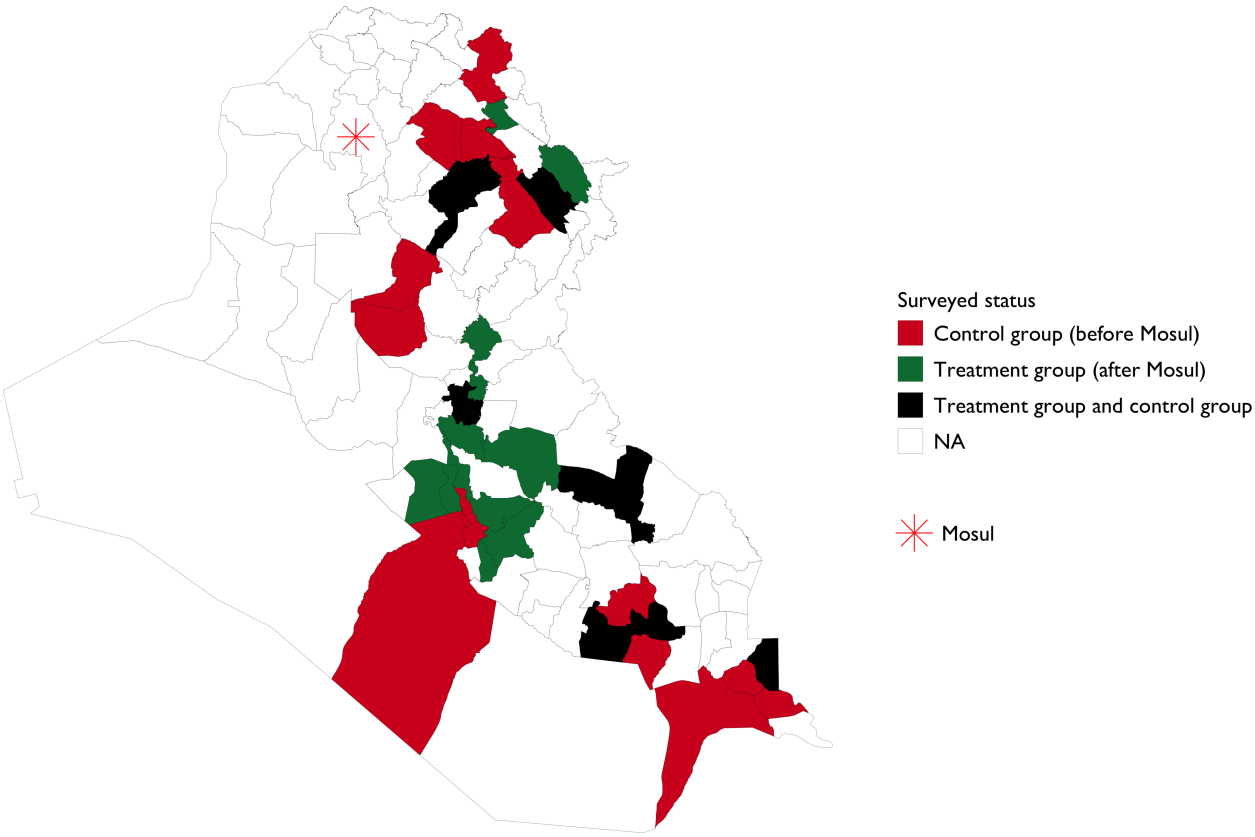


Figure 6: Map of survey districts before and after Mosul.

you were being asked to identify yourself, with which of the following would you most likely identify?". Six options are offered: "Your country of origin (*balad al-aṣl*)"; "Arab (Ethnicity) (*al-'umma al-'arabiyya (al-'irq)*"); "Muslim (Religion) (*al-islam (al-diyānna)*)"; "Region (*al-mintaqa al-jighrāfiyya*)"; "Local community, city where you live (*al-mujtama'/al-medina alati ta'ish biha*)"; "Other (*ukhra*)". All respondents reported that they lived in their country of birth. I thus take the first item to indicate identification with the Iraqi nation. In using self-reported identity as the dependent variable, I follow several recent notable contributions utilizing similar measures (e.g., Elkins and Sides 2007; Eifert et al. 2010; Gibler et al. 2012). In the main analysis I remove respondents from Kurdish regions (Erbil and Sulaymaniyah) since it is not clear the identity attachments they are professing in response to these survey

questions (e.g., with Iraqi Kurdistan or Iraq as their "country of origin"). This reduces the total sample size from 1,613 to 1,387.

I combine these survey data with available ecological measures at the district level provided by the Empirical Studies of Conflict Project (ESOC) Iraq Civil War Dataset Version 3.0.[16] Local ecologies likely shape patterns of identification independent of the fall of Mosul. To account for this, I use basic measures of the ethnic demographic profile of each of the districts included in the survey (% Sunni/% Shi'i), and also include information on prehistories of violence (2003-2009) in the survey districts using the Iraq Body Count (IBC) database, cleaned and coded at the district level by ESOC.[17] This measure is transformed to its square root.

To gauge the impact of tribal ties on patterns of identification and identity responses to the fall of Mosul, I use a district-level measure of the percentage of households reporting a member of their clan living in the same neighbourhood (*mahalla*). This is taken from the 2004 Iraq Living Conditions Survey (ILCS), and again cleaned and coded at the district level by ESOC.[18] Districts with a higher density of tribal ties are expected to house tribal mobilization structures conducive to collaborative mobilization efforts. The measure is converted to a rate per ten thousand individuals for easier interpretability. Descriptive statistics for all variables are displayed in Appendix Table A12.

The analysis relies upon the exogenous variation in threat of war, and attendant mobilization efforts, produced by the fall of Mosul to ISIS. Separating into distinct before and

[16]For more information, see `https://esoc.princeton.edu/country/iraq`.

[17]The SIGACT III data only include reports where US forces were present, meaning that they likely undercount sectarian violence. For this reason, I test data from the IBC.

[18]The ILCS is a survey of 21,668 households conducted in Iraq in 2004. For more information, see the Appendix and `https://reliefweb.int/report/iraq/iraq-living-conditions-survey-2004`.

after groups (or control and treatment groups) is made possible by the speed with which Mosul fell.[19] Figure 7 displays the raw proportions of respondents answering for each identity item across both sects and time periods. There are evidently sizeable differences across the two periods in the proportions answering for each identity category. In what follows, I focus on the national, Arab, and Islamic identity categories given that very few respondents select either of the remaining two items. Each outcome is operationalized as a binary variable coded 1 for the outcome of interest, and 0 otherwise.

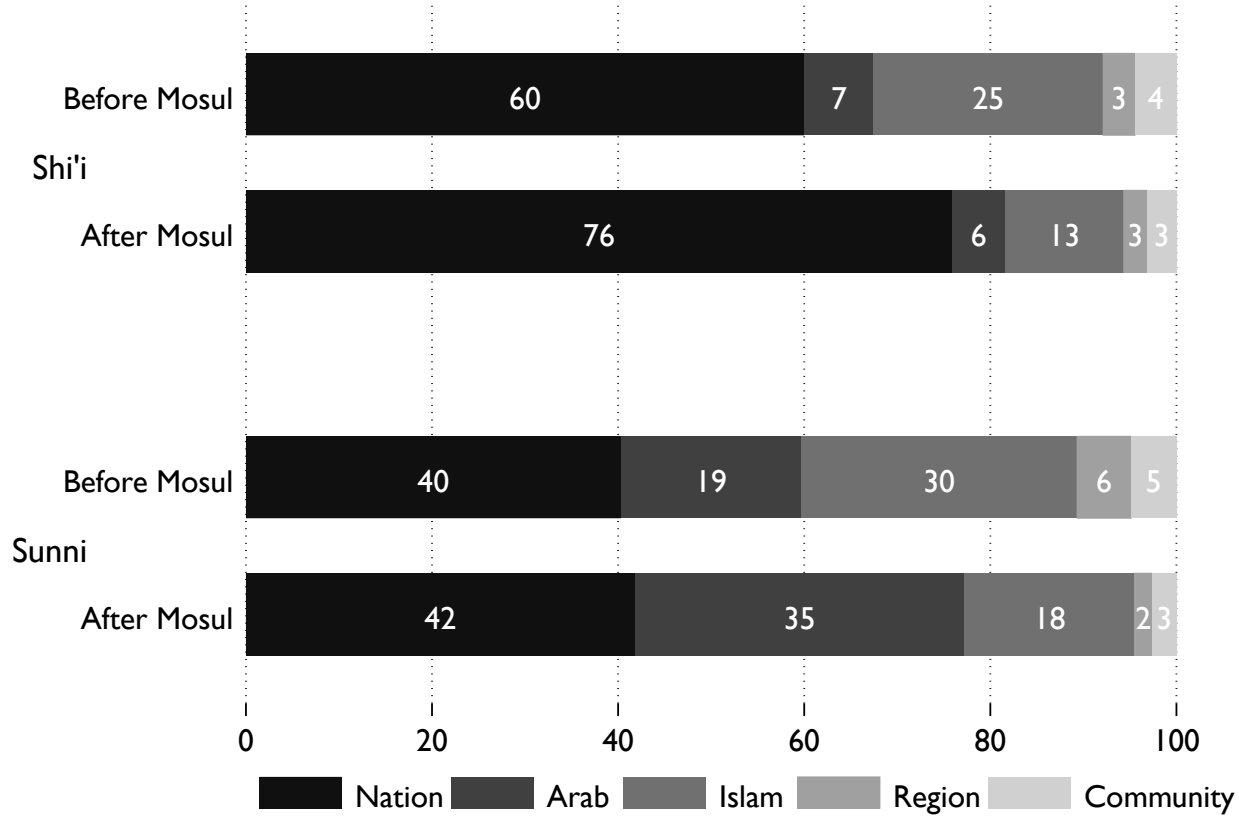


Figure 7: Self-dentification before and after Mosul: all identity items. Note: respondents in Kurdish regions not included.

Under assumptions of perfect randomization, we would be able to run simple difference

[19] A key concern in natural experimental setups relates to the "endogenous timing of the event" (Muñoz et al. 2019). The lightning fall of Mosul makes these concerns less relevant to the current research design.

of means tests on the observed proportions identifying with each category.[20] However, such a strategy would make strong assumptions; namely, that there were no systematic differences between the regions sampled before and after Mosul's fall, and that there were no systematic differences between the individuals surveyed before and after June 10. In other words, ignorability of treatment assignment at both ecological and individual levels would be assumed (see Rubin 1978; Muñoz et al. 2019).

In a first stage, the fall of Mosul is operationalized as a dichotomous variable coded 1 if the respondent was interviewed after June 10, and 0 if on June 10 or before. Ignorability of treatment assignment is assumed by conditioning on relevant pre-treatment covariates in a multilevel logistic (ML) context, formally: $Y^0, Y^1 \perp\!\!\!\perp Z|X$, where Y^0, Y^1 are potential outcome means, Z is binary variable indicating assignment to treatment or control, and X is the vector of pre-treatment covariates. Here, I follow notable recent studies leveraging within-survey exogenous variation that use multilevel designs to assess the impact of a dichotomous treatment (Cerdá et al. 2012; Legewie 2013). Individual-level covariates are included for age, gender, and whether the respondent attended college. Importantly, the fall of Mosul is unlikely to affect reporting on these basic demographic parameters, which helps guard against post-treatment bias (Montgomery et al. 2018; Muñoz et al. 2019). Introducing random intercepts at the district level, I also include district-level covariates for ethnic demographics (% Sunni/% Shi'i), prehistories of violence, and density of tribal ties.[21] The coefficient on

[20] Running two-tailed t-tests for each identity item subsetted by sect reveals that the increase in national identification for Shi'is, Arab identification for Sunnis, and reduced Islamic identification across both sects are all significant at the .001 level

[21] Covariates to include were selected on the basis of an iterative process whereby variables were added to the model if they significantly improved model fit. Numerous variables were tested, including, at the individual-level, categorical variables for individual wealth, religiosity, attitudes towards Islam in public life, interest in politics, attitudes to democracy/authoritarian government, trust in government, trust in the military, and interest in the news (note that, with the exception of wealth, the inclusion of these

the binary treatment indicator can be interpreted as the as the average treatment effect (in log-odds) of the fall of Mosul on the given identity attachment of interest conditional on pre-treatment covariates, i.e.: $E(Y^1|Z = z, X = x) - E(Y^0|Z = z, X = x)$. Treatment interactions with sect (Sunni/Shi'i) in the full sample are also then included to test for significant inter-ethnic differences in response to the fall of Mosul. To test for subethnic heterogeneity in Sunni identity responses, I then include a treatment interaction with the ecological variable measuring density of tribal ties.

While previous studies (e.g., Legewie 2013) have applied a causal interpretation to these results, a number of further steps are required before confident causal claims can be made. Ignorability in this first stage of analysis is partially achieved by conditioning on pre-treatment covariates. However, recent statistical scholarship recommends employing matching procedures as a pre-processing technique prior to any parametric estimation (Ho et al. 2007). I thus use the multilevel (ML) analysis results as a first stage to inform subsequent matching. So-called "doubly robust" estimation procedures combine models predicting both treatment and outcome and have the particular quality that only one of the models must be correctly specified in order to obtain accurate estimates of treatment effects (see Bang and Robins 2005). Below, I elect to use augmented inverse probability weighting (see Glynn and Quinn 2009) to estimate treatment effects, using logistic regression in both the treatment and outcome equations.[22] Guided by the ML results, I model treatment assignment and the outcome as a function of age, gender, college education, ethnic demographics (% Shi'i), prehistories of violence, and density of tribal ties. I also demonstrate the results are robust to multiple

variables may introduce post-treatment bias). Further ecological variables tested included a measure of militia presence in 2004 (from ILCS) and a measure of unemployment rate (again from ILCS).

[22] I use the *teffects* suite of commands in Stata 15.1 to estimate these.

different matching procedures as well as the use of additional matching covariates. To test for the robustness of the tribes interaction, I first obtain weights using a genetic matching procedure (see Diamond and Sekhon 2013), and then rerun the parametric analysis using the reweighted sample.[23] Employing matching procedures helps alleviate any concerns relating to potential violations of the positivity assumption, which requires that the probability of treatment assignment be greater than zero for all individuals within all strata of a set of pre-treament covariates, formally: $\forall z, x, P(Z = z|X = x) > 0$ (see Rosenbaum and Rubin 1983).

Crucially, the above estimation procedures implicitly disregard the potential for heterogeneity in treatment exposure. Rather than the average treatment effect (ATE), then, the methods described above can more properly be interpreted as estimating the intent-to-treat effect (ITTE) since we do not know exactly when respondents became aware of the fall of Mosul. What is more, the empirical strategy described above imposes, in experimental language, a stable unit treatment value assumption (SUTVA) on the data (Rubin 1978). The SUTVA has two components, the first of which requires that all units of observation (i.e., survey respondents) are independent of each other. We can safely assume that no survey respondents were able to influence the responses of any other respondent. However, the second component requires that there be only one version of the treatment. Although the fall of Mosul was sudden and unexpected, the precise treatment may have fluctuated over the observation period as ISIS advanced, militias mobilized, and new information became available—what Muñoz et al. (2019) refer to as "collateral" and "simultaneous" events. This

[23]Genetic matching was carried out in R using the *MatchIt* package. Parametric estimation was conducted in Stata 15.1. R was used for the matching here as Stata does not allow the user to obtain the weights generated by the *teffects* commands prior to the estimation of ATEs.

situation is analogous to so-called "contaminated" randomized control trials wherein individuals might not comply with treatment assignment (see e.g., Sussman and Hayward 2010). Here, "compliers" would be those that were, firstly, aware of the fall of Mosul and, secondly, induced to exposure of enhanced threat as a result (i.e., treated). Thus, instead of being understood as the treatment itself, Z would be understood as randomization to treatment, and A as the treatment received. The average treatment effect, then, given additional covariates X, would be estimated as: $E(Y^{z=1}|A=a, X=x) - E(Y^{z=0}|A=a, X=x)$.

Fortunately, the survey does contain two questions of relevance that can help us to estimate one such quantity. All respondents were asked "To what degree are you worried about" a series of situations, including "A war in my country". I take this question as a measure of perceived "sociotropic" threat; that is, as a perceived threat to the nation. A second question provides us with a measure of local, or "community-level", threat, which is understood as a threat to immediate surroundings (Stevens and Vaughan-Williams 2016).[24] The wording of this question was as follows: "Where on a 5-point scale would you put the security in your neighbourhood (*hayy*) if "1" is the lowest mark and "5" the highest?". I operationalize these questions as binary indicators for whether the individual was "worried or very worried about war" versus "not worried or not worried at all about war" and whether the individual rated local security to be bad (from 1-3) versus good (4-5). The first provides our measure of perceived national security threat, and the second a measure of local security threat. Utilizing these questions, we can then use the treatment assignment not as the treatment variable itself but as an instrument for these national and local security threat

[24]Following Stevens and Vaughan-Williams (2016), I understand community-level threat as distinct from, but closely aligned to, personal or "egocentric" threat. Using an alternative question probing security ratings of household/family security, findings are similar, as I go on to discuss.

treatments. By investigating the effects of threat perception at these different levels, we can more precisely identify any threat perception mechanisms underpinning observed outcomes.

Given that both the endogenous variable and instrument are binary, (recursive) bivariate probit is preferred to 2SLS (see Terza et al. 2008; Chiburis et al. 2012).[25] Following Chiburis et al. (2012), bootstrapped confidence intervals are calculated for the LATE to overcome problems of undercoverage in the bivariate probit model.[26] The bivariate probit model is a system of simultaneous equations predicting the outcome (i.e., identity attachments) and selection (i.e., treatment) (Heckman 1978). The model without controls takes the form:

$$Y_i^* = \beta_0 + \beta_1 X_i + \epsilon_Y \tag{1.1}$$

$$X_i^* = \alpha_0 + \alpha_1 Z_i + \epsilon_X \tag{1.2}$$

, where Y_i^* and X_i^* represent the latent propensities to identify with a particular identity and to be worried by war/local securityt respectively, X_i represents the observed war/local security threat, and Z_i is the instrument for random treatment assignment. It is further assumed that ϵ_Y and ϵ_X are jointly bivariate normally distributed. The local average treatment effect (LATE) of national/local threat can then be estimated as: $\Phi(\beta_0 + \beta_1) - \Phi(\beta_0)$, where Φ represents the standard normal distribution and β_0 and β_1 are maximum likelihood values to be estimated.

The same set of controls as used in the ML and matching procedures above are used in

[25]Bivariate probit is also preferred when the sample size is less than 5,000 and when the probability of treatment differs significantly from 0.5, as is the case here.

[26]Here, 199 bootstrapped replications are used. The user-written command *biprobittreat* in Stata is used to generate these estimates.

both the selection and outcome equations. Several further assumptions must be satisfied in order for the LATE to be identified, however. The first, the monotonicity assumption, requires that we can plausibly discount a preponderance of "defiers" (Angrist and Imbens 1994). Here, this would mean that we can assume that individuals were not consistently induced to perceive reduced threat as a result of the fall of Mosul and can be safely assumed. The second, the exclusion restriction, requires that Z is independent of Y conditional on A; in other words, there are no backdoor effects of the fall of Mosul on our outcome of interest net of perceived national/local security threat. This is a stronger assumption. Thus, in a further robustness section, I first condition on an additional set of covariates that might plausibly connect the fall of Mosul to particular identity attachments. Second, I conduct a series of causal mediation analyses in order to recover the proportion of the total effect of Mosul's fall that is mediated through differential threat perception.

5 Results

Full results from the ML models are displayed in Appendix Tables A1-A5. Fitting null multilevel models for each identity category points to strong evidence of non-zero between-district variance, as can be seen in Appendix Figure A12. This should alert us to the need to control for relevant ecological covariates. The models in Table A1 show the effect of the fall of Mosul split into subsamples by sect. The basic patterns in the raw proportions displayed above are partially confirmed: Shi'is are more likely to identify with the nation (p=.052), while Sunnis are more likely to identify with an Arab identity attachment, and both Sunnis and Shi'is are less likely to identify with Islam though effects for the Islam category fall below

convential thresholds of statistical significance.[27] Including an interaction between sect and the the treatment variable for the fall of Mosul, as displayed in Table A2, we see that Shi'is are significantly more likely than their Sunni counterparts to identify with the nation as a result of the fall of Mosul, while Sunnis are more likely to identify with an Arab identity dimension. We thus have initial support for hypotheses *H1* and *H2*.

These systematic differences in identity responses justify separating subsequent analyses into subsamples by sect. Including cross-level interactions between sect and ethnic demographic measures, we see that most variation is among Sunnis, and that ethnic demographics and prehistories of violence both impinge on identity attachments. Sunnis living in more homogeneously Sunni areas are significantly less inclined to identify with the nation while the converse is true in more homogeneously Shi'i areas. Prehistories of violence are also associated with heightened national identification across both Sunnis and Shi'is (see Tables A3-A5).[28] Age, gender, and college education are also associated with identity attachments. For the effect of conflict threat on identity to be identified, the distribution of relevant ecological and individual-level covariates must, then, be accounted for.

Notably, much of the variance in identification is observed among Sunnis. The between-district variance in Sunni identification patterns should alert us to the potential for systematic subethnic differences in Sunni responses to the fall of Mosul. Including a three-way interaction between sect, the treatment indicator, and the measure of tribal ties, we see that while the main effect of the fall of Mosul on Sunni identification is towards an Arab identity,

[27] This may be explained by the hierarchical design. Multilevel models use "partial pooling" or "shrinkage" to estimate the level 2 residuals (the empirical Bayes estimates). This is an inherently more conservative test and results in point estimates being shrunk toward the overall group mean. This is also the preferred approach when some level 2 units might contain only a small number of responses (Gelman et al. 2012).

[28] No interaction with sect was introduced for the variable measuring prehistories of violence as effects were similar across both Sunnis and Shi'is.

this is confounded by the density of tribal ties (see Appendix Table A5). Sunnis living in densely tribal areas before Mosul were less likely to identify with the nation, reflecting the alienation felt by these communities at the time. However, after the fall of Mosul, this trend is reversed, and Sunnis in areas with dense tribal ties rally strongly behind the nation, as can be seen in Figure 8. There is no comparable effect for Shi'is. This reversal is striking and provides primary evidence of situational intra-ethnic variation in self-identification.[29] What is more, this reversal points to strongly suggestive evidence of the generative role of intergroup cooperation in impelling common national identification at the population level: in tribal regions, where mobilization structures were in place to facilitate the common inclusion of their ethnic counterparts in defensive national war efforts, Sunnis were significantly more likely to rally behind a national identity. This provides support for hypothesis *H3*.

Ignorability of treatment assignment is assumed, in this first stage, through conditioning on relevant pre-treatment covariates. To calculate estimates of average treatment effects (ATE), I use an augmented inverse probability weighting matching procedure, using the same set of individual- and district-level controls as used in the ML models. Standardized mean differences between the treatment and control groups for each of these covariates in each reweighted subsample by sect are all lower than the accepted 0.1 threshold (Stuart et al. 2013) and considerably lower than the previously cited 0.25 threshold (Imai et al. 2008).[30] The results from the augmented inverse probability weighting matching procedure are displayed below in Figure 9.

[29]This result is robust to the inclusion of district-level measures of unemployment (measured in 2004–the same year as the tribal measure), ethnic demographics (% Sunni), and prehistories of violence (using either one of IBC or SIGACTS data).

[30]In matching on individual-level and ecological covariates I follow notable recent studies employing the same procedure (e.g., Gilligan et al. 2013).

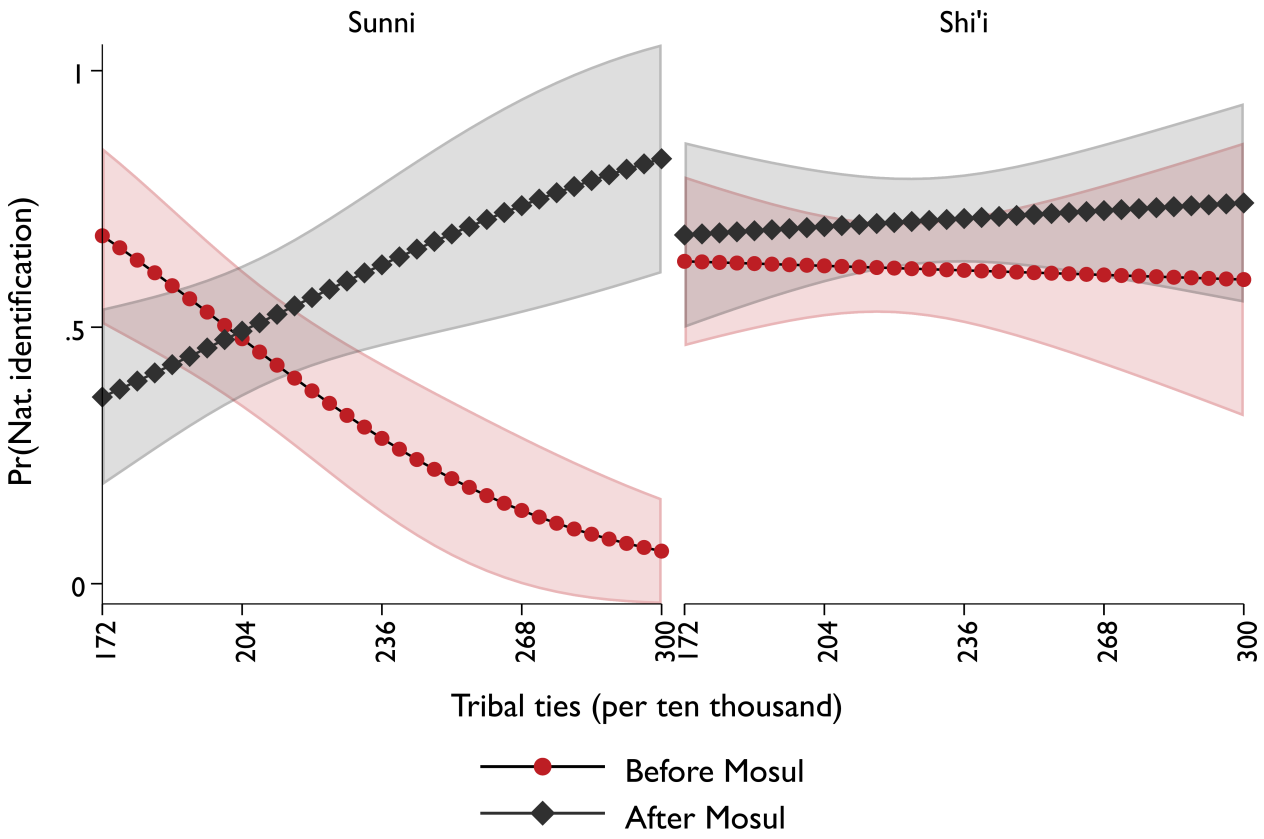


Figure 8: Predictive margins of tribal networks on Sunni and Shi'i national identification before and after fall of Mosul

Here, consistent with the ML models above, we see that the fall of Mosul has a significant positive effect on Shi'i national identification (14%) and Sunni Arab identification (20%), providing further support for hypotheses *H1* and *H2*. We also see a decrease in Islamic identification for Shi'is (11%) and a marginally significant decrease for Sunnis (7%). Results are robust to multiple alternative matching procedures, including inverse probability weighting with regression adjustment, propensity score, and nearest neighbour matching. Augmented inverse probability was selected as it achieved best overall covariate balance. The results are also robust to the inclusion of multiple additional individual-level covariates in both the outcome and treatment equations for the inverse probability weighting procedure, which included measures of religiosity, household wealth, interest in the news, interest in politics,

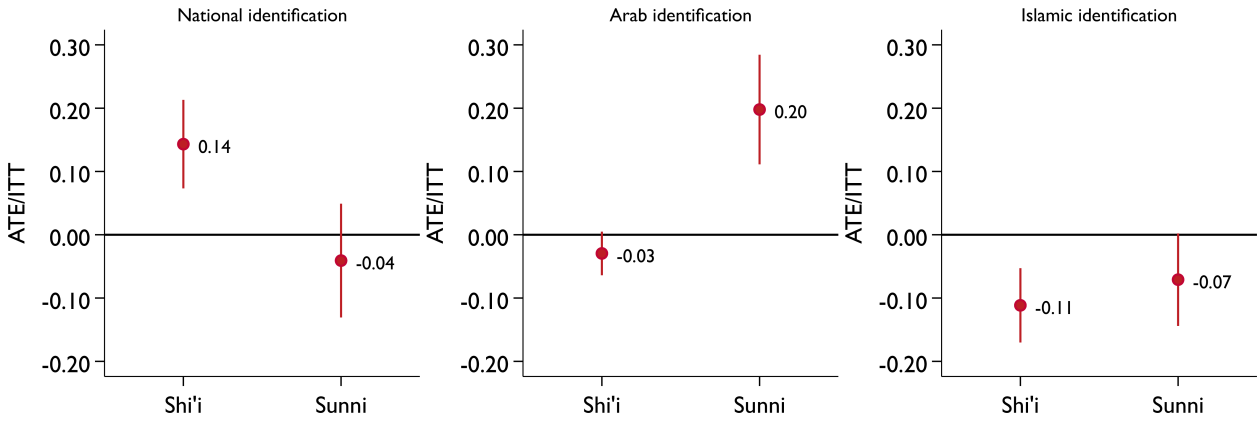


Figure 9: ATE/ITTE of fall of Mosul for each sect using augmented inverse probability weighting, with 95% confidence intervals

trust in government, and trust in the military (see Appendix Figure A15). Rerunning the analysis for the tribes interaction with matched data, we see too that the finding of sub-ethnic differences in Sunni national identification holds, as can be seen in Appendix Table A6 and Figure A13, providing further confirmation of hypothesis *H3*.[31] In the Appendix, I conduct further tests to investigate the observed reduction in Islamic identification. I find little evidence of social desirability driving these results. Nor do I find evidence that they are mediated by a rejection of political Islam. Instead, it appears that security threats made more salient alternative identity categories, and these push factors outweighed the pull of religious identity. It is nonetheless notable, in this regard, that psychological security is not sought in Islam. In what follows, I restrict attention to the two identity categories toward which respondents cleaved: national and Arab.

The analysis thus far has proceeded on the assumption of homogeneous treatment exposure. Given that certain individuals may not have been as immediately aware of the fall of Mosul as others, and that the level or type of threat to which they were exposed may

[31] Standardized mean differences in these genetically matched data are all significantly lower than the 0.25 threshold as can be seen in Appendix Figure A14a. The same covariates as used above in the augmented inverse probability weighting procedure are used here.

have fluctuated, we would be better to interpret the above findings as intent-to-treat effects (ITTEs) rather than ATEs. Results from the bivariate probit models, however, which instrument questions probing national and local security threat with the binary post-Mosul indicator do allow us to identify threat perception mediators driving the results. Results are displayed in Figure 10. Full regression outputs are displayed in Appendix Tables A8-A9. Here, we can see that, for those exposed to heightened threat, the threat of war made Shi'is 64% more likely to identify with the nation, while local security threats exhibit a positive but insignificant effect. Sociotropic threat, in other words, mediated national identification for Shi'is. Conversely, for Sunnis, it appears that the move towards an Arab identity attachment was driven by local security threat perception. This community-level threat saw Sunnis 37% more likely to identify as primarily Arab, while (national-level) threat of war exerted a negative but insignificant effect.

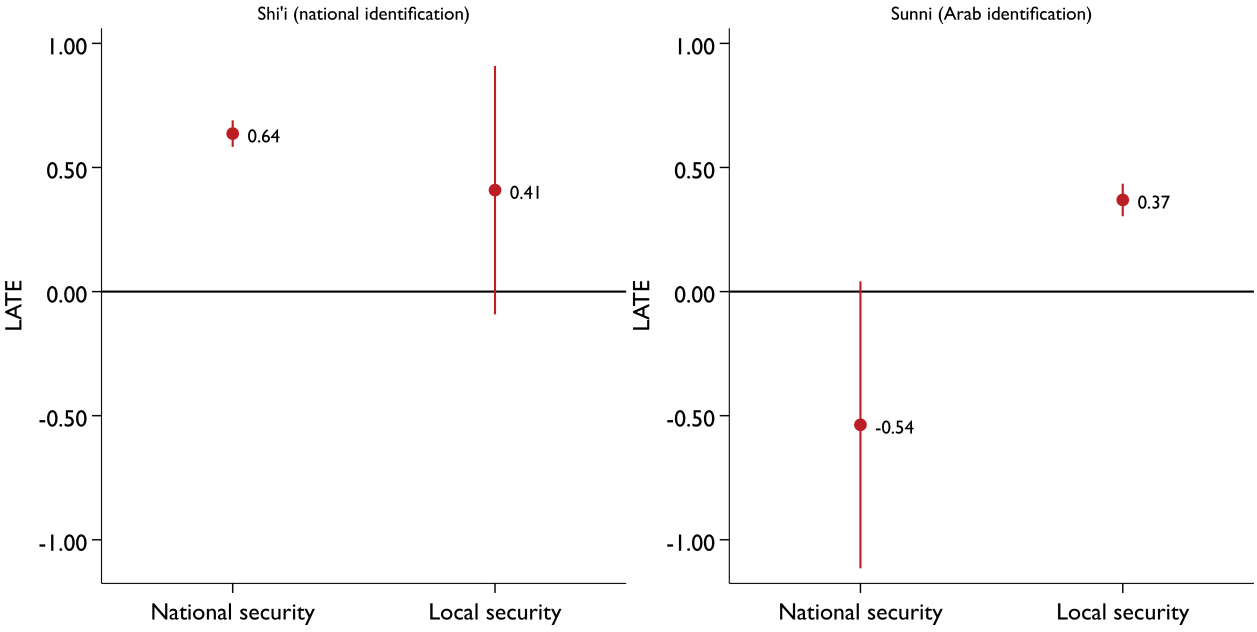


Figure 10: ATEs of national and local threat on Shi'i national identification and Sunni Arab identification, with 95% confidence intervals

We have, then, some support for hypothesis *H4*. Perceiving the fall of Mosul to ISIS as a threat to the nation, Shi'is would rally behind a national identity. These empirical observations tally with testimony from PMF volunteers who saw themselves as fighting not a Sunni force (i.e. as engaging in civil conflict), but a foreign incursion: "this is not a war against Sunnis," one such volunteer declared, "what we are fighting is similar to the Mongol invasion" (ICG 2014, 17). Sunnis, on the other hand, faced with a mass mobilization of Shi'is into militia formations and the Iraqi army, perceived this threat differently. For them, the fall of Mosul to ISIS was perceived not as a threat to the nation but primarily as a threat to local security. In response, Sunnis did not rally behind the nation but instead sought refuge in a more expansive Arab identity category.

These results are robust to the inclusion of multiple additional controls in the outcome equation of the bivariate probit models to guard against potential violations of the exclusion restriction (see Appendix Tables A10-A11). It remains that the exclusion restriction is likely violated in this design and that backdoor effects do exist. How much of the overall effect of Mosul's fall, then, is mediated by perceived threat? Mediation analysis (Imai et al. 2010) provides one approach to answering this question. Here, the quantity of interest is the so-called indirect effect, or average causal mediation effect (ACME), of a change in a given mediator when holding treatment status constant. For this quantity to be identified, the sequential ignorability assumption must be satisfied (Imai et al. 2011). This has two components. The first requires that treatment be exogenous conditional on pretreatment covariates. The second requires that, given treatment status and pretreatment covariates, the mediator is conditionally independent. For our purposes, this means that we must control for relevant pretreatment covariates that might affect threat perception and identity

loyalties such that the mediator can be considered ignorable. This assumption cannot be directly tested, and practictioners propose the use of sensitivity tests as a check on validity. I elect to use the same set of individual- and district-level controls as used above for both the mediator and outcome equations.[32] Overall, 10% of the effect of Mosul's fall on Shi'i national identification is mediated through perceived (national-level) threat of war (versus 0% for local threat), while 14% of its effect for Sunni Arab identification is channeled through perceived (community-level) local security threat (versus 0% for war threat). Sensitivity analyses for both sects indicate that, for the ACME to equal zero, a given omitted confounder must explain 20% of the variance in the outcome or mediator equations (see Figure A16).

6 Discussion

This paper has provided the first systematic empirical test of intergroup identity formation *within* a major conflict episode. In so doing, I am able to scale the laboratory-level findings of a wealth of social psychology to a real-world setting. I find that conflict outbreak, and attendant threat, do have profound impacts on individuals' attachments to group identities. Understood in terms of its ability to unite previously disparate groups, however, war did not make the state. In fact, in the Iraqi case at least, it had disintegrative effects: aggregate intergroup distances between Sunni and Shi'i identity loyalties increased after the fall of Mosul. But this is not the whole story. In districts that housed organizational structures conducive to cross-ethnic collaboration, the prosecution of war did cause ethnic groups to

[32]The mediator variables use the original scales used in each survey item. These run from 1-4 for the question relating to "a war involving my country", and 1-5 for the question asking respondents to rate local security. This scale on the local security item is reversed to reflect the increasing scale used in the national security item. 1000 simulations are used for the estimation procedure.

rally behind a common national identity. War *can* make the state, then, but it requires an organizational antecedent.

In the absence of such organization, I argue, the exclusion of a given group (or groups) means that, when faced with the threat of war, they are unlikely to feel any increased loyalty to the nation. Instead, groups with low levels of prior attachment to, and trust in, the national collectivity seek security elsewhere. The identity refuge for Iraq's sunni minority was an Arab identity dimension. In other contexts, recent scholarship demonstrates, individuals search out psychological security in other border-crossing, even global, identity categories (Gorman and Seguin, 2018). But it is not just security motives, I argue, that lay beneath changes in self-categorization. The instrumental variable and causal mediation analyses provide evidence that threat perception plays an important mediating role. Groups with low prior attachment to the state may seek security elsewhere but this security orientation results, at least in part, from differential threat perception. Shi'is, who were on average more trusting of the state, perceived the fall of Mosul in sociotropic terms as a threat to the Iraqi nation. Conversely, Sunnis perceived Mosul's fall not as a threat to the nation but as a threat to their local community.

How does threat perception relate to organizational demand? In the case of Iraq, intergroup cooperation was made possible by the existence of abeyant tribal defence organizations. Laboratory-level findings indicate that when cooperation is secured between groups a common ingroup identity can result. More recent contributions in social psychology show that, for it to decrease intergroup bias, cooperation between groups need not be directly experienced by an individual; the observation and knowledge of collaboration between groups is sufficient to reduce intergroup biases and perceptions of intergroup threat (Mazziotta et al.

2011; Crisp and Turner 2012; Böhm et al. 2018). In the case of Iraq, I argue that proximate collaboration between Sunni tribal groupings and the Iraqi army led to a perception of shared threat and found expression in renewed national identification among Sunnis living in these areas. In this way, cross-ethnic collaboration in wartime can reduce intergroup bias and promote national unity. This finding represents an important extension to recent scholarship in the sociology of nation-building. Wimmer (2015, 2018) argues that cross-cutting (cross-ethnic) organizations are of central importance in the generation of national loyalties. In this paper, I have detailed a further mechanism by which such organizational ties may exert these effects—by making possible intergroup alliances in wartime.

The identity responses of Sunnis in tribal areas highlights the need to take account of the "nested", multilevel nature of ethnic identity (Wimmer 2008, 2013), and the related potential for "multidirectional identity transformations" in response to conflict outbreak (Kalyvas 2008, 1045). In the six months after the fall of Mosul, anti-ISIS Sunni tribal groupings participated in over 140 separate combat events, often alongside the Shi'i-dominated PMF and Iraqi army (ISW 2014).[33] In a telling episode that took place on November 2, 2014, ISIS would attack and kidnap tens of members of the al-Juburi tribe in Alam, east of Tikrit, after youths from the region had torn down ISIS banners and rehoist the Iraqi national flag. In the summer of 2015, the recapture of Tikrit was achieved by a combined force of the Iraqi Army, PMF, and also Sunni tribal volunteers. Over time, the tribal forces would be integrated

[33]These figures represent the my own calculations from codings of events included in the ISW-produced "Iraq Situation Reports". Further illustrative examples of Sunni tribal mobilization in the main text derive, unless otherwise stated, from the same source material. Tribes and clans participating in these anti-ISIS efforts included the: Abbasiyen; Albu Alwan; Albu Fahad; Albu Ghanim; Albu Issa; Albu Khas; Albu Mahal; Albu Nimr; Albu Rayash; Albu Salman; Alus; Bani Aziz; Bayatin; Dulaim; Izza; Jaghaifa; al-Jisat; al-Juburi; Jumailat; Karabla; Khazraj; Korawi; Lihib; Mowali; Sabawi; Shammar; and Ubaidi.

into the PMF under the name of the Tribal Mobilization Forces.[34] The mobilization of Sunni tribes came despite their marginalization and repression at the hands of the ethnically exclusive Iraqi state in the years and months preceding the fall of Mosul (see Benraad 2011; ISW 2013; Gerges 2016). The observed subethnic dynamics for Sunnis in tribal regions would suggest, then, that identity responses are not the result simply of deep-seated resentments that take hold in ethnically exclusive contexts but of the contingencies of conflict outbreak, perceived threat, and efforts by political elites to mobilize across ethnic divides through existing organizational networks. This perspective accords with existing work highlighting the pivotal role of state responses in the evolution of civil war dynamics (Kalyvas and Kocher 2007).

Before concluding, an acknowledgment of several limitations to this analysis is appropriate. Firstly, while this example of exogenous variation provides us with a unique identification tool for assessing identity dynamics, it does only provide us with a snapshot of the immediate aftermath of the fall of Mosul. If identity is endogenous to conflict, it could equally well be subject to endogenous reversals and fluctuations over the course of a conflict cycle; something which cannot be assessed with the data available. [35]. Secondly, two of the the ecological measures used date from 2003-2004. War causes demographic change and disrupts social networks (Weidmann and Salehyan 2013). We cannot be completely confident, then, that inferences made from these ecological data are unaffected by measurement error. Thirdly, and notwithstanding the use of numerous matching procedures and tests of

[34] Acknowledging these episodes of interethnic cooperation is in no way to minimize the sectarian abuses committed in the aftermath of this event and others (HRW 2015; Mansour 2016). What it does point to is the potential for united, cross-ethnic responses to territorial threat even in ethnically exclusive settings.

[35] Be this at it may, a relatively brief observation window, recent methodological scholarship suggests, may be beneficial for the purposes of causal identification (Muñoz et al. 2019)

robustness outlined in the Appendix, the impediments to the reachability of respondents in certain districts (most obviously: al-Anbar and Mosul), may introduce forms of sampling bias. Finally, it should be noted that while natural experiments make possible the external validation of laboratory findings, the requirement to reverse engineer the experimental setting means they suffer from some imprecision in instrument design. Our measures of national and local security threat are imperfect and not completely comparable, potentially contributing to the relatively low percentage of the overall effect they mediate. Numerous other cognitive pathways related to threat (see e.g., Feinstein 2016) may also have been tested had suitable questions been included in the survey. Thus, while we can while we can confidently estimate effects of causes, identifying the precise causal pathways to these effects will be a task for future research.

7 Conclusion

Writing in the late 1970s, Hana Batatu, a pioneering historical sociologist of the Middle East, would argue that, much as in the rest of the world, the combined effects of demographic change, education, state centralization, and communication technologies had helped foster a national imaginary in Iraq. However, Batatu was to qualify this vision of a slowly sedimenting national identity. While these processes mattered, the ability of Iraqis to imagine themselves members of a unified Iraq was not infrequently propelled forward by major crises and episodes of mass mobilization: "it should be borne in mind," he writes, "that what is becoming the Iraqi community has also grown in crises, in moments of great danger and common suffering, in the tremors of agitated masses and their outbursts of anger" (1978, 36). Citing

multiple instances of collective mobilization and political crisis that preceded Iraq's eventual independence, he forecasts that, should Iraq maintain its territorial integrity, "the Uprising of 1920, the War of 1941, the *Wathbah* of 1948, the *Intifāḍah* of 1952, and the Revolution of 1958, though not free of divisive aspects, will be seen as stages in the progress of Iraq towards national coherence" (1978, 36).

The fall of Mosul to ISIS represents the most recent addition to this inventory of transformative events. Whether it will also represent a step towards national coherence is less certain. The findings outlined above point instead to the ability of ISIS to exacerbate identity cleavages in Iraq. They also point, however, to the potential for cross-ethnic national identification in conditions of common inclusion. The identity consequences of war, in other words, are multidirectional and contingent on the dynamics of conflict outbreak. Further work should seek to elaborate on and extend these findings. Does territorial threat always exacerbate identity cleavages or can credible national mobilization efforts overcome such dangers? What are the determinants of interethnic cooperation in the context of conflict? To what extent are identity loyalties subject to variation over the conflict cycle? What are the consequences of identity shifts for social attitudes? More broadly, given the nature of the phenomenon in question, and the growing availability of survey data, scholars would do well to locate and exploit similar sources of exogenous variation in future scholarship. Wars are convulsive, destructive, transformative events. Making use of their eventful quality allows us to ask not just why wars occur, but what their felt consequences might be.

Appendix 1

A1.1 Iraq newspapers



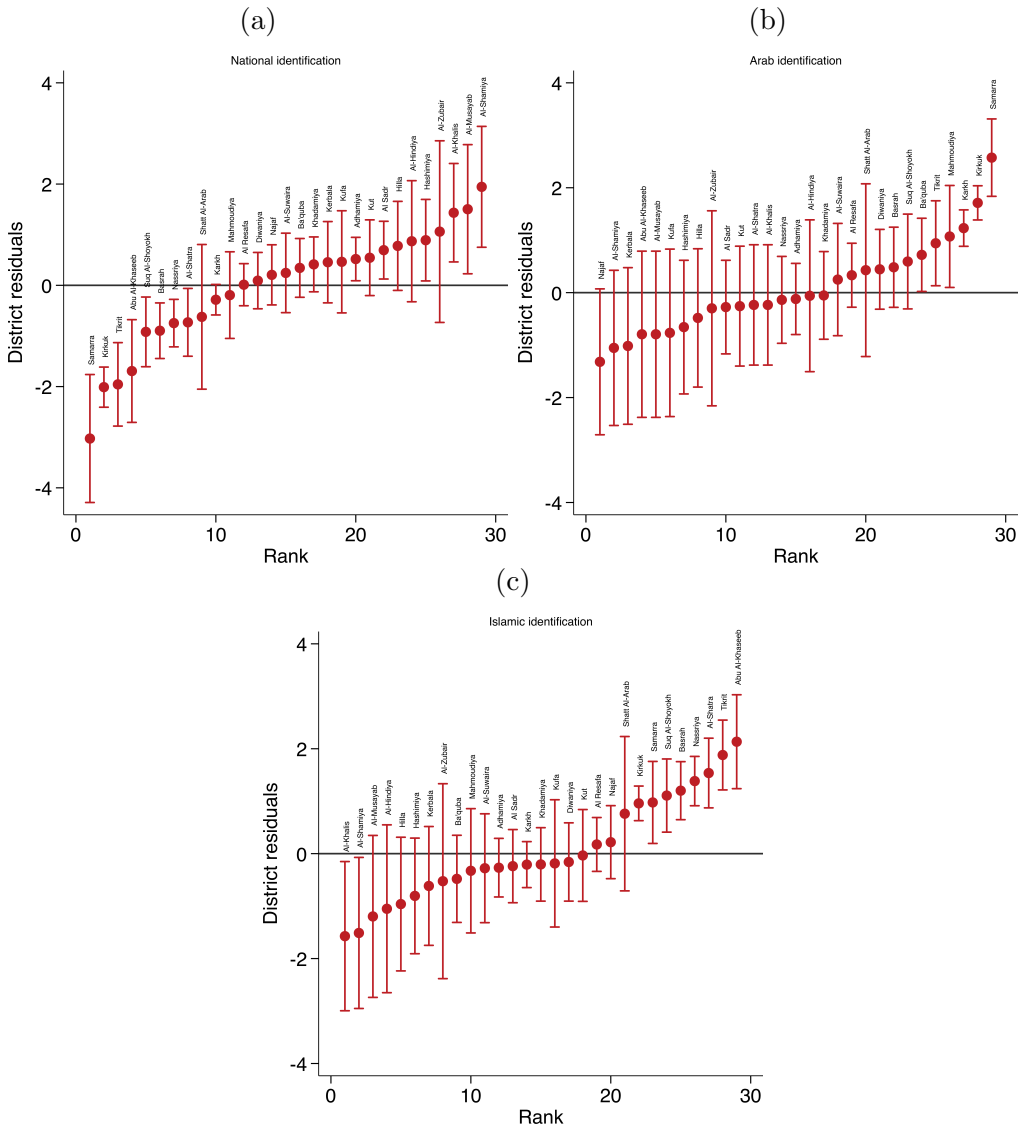
Figure A11: From left to right: front pages of *al-Mashriq*, *al-Mada*, and *al-Zaman* newspapers, June 9/June 10 (A); June 11 (B). Stories concerning ISIS/Mosul bordered in black.

A1.2 Multilevel model results

District-level residuals for each identity item in null random intercepts models are displayed in the caterpillar plots below in Figure A12.

Multilevel models for each subsample by sect, as well as for the full sample with sect

Figure A12: Caterpillar plots



treatment interactions are displayed in Tables A1-A5. Tables A6 and A7 display results for the threeway tribes interaction in the full sample, and for the interaction with treatment in the matched Sunni subsample.

Table A1: Multilevel logistic regression for three main identity items by sect

Variables	Model 1: Shi'i Nat. ident.	Model 2: Sunni Nat. ident.	Model 3: Shi'i Arab. ident.	Model 4: Sunni Arab. ident.	Model 5: Shi'i Isl. ident.	Model 6: Sunni Isl. ident.
Treatment	0.477†	-0.271	-0.563	1.249***	-0.035	-0.361
	(0.245)	(0.233)	(0.379)	(0.270)	(0.324)	(0.250)
Age	-0.005	0.005	-0.012	-0.003	0.019*	0.005
	(0.006)	(0.008)	(0.011)	(0.008)	(0.007)	(0.008)
Gender (1=female)	-0.352*	-0.359	-0.093	0.095	0.647***	0.233
	(0.160)	(0.224)	(0.286)	(0.220)	(0.194)	(0.236)
College education	-0.480†	-0.559†	0.796*	0.515†	0.381	0.270
	(0.280)	(0.307)	(0.406)	(0.292)	(0.347)	(0.328)
% Shi'i	-0.013	0.052***	0.010	-0.033***	0.011	-0.030***
	(0.011)	(0.006)	(0.013)	(0.007)	(0.016)	(0.007)
Prehist. violence	0.007	-0.037*	0.041	0.057**	-0.023	0.013
	(0.024)	(0.016)	(0.030)	(0.018)	(0.035)	(0.019)
Tribal ties	0.516	-1.107	1.333	2.139**	-1.324	0.520
	(0.722)	(0.681)	(0.992)	(0.651)	(1.059)	(0.635)
District variance	0.407†	0.000	0.282	0.000	0.968*	0.000
	(0.210)	(0.000)	(0.283)	(0.000)	(0.493)	(0.000)
Number of groups	27	16	27	16	27	16

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table A2: Multilevel logistic regression for three main identity items full sample with treatment sect interactions

Variables	Model 1: Nat. ident.	Model 2: Arab. ident.	Model 3: Isl. ident.
Treatment	-0.485†	1.315***	-0.170
	(0.253)	(0.293)	(0.275)
Shi'i	0.297	-0.213	-0.067
	(0.277)	(0.395)	(0.334)
Treatment*Shi'i	0.783*	-1.762***	0.150
	(0.350)	(0.484)	(0.402)
Age	0.000	-0.006	0.012*
	(0.005)	(0.007)	(0.006)
Gender (1=female)	-0.335*	-0.001	0.486**
	(0.130)	(0.176)	(0.150)
College education	-0.550**	0.645**	0.337
	(0.207)	(0.244)	(0.240)
% Shi'i	0.021**	-0.013†	-0.014†
	(0.008)	(0.007)	(0.008)
Prehist. violence	0.054*	0.007	-0.051†
	(0.026)	(0.025)	(0.026)
Tribal ties	0.774	0.990	-1.330
	(0.868)	(0.908)	(0.906)
District variance	0.992**	0.583†	0.933*
	(0.381)	(0.306)	(0.421)
Number of groups	29	29	29

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table A3: Multilevel logistic regression with cross-level interactions for national identification

Variables	Model 1: % Sunni	Model 2: % Shi'i	Model 3: Prehist. violence
Treatment	-0.443†	-0.424†	-0.441†
	(0.250)	(0.254)	(0.252)
Shi'i	-1.939*	3.175***	0.472†
	(0.856)	(0.728)	(0.271)
Treatment*Shi'i	0.827*	0.870*	0.779*
	(0.348)	(0.344)	(0.352)
Ecological var.	-0.044**	0.046***	0.019
	(0.014)	(0.010)	(0.020)
Shi'i*Ecological var.	0.048**	-0.056***	
	(0.017)	(0.014)	
Age	-0.001	-0.001	0.000
	(0.005)	(0.005)	(0.005)
Gender (1=female)	-0.343**	-0.353**	-0.343**
	(0.130)	(0.130)	(0.130)
College education	-0.525*	-0.530*	-0.556**
	(0.208)	(0.207)	(0.208)
District variance	0.773*	0.523*	1.270**
	(0.315)	(0.250)	(0.483)
Number of groups	29	29	29

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table A4: Multilevel logistic regression with cross-level interactions for Arab identification

Variables	Model 1: % Sunni	Model 2: % Shi'i	Model 3: Prehist. violence
Treatment	1.366***	1.314***	1.243***
	(0.296)	(0.289)	(0.289)
Shi'i	1.008	-1.511†	-0.609
	(0.932)	(0.856)	(0.371)
Treatment*Shi'i	-1.708***	-1.651***	-1.681***
	(0.466)	(0.464)	(0.491)
Ecological var.	0.031*	-0.028**	-0.002
	(0.013)	(0.010)	(0.018)
Shi'i*Ecological var.	-0.026	0.025	
	(0.017)	(0.015)	
Age	-0.006	-0.006	-0.006
	(0.007)	(0.007)	(0.007)
Gender	0.006	0.007	0.013
	(0.176)	(0.176)	(0.176)
College education	0.621*	0.634**	0.652**
	(0.243)	(0.243)	(0.245)
District variance	0.471†	0.462†	0.807*
	(0.270)	(0.267)	(0.400)
Number of groups	29	29	29

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table A5: Multilevel logistic regression with cross-level interactions for Islamic identification

Variables	Model 1: % Sunni	Model 2: % Shi'i	Model 3: Prehist. violence
Treatment	-0.175	-0.197	-0.200
	(0.274)	(0.273)	(0.273)
Shi'i	1.640†	-2.236**	-0.229
	(0.919)	(0.864)	(0.312)
Treatment*Shi'i	0.042	0.015	0.124
	(0.413)	(0.411)	(0.403)
Ecological var.	0.029*	-0.031**	-0.015
	(0.014)	(0.011)	(0.019)
Shi'i*Ecological var.	-0.037*	0.042**	
	(0.017)	(0.016)	
Age	0.013*	0.013*	0.012*
	(0.006)	(0.006)	(0.006)
Gender	0.491**	0.496***	0.492**
	(0.150)	(0.150)	(0.150)
College education	0.319	0.323	0.344
	(0.240)	(0.240)	(0.240)
District variance	0.837*	0.715†	1.081*
	(0.404)	(0.371)	(0.492)
Number of groups	29	29	29

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table A6: Multilevel logistic regression with three-way tribes interaction for national identification

Variables	Model 1: Tribal ties
Treatment	-9.897***
	(2.175)
Shi'i	-5.168*
	(2.070)
Treatment*Shi'i	9.463***
	(2.860)
Tribal ties	-0.030**
	(0.009)
Treatment*Tribal ties	0.049***
	(0.011)
Shi'i*Tribal ties	0.029**
	(0.010)
Treatment*Shi'i*Tribal ties	-0.045**
	(0.014)
Age	0.001
	(0.005)
Gender(1=female)	-0.339**
	(0.130)
College education	-0.505*
	(0.209)
District variance	0.638*
	(0.259)
Number of groups	29

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table A7: Multilevel logistic regression with tribes interaction for national identification with matched sample for Sunnis

Variables	Model 1: Tribal ties w/ matched sample
Treatment	-12.586***
	(3.397)
Tribal ties	-0.040*
	(0.016)
Treatment*Tribal ties	0.063***
	(0.018)
Age	0.013†
	(0.007)
Gender (1=female)	-0.388*
	(0.193)
College education	-0.449
	(0.285)
District variance	0.826*
	(0.411)
Number of groups	13

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

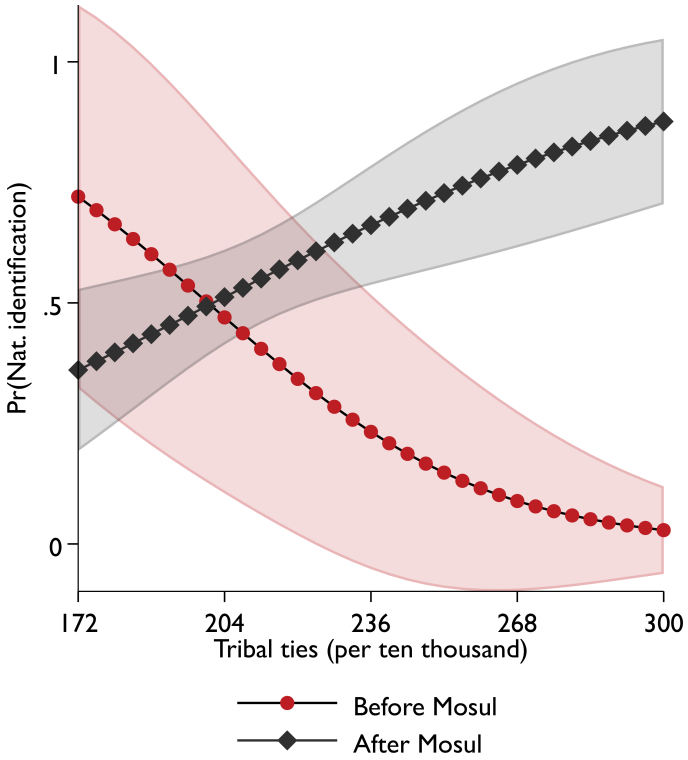


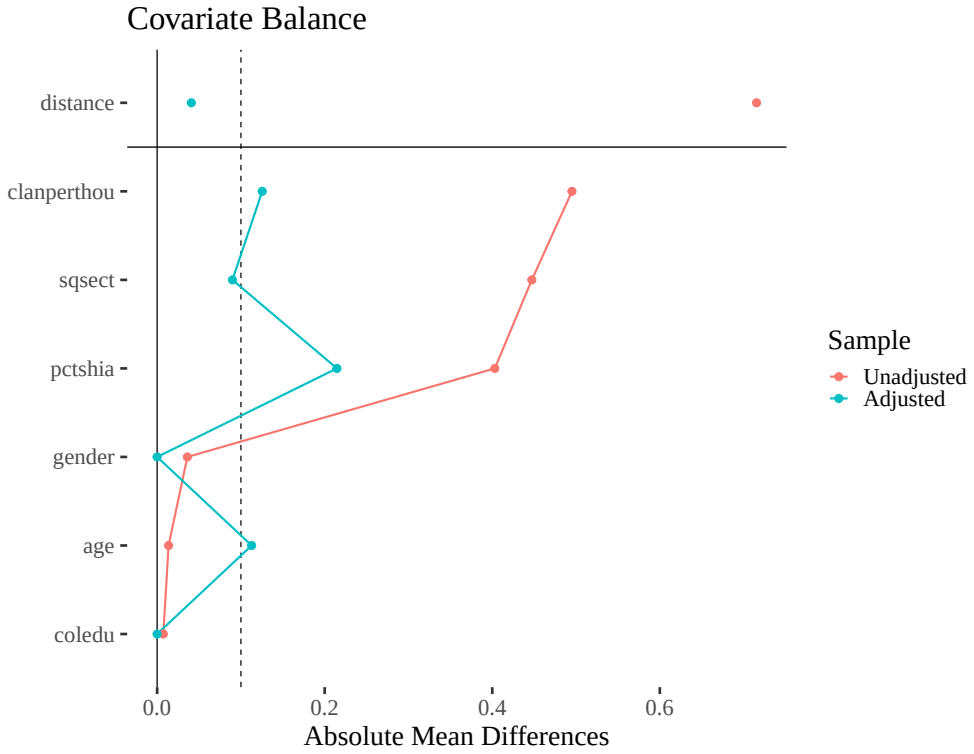
Figure A13: Predictive margins of tribal ties on Sunni national identification before and after fall of Mosul with matched data

A1.3 Covariate balance before and after Mosul for genetically matched data

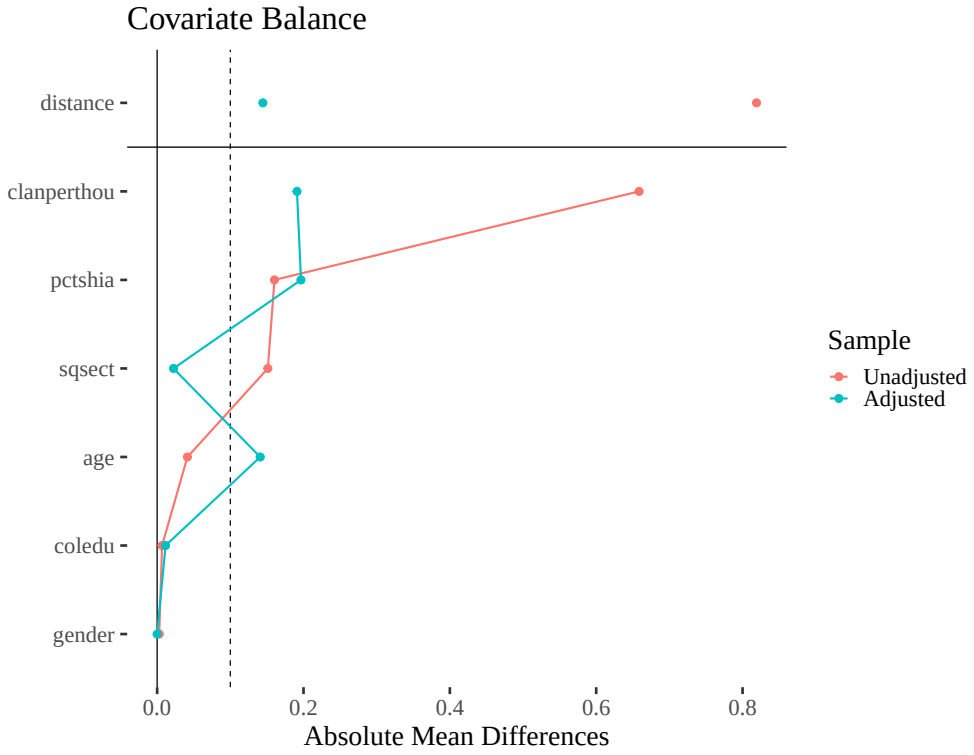
Covariate balance in the augmented inverse probability weighting procedure was significantly below the 0.1 threshold for all covariates.

Figure A14 below display covariate balance for the genetically matched samples used in both the multilevel model with tribes interaction for Sunnis (A14a), and the bivariate probit models (A14b). Note: *clanperthou*= Tribal ties; *pctshia*= %Shi'i; *coledu* = College education; *gender* = Gender; *age* = Age; *sqsect*= Prehist. violence. As should be clear, balance is achieved on all covariates at or below the 0.1 or 0.25 thresholds.

Figure A14: Balance plots. Vertical lines at 0.1.



(a) Covariate balance for matched Sunni data used in multilevel model with tribes interaction and bivariate probit model.



(b) Covariate balance for matched Shi'i data used in bivariate probit model.

Results from the augmented inverse probability weighting procedure are robust to the inclusion of multiple additional controls, which included a categorical variable for religiosity from a question asking : "In general, you would describe yourself as: 1. Religious; 2. Religious to some extent; 3. Not religious"; a categorical variable for household wealth from a question asking "Which of these statements comes closest to describing your household income?: 1. Our household income covers our expenses well and we are able to save; 2. Our household income covers our expenses without notable difficulties; 3. Our household income does not cover our expenses and we face some difficulties in meeting our needs; 4. Our household income does not cover our expenses and we face significant difficulties in meeting our needs"; a categorical variable for interest in the news from a question asking: "How often do you follow news about politics and government in your country?: 1. Very often; 2. Often; 3. Sometimes/rarely; 4. Never"; a categorical variable measuring interest in politics from a question asking: "Generally speaking, how interested would you say you are in politics?: 1. Very interested; 2. Interested; 3. Somewhat interested; 4. Not interested at all"; and two variables measuring trust in the government and military from a question asking: "I'm going to a name a number of institutions. For each one, please tell me how much trust you have in them.: 1. No trust at all; 2. Not very much trust; 3. Quite a lot of trust; 4. A great deal of trust". Results are displayed in Figure A15.

A1.4 Bivariate probit regression outputs

Results from the instrumental variable bivariate probit analyses are displayed below in Tables A8-A9.

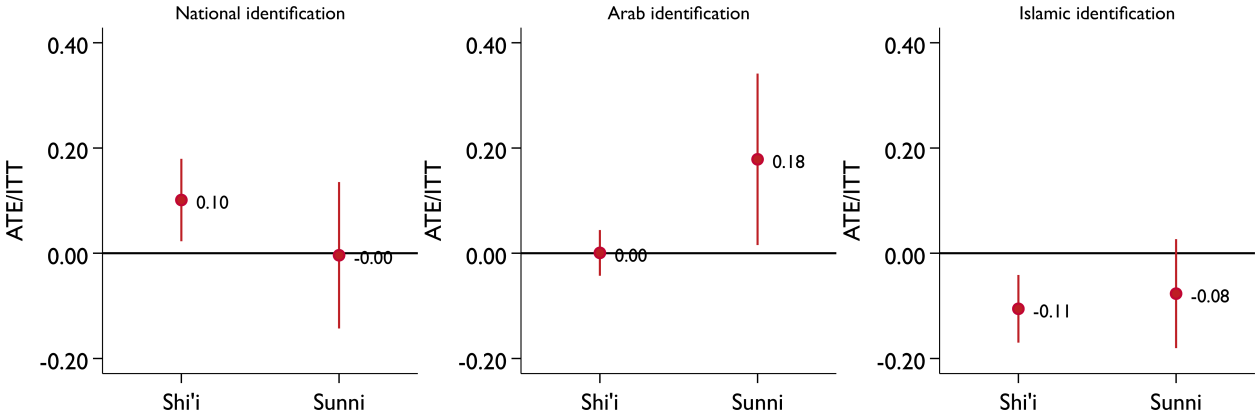


Figure A15: ATE/ITTE of fall of Mosul for each sect using augmented inverse probability weighting, with 95% confidence intervals, robust to inclusion of additional covariates

Table A8: Bivariate probit model of national and local threat on Shi'i national identification

Variables	Model 1: Shi'i Nat. ident. national threat	Model 2: Shi'i Nat. ident local threat
Threat	1.851***	1.203
	(0.090)	(0.751)
Age	-0.004	0.000
	(0.003)	(0.004)
Gender (1=female)	-0.226**	-0.128
	(0.081)	(0.092)
College education	-0.034	0.015
	(0.142)	(0.181)
% Shi'i	0.003	0.005
	(0.003)	(0.007)
Prehist. violence	0.007	-0.001
	(0.006)	(0.009)
Tribal ties	0.002	0.004
	(0.002)	(0.003)
Treatment	0.400***	0.343
	(0.098)	(0.177)
Age	0.001	-0.002
	(0.004)	(0.003)
Gender (1=female)r	0.096	-0.151
	(0.086)	(0.102)
College education	-0.427*	-0.236
	(0.170)	(0.160)
% Shi'i	-0.016***	-0.022***
	(0.004)	(0.004)
Prehist. violence	-0.010	0.025**
	(0.007)	(0.010)
Tribal ties	-0.005*	0.001
	(0.002)	(0.002)
ρ	-13.466*	-0.862
	(6.502)	(1.336)
ATE	0.636***	0.409
	(0.024)	(0.245)
ATT	0.701***	0.500*
	(0.028)	(0.252)

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table A9: Bivariate probit model of national and local threat on Sunni Arab identification

Variables	Model 1: Sunni Arab. ident. national threat	Model 2: Sunni Arab ident. local threat
Threat	-1.684	1.764***
	(1.083)	(0.210)
Age	-0.000	0.009
	(0.005)	(0.006)
Gender (1=female)	0.061	-0.229
	(0.133)	(0.127)
College education	0.259	0.230
	(0.190)	(0.260)
% Shi'i	0.002	0.003
	(0.011)	(0.004)
Prehist. violence	0.039**	0.014
	(0.014)	(0.012)
Tribal ties	0.011**	0.011**
	(0.004)	(0.004)
Treatment	-0.316	0.996***
	(0.271)	(0.153)
Age	0.005	-0.005
	(0.006)	(0.005)
Gender (1=female)	-0.014	0.145
	(0.152)	(0.166)
College education	-0.098	0.164
	(0.226)	(0.180)
% Shi'i	0.027***	-0.013***
	(0.004)	(0.004)
Prehist. violence	0.032**	0.007
	(0.012)	(0.010)
Tribal ties	0.007	0.002
	(0.004)	(0.004)
ρ	1.078	-1.118
	(4.411)	(2.861)
ATE	-0.537	0.369***
	(0.327)	(0.033)
ATT	-0.645*	0.308***
	(0.321)	(0.025)

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

A1.5 Bivariate probit regression robustness

The results from the bivariate probit models are robust to the inclusion of additional covariates in the outcome equation to guard against violations of the exclusion restriction. Plausibly, the fall of Mosul may, for example, have induced heightened national identification due to "rallying effects" (Mueller 1970), whereby individuals are moved to trust in the government/military, and by extension, identify with the nation in times of war or threat. I thus include, in addition to the set of controls used for the matching analysis above, further controls in the outcome equation for both trust in the military and trust in government, which are derived from questions in the survey asking respondents to rate on a four-point scale their trust in the military and government (1= "No trust at all"; 4= "A great deal of trust"). For Sunnis in particular, the perceived potential for heightened Iranian influence in public life after Mosul's fall, may also have contributed to increased non-national identification. I thus include a further control in the outcome equation that asks whether Iran "poses a factor of stability or instability to [Iraq]". This was coded on a three-point scale (1= "Factor of instability"; 2= "Does not affect my country"; 3= "Factor of stability"). Results are detailed below in Tables A10-A11 and point to substantively identical conclusions.

Table A10: Bivariate probit model of national and local threat on Shi'i national identification including additional controls

Variables	Model 1: Shi'i Nat. ident. national threat	Model 2: Shi'i Nat. ident. local. threat
Threat	1.830***	1.237
	(0.129)	(0.657)
Age	-0.004	-0.003
	(0.003)	(0.004)
Gender (1=female)	-0.263**	-0.115
	(0.085)	(0.106)
College education	-0.035	-0.252
	(0.150)	(0.220)
Trust in government	0.090	0.134*
	(0.056)	(0.056)
Trust in military	0.036	0.003
	(0.058)	(0.076)
% Shi'i	0.001	0.006
	(0.003)	(0.004)
Prehist. violence	0.003	0.001
	(0.007)	(0.010)
Tribal ties	0.002	0.001
	(0.002)	(0.003)
Treatment	0.496***	0.316*
	(0.102)	(0.160)
Age	-0.001	-0.001
	(0.004)	(0.003)
Gender (1=female)	0.098	-0.152
	(0.099)	(0.113)
College education	-0.401*	0.059
	(0.193)	(0.171)
% Shi'i	-0.015***	-0.022***
	(0.004)	(0.007)
Prehist. violencet	-0.005	0.026*
	(0.008)	(0.011)
Tribal ties	-0.004	0.004
	(0.003)	(0.002)
ρ	-1.754	-0.829
	(7.475)	(1.186)
ATE	0.630***	0.414
	(0.035)	(0.212)
ATT	0.684***	0.504*
	(0.042)	(0.224)

Standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05

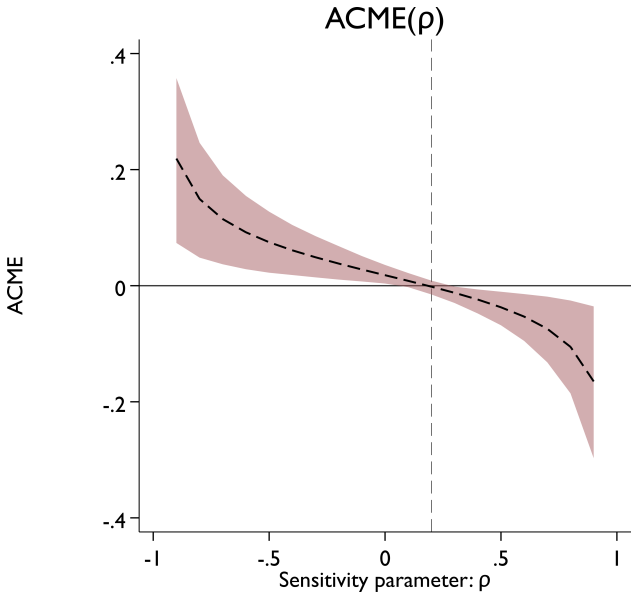
Table A11: Bivariate probit model of national and local threat on Sunni Arab identification including additional controls

Variables	Model 1: Sunni Arab ident. national threat	Model 2: Sunni Arab ident. local threat
Threat	-1.657	1.782***
	(1.242)	(0.228)
Age	-0.000	-0.005
	(0.005)	(0.005)
Gender (1=female)	0.078	0.171
	(0.120)	(0.160)
College education	0.251	0.241
	(0.181)	(0.230)
Iran influence	-0.036	-0.300
	(0.289)	(0.273)
% Shi'i	0.001	0.003
	(0.013)	(0.003)
Prehist. violence	0.041*	0.017
	(0.017)	(0.010)
Tribal ties	0.012*	0.011**
	(0.005)	(0.004)
Treatment	-0.275	0.982***
	(0.282)	(0.179)
Age	0.005	0.010
	(0.005)	(0.006)
Gender (1=female)	-0.031	-0.256
	(0.155)	(0.136)
College education	-0.109	0.144
	(0.240)	(0.164)
% Shi'i	0.027***	-0.015***
	(0.004)	(0.004)
Prehist. violence	0.032**	0.008
	(0.012)	(0.012)
Tribal ties	0.008	0.003
	(0.004)	(0.004)
ρo	1.084	-1.133
	(7.971)	(12.253)
ATE	-0.528	0.369***
	(0.370)	(0.033)
ATT	-0.633	0.305***
	(0.355)	(0.025)

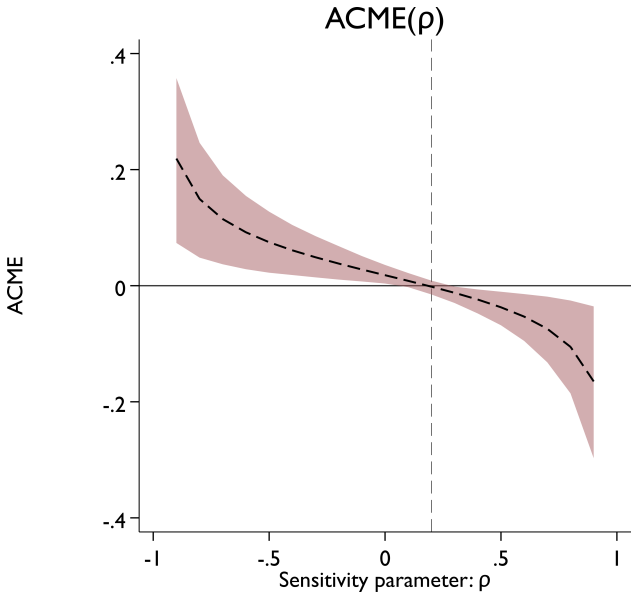
Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

A1.6 Sensitivity plots for causal mediation analysis

Figure A16: Sensitivity plots. Vertical lines at 0.2.



(a) Sensitivity plot Shi'i national identification and national war threat



(b) Sensitivity plot Sunni Arab identification and local threat

A1.7 Islamic identity, social desirability, and rejection of political Islam: robustness checks.

In-person surveys may be at risk of social desirability bias. In our case, this may be particularly pronounced given the heightened negative connotations of religion in public life after the fall of Mosul. As a test of this, we can use a set of questions included in the survey. Questions pertaining to attitudes to Islam contained a heightened number of missing responses. This would indicate that respondents were less willing to reveal their preferences on these items. However, what matters here is whether they were systematically less willing after the fall of Mosul. We can check whether respondents were more likely to refuse to provide an answer to these questions by recoding missing values on each item as '1' and entering these as binary outcome variables using the same multilevel model and controls used in Table A2 for each identity outcome. Running separate regressions on each item, no single item is more likely to be missing after Mosul, across both Sunnis and Shi'is, thus providing strong evidence against heightened social desirability bias after the fall of Mosul. We can also test whether respondents were less likely to admit to more conservative Islamic beliefs after Mosul by regressing a factor variable created from questions pertaining to the role of Islam in public life on the treatment and controls. Questions used in the construction of the factor are listed below. Results indicate that conservative Islamic beliefs are no more or less likely after the fall of Mosul, thus providing further evidence against social desirability bias being behind the results. Finally, I conduct a series of mediation analyses to discern whether the move away from Islam as an identity is mediated by a rejection of political Islam (as embodied in ISIS). Here, the first two items below asking respondents about the suitability

of forms of Islamic rule allow us to check if decreased identification with Islam is channeled through a rejection of these forms of political Islam. Here, I use the same form of mediation analysis and set of controls as used in the main analysis. Opinions relating to political Islam are found not to significantly mediate reduced identification with Islam for either Shi'is or Sunnis.

A1.8 Attitudes to Islam questions

All questions were answered according to a four point scale. The first two questions sought to ascertain the respondent's view on the suitability of various systems of governance (1="Not suitable at all; 2="Somewhat suitable"; 3="Suitable"; 4="Very suitable"). The remaining questions (items 3-14) asked the respondent their views on the interpretations of Islam given (1="Strongly agree"; 2="Disagree"; 3="Agree"; 4="Strongly agree").

To construct a factor from these, I use exploratory principal-factor factor analysis on the fourteen items relating to Islamic values and attitudes to Islam in public life and create a single factor from the items with the highest loadings on questions relating to Islam in public poltical life. Cronbach's α on the items used to construct this factor is 0.68. There are a large number of missing values on this item due to heightened non-response to these questions over this period. Alpha also falls slightly below a conventional threshold of 0.7. As such, we should draw inferences from this factor with some caution.

1. A system in which only Islamic parties compete in parliamentary elections. (Included in factor var. #missing: 132)

2. A system governed by Islamic law in which there are no political parties or elec-

tions.(Included in factor var. #missing: 231)

3. Democracy is a Western form of government that is not compatible with Islam (#missing: 96).

4. Islam requires that in a Muslim country the political rights of non-Muslims should be less to those of Muslims (#missing: 91).

5. Banks in Muslim countries must be forbidden from charging even modest interest on loans because this is forbidden by Islam (#missing: 165).

6. It is acceptable in Islam for male and female university students to attend classes together (#missing: 84).

7. If a Muslim converts to another religion, s/he must be punished by execution (#missing: 235).

8. I prefer a religious party over a non-religious based political party. (Included in factor var. #missing: 294)

9. The government and parliament should implement only the laws derived from the sharia. (Included in factor var. #missing: 142)

10. The government and parliament should make criminal law according to sharia. (Included in factor var. #missing: 167)

11. The government and parliament should make personal status/family law according to sharia (#missing: 68).

12. Religious clerics should not influence how people vote in elections (#missing: 102).

13. Religious clerics should have influence over the decisions of government (#missing: 146).

14. Religious practice is a private matter and should be separated from socio-economic life (#missing: 217).

A1.9 Arab Transformations Survey information

The Arab Transformations survey project covered six countries in the MENA region. For Iraq, the survey was administered by the Independent Institute for Administration and Civil Society Studies, a non-governmental body that has been conducting survey work in Iraq for more than ten years, and was directed by Dr Munqith Dagher. This is the same institute that conducted the widely used Arab Barometer surveys for Iraq, see `http://www.arabbarometer.org`. A three-stage sampling design was used. Probability of governorate selection was proportionate to size. In the second stage, towns within governorate were selected by simple random sampling from residential lists. Households were then selected with random number tables, and respondents in households were selected using the 'next birthday' method. Surveys were conducted in person by trained interviewers. For more information, see `http://www.arabtrans.eu/`.

Districts surveyed exclusively before the fall of Mosul were: Abu al-Khaseeb; Al-Shatra; Al-Zubair; Basrah; Chamchamal; Erbil; Hilla; Koisnjak; Kufa; Najaf; Samarra; Soran; Suq al-Shoyokh; Tikrit (n=419). Those surveyed exclusively after were: Al-Hindiya; Al-Khalis; Al-Musayab; Al-Shamiya; Al-Suwaira; Ba'quba; Diwaniya; Hashimiya; Kerbala;

Mahmoudiya; Rania; Sharbazher (n=342). Those surveyed both before and after were: Adhamiya; Al-Resafa; Al Sadr; Karkh; Khadamiya; Kirkuk; Kut; Nassriya; Shatt al-Arab; Sulaymaniya (n=818). Note, Kurdish districts are listed here. For the main analyses, these were removed, for reasons I explain in the main text. Seven Kurdish districts were in the sample. One district (n=34) was coded just as "23" in the survey data and thus could not be identified. Its removal does not alter results.

A1.10 Reachability/regional sampling/social desirability bias

It is the case that as a result of the fall of Mosul, as well as the ongoing security risks in certain regions of Iraq (particularly in Anbar) that preceded this event, some regions of the country were inaccessible to field researchers. This evidently introduces "regional sampling bias" (Legewie 2013; Muñoz et al. 2019) to the data. Nonetheless, a full thirty-six districts were still surveyed, and over two thirds of Iraq's nineteen governorates. Further, given that the main outcomes of interest are identity responses to war and civil war threat, the systematic sampling bias against regions closer to ISIS activities is likely only to downwardly bias outcomes. Moreover, I employ multiple means of overcoming heterogeneity in district-level identification patterns by using a multilevel design, as well as matching procedures. By also controlling for, and matching on, individual-level attributes, I am able to minimize any potential "reachability bias" (Legewie 2013; Muñoz et al. 2019). There is also potential for social desirability bias. It may be that in the wake of the fall of Mosul, and heightened negative connotations of religion in public life, that individuals would be less willing to identify as primarily Muslim. The survey was undertaken by a non-governmental body in

complete confidence and in a private setting, however, thus limiting the potential for such bias to be introduced. Further, respondents were only asked whether they were Sunni or Shi'i at the end of the survey, after the main identity questions had been asked, thus likely limiting any reticence to disclose potential sectarian preferences. Below, I also include several tests for social desirability bias, and show that there is little evidence of it in the survey sample. Nonetheless, the potential for such bias cannot be completely discounted.

A1.11 Iraq Living Conditions Survey information

The Iraq Living Conditions survey was a survey of 21, 688 households conducted in Iraq in April and May of 2004. The survey covered each of Iraq's governorates and provided representative ecological measures at the district level. These were cleaned and coded by ESOC. The surveys were administered in Arabic or Kurdish. The survey followed a two-stage cluster desigg, using 1997 census records for all the non-Kurdish governorates (lists of localities were used for Kurdish governorates in the absence of census records). In the first stage, samples were selected with probability proportionate to the number of households in the sampling unit. Ten households were then selected in each primary sampling unit, and heads of household provided responses to questions. Interviews were conducted in-person by trained staff from the Central Statistical Organization in Iraq. The survey itself was conducted under the broader auspices of the United Nations Development Programme. Interviewers were supervised and unclear information was reconfirmed by repeat visits to households. Quality control was subsequently conducted by both COSIT and the Fafo Research Foundation in Oslo.

From this survey, a question pertaining to whether there were other members of the household's clan living in the same neighbourhood (*mahalla*) was used. ESOC then used responses to this question to provide a district-level measure of clan ties, coded as the percentage of households reporting a member of their clan living in the same neighbourhood. I use this as a measure of the density of tribal ties at the district level. A map of density of tribal ties, taken from this variable, is displayed below in Figure A17. The measure is converted here to a rate per ten thousand population. Districts included in the survey span the full range of the tribal ties variable (1.7-3) as can be seen in Table A12.

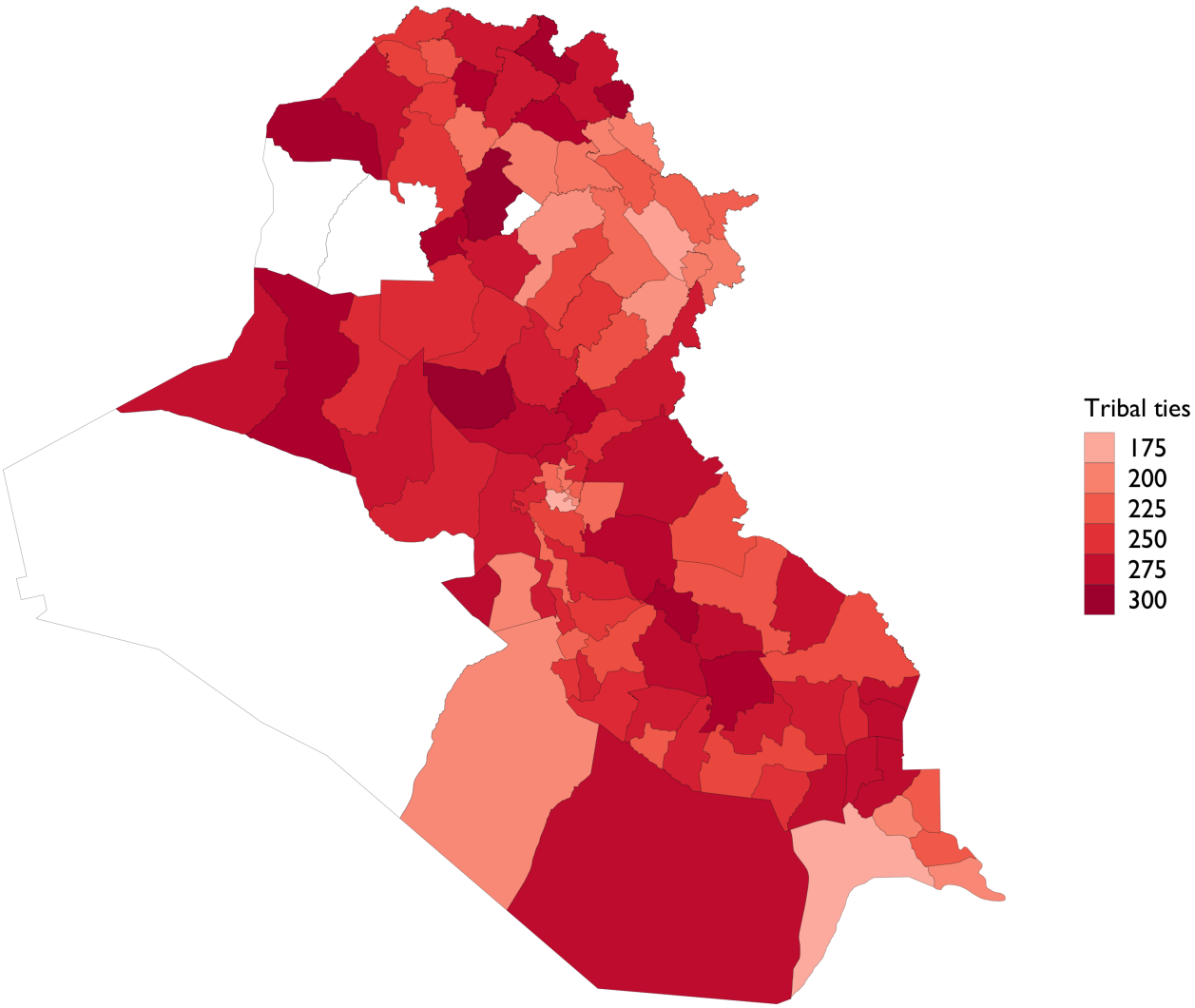


Figure A17: Map of density of tribal ties by district. Taken from 2004 ILCS.

A1.12 Descriptive statistics

Table A12: Descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
National identification	0.578	0.494	0	1	1371
Arab identification	0.146	0.353	0	1	1371
Islamic identification	0.206	0.404	0	1	1371
Treatment	0.477	0.5	0	1	1387
Shi'i	0.639	0.481	0	1	1337
Sunni	0.361	0.481	0	1	1337
Age	36.837	13.168	18	84	1387
Gender (1=female)	0.479	0.5	0	1	1387
College education	0.107	0.31	0	1	1387
% Shi'i	62.552	35.404	0	100	1353
% Sunni	31.887	28.16	0	100	1353
Prehistories of violence	19.932	14.895	0	51.904	1353
Tribal ties	218.527	33.554	170.697	300	1353

Chapter 2

Paper Two

The Process of Revolutionary Protest: Development and Democracy in the Tunisian Revolution

Abstract

Research on democratic revolution treats revolutionary protest, and revolutionary protest participation, as unitary events. This conceptualization is at odds with how 'revolutionary' protest often unfolds—protest does not begin life as democratic or revolutionary but grows in a process of positive feedback, incorporating new constituencies and generating new demands. Using an original protest event catalogue for the twenty-nine days of the Tunisian Revolution, alongside survey data, I show that the correlates of protest occurrence and participation change significantly during the uprising. The effect of economic development on protest diffusion reverses sign, while a commitment to democracy is a substantive predictor of protest participation only at its close. If protest is not revolutionary at its onset, I argue, theory should reflect this and be able to explain the endogenous emergence of democratic demands. In this understanding, the formation of protest coalitions becomes essential, rather than incidental, to democratic revolution.

1 Introduction

Protest has, in recent years, become an increasingly central part of theoretical and empirical scholarship on democratization. So much so that mass mobiliziation is often elided with democratization itself. But while political transition to democracy can be marked in time—by the ouster of an authoritarian or the holding of elections—mass mobilization constitutes a process. Empirical work in the democratization literature nonetheless treats revolutionary protest, or revolutionary protest participation, as discrete, unitary events amenable to cross-sectional forms of analysis. A separate body of work, particular to the formal modelling tradition, incorporates elements of endogeneity and process but assumes common thresholds governing participation dynamics, thereby again conceiving of revolutionary protest as unitary. In this article I propose that this ontology is wrongheaded; protest is rarely revolutionary at its onset and the goals and orienting demands of protest waves can be generated in the context of contention. To illustrate my argument, I use both original and previously analysed data, and take as my case the Tunisian Revolution of 2010-2011.

The Tunisian Revolution did not begin life as revolutionary. Starting with the self-immolation of Mohamed Bouazizi on December 17 2010, protest during the uprising would gradually diffuse across diverse regions of the country, incorporating new constituencies, and advancing demands that were initially parochial and economic, but which culminated in expansive, revolutionary demands for democracy. This processual emergence of expansive contentious claims, I argue, is not specific to Tunisia. Variously parochial or disconnected contention can conduce to mass demands for democracy absent any organized campaign.

Put otherwise, that democracy is the outcome of mass contention should not imply that democratic demands motivated protest outbreak; mass mobilization and democratization are causally connected but conceptually distinct. This has profound implications for how we understand both revolutionary mobilization and democratization. Rather than assuming a set of collectively held grievances flowing from a set of structural conditions at a single point in time, scholars should redirect attention to the mechanisms governing the emergence of mass contention.

To support these claims, I use an original spatially and temporally disaggregated event dataset on protest occurrence during the twenty-nine days of the Tunisian Revolution. I combine these with available ecological data to assess the changing correlates of 'revolutionary' protest diffusion over the course of the uprising. I bolster these findings with evidence from available survey data, disaggregating temporally by date of respondent's first participation. The assumptions implied by, or explicit in, a conceptualization of protest as unitary events each have their cognates in the statistical literature. It is around these that I formulate the empirical analysis. I find that a commonly cited structural precipitant for protest and democratic breakthrough—economic development—exerts effects that are far from constant, with its coefficient in fact reversing sign over the course of the protest cycle. A supplementary analysis demonstrates that several further measures of deprivation and development also exhibit strongly time-dependent effects. Consistent with this evidence of the changing correlates of protest, I show with a renalysis of published findings from survey data that a commitment to democracy had no association with protest participation at the onset of protest, but was a substantively positive predictor by its close. Overall, the findings point to the endogenous emergence of democratic claims in a protest wave that nonetheless began

life as parochial, unorganized, and divorced from broader political campaigns.

The article holds out important theoretical and methodological lessons. On the methodological level, it points to the pitfalls of overaggregation and potential for faulty inference when analysing revolutionary protest occurrence and revolutionary participation as unitary events. On the theoretical level, it demonstrates the importance of shifting our attention away from large macrostructural causes of uprisings for democracy. If protest begins life as parochial and is not motivated by revolutionary demands for democracy, theory building should reflect this and be able to account for the endogenous emergence of democratic claims. In a final section I rely on interview data to elaborate on this claim, pointing to a key mechanism governing the expansion of contention—brokerage—and argue that, rather than being considered epiphenomena of democratic revolution, the formation of mass coalitions for democracy should constitute the object of explanation in future scholarship.

2 Revolution for democracy

For earlier generations of revolution scholars, the processual dynamics of revolutionary protest were central. In response to the "natural histories" school, James Rule and Charles Tilly would advocate a renewed attention to revolution as political process and to "shifts in the form, locus, and intensity of conflict as the struggle for power continues" (1972, 62).[1] Taking as their case the 1830 Revolution in France, and making early use of event data, these authors note that revolutionary protest was far from a unitary phenomenon, concluding that "other studies which have found strong relations between levels of conflict and

[1]Despite its programmatic and organicist bent, natural historical scholarship (e.g., Brinton 1938) about revolutions did conceptualize revolution as a process with stages.

structural variables at a single point in time may well have mistaken historically contingent relationships for general effects of structure" (Rule and Tilly 1972, 68; see also Tilly 1973). James Scott (1979) would similarly argue that labelling revolution as "nationalist", "communist" or otherwise, obscures the process of its unfolding, ascribing to it characteristics that fail to represent the diversity of motivations animating the "revolution in the revolution." In the same year, Rod Aya warned against the assessment of revolutions on the basis of retroactively ascribed intentions or outcomes: "any viable conception of revolution", he argued, "must take into account that those who initiate, lead, provide mass support for, and ultimately benefit from revolutions are often very different groups of people" (1979, 45). From a structuralist perspective, the foremost statement against "intentionalism" in revolutions research came from Skocpol (1979). The notion that uprisings began life with the purposive intention of revolutionary overthrow was fallacious, Skocpol argued: "In fact, in historical revolutions, differently situated and motivated groups have become participants in complex unfoldings of multiple conflicts" (1979, 17).

Such an appreciation of the process-bound dynamics of revolutionary upheaval has been lost in most recent scholarship on revolution, and democratic revolution in particular, which is beset by a tendency to understand revolutionary protest, and revolutionary protest participation, as discrete, unitary events.

This comes in several forms. A first, specific to survey work, treats as revolutionaries any individual that has protested in a certain place during a certain time period. A common finding from these cross-sectional analyses is that protesters are drawn from diverse class backgrounds and are motivated by diverse, and often divergent, motivations (Thompson 2004; Beissinger 2013; Beissinger et al. 2015; Rosenfeld 2017). As a result, Beissinger

(2013) argues, we can only speak of a "semblance" of democratic revolution: in actuality, participants in such protests had multiple grievances that cannot be reduced to the post-hoc democratic master frame attributed to the protests. Rather, contemporary "urban civic" revolutions are characterized by "negative coalitions" of diverse protesting constituencies united only by anti-incumbency goals (Beissinger 2013; Dix 1984). Recent research, using two separate surveys and focusing specifically on the Tunisian Revolution, reaches a similar conclusion. Despite its ostensibly democratic character and ultimate democratic outcomes, these scholars argue, there is no evidence of an association between democratic convictions and protest participation during this episode (Doherty and Schraeder 2018).

A second body of work, utilizing cross-national datasets or formal models, conceives of democratic revolution as a product of structural factors generative of revolutionary democratic aspirations. Here, understood as an outgrowth of structure, revolutionary protest again constitutes a discrete event; any endogenous or processual elements of its unfolding are viewed as incidental to the larger structural determinants of its outbreak. Notably, key variables are theorized to have opposing effects; while some cite economic development or reduced inequality as predictive of mobilization, or threat of mobilization, for democracy (Lipset 1959; Inglehart and Welzel 2005), others find an association between economic downturn and democratization or democracy protest (Haggard and Kaufman 1997; Acemoglu and Robinson 2006; Brancati 2014). More recent scholarship in this vein concludes that macrolevel political economic variables have only limited explanatory power for understanding the onset of democratic or "distributive conflict" transitions (Haggard and Kaufman 2016).[2]. Notably, for both of the above bodies of literature, the implicit assumption in

[2]The same authors point to the multiple forms taken by mass mobilization for democracy. Nearly 20% of

their analyses, corollary of conceptualizing revolutionary protest as a unitary phenomenon, is that revolution is "everywhere in equilibrium" (Tsebelis and Sprague 1989).[3] In other words, the effects of a covariate, or set of covariates, are assumed to be constant over the entire observation period.

A third body of literature does seek to account, in a formal modelling context, for the processual, endogenous dynamics of protest but again conceives of all participation as revolutionary. Here, the assumption is of common but varying "revolutionary thresholds" in a population that can be triggered as a function of the participation of others. Thresholds are heterogeneous within a population, and early-risers with lower participation thresholds have the capacity to impel the participation of higher-threshold groups in a recursive process (DeNardo 1985; Karklins and Petersen 1993; Kuran 1995). As such, all protest in such conceptions is revolutionary; what varies is the distribution of thresholds in a population. The assumption here, then, is that the participation calculus of protesters in revolutionary wave can be modelled as a function of an underlying latent revolutionary propensity. These models are, however, difficult to reconcile with the empirical record of mass mobilization events and the observation that the targets and orienting demands of protest often change over time (Lohmann 1994).[4] If the demands and targets of a protest wave change over time,

the so-called "distributive conflict" transitions (democratic transitions preceded by mass mobilization waves related to redistributive demands) were accompanied by significant rioting, 30% involved ethnonationalist protest, while 70% involved significant labour protest in the form of strikes or union-led demonstrations (Haggard and Kaufman 2016, 103). This diversity of protest forms should alert us to the potential problem of overaggregation when studying democratic revolution. It should also provide warning against aggregating mass mobilization events into "violent" or "non-violent campaigns" (Chenoweth and Stephan 2011; Chenoweth and Ulfelder 2017, cf. Kadivar and Ketchley 2018).

[3]For an early critique of ahistoricism, and assumptions of time-invariant covariate effects, in quantitative sociological analysis, see Isaac and Griffin (1989).

[4]A second, related, body of work investigates the variable effects of a "critical mass" in stimulating collective action (Marwell and Oliver 2007). Here, again, participation in protest is understood as a unitary phenomenon since the model assumes public knowledge of a singular collective good (e.g., democracy) to be obtained. This assumption is shared by the more recent scholarship on the centrality of distributive conflicts

we cannot legitimately assume the determinants of a hypothesized underlying latent variable to be constant over the period under observation.

In sum, each of these bodies of literature shares a conception of revolutionary protest and participation as unitary phenomena. The problems of overaggregation inherent to such an approach likely lay behind the inconsistent, and often highly divergent, findings of the empirical literature. This is a central concern in conflict scholarship (Kalyvas 2006; Cederman and Gleditsch 2009) but is something that has largely escaped the attention of revolution and democratization scholars.[5] An understanding of revolutionary protest as a unitary phenomenon occludes the diversity of contentious forms and actors that propel mass mobilization episodes and omits the processual elements of its unfolding. Revolutionary protest may not, and often does not, begin life as revolutionary but incorporates multiple, competing constituencies of contenders, takes on diverse forms, and advances demands that emerge only in the context of contention. Recent theoretical scholarship on revolution advocates a return to the study of process in revolution. Disavowing attributional taxonomies of revolution and an emphasis on antecedent causes of "instability", Lawson (2016) advocates an explicitly processual ontology of revolution as "sequences of events that attain their significance as they are threaded together in an through time" (see also Beck 2014). To date, however, this theoretical wager has not been subject to systematic empirical scrutiny. It is this gap I intend to fill. Before doing so, an account of our main empirical focus—the twenty-nine days of the Tunisian Revolution—is in order.

to collective demands for democracy (e.g., Boix (2003); Acemoglu and Robinson (2006)). For criticisms of these informational assumptions see Andrews and Jackman (2005); Aidt and Leon (2016).

[5]In fact, there is very little research into the coding and conceptualization of protest in empirical social science research. For one of the only such examples see Biggs (2015). For a recent overview of the measurement of protest in political science research see Vassallo (2018)

3 The Tunisian Revolution

Protest broke out in Tunisia on December 17, 2010 at around midday in the central region of Sidi Bouzid.[6] Initial protests were spurred by the actions of one individual—Mohamed Bouazizi, a fruit and vegetables vendor—who had set himself on fire outside the municipal Governorate (*Wilaya*) building in protest at his treatment by a local police officer. In response to Bouazizi's extraordinary act, a crowd assembled who collectively vowed to avenge him with the chant "*b-il-rūḥ b-il-damm, nafdīk yā Mohamed*" ("We will give our blood and souls for you, Mohamed") (Salmon 2016, 79). That evening, crowds dispersed peacefully. Meanwhile, members of a hastily assembled "Committee for the Defence of the People of Sidi Bouzid" were interviewed on France 24 and Al-Jazeera. Bouazizi's act would soon take on wider significance. The following day, at the prompting of local trade union activists, protesters began to proclaim "*al-tashghīl istiḥāq yā 'issābat as-sarrāq!*" ("Work is a right, you gang of thieves!"). What is more, Bouazizi would be identified to news media as an unemployed graduate; an untruth propagated by local activists with the intention of associating Bouazizi's act more directly with problems of underdevelopment and unemployment in Tunisia and Sidi Bouzid specifically (Lim 2013). On December 20, protest spread to two southern delegations of Sidi Bouzid: Meknassy and Menzel Bouzaiane. These were the first protests to occur outside the centre of Sidi Bouzid. The following day, protest was seen in three further regions of Sidi Bouzid: Jilma, Sidi Ali Ben Aoun, and Regueb.

With the exception of some small isolated protests at the local offices of Tunisia's national

[6]Details of protest derive, unless otherwise stated, from the event catalogue. The methodological appendix lists the source material and coding conventions employed in this data collection process.

trade union federation (UGTT) in the governorate of Kasserine on December 22, protest did not leave the Sidi Bouzid governorate until December 24, when protests broke out on the island of Kerkenah in Sfax and the city centres of Sousse and Bizerte. On this day the first martyr of the uprising was recorded in Menzel Bouzaiane when Mohamed Ammari was shot dead by the National Guard during violent clashes with police. On December 25, protest reached Tunis for the first time, with a small protest outside the UGTT head offices called by the Secondary Education Union. At this stage, the National Executive of the UGTT disavowed any connection with the protests.

For much of the early and middle periods of the uprising, protest was concentrated in mid-western and southern regions of Tunisia (referred to locally as the "interior"). In the intervening week from January 3–January 10, school children and university students would also begin to participate more forcefully in the uprising, as schools and universities reopened after a December holiday period. For this period, there are records for 135 separate student protest events. Over time, protest did gradually diffuse to more affluent urban centres of northeastern coastal regions (known as the "Sahel"). It would not be until January 12–January 13, however, that large-scale protest was witnessed in major urban centres, as mass demonstrations and strikes were witnessed in all of Gabes, Jendouba, Kairouan, Kasserine, Sfax, and Sidi Bouzid.[7] January 14—the day of Ben Ali's ouster—was the first time that large-scale protest was witnessed in the Tunisian capital.

The diffusion of protest can be seen in Figure 1.[8] In total, 148 of Tunisia's 264 delegations (represented by single hexagons) would see protest of some form over the course of the

[7] I define large-scale protest as any event involving 10,000 individuals or more.

[8] Hexagonal cartograms of Tunisia were generated using a combination of the *geogrid* package in R developed by Joseph Bailey (see `https://github.com/jbaileyh/geogrid`) and the *cartogram* package developed by Sebastian Jeworutzk (see`https://github.com/sjewo/cartogram`.)

revolution.[9] The importance of the spatial patterning of protest is rehearsed in debates over naming rights to the revolution. For some, since the revolution only latterly incorporated the Sahel, the "Alfa Grass Revolution" (a type of grass specific to the Tunisian interior) is a more appropriate moniker than the more common "Jasmine Revolution" (a plant grown and sold in the north) (Ayeb 2011). As can be seen in Figure 1, most of the protest in the northeast and capital city came in the final five days of the uprising. Until that time, participation in the isolated protests that did occur in the northeast and the capital numbered in the tens or hundreds, and were launched in solidarity with the demands of those protesting in the interior. Available survey data provides a further window onto this dynamic. Using Wave II of the Arab Barometer, and disaggregating by date of first participation, we see that 39% of those that reported having protested over the twenty-nine days of the Tunisian Revolution only participated in these final five days of protest, when large protests reached major urban centres.[10]

The sudden growth in protest size in the final days of the Tunisian Revolution coincided with the brutal repression of demonstrations in Kasserine and Thala on January 8 and 9, during which at least eighteen were shot dead at the hands of the police—the bloodiest two days of the uprising. It was following these events, and the subsequent decision by the National Executive of the UGTT to launch regional general strikes, that we see a surge in protest size, with protest participation growing from the hundreds to the thousands and the tens of thousands. It was also only after these events that the chant "*as-sha'b yurīd isqāt an-nizām*" ("The people demand the fall of the regime") was first heard. On January 14,

[9]See below and methodological appendix for event data coding criteria.

[10]See below and the methodological appendix for wording of survey questions and details of survey design and implementation.

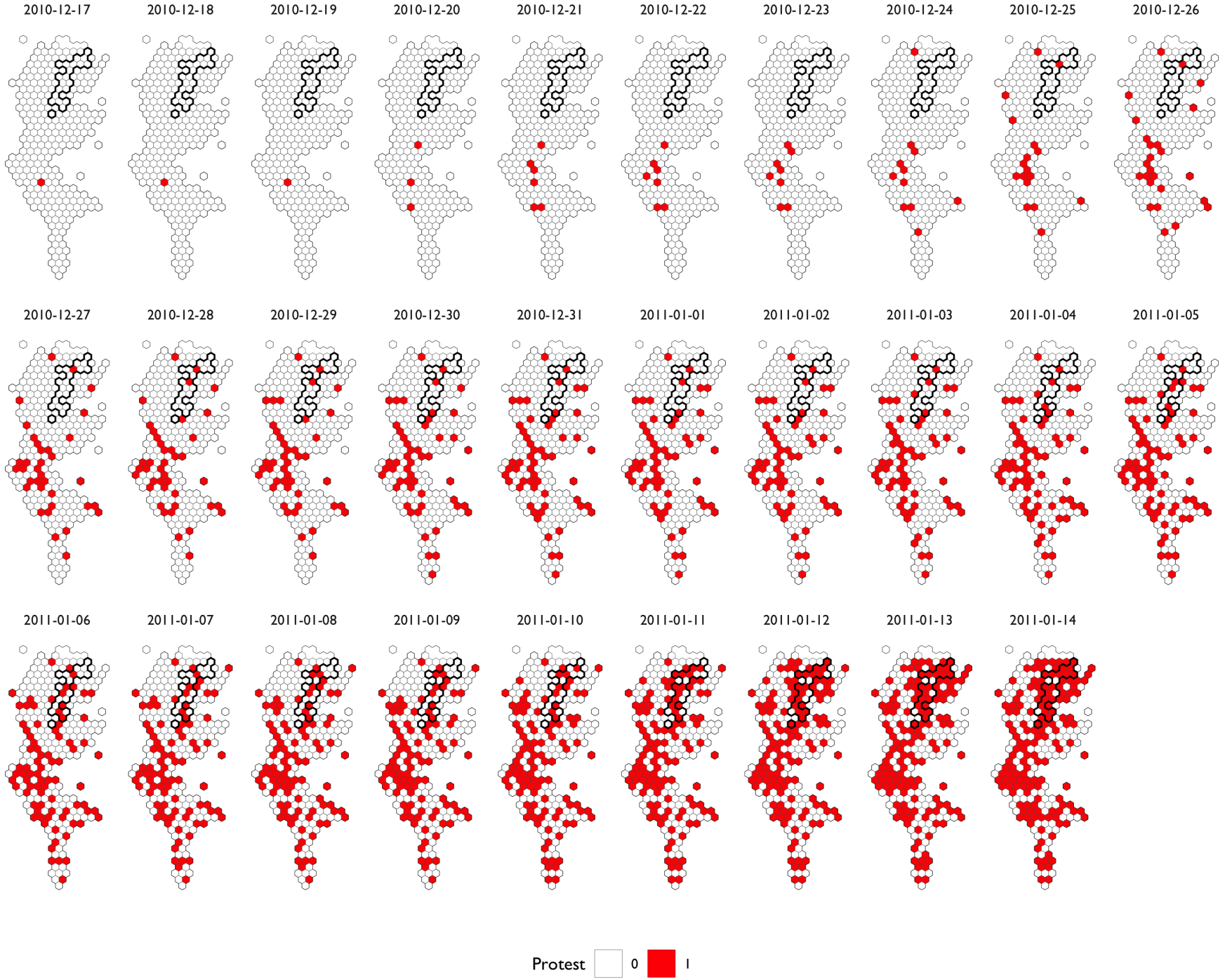


Figure 1: Diffusion of protest during the Tunisian Revolution. Hexagons in bold represent delegations in capital city, Tunis.

after a massive protest in Tunis city centre, Tunisia's authoritarian President of over twenty years, Zine El-Abidine Ben Ali, fled the country. Ten months later, Tunisia would see its first elections. At the time of writing it remains a functioning democracy.[11]

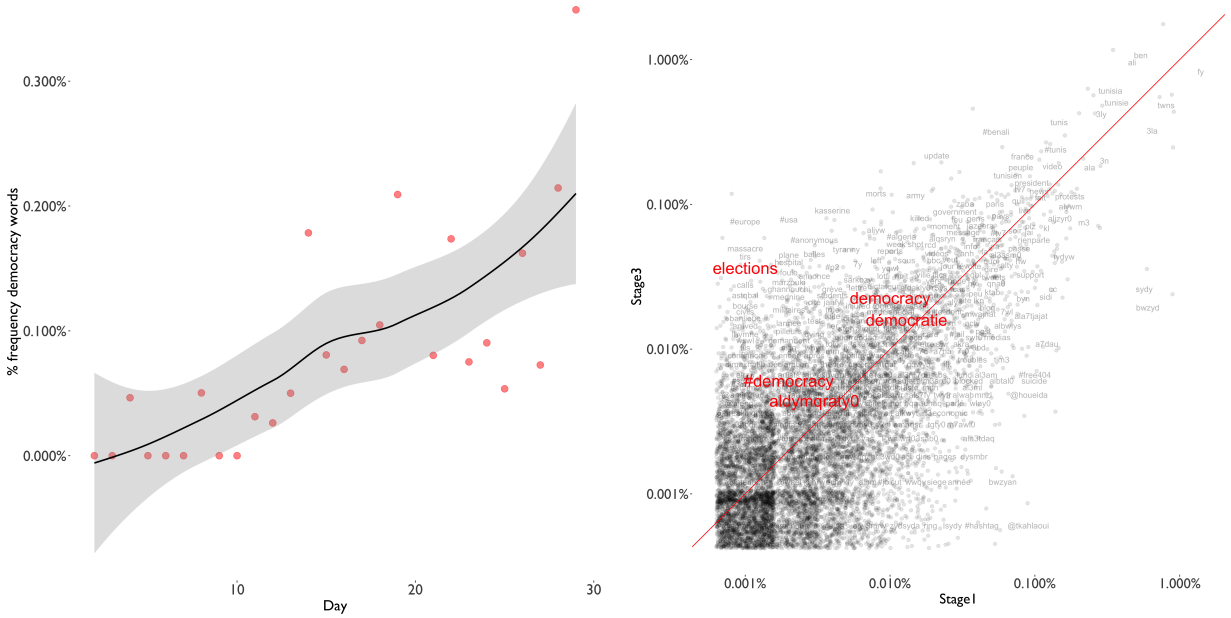
Twitter data provides a further lens onto these dynamics. Analysis of the content of a Twitter sample streamed during the course of the Revolution reveals a marked increase in the percentage of democracy-related words over the course of the uprising (Figure 2a).[12] Comparing the final five days of the uprising ("Stage 3") to the first fourteen days ("Stage 1"), we see that frequently used democracy words are significantly more likely to be used during Stage 3 than Stage 1.[13] This is displayed in Figure 2b: words falling on the diagonal line are equally distributed between stages, whereas those that appear above (below) are more likely to have been used in Stage 3 (Stage 1).

The foregoing account should alert us to the omissions involved in understanding 'revolutionary' protest as a unitary phenomenon. The Tunisian Revolution demonstrates that variously parochial, unorganized, economic protest may, over the course of a revolutionary protest wave, conduce to mass mobilization for democracy. On December 17, 2010, a revolutionary overthrow of Ben Ali would have been unthinkable. During the ensuing weeks, protest took diverse forms, incorporated different protesting constituencies, and included significant rioting, violence, strikes, peaceful demonstrations, and occupations. The demands

[11] Freedom House classes Tunisia "Free". The latest available Polity IV score (2016) for Tunisia is 7.

[12] Full details of these Twitter data and how they were obtained are provided in the Appendix. A complete list of democracy-related words can be found in Appendix Table A3. Figure 2a uses non-parametric "loess" regression with α set to 1 to plot the best fit line(s) and associated confidence intervals (see Jacoby 2000). Day 29 (January 14) was removed as by this point Ben Ali's ouster was secured, prompting many to begin speaking about democracy and elections, thereby spuriously inflating democracy talk. Our interest here is, instead, the contents of online activity before any outcomes were known.

[13] For the purposes of comparison, periodization of "Stages" is on the basis of those used in the survey data analysed below.



(a) (b)

Figure 2: (a) Percentage frequency of words related to democracy in #sidibouzid data; (b) Relative democracy word frequency by Stage (1 versus 3)

advanced by protesters also shifted drastically over the course of the brief uprising. Originating in an act of voiceless protest by one individual, subsequent protests took up broader economic demands and were concentrated in deprived regions of the Tunisian interior. Over time, protest would diffuse to more developed regions of the Tunisian Sahel. It was only in the wake of institutional support, on the part of the UGTT, itself provoked by the repression of protest in Kassserine governorate, that protest swelled and took up more expansive political demands. It was also only at this later stage that large-scale protest reached Tunis and other major urban centres. In short, only in the final days of the uprising did protest begin to resemble a mass participation, urban civic, democratic revolutionary event. If revolutionary protest exhibits such heterogeneity, this begs the question: how should we study such events?

4 Data and Method

4.1 Sources

This paper makes use primarily of an original event catalogue constructed using multiple online and offline source materials. Scholars conventionally make use of local and national print news media in the construction of event catalogues (see Earl et al. 2004a). The national news media in Tunisia were almost exclusively pro-regime and the national dailies did not report on the unfolding of protest until the final days of the uprising. In the absence of reporting by national news media, however, Tunisians took to the Internet to post details of unfolding protests on dedicated Facebook pages. I have systematically coded protest reports from four of these pages. In addition to these Facebook pages, some local and national news media did report on protest. One Radio Station—*Radio Kalima*—founded in 2008 as one of the few oppositional outlets in Tunisia and run by human rights campaigners, published multiple reports daily of the escalating wave of protests in Tunisia, which were archived by online news aggregator `turess.com`. These reports were also coded. By the closing stages of the revolutionary uprising, when protest was particularly widespread, national news media, and one newspaper in particular *Al Chourouk*, did begin to report on protest. Articles from these issues were also obtained from `turess.com` and coded. Finally, multiple international news sources, a post-revolution investigatory commission (detailed below), and the digital archive of the Tunisian Revolution were consulted for further information on protest occurrence.

In all, twenty-nine separate sources of protest event data were consulted, systematically

coded for each day of the revolution, and triangulated with each other. The methodological appendix gives fuller details of the pages and coding criteria used. Table A4 in the Appendix details each source, as well as the number of events that derive from each in the event catalogue. In identifying protest events, I follow Horn and Tilly's (1988) definition of contentious gatherings as "occasions on which at least ten or more persons assembled in a publicly-accessible place and either by word or deed made claims that would, if realized, affect the interests of some person or group outside their own number". Records were located for some 670 separate protest events over the twenty-nine days of the revolution.

Alongside these data, I include data on repression from the "Bouderbala Commission", an investigatory commission launched in the aftermath of the revolution that published, in May 2012, a list of deaths and injuries during the uprising and its aftermath. Overall, the investigatory commission provides data verified by either family visits or medical records (and for the overwhelming majority both) for 98 deaths at the hands of security forces. This is almost certainly an undercount, but nonetheless tallies very closely with reports of the occurrence of deaths in the event catalogue. For the purposes of the analysis, only the Bouderbala data is used to provide a measure of repression.

Finally, I include delegation-level ecological data. The principal ecological variable of interest is a regional development index (IDR) developed in the immediate aftermath of the revolution by the Tunisian Ministry of Regional Development and Planning to provide a composite measure of regional inequalities in economic development. The index ranges from 0-1, with 1 representing the most developed delegation and 0 the least. I use this as a measure of economic development. Figure 3 displays the diffusion of protest during the Tunisian Revolution alongside this measure of local economic development (by quantile). As

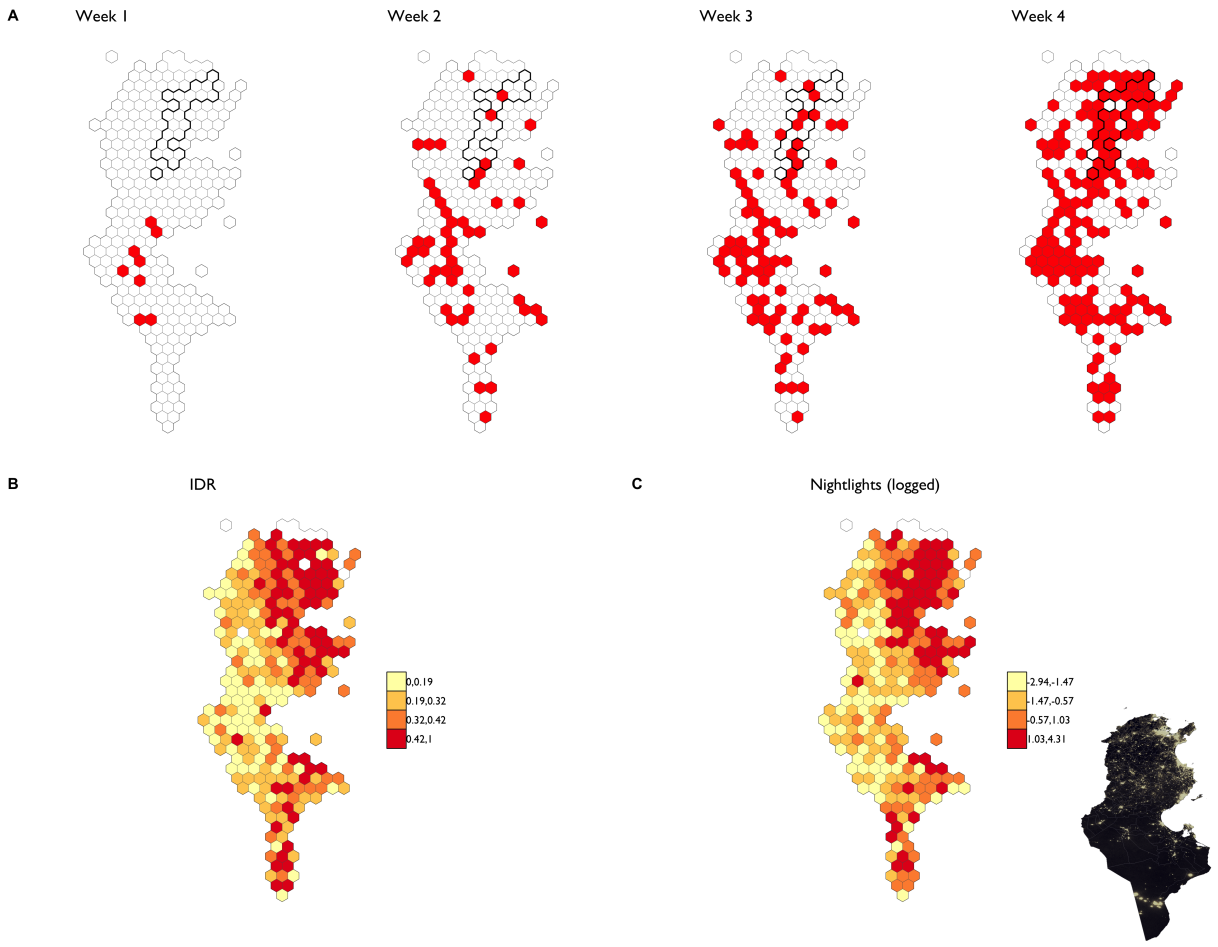


Figure 3: **A**:Diffusion of protest during Tunisian Revolution, weeks1-4; **B**: Local economic development (IDR) by quantile; **C**: Nightlights (logged) by quantile; inset: VIIRS DNB nightlights raster from April, 2012.

should be clear, it is only in the final stages of the uprising that protest begins to diffuse to more developed regions.[14] Alongside these measures, I use data deriving from censuses conducted in 2004 and 2014.[15]. Full details of the sources used for these data are provided in the methodological appendix.

Two concerns can be raised about the choice of main independent variable. While the

[14]Weeks refer to seven day periods beginning Friday December 17, 2010. Week 4 includes eight days to incorporate the entirety of the twenty-nine day period of the revolution.

[15]For the data that postdates the revolution, I verify its accuracy against available governorate-level measures of relevant indicators from 2010. I also verify findings against the 2004 data, testing for any significant differences in the size and direction of effects between measures that are available from both years. See metholodogical appendix for further details.

majority of district-level measures used to construct the IDR predate the Revolution, some do postdate the uprising. Several of those that predate the uprising were taken in 2004. This temporal distance raises concerns around measurement error. A second potential source of measurement error relates to the political context. Scholars have provided evidence to be skeptical of the reliability of labor market indices supplied by authoritarian regimes (Martinez 2019). Since several of the variables used to construct the IDR measure date from the period of the Ben Ali dictatorship, this concern applies to the current paper. In the absence of alternative development indices taken from a period more temporally proximate to the Revolution, I elected to use nightlights data as a proxy for local economic development. Data are taken from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band Nighttime Lights. [16] Following recent contributions (Chen and Nordhaus 2011; Michalopoulos and Papaioannou 2013), I take the natural log of mean nighttime lights at the delegation level.[17] The correlation between this proxy for economic development and IDR is strong (r=.81).[18] Given the wealth of evidence that nighttime lights data provide a reliable proxy for economic development (Elvidge et al. 2013; Mellander et al. 2015; Weidmann and Schutte 2017; Bruederle and Hodler 2018), this gives us greater confidence in the relability of our IDR measure. For the event history analyses I go on to describe below, I repeat each analysis with nighttime lights proxy measure to verify consistency of findings.

[16] See `https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html`, last accessed: October 3, 2019. In the Appendix I provide a more detailed overview of these data and their use.

[17] Light intensity was calculated in QGIS. Mean intensity is calculated as the sum of pixel values denominated by the total number of pixels in a given delegation. Unlike the DMSP-OLS satellite, which are measured on a 0-63 relative scale, VIIRS DNB pixel radiance is calculated as $\frac{nanoWatts}{(cm^2 sr)}$, and does not suffer from known problems of pixel saturation as a result of scale limitation (Elvidge et al. 2013; Wu and Wang 2019).

[18] The correlation when using the DMSP-OLS Global Radiance Calibrated Nighttime Lights (GRCN) data taken in November 2010, which uses a technique to overcome problems of saturation, is almost identical at r=.80.

4.2 Event history analysis

For the main analysis, I use discrete-time event history analysis to estimate the conditional, time-varying, effects of ecological covariates on protest diffusion during the twenty-nine days of the Tunisian Revolution (December 17 2010-January 14 2011). Standard errors are clustered at the delegation level.[19] Event history analysis is ideally suited to the task at hand as it allows us to examine changing dynamics endogenous to protest, rather than unitary outcomes a single point in time (Abbott 1988; Biggs 2003).[20] Duration dependence, and the related potential for conditional covariate effects, are central methodological concerns in the conflict scholarship (see e.g., Licht 2011; Jones and Metzger 2018) but largely ignored in the democratization literature.

The assumption that structural variables exert time-invariant effects has its correlate in the statistical literature. If it is the case that revolutionary processes are at equilibirum throughout the protest cycle, we can assume the existence of "proportional hazards"; that is, we can assume covariate effects to be constant over time. To investigate this assumption, I estimate covariate effects with and without time interactions of the key ecological covariate of interest. This allows us to test for evidence of time dependence and gauge improvement in model fit resulting from the inclusion of a time interaction. The interpretation of interactions is complicated in nonlinear models (Ai and Norton 2003). To aid interpretation, I aggregate the ecological measure into quartile bands and reenter it (as an interaction) in the same model used in Model 2 in the first analysis, displaying predictive margins over

[19] The use of random intercepts produces substantively identical results.

[20] As Abbott himself notes (1988, 182), we must pay attention to the definition of events (their colligation) and be alive to the potential for the "variable properties of the entity itself [to] change".

the course of the uprising. Finally, and following (Karaca-Mandic et al. 2012), I compute cross-partial derivatives to illustrate the marginal effects of the time interaction. Here, for ease of interpretation, and to facilitate comparison with the survey analysis that follows, I split time into three stages corresponding to the three time periods analysed in the Arab Barometer data.[21]

Dependent variable

The unit of analysis is the delegation-day. Tunisia is split into 24 governorates (*wilayāt*) and 264 delegations (*mu'tamadīāt*). For the purposes of the analysis, a dataset was constructed to include rows for each delegation and day of the twenty-nine days of protest that preceded Ben Ali's fall. Protest events were located in their delegation, making possible the inclusion of the delegation-level social context data in the analysis. From this, a dataset was constructed to measure the diffusion of protest. Here, the data is structured in split-spell format wherein only the first occurrence of an event in a given delegation is recorded (see e.g. Andrews and Biggs 2006).[22] After its first occurrence, the delegation drops out of the analysis. The dependent variable is binary and records the day that a given delegation first witnessed protest. The state space thus consists of two values, 1 if a delegation has witnessed protest, and 0 if it has not. The dataset used for the analysis contains a total of 5,921 spells. In total, 116 delegations saw no protest over this time period (i.e., were censored at day 29). In order to investigate time effects, I interact ecological covariates of interest with a linear

[21] i.e, into stages one, two, and three corresponding to the dates December 17, 2010-January 1, 2011; January 2–January 9, 2011; and January 10–January 14, 2011.

[22] Data structures of this sort are also referred to as "person-period" data sets in the life course and epidemiological literature.

function of time (measured in days).[23]

Independent variables

The choice of structural variables to include in the analysis is informed by the existing scholarship on the Arab Spring and democratic revolution generally. As noted above, while some see economic development as predictive of mobilization for democracy (Lipset 1959; Inglehart and Welzel 2005), others cite economic downturn and deprivation as precipitants of democratic transition or democracy protest (Haggard and Kaufman 1997; Acemoglu and Robinson 2006; Brancati 2014). The research on Tunisia specifically points to deprivation in the interior and regional inequalities in development as a key factor in the outbreak of protest (Ayeb 2011; Hibou 2011). I use the local development index (IDR)—detailed above—as the key measure of economic development at the delegation level.

Scholars have also pointed to the considerable youth population (or "youth bulge") and attendant underemployment in the Middle East and North Africa (MENA) as central factors in the uprisings (Campante and Chor 2012; Malik and Awadallah 2013). Thus, I also test a measure of delegation youth population (% population aged 20-29). In an Appendix robustness section, I test for time dependency in three alternative delegation-level measures of development and deprivation. These are: illiteracy rate (% illiterate population aged 10 or over); graduate unemployment (% unemployed with higher education certificate); and internet usage (% households connected to Internet).

[23]Results detailed below are robust to alternative functional forms of time, e.g., the log of days.

Control variables

In order to parse structural effects and contagion (see Braun and Koopmans 2010), I construct a general protest diffusion variable capturing all nearby protest. I follow previous research on protest diffusion (e.g., Hedstrom et al. 2000; Andrews and Biggs 2006) in using an inverse square root distance weighted sum of nearby protest days at time *t-1*, taking the functional form:

$$P_{1it} = \sum_{\tau=t-1}^{t-1} \sum_{j=1}^{J} \frac{P_{j\tau}}{\sqrt{d_{ij}}}$$

, where $d_{ij}^{-0.5}$ represents the square root of distance between the centroid of delegation i and delegation j and $P_{j\tau}$ represents a binary indicator of whether delegation j witnessed any protest at time τ.[24] I also include a control for repression, entered as the square root of deaths resulting from protest repression (taken from the Bouderbala data) at day *t-1* at the national level. Finally, I include a control for delegation population-size (logged).

4.3 Survey analysis

In a secondary analysis, I use Arab Barometer data, replicating the analysis of recently published research but disaggregating by date of respondent's first participation.[25] Wave II of the Arab Barometer asked respondents a battery of questions relating to participation in the

[24]These variables were generated with Keisuke Kondo's *spgen* set of commands Kondo 2017. A distance of 15 km was used to capture nearby protest—the mean distance between two polygon centroids is 14.02 km. Varying this buffer from 10-40km does not substantively alter findings. Results described below are also robust to the inclusion of an interaction term of the protest diffusion variable with time. These were not included in final models as they do not significantly improve model fit.

[25]The Arab Barometer is a widely used cross-national series of nationally representative surveys conducted in the MENA. See `http://www.arabbarometer.org/` and the methodological appendix for further details.

Tunisian Revolution and its aftermath. The survey includes responses for 1,196 respondents. Respondents were asked first "Did you participate in the protests against former president Zain Al Abdeen Ben Ali between December 17th, 2010 and January 14th, 2011?". For those that answered in the affirmative, they were then asked "Did you participate in any of the following protests?", and were offered three time intervals: "December 17, 2010 to January 1, 2011"; "January 2–January 9, 2011"; and "January 10–January 14, 2011". I will refer to these as Stages "1", "2", and "3." Of the 192 respondents who reported protesting at some stage, 75 reported only protesting in the final stage of the uprising (i.e., 40%).[26] This would accord with the account of the uprising above. Only in its final stages did protests in the Tunisian Revolution become mass participation phenomena articulating explicitly anti-incumbency demands.

I use these questions to generate several separate outcomes relating to participation. A first uses the initial question that does not disaggregate by time and measures whether the respondent protested at any stage. This is the question used in published research to date (e.g., Hoffman and Jamal 2014; Beissinger et al. 2015; Doherty and Schraeder 2018). I then use the questions probing the stage at which the respondent first participated to convert this outcome measure to an ordinal scale measuring date of first participation. This allows us to test whether we can be confident of odds proportionality, in an ordinal logistic context, when discretizing our participation variable in this way.

The 'proportional odds" (or "underlying latent variable"/"parallel regressions") assumption is analogous to the assumptions underlying the threshold models in the formal modelling

[26]Note that participation numbers detailed below are slightly reduced. This results from the use of a restricted sample in the analysis by Doherty and Schraeder (2018) that I am replicating.

literature described above. Here, the assumption is that we can assume the existence of heterogeneous revolutionary thresholds in a population. While individual thresholds for participation might vary, an underlying continuous latent variable (e.g., revolutionary propensity) can be assumed to exist. Since the odds in an ordinal model can be interpreted as corresponding to the odds of exceeding a certain category, the categories of an ordinal scale have a threshold interpretation (Winship and Mare 1984). A violation of this assumption would mean that the odds of participating at each stage of the revolution were *not* proportional to each other, and would thus provide evidence against the conceptualization of protest in revolution as a unitary outcome of interest. The rationale for testing this assumption, in other words, is taken from the central theoretical propositions of this paper.

Of particular interest is the influence of reported commitment to democracy on the decision to protest. If it is the case that democratic motivations emerged endogenous to the protest cycle, we should expect this variable to violate assumptions of odds proportionality. In other words, democracy protesters should be disproportionately likely to protest at a given stage of mobilization cycle. To investigate this, I use a mean index used in previous published research (Hoffman and Jamal 2014; Doherty and Schraeder 2018; Ketchley and El-Reyyes 2019) constructed using responses to three statements relating to democratic governance in the survey. A response scale of 1-4 was offered, with 1 indicating strong agreement, 2 agreement, 3 disagreement, and 4 strong disagreement. The questions were worded as follows: "Democratic regimes are indecisive and full of problems"; "A democratic system may have problems yet it is better than other systems"; "Democracy negatively affects social and ethical values in [Tunisia]." Together, responses to these questions are used as a measure of commitment to democracy. The index was scaled such that higher values indicate stronger

commitment to democracy. Missing values were coded as 2, giving a 0-4 scale, which was then index by its mean.[27]

Using this index, I replicate the results of Doherty and Schraeder (2018) but test for the robustness of their findings with the temporally disaggregated participation outcomes. The model I replicate also includes measures for individual income (logged)[28]; education (six categories of schooling); age (years); gender (male=1); employment status (binary); retired/housewife (binary); student (binary); religiosity (index based on three questions relating to prayer, Qur'an reading, and self-reported religiosity); mosque attendance (five items of regularity of attendance); whether district of residence rural (binary); interest in politics (four items of level of interest); whether friends participated in protests (binary); whether member of any civil society group (binary). The model also included governorate indicators for all twenty-four governorates, and used post-stratification weights provided with the dataset.[29]

[27]This is the same index used in Doherty and Schraeder (2018). An additive index of the form used by Hoffman and Jamal (2014) gives substantively identical results. Results were robust to, and in fact strengthened by, the inclusion of another question in the index that asked for responses to the statement "Democratic systems are not effective at maintaining order and stability". The alpha on this index is also considerably higher (0.78) than that used in the published research (0.43). I elect to use the index used in Doherty and Schraeder (2018), however, to facilitate comparison. See metholodogical appendix for further details of alternative indices.

[28]Following Doherty and Schraeder (2018), I use the same procedure for dealing with missing values on income, setting missings to the sample mean and entering a separate binary indicator of whether information is missing for income.

[29]Replication data and supplemental materials detailing the coding of each of these variables can be found at `https://dataverse.harvard.edu/dataverse/jop`. Codings can be also be found listed in the supplementary methodological appendix to this paper.

5 Results

Full results for the event history models with and without time interactions are displayed in Table 2. In a first model, I include all covariates of interest but do not interact our measure of economic development (IDR) with time. In a second model, I include a time interaction with IDR.[30] As should be clear, we have evidence of significant time dependence. While high levels of local development are initially negatively associated with protest diffusion, this association gradually weakens over time. Youth population, on the other hand, is consistently predictive of protest diffusion over the course of the uprising.[31] The coefficient on the lagged protest control is positive, as expected, indicating significant protest contagion. Repression has a negative and significant effect on protest diffusion. Delegations with larger populations are also more likely to have witnessed protest. We also have evidence of significant improvement in model fit between Model 1 and Model 2: both the AIC and BIC are significantly reduced, while McFadden's R^2 suggests that Model 2 explains significanly more of the variance in protest diffusion than the baseline Model 1. It is also worth noting that these time effects are not simply artifactual of the late arrival of protest in the capital, Tunis, where development and deprivation is comparatively lower. Excluding Tunis from the analysis, results are substantively identical. In Appendix Table A8 and Figure A10, I show that conclusions

[30] The results displayed in Model 2 are robust to the inclusion of time interactions with all other covariates but since these do not significantly improve model fit they were excluded. To arrive at a parsimonious model, time interactions were introduced with each of the covariates included in the model in turn, checking for significant differences in goodness of fit at each iteration compared to an updated baseline model (not shown here). Akaike's Information Criterion (AIC), the Bayesian Information Criterion (BIC) and McFadden's R^2 were used to infer model fit. I benefited from Long and Freese's (2014) *SPost13* package of commands to compute scalar models of fit

[31] The inclusion of a time interaction with this measure showed no significant effect and did not improve model fit.

are substantively identical when using the nightlights proxy for development. Appendix Table A9 and Figures A11 and A12 demonstrate that similar conditional covariate effects are found when using alternative measures of development and deprivation.

Table 1: Discrete-time logistic regression of IDR with and without time interaction, cluster robust standard errors

Variables	Model 1: Without time interaction	Model 2: With time interaction
Lagged protest	0.621**	0.370**
	(0.201)	(0.141)
Time		-0.012
		(0.030)
IDR	-1.209	-6.895***
	(0.782)	(2.092)
IDR*Time		0.318***
		(0.096)
Youth pop.	0.080	0.086
	(0.044)	(0.049)
Population (logged)	0.874***	0.924***
	(0.169)	(0.183)
Repression	0.241***	-0.021
	(0.049)	(0.066)
Constant	-13.964***	-14.018***
	(1.837)	(2.018)
Observations	5,921	5,921
AIC	1288	1245
BIC	1328	1298
McFadden's R^2	0.0732	0.108

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

In sum, then, covariate effects on protest diffusion are conditional on the stage of the uprising. Indeed, in the absence of a time interaction, IDR seems not exhibit any significant association with protest diffusion. This provides compelling initial evidence that understanding 'revolutionary' protest as a unitary outcome measurable at a single point in time

is wrongheaded. Indeed, we risk committing a Type II error when not accounting for the presence of time-dependent covariate effects. The substantive size of these offsetting effects is difficult to ascertain from raw regression outputs. As such, below, I aggregate the IDR into quartile bands and plot adjusted predictions for its upper and lower quartiles over the course of the twenty-nine days of the uprising.[32] These are displayed in Figure 4a. In Figure 4b, I compute, following Karaca-Mandic et al. (2012), cross-partial derivatives to demonstrate the marginal effects at each stage of the uprising, using the same dates of stages used in the survey data analysed below. These plots display the difference in predicted probabilities of protest at representative values of our ecological covariate of interest at different stages of the uprising.[33] The horizontal line at y=0 represents no difference between stage 1 and the stage in question.

As should be clear from Figure 4a, the effect of IDR is far from constant over time. While a low level of development is initially more predictive of protest, the association reverses over the course of the uprising. Similarly, in Figure 4b we see that during the closing stage of the uprising, protest was significantly more likely in developed regions than it was in the first stage.[34] These findings provide strong evidence that the structural correlates of protest can shift dramatically over the course of an uprising. They also accord with the qualitative case detail above: it was only in the closing stages of the uprising that protest emerged in more developed regions.

It was also when protest reached these more developed regions that participants began to voice more expansive demands. If the ecological correlates of protest occurrence display

[32]The lagged protest control remains in this model as a control as do all other covariates in Model 2.
[33]The only difference between this model and Model 2 above, in other words, is that IDR is interacted with a categorical variable measuring stages rather than a vector of days.
[34]There are no significant differences between stages 1 and 2.

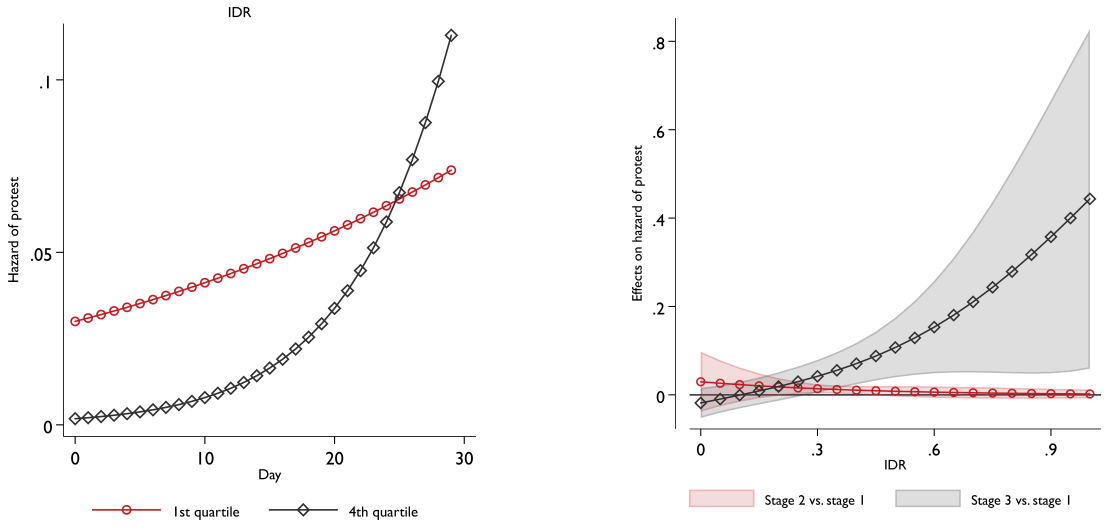


Figure 4: (a) Predictive margins of IDR over time, upper and lower quartiles; (b) Marginal effects of IDR by stage of uprising, with 95% CIs

significant time dependence, what, then, of the correlates of protest participation? Table 2 displays the number of observed sequences of participation and percentage of total respondents corresponding to each sequence in the Arab Barometer survey data. [35] Stage 1 corresponds to participation in a first stage (December 17, 2010-January 1), Stage 2 to participation in a second stage (January 2–January 9, 2011) and Stage 3 to participation in a third stage (January 10–January 14, 2011). As noted above, a large proportion of those who protested began protesting only at Stage 3—circled red.[36]

I first compare results for our key independent variable of interest, commitment to democracy, when using differently aggregated protest participation outcomes. Specifically, I compare the results produced by using the aggregated outcome measure (i.e., replicating the analysis of Doherty and Schraeder (2018)) to those produced when using an ordinal outcome measure. I compute an ordinal scale running from 1-4, where 1 corresponds to those who

[35]The number of possible sequences is equal to 2^n, where n is the length of possible sequence.

[36]The restricted sample used in the replicated analysis reduces observations from 1,196 to 1,115. Of these, seven respondents are missing on this item, thus explaining the total of 1,108 given.

Table 2: Sequences of participation in the Tunisian Revolution from Arab Barometer Wave II

	Stage 1	Stage 2	Stage 3	Number	Percent
No stage	0	0	0	933	84
Stage 3	0	0	1	74	7
Stage 2	0	1	0	10	1
	0	1	1	21	2
Stage 1	1	0	0	10	1
	1	0	1	5	0
	1	1	0	1	0
	1	1	1	54	5
Total			1,108	100	

began protesting at stage 1, 2 to those who began protesting at stage 2, 3 to those who began protesting at stage 3, and 4 to those who did not protest. This scaling theoretically reflects increasing thresholds of participation: those with the lowest thresholds (those who protested from the beginning) are coded 1, and those with the highest (those who never protested) are coded 4. Full regression outputs from these two models are provided in Appendix Table A11.

As noted above, for an ordinal scale to be viable, we must satisfy the assumption of proportional odds. Reestimating the replicated model from Doherty and Schraeder (2018) with this newly coded ordinal outcome, and performing a Brant test of odds proportionality, points to a significant violation of this assumption at the .001 level.[37] The variable that

[37]Note that the STATA procedure for running Brant tests does not allow for inclusion of survey weights and governorate indicators. There is also significant evidence against the proportional odds assumption when computed with score (Lagrange multiplier) tests, likelihood ratio tests, and Wald tests.

most strongly violates the assumption of proportional odds is that measuring commitment to democracy.[38] This provides initial evidence against the assumption of common underlying revolutionary propensities.

Given the violation of odds proportionality, I choose instead to run a multinomial logistic regression, discretizing the dependent variable into four outcomes once again, and taking those who never protested as the reference category. Here, no assumptions are made about the ordinality of outcomes and coefficients correspond to the probability of belonging to a particular category. Full results are displayed in Appendix Table A12. In order effectively to visualize the relationships between categories and the underlying predictors of membership in each, I provide a link plot (see Figure 5a), which visualizes differences between all pairs of outcomes (i.e., not just with the base category). Here, the distance between two outcomes reflects the magnitude of the contrast in coefficients between two categories for a range change in the independent variable of interest (i.e., from its lowest to highest values). If a coefficient is not significantly different from 0 at the .05 level, a line connects the two outcomes.[39] I select for display four independent variables that show particularly pronounced differences: commitment to democracy, education, age, and student status.[40]

Notable contrasts are picked out in red in the link plot. We can clearly see that, while a commitment to democracy has a weakly negative, and insignificant (relative to the baseline category of no protest) association with protest participation in stages 1 and 2, in stage 3

[38] Here, I use the *fitstat* command written by Long and Freese (2014) to give details of which variables violate the proportional odds assumption according to the Brant test. To compute these, the command essentially runs a series of binary logistic regressions for the J-1 outcomes of interest, testing for significant differences in the βs of each independent variable.

[39] I use the *mlogitplot* command provided as part of Long and Freese's (2014) *Spost13* package in STATA to produce these plots.

[40] Following Doherty and Schraeder (2018), the reference category for student is unemployed respondents.

it is strongly positively predictive of participation. We also see that more highly educated individuals, as well as students, are more likely to protest at stage 2 (relative to stage 3 and the baseline category). This would accord well with the what we know about the process of the Tunisian Revolution, with students participating in large numbers in the middle period of the uprising. Finally, and consistent with the results for the event history analysis where youth population consistently predicted protest diffusion, younger individuals are consistently more likely to have participated in two of the three stages relative to those who did not participate (the contrast between stage 2 and the baseline is significant at the .1 level (p =.092)). In order more clearly to visualize the effect of our key independent variable of interest—commitment to democracy—on protest participation, I also plot, in Figure 5b, adjusted predictions for each stage of the uprising at representive values of the democracy index. Here, we see clearly that while in stages 1 and 2 there was no, or a weak negative, association between commitment to democracy and protest participation, in stage 3 there is a strongly positive association.

Once again, then, we see the importance of proper temporal disaggregation when assessing the correlates of protest. Analysed in the aggregate, a commitment to democracy exhibits no predictive power. But given what we know of the origins and development of the Tunisian Revolution, this should be unsurprising. Protest did not begin life as revolutionary nor as motivated by broader democratic aspirations. In the later stages of the uprising, however, and amid significant repression, the mounting wave of contention did lead to mobilization for democracy. These observations are borne out in the quantitative analyses. If protest began life as parochial and concentrated in marginalized regions of the Tunisian interior, it would later spread to the Sahel and begin to launch more expansive demands for democracy.

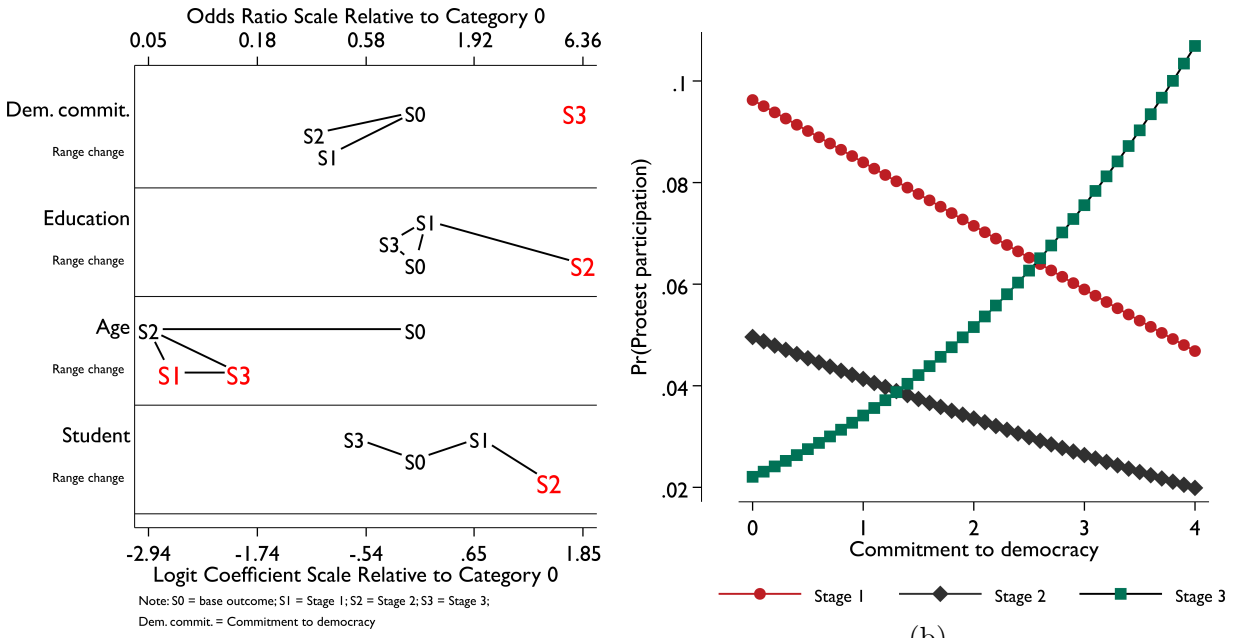


Figure 5: (a) Multinomial logistic link plot of coefficient contrasts for separate predictors. Joining lines indicate no significant difference at .05 level; (b) Predictive margins of commitment to democracy on protest participation. Multinomial logistic regression by stage of first participation

The correlates of both protest occurrence and participation shifted significantly during the course of this process. The implications of these findings for a processual understanding of democratic revolution are discussed below.

6 Discussion

6.1 Revolution as process

Do the dynamics observed in the Tunisian Revolution represent an aberration? Mass protest in Tunisia was not prompted by a political opening or systematic state violence, did not follow immediately from stolen elections or from an economic downturn, and was not spurred by uprisings in neighbouring countries—all factors commonly cited for explaining such events

(McAdam 1982; Goodwin 2001; Acemoglu and Robinson 2006; Tucker 2007; Bamert et al. 2015). In this, one could suggest that the revolutionary overtthrow of Ben Ali was, in various respects, atypical. But understood at the more general level—as an uprising wherein demands emerged endogenous to protest—it shares with numerous other episodes of mass protest the central characteristic that, owing to this processual logic, outcomes cannot be reduced to origins.

The French Revolution did not begin life as an assault on feudalism; anti-seignurial sentiment developed not over centuries but during the three-year period after the onset of protest (Markoff 1997). In the nine months preceding the convocation of the Estates General in May 1789, 12% of all "insurrectionary events" involved anti-seigneurial claims, while the overwhelming majority concerned basic subsistence; by January 1790, after peasants formed common cause with the bourgeoisie, 87 % of events were anti-seigneurial in character (Markoff 1997, 1121-1122).

The 1830 dethronement of the Charles X in the *Trois Glorieuses* was achieved by "a genuine coalition of groups with rather different objectives," and, in the ensuing insurrection, "the locus and character of the issues about which Frenchmen were fighting shifted dramatically as the revolution moved from phase to phase" (Rule and Tilly 1972, 62-68).

The 1871 Paris Commune, posthumously awarded the title of working-class revolt, had more to do with the defence of municipal liberties. Moreover, the impulse to defend municipal liberties developed through organizational ties forged during the insurrection itself (Gould 1995).

In surely one of the earliest examples of survey instruments being deployed to episodes of insurrection, a correspondence survey conducted in 1908 by the Russian Imperial Free

Economic Society on the causes of participation in the agrarian revolt of 1905-1906, found that participation "was determined primarily by local conditions, and by the forms assumed by the [agrarian] movement in individual localities" rather than any overarching structural cleavage (Perrie 1972).

What became the Bolshevik Revolution in 1917 Russia was precipitated by a wave of labour protest. Motivating these strikes, historians have documented, were over 250 separate demands, leading them to conclude that it would be "innacurate to conceptualize strikes in 1917 simply as revolutionary episodes" (Koenker and Rosenberg 1989b, 73-89). In fact, the ecologies of protest shifted dramatically from March-July and July-October as semi-skilled workers were incorporated into an emerging "mass movement" (Koenker and Rosenberg 1989b, 319). The class content of the collective identities broadcast by industrial workers shifted alongside a constant reordering of the political field (Haimson 1988). This very fact of "constant change" during the revolutionary year of 1917, these scholars conclude, "raises further problems about using constant [time-invariant] figures" to estimate the statistical correlates of protest (Koenker and Rosenberg 1989a, 170).

In Mexico, organized labour mobilization largely postdated the revolutionary overthrow of General Porfirio Díaz, as new associational forms developed over the revolutionary conjuncture (Knight 1984, 72). From 1910 onwards, the apparent master cleavage of clerical loyalties animating separate revolutionary camps was, in actuality, "not usually a crucial determinant of intra-revolutionary loyalties, still less of the Revolution's final outcome" Knight 2010, 236.

The coincidence of police brutality and rigged elections in South Korea provoked localized protests which grew into a mass student-led revolt that toppled the regime of Syngman Rhee

in under two weeks during April 1960. Surveys of participants revealed that almost none of the students anticipated or targeted Rhee's ouster; rather, objectives "were either vague, peripheral, and impulsive rather than concrete, central, and calculative" (Yang 1973, 58) and a "general consensus" around the objectives of protest "came into being on its own" (Kim and Kim 1964, 91).

The Iranian Revolution was a site of multiple competing mobilization attempts on the part of diverse ideological groups (Ahmad and Banuazizi 1985; Rasler 1996). This revolution "came in heaving waves," the second of which would align the urban intelligentsia with the merchant (*bazaari*) class (Ahmad and Banuazizi 1985, 4). Absent organizations with the capacity to direct the flow of demands, religion came to provide the ultimate infrastructure and orienting frame of revolt (Ahmad and Banuazizi 1985; Bayat 1998).

Popular protest during the collapse of the Soviet Union took on ethnonationalist or secessionist hues only in the course of its unfolding; "structural influence was not a constant" and often weakened over time (Beissinger 2002, 140). Protests in East Germany from 1989 onwards would variously incorporate radicals and moderates, with the targets and demands of protests shifting at each stage of the cycle. Support for unification goals increased over this conjuncture and, through a recursive process, the attitudes of protesters often led those of the population (Lohmann 1994).

The 2004-2005 Orange Revolution in Ukraine united a diverse coalition of protesters with often divergent aims. The democratic "master narrative" crafted over the course of the episode mapped poorly onto the professed aims of actual participants, the majority of whom did not support a transition to multi-party democracy (Beissinger 2013). The 2013-2014 Euromaidan movement in Ukraine represented a complex unfolding of multiple

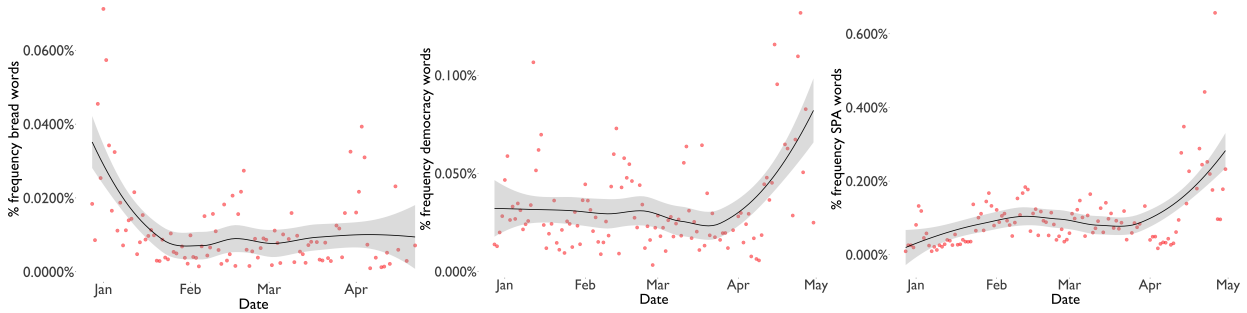
claims (Onuch and Sasse 2016). Survey evidence demonstrates that participation itself was generative of attitudinal change, with protesters adopting a significantly more favourable orientation toward the European Union internal to the protest cycle (Pop-Eleches et al. 2018).

A sustained wave of mass mobilization more recently struck Sudan from 2018-2019, initially in response to the cutting of bread subsidies. Beginning in Atbara, protest would in time gain the backing of the Sudanese Professionals Association (SPA), culminating in the removal of dictator Omar al-Bashir on April 11 and calls for democratic transition (Berridge 2019). Systematic scholarly explorations of this episode are yet to be written but Twitter data for the hashtag associated with the uprising #tasgot_bas (تسقط_بس) provide a window onto protest dynamics.[41] Here, we see that while mentions of bread were relatively frequent in the month of January (Figure 6a), they decreased in frequency over subsequent months while mentions of democracy and the SPA increase (Figures 6b and 6c). This tallies with our qualitative understanding of an episode where, analogous to the Tunisian case, economic protest spawned democratic demands that were carried forward by emergent institutional support.

6.2 Democratization and contention

A survey of the empirical record demonstrates, then, that the processual dynamics of the Tunisian Revolution are shared by multiple historical instances of mass insurrection. Outcomes can rarely be read from origins and the grievances driving protest are often heteroge-

[41] The Python library "GetOldTweets3" was used to retrieve tweets. For further information, see: `https://pypi.org/project/GetOldTweets3/`. The sample contained 212,361 tweets. We cannot be confident all of these tweets derived from Sudan. These data nonetheless give us a window into the content of online conversations relating to the Sudan protests.



(a) (b) (c)

Figure 6: (a) Percentage frequency of words related to bread in #tasgotbas data; (b) Percentage frequency of words related to democracy in #tasgotbas data; (c): Percentage frequency of words related to SPA in #tasgotbas data

neous and develop over time. This observation sits uncomfortably alongside existing work on democratic revolution. Scholarship that conceives of democracy protest and revolution as unitary outcomes proceed from the implicit assumption that revolutionary processes are everywhere at equilibrium. Thus, survey work treats protest participation as amenable to cross-sectional forms of analysis while structuralist accounts see protest as motivated by the benefits that will prospectively accrue to the actor in question if democracy is achieved (Boix 2003; Acemoglu and Robinson 2006; Beissinger et al. 2015; Doherty and Schraeder 2018).[42] The formal modelling literature similarly conceives of protest participation as unitary and makes the additional assumption that underlying revolutionary propensities govern participation (DeNardo 1985; Karklins and Petersen 1993; Kuran 1995).

This article has demonstrated that such assumptions are likely wrongheaded. What is clear from the Tunisian case, and the empirical record more generally, is that democracy protest is just as often the culmination as it is the precipitant of mass mobilization, and

[42]The narrowly instrumentalist accounts of distributive conflict theorists fail to explain why members of more than one social class would participate in such protest (Slater 2009, see also Clarke 2017) while more expansive structural accounts choose to array an ever more diverse set of structural precipitants, or "conjunctural amalgams" (Lawson 2016), generative of mass contention.

outcomes map onto origins only at several steps removed. Even when protest begins by mounting democratic demands, as is often the case in the aftermath of stolen elections, the assumption that a democratic master cleavage separates the quiescent from the revolutionary is often disappointed by the actual distribution of preferences within a crowd.

If we take mobilization for democracy as a key stage in the onset of democratic transition (Acemoglu and Robinson 2006; Przeworski 2009; Teorell 2010; Haggard and Kaufman 2016; Kadivar and Caren 2016; Kadivar 2018), we must begin to conceptualize democratization appropriately as an arena of contentious politics.[43] The object of explanation then becomes protest and not democratization as a whole. Furthermore, if protest does not begin life advancing demands for democracy, our theories should reflect this. An alternative, processual, understanding of democratic revolution has it that democratic claims may emerge endogenously in the context of contention. Here, while structural factors might inhere in mobilization processes in important ways, the democratic outcomes of a revolutionary protest wave must be distinguished from its origins; while structural conditions might make protest more likely, its ultimate democratic character cannot be retroactively attributed to these same conditions.[44] The task thus becomes explaining why complex episodes of multiple forms of contention might ultimately conduce to mass mobilization for democracy.

How should we go about this? In what follows, I suggest one way forward. The reader will not, by this stage, be surprised to learn that some as-yet-unexcavated element of struc-

[43]Bermeo and Yashar (2016) make a similar proposition, advocating that scholars focus their analytical lens on the "political mechanisms" internal to contentious politics that connect structural conditions to democratic outcomes. Other recent scholarship points to the potential of this research agenda, focusing as it does on the occurrence of "democracy protest", "disruptive democratization" or "democratic windows of opportunity" rather than democratization as a whole (Brancati 2014; Aidt and Leon 2016; Kadivar and Caren 2016).

[44]This is a core tenet of the contentious politics literature but one that is largely ignored in accounts of mobilization for democracy (see McAdam et al. 2001a; Tarrow 2011).

ture provides the key.[45] Instead of enumerating more complex assemblages of structural antecedents for democracy protest and democratization, an approach that has yielded limited explanatory power (Haggard and Kaufman 2016; Chenoweth and Ulfelder 2017), I argue that answering this question requires an attention to generalizable causal mechanisms that inhere *within* episodes of mass insurrection (Tilly 1993). Foremost among these is brokerage, defined as "the linking of two or more previously unconnected social sites by a unit that mediates their relations with one another and/or with yet other sites" (McAdam et al. 2001a, 206).

6.3 Democratic coalitions, brokerage, and *ta'ṭīr*

Why brokerage? Literature on revolution almost universally recognizes episodes of revolutionary mass mobilization as characterized by the formation of contentious coalitions of diverse class actors (Tilly 1973; Skocpol 1979; Dix 1984; Foran 1993; Goldstone 2001; Parsa 2001; Thompson 2004; Slater 2009; Beissinger 2013). Cross-class, or "negative" (Dix 1984; Beissinger 2013), coalitions of this sort are nonetheless generally considered epiphenomena of democratic revolution rather than the outcome to be explained. If we instead take these coalitions as the object of explanation, brokerage emerges as the key mechanism underpinning the formation of common fronts. Coalitions in such contexts are distinct from the more formal alliances of mutual cooperation that constitute the focus of much civil conflict scholarship, although they share with these their endogenous dimension (Christia 2012; Kalyvas 2008). Brokerage within coalition formation instead means, following the definition provided

[45]Tilly (1995) provides the most sustained warning against such an approach. Instead of elaborating new theory, he observed, scholars of revolution went about "improving the model", which most often entailed unjustifiable modifications aimed at salvaging "invariant universals" in the study of revolution.

above, the linking of otherwise unconnected social groups or sites in a common mobilization effort.

In the Tunisian case, institutional support from the UGTT contributed to the scaling up of more limited forms of contention, and to the uniting of diverse groups behind common anti-incumbancy demands.[46] In this sense, abeyant organizational structures were key in transforming parochial forms of contention into mass-based demonstrations for democracy. A particular word used by trade unionists in Tunisia—*ta'ṭīr*—eloquently articulates this process. Ta'ṭīr can be understood in its literal translation as "framing" or in its French equivalent of *encadrement*, which implies monitoring or, more actively, bringing into the fold (of a given actor or institution) and the assumption of leadership. Both translations capture something of its meaning and help us understand what is at stake in brokerage.

The first translation recalls the influential body of social movements scholarship on framing processes that conceives of movement actors not merely as vehicles for the channeling of existing grievances but as "signifying agents actively engaged in the production and maintenance of meaning" (Benford and Snow 2000, 613). In the Tunisian case, trade unionists recall making active efforts, in their choice of slogans and media communiques, to couple the economic demands that animated initial protest with explicitly political claims and to frame Bouazizi as a political martyr and victime of the regime (ICG 2011, 4; Yousfi 2015, ch. 2). As one militant member of the Tunis UGTT branch put it, trade unionists felt it their task "to give a meaning and clear aims to the movement" (interview Kais, February 2017). Describing the role of the UGTT in times of crisis, Zied, a resident of Tunis, described the

[46]Interview data cited in this section derives from fieldwork conducted in Tunisia in the spring of 2017 and 2019. See Appendix for details of fieldwork and methodology. All names are anonymized.

UGTT as an organization that both "follows and leads the street" ("*qui suit et encadre la rue*"). In sum, ta'ṭīr meant, as one young protester from Sidi Bouzid explained: "making clear that we're organising together, [that] we have the same enemy" (interview Lilia, April 2019).

The second understanding of ta'ṭīr—as encadrement—invokes the coordination function of institutional actors and their role in brokering a collective mobilization effort. Local instances of the UGTT represented a "melting pot" (Hmed 2012) of civil servants and other public functionaries with the requisite networks to coordinate action and subsume otherwise unaffiliated youth or peripheral civil society actors under a common front (Yousfi 2015). In assuming this leadership role, UGTT members also made efforts to ensure that protest remained nonviolent (interview Yassine, February 2017; interview Taha, March 2017; interview Med and Ali, March 2019). That is, they "coordinated to control the situation", because young protesters, often involved in violent nighttime clashes, "did not coordinate with others or have any big project for society" (interview Firas, March 2017). This coordination role would eventually prove decisive after the National Executive of the UGTT elected to side with protests, granting permission for branches to launch regionwide strikes, and recognizing the "right of citizens of other regions and professional sectors to express their active solidarity through peaceful protests, and in coordination with the National Executive Office" (ICG 2011, 6).

At a more general level, the Tunisian case demonstrates the centrality of organization to episodes of popular insurrection. Notable recent contributions to the cross-national study of democratization share this concern with the organizational foundations of democratic mobilization. These arguments take multiple forms. Butcher et al. (2018) find that abeyant

oppositional organizations under authoritarianism, notably national trade union federations, provide "leverage" for civil resistance campaigns, increasing the chances of success by boosting participation and sustaining resistance in the face of repression. Kadivar (2018) makes a similar argument and further suggests that organizations built through sustained mobilization provide vehicles through which protesters can channel grievances as well as potential "leadership cadres," thereby raising the probability of democratic survival. Haggard and Kaufman (2016) and Usmani (2018), for their part, find that the "capacity for collective action" or "disruptive capacity" of a given country—as measured by the organizational strength of labour—is a key predictor of democratization from below.[47]

Given the accumulating evidence that organizational strength is a key correlate of democratization, future scholarship should aim to unpack the microlevel mechanisms underpinning these macrolevel associations.[48] The Tunisian case, and evidence from numerous empirical examples sketched out above, indicates that foremost among the candidates is brokerage; organizational brokerage helps explain why diverse groups are able to unite in episodes of contentious collective action. In this, it illuminates a central problematic in revolutions and democratization research—the formation of democratic coalitions. Specifying the object of explanation as this key dimension of mass protest brings into relief the analytical gap between antecedent conditions and democratic outcomes, and forces us to recognize democratic transitions as a domain of contentious politics (McAdam et al. 2001a). It is in and through

[47] Haggard and Kaufman (2016) refer to such episodes, following the so-called "distributive conflict" literature (Acemoglu and Robinson 2006) as "distributive conflict transitions."

[48] In this, scholarship on democratization would benefit from a conversation with the conflict literature. Here, an attention to the microlevel implications of macrolevel theory has become a central focus (Kalyvas 2006; Cederman and Girardin 2007. More generally, we may look to variant societal cleavage structures as generating, or inhibiting, cross-class mobilization (Selway 2011).). This has been notably absent in the literature on mass mobilization for democracy.

mass mobilization, after all, that protests might conduce to broader democratic demands or, to paraphrase Tilly (1973), to a "democratic situation."

7 Conclusion

This paper has made several key findings that have important theoretical and methodological implications for the study of mobilization for democracy and democratization. Current theoretical frameworks treat democracy protest, and protest participation, as unitary outcomes amenable to cross-sectional analysis. These frameworks implicitly conceive of revolution as everywhere at equilibrium. The empirical record runs counter to such understandings. What emerges clearly from the discussion above is that revolution often does not begin as revolutionary; targets of protest emerge endogenously as common coalitions form and new opportunities arise. Revolution, in other words, is a process.

To support this argument, I show that the correlates of both protest occurrence and protest participation shifted drastically over the course of the Tunisian Revolution of 2010-11. Despite being nominally a democratic revolution, a commitment to democracy positively predicts protest participation only in the final stage of the uprising. Consistent with this, the ecological correlates of protest diffusion effectively reverse over time. While in its early stages protest diffused mainly to deprived internal regions of Tunisia, by the closing stages of the uprising protest was more likely to occur in affluent, developed regions. These findings provide strong support for an understanding of revolution as process. The Tunisian case, in this regard, is not unique—numerous historical instances of mass insurrection share this fundamentally processual character. More specifically, the findings demonstrate the potential

for democratic demands to emerge endogenously within a protest wave that begins life as parochial and motivated by narrow economic demands.

The above insights should give us reason to reconsider the ontological underpinnings of existing work on mobilization for democracy. Mass contention unites diverse actors advancing diverse claims. The emergence of mass mobilization, and the mechanisms that give rise to democratic contention, should constitute a new focus for future scholarship. Underpinning some of the association between organizational strength and democratization, I suggest, is brokerage, and the role of organizations in coordinating a common front and collective identity. In recognizing that dynamics internal to revolt may be decisive for democratic transition, we may also rescue multiple instances of attempted, but ultimately unsuccessful, mobilization for democracy from the ash heap of history. While protest in Tunisia managed to scale up and successfully advance democratic demands, numerous instances of mobilization in its wake, in all of Egypt, Morocco, Algeria, Yemen, Bahrain, Libya, and Syria failed ultimately to see similar outcomes. Salvaging such cases would both improve our empirical models and help disentangle the theoretical mechanisms governing the outcomes of popular struggle.

Appendix 2

A2.1 Twitter data

Twitter data comes from the 1% Twitter streaming API for the hashtag #sidibouzid. This captures 1% of all tweets (from any location) using this hashtag. Data were collected during the course of the uprising by the editor of Nawaat Sami Ben Gharbia and provided to the author in person during a fieldwork stay in Tunis in April, 2017. These data comprise some 85 thousand tweets over the period 18/12/2010-14/11/2011. Data collection only began after the first day of protests in Sidi Bouzid, thus explaining the lack of data for December 17. For the purposes of the text analysis in Section 3 of this article, I employed the R package *arabicStemR* authored by Rich Nielsen, which allows users to stem, clean, and transliterate Arabic text(see `https://cran.r-project.org/web/packages/arabicStemR/arabicStemR.pdf`). By transliterating Arabic text into Latin script, the user is able to conduct textual analysis within one sample. Words used in these analyses are listed in Table A3. Words highlighted in red in Figure 2b are those democracy words with the highest frequency in the data that appear in both stages under comparison.

The Twitter data for Figure 6 were extracted using the Pythin Library *GetOldTweets3* (see `https://pypi.org/project/GetOldTweets3/`). This enables the user to obtain tweets further back in time than permitted by the official Twitter API and functions simply by using a progressive web crawl.

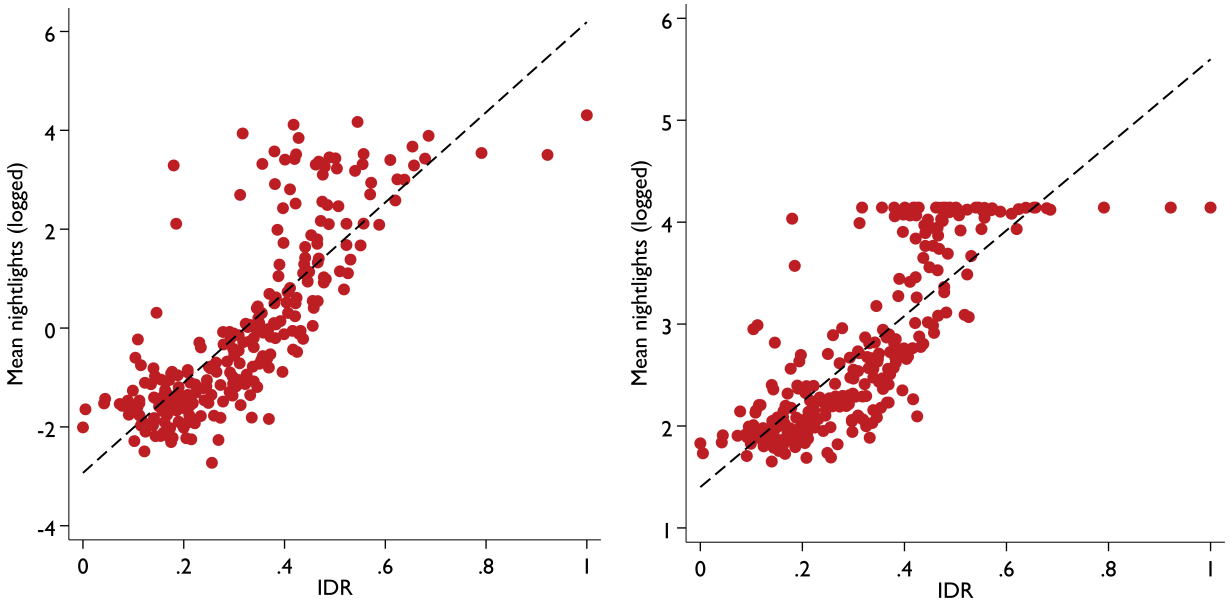
Table A3: Democracy words in #sidibouzid data. Note: arabicStemR converts quotation marks to "quot" thus explaining the appearance of this suffix on certain of the words.

Words
democracy
democratic
prodemocracy
#democracy
democratize
#democrates
#democracy
#democratie
democracyquotasks
democracyquot
#democracymyass
atheniandemocrac
democracyjustice
democratically
democrat
democracyhistory
democratique
quotdemocratic
democracyproxy
quotdemocracy
democraciesquot
democratization
democratia
democrasy
democrazia
démocratie
#démocratie
démocratique
démocrate
démocratiece
démocrates
démocratiquequot
démocratieà
#libertétravaildignitédémocratie
démocratiques
démocraties
démocratiquement
démocratiessidibouzid
dymqratyat
aldymqraty0
dymqratyth
wdymqraty0
aldymqratyyn
baldymqraty0

Words
aldymqraty0quot
antkabat
lantkabat
alantkabat
wantkabat
llantkabat
balantkabat
alantkaby0
#sidibouzidalantkabat
bantkabat
elections
election
#elections
electionsnew
#tunisiairanelection
#electionslibresentunisie
lelection
élections
délections
électionsquot
électionsquotqui

A2.2 Nightlights data

Nighttime lights data for the Visible Infrared Imaging Radiometer Suite Day/Night Band Nighttime Lights (VIIRS DNB) are retrieved from `https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html` and for the Defense Meteorological Satellite Program Operational Linescan System Global Radiance Calibrated Nighttime Lights (DMSP-OLS GRCN) from `https://ngdc.noaa.gov/eog/dmsp/download_radcal.html`, last accessed: October 3, 2019. VIIRS data should be preferred over DMSP-OLS data due to known problems of pixel saturation and low resolution in the latter (Elvidge et al. 2013). In order to calculate delegation-level values of light intensity, the QGIS mapping software was used. A shapefile of each of Tunisia's 264 delegations was clipped to the GEOTIFF files in which the VIIRS data are supplied. Using the "zonal statistics" plugin, mean pixel values for each geographical unit (delegation) were then calculated. The VIIRS data are only available from April 2012 onwards. This evidently postdates the revolution. In order to compare against a light intensity development proxy recorded from before the revolution, I rely on GRCN data. The correlation between the log-transformed values of mean pixel values and IDR by delegation for each of these satellite data are displayed below in Figure A7 below. The strength of the correlation with IDR for each measure is almost identical at $r \sim .8$.



(a) (b)

Figure A7: (a) Correlation between delegation-level VIIRS DNB satellite data (logged) and IDR; (b) Correlation between delegation-level DMSP-OLS GRCN data (logged) and IDR)

A2.3 Event data sources

While the majority of protest event analyses derive their data from newspaper reports, this was not possible during for the twenty-nine day revolutionary uprising in Tunisia where a media blackout aimed specifically at stymieing the flow of information. I overcome this obstacle by triangulating multiple alternative sources of information. I made use first of Facebook pages, two of which were already in operation before the uprising, and two of which were created for the specific purpose of posting news of protests. The names and details of these pages are below. The pages were archived in PDF format, retaining the link structure, thereby enabling the manual coding of protest events, photos, and videos from each of them. These sources were then supplemented with multiple further sources of information, including national newspapers, international newspapers, a post-revolutionary investigatory commission, an archive of protest reports from the dissident blog *Nawaat*, as well as the *Archive Numérique de la Révolution*—a digital archive at the Tunisian National Archives devoted to the collection and archiving of photos and videos from the period of the uprising. The groups used, as well as further sources used for constructing the event catalogue for the revolutionary period, are listed below. Table A4 details the number of protest reports that derive from each source for the full event catalogue (EC) dataset and the event history (EH) dataset, which only records information for first protest occurrence in a given delegation. Only the EH dataset is used in the analyses for this article.

Table A4: Number of reports by source in event catalogue, full event catalogue (EC) and event history (EH) dataset.

Source	Freq. *EC*	Freq. *EH*	Source	Freq. *EC*	Freq. *EH*
AFP	8	1	Kalima Tunis	343	87
Al-Jazeera News	8	3	Le Monde	1	-
Al-Jazeera Video	18	3	Le Point	2	-
Al-Badil	1	-	MAMN (FB)	33	6
Al-Wasat	1	1	NATS (FB)	195	48
ANR	63	10	Nawaat	144	35
ANR Video	61	10	Nawaat Video	106	27
BBC	1	-	Paris Match	1	-
Bouderbala	29	7	Photo	25	4
BusinessNews	4	2	PTON (FB)	193	68
Chourouk	85	13	Reuters Arabic	4	1
Elaph	1	-	Takriz (FB)	42	22
France24	2	1	Video	106	41
France24 Video	2	1			

Facebook

- شعب تونس يحرق في روحو يا سيادة الرئيس *Chaab Tunis Yahriq fi Ruhu ya Siyyadat al-Ra'is* (Mr. President, the People of Tunisia are On Fire (PTON)). This page was set up upon the outbreak of protests, as the title of the group suggests. It went through six iterations as it was continually hijacked by unknown cyber attackers, likely linked to the Ben Ali regime.[49] When hijacked, the founders would set up a new page by the same title but with the number of the version of the group appended. The pages contained information on protest for everyday of the uprising with the exception of the period 02/01/11-08/01/11 when the page was down. Protest reports would often report on the type of protest (e.g., march, occupation, demonstration), include some

[49] An interview with the founders of the page can be accessed here: `http://www.thedailybeast.com/articles/2011/01/15/tunisa-protests-the-facebook-revolution.html`, last accessed: 19/03/2018.



Figure A8: Typical video protest report from PTON. Text underneath reads: 31/12/10: Er-Rouhia—Siliana Governorate. Subsequent lines detail chants heard during the protest, including: "Don't be a coward, go out onto the street!"; "Work, freedom, national dignity!"; "Work is a right, you gang of thieves!", "No to tyranny and corrupt government!".

mention of size (e.g. 'a group of', 'large', 'huge'), and give some mention of source (most often 'union sources'). When the report cited 'unconfirmed reports', the report was not included in the event catalogue. In total these pages provided information on 193 protest events, 140 of which were corroborated with at least one other source. Out of the 193 protest events recorded from this source, 94 could be checked against video evidence. Figure A7 gives an example of a video protest report posted to this page.

- وكالة أنباء تحرّكات الشارع التونسي *Wikalat Anba' Taharrukat al-Shari'a al-Tunisi* (News Agency of the Tunisian Street (NATS)). This page was also set up upon the outbreak of protests in Sidi Bouzid and protest reports followed a similar formula to the above



Figure A9: Typical protest report from NATS. Text reads: "Kasserine, today 06/01/2011: A large march of students, teachers, unemployed and unemployed graduates left this morning from the UGTT offices, circling the city before stopping outside the RCD office at which point the chant "Down with the Dostour Party, down with the executioner of people" was heard alongside other chants calling for work, freedom, and national dignity. Lawyers also joined in the protest as the march went past the court building, at which point the police forcefully intervened. We will keep you updated".

page. It has two iterations, after the first was also hijacked. The pages contained information on protest for the period 02/01/11-14/01/11. In total, this page provided information on 195 protest events, of which 106 could be matched with a secondary source. Out of the 195 protest events recorded from this source, 71 could be checked against video evidence. Figure A8 gives an example of a typical protest report from this page.

- ما عندي مانقلك *Ma 'Ayndi Mankolek* (I Have Nothing to Say to You). This page was already in existence prior to the revolution. It was a forum for dissident opinion and took positions against, for example, online censorship. This page was active for the entire period of the uprising. In total, this page provided information on 33 protest events, 29 of which could be matched with a secondary source, and 18 of which could be checked against video evidence.

- ***TAKRIZ*** (Ball-Breaker). This page was already in existence prior to the revolution and ran alongside the now-defunct website *takriz.com*, founded in 1998. It was a forum for dissident opinion, anti-censorship activism, and often irreverent commentary on Tunisian affairs. Upon the outbreak of the revolution, its administrators began posting videos and reports of protests, encouraging their members to go out and protest at the same time. Unfortunately, the page was not available for the period 02/1/11-14/01/11. In total, this provided information on 42 protest events, of which 30 could be verified against a secondary source.

Radio/National News

- راديو كلمة تونس *Radio Kalima Tunis* (Word of Tunisia Radio). Kalima Tunis is a radio station set up in 2008 by journalist and human rights campaigner Sihem Bensedrine, and Omar Mestiri. The radio station operated from France after being banned in 2009, but still had journalists on the ground. It published multiple dispatches daily on the unfolding of protest events that have been archived by online news aggregator `turess.com`. In total, Kalima Tunis provided information on 342 protest events, of which 199 could corroborated with a secondary source.

- الشروق *Al Chourouk* (Sunrise). Pro-regime newspaper that only began to report on protest in the closing stages of the uprising. Nonetheless, it provided information on 86 protest events, of which 44 could be checked against a secondary source. Copies of these reports were obtained from `turess.com`. These articles were also checked against archived paper copies of the newspaper in the Centre de Documentation Nationale

archive in Tunisia in order to check for any omissions on the `turess.com` website. No significant omissions were found.

Other sources

- Two weekly newspapers of the few oppositional parties nominally authorized in Tunisia, *Attariq Al Jadid* (of the centre-left Ettajdid party), and *Al Mawkif* (of the leftist Parti démocrate progressiste), as well as one, *Echaab* (of the national trade union federation the UGTT), were sought out from the Centre de Documentation Nationale and the UGTT's own archives to provide further information with which to cross-check the Facebook protest reports, however these provided only limited information on protest occurrence.

Nawaat Archive

- Over the course of the revolution, *Nawaat*, a dissident blog established in 2004, reported on protest events. Most of these reports became unavailable after the shutdown of blogging host platform `posterous.com`. Using the Wayback Machine Internet Archive, however, I was able to retrieve this content. These yielded reports on 140 protest events, 127 of which could be triangulated with other sources.

Digital Archive of the Revolution

- A cache of videos and photos, collected by Jean-Marc Salmon in conjunction with archivists at the Tunisian National Archives, was handed over to the National Archives in Tunis in March 2017. Reporting on the collection can be accessed here: `https:`

//tinyurl.com/ANRtiny, last accessed: October 10, 2019. The collection contains around 1000 photos and 800 videos. Researchers focused their efforts on Greater Tunis, Kasserine, and Sidi Bouzid meaning that documents from other regions may have yet to find their way into the archive. Nonetheless, the archive contains documents for each of Tunisia's twenty-four governorates, and nearly all photos and videos are datestamped. I searched through each date for every district in every governorate over the period of the revolution and triangulated protest reports with the event catalogue, updating e.g., protest sizes according to photo and video availability, and adding new events when omitted. The archive yielded reports on 63 protest events that could reliably be located in a delegation, and 40 of these could be triangulated with other sources.

Videos and Photos

- Videos. Videos were often posted to the Facebook groups listed above accompanied with reports on the protest itself. In total 222 videos were found, all of which were matched with a protest report. Videos were nearly all accompanied by a date in the comments under the video. Alternatively, videos would be accompanied by a comment such as "Situation today in [name of town/city]", meaning the date could then be assumed as the date of the posting itself.

- Photos. Photos were also often posted to the Facebook groups listed above accompanied with reports on the protest itself. In total 25 photos were used and matched with protest reports. Photos would also either be accompanied by a date or the date of the event could be deduced from comments in the post e.g. "Photos from protest

yesterday in [name of town/city]".

International News

- International news sources were also used when available. Two of these took the form of evening news reports, archived versions of which were posted on the Facebook pages described above. The first of these is *Al Jazeera: The Maghreb Harvest* (الجزيرة: الحصاد المغربي). This was a daily news round up of events in Arab North Africa that, given the ongoing protests in Tunisia, focused primarily on Tunisian affairs over the twenty-nine days of the uprising. *France 24* (24 فرانس) also provided a daily round of news in North Africa, with a particular focus on Tunisia over the twenty-nine days of the revolt. News articles from Arabic-, French-, and English-language news outlets were also archived when posted on the Facebook groups listed above. These included: *BBC News*, *Agence France Presse*, *Le Point*, *Le Monde*, *Reuters Arabic*, *Agence Tunis Afrique Presse*, *Business News Tunisia*. Further articles from international news media were extracted from Google News. These were then all matched against existing protest reports. In total, these sources together provided information on 53 separate protest events, all of which were verified against a secondary source.

Bouderbala Commission

- The full name of the investigatory commission, now commonly referred to after its Head, Taoufik Bouderbala, is the "Commission nationale d'investigation sur les abus enregistrés au cours de la période allant du 17 décembre jusqu'à l'accomplissement de son objet". The full report is available online here: `http://www.leaders.com.tn/`

uploads/FCK_files/Rapport%20Bouderbala.pdf In this first report, the Commission looked into abuses committed from 17 December 2010 up to the first elections on 23 October 2011. Bouderbala is himself a lawyer and Honourary President of the Tunisian Human Rights League (Ligue tunisienne des droits de l'homme). The report is itself the subject of some scrutiny as it is perceived not to have gone far enough in identifying individuals responsible for the deaths of protesters. Further, the list of deaths published was described as "provisional" and the Commission has yet to publish its final version. While the existing list may only be provisional, and it does not identify police responsible, the report is nonetheless comprehensive (running to over 1,000 pages) and provides a rich source of information for the purposes of this study. While reports of injuries contain sometimes sparse information, the Bouderbala Commission verified deaths with visits to the homes of the bereaved and checked reports against available medical records, thus providing a confident estimate of levels of repression witnessed during protests. The reports included the circumstances of the death, the date of the incident, and the institutional identity of the perpetrator. Only those that stated explicitly that the individual was killed at the hands of state security (police, national guard or army), or was killed during a protest, were included for the analysis. The report also contains information on the locations of protest, but limits its reports to the closing stages of the revolution. The information contained therein was nonetheless checked against the event data for purposes of further corroboration.

A2.4 Event catalogue codebook

The variables, and their codings, for the event catalogue are listed below. Note that not all variables are used in the abaove analysis. They are listed here for completeness. Relevant variables for the present article include: *date*; *governorate*; *delegation*; *ppart*; *noofkilled*; *source*; *facebook*.

1. Date (*date*): The date of the protest occurring. This could be deduced from the report itself and the date attached to the post in Facebook, for example, or the date of the article posted on the website of the Radio Station or newspaper. In one or two cases, protests were reported as having been ongoing for X number of days. In such cases they were backcoded to the first day of the protest based on the length of time it had been reported as ongoing.

2. Governorate (*governorate*): The Governorate (one of 24) in which the protest took place. These would normally be reported in the protest reports themselves. Otherwise, reports would include reference to the specific town or area in which the protest took place, from which one could deduce the Governorate from the list of delegations in each Governorate or by Google searching the name of the town/city. There were no cases in which the location of the protest could not be located in its Governorate. On a few cases, reports would refer to e.g. "protest across [name of Governorate]". In such cases, three protest events within the Governorate were coded.x

3. Delegation (*delegation*): The Delegation (one of 264) in which the protest took place. Normally the delegation could be deduced by Google searching the specific location

of the protest (e.g. name of school, *Wilaya* building, UGTT building) or would be specifically reported. Only 66 protest reports could not be located in their respective delegation and these were dropped from the analysis.

4. Protest participation (*ppart*): Estimated participation in the protest. Here, I employed the coding convention used in the European Protest and Coercion Dataset (Francisco 2000). Protest size is often reported in factors of ten—e.g., "tens", "hundreds", "thousands". In such cases, these are coded as "31", "301", and "3001" respectively. Protests would occasionally also be described as "large" or "huge", in such cases, participation was increased by a factor of ten. When no further information was provided "demonstration/protest" (manifestation/protestation or مظاهرة/احتجاج) was coded as "301", as was march (marche or مسيرة) and strike (grève or إضراب), while a regional general strike (grève régionale or إضراب عام محلي) would be coded as 3001 if in just one delegation and 30,001 if in an entire governorate. Blockade (bloquer la route or قطع الطريق) and attack (attaque or مهاجمة) would be coded as 31. Occupations (occupation or اعتصام) would be coded as 301 when outside and 31 when occupying the inside e.g. of a building. Sit-ins (sit-in or وقفة احتجاجية) would be coded as 31. For the purposes of the present paper, participation is not used.

5. Repertoire (*repert*): The type of protest. This was normally contained within the protest report itself or could be identified in the videos or photos of the protests. Repertoire could be one of "demonstration" (manifestation/protestation or مظاهرة/احتجاج); "march" (marche or مسيرة); "strike" strike (grève or إضراب); "general strike" (grève régionale or إضراب عام محلي); "blockade" (bloquer la route or قطع الطريق); attack (at-

taque or مهاجمة); "occupation" (occupation or اعتصام) or "sit-in" (sit-in or وقفة احتجاجية).

6. Secondary repertoire (*reper2*): The secondary repertoire of the protest. Sometimes, protests or sit-ins would e.g. break out into marches along the surrounding streets. In such cases, a secondary repertoire would be recorded.

7. Protest location (*protlocation*): The specific location of the protest e.g. outside Wilayat building or UGTT offices.

8. Starting location (*protstartlocation*): A general identifier for the start location. One of "city centre"; "govt building" (e.g. any official building such as police station, local government building, RCD (ruling party) offices); "hospital"; "main road"; "public transport" (e.g. railway/bus station); "residential street"; "saha" (square); "school" or "university".

9. Moving to (*movingto*): Where the protest moved to, if it did move.

10. End location (*protendlocation*): General identifier for where the protest ended, from among those listed in variable #8.

11. Organizer (*organizer*): Organizer of the protest. This was coded for both those specifically identified as organizing the protest e.g. "unionists" normally from the national trade union federation the UGTT, or it was coded for the principal participants e.g. "teachers" or "students".

12. Repression (*repression*): Binary variable recording whether the protest met any form of repression. Repression could take the form of "crowd control" (e.g. when police

reported to prevent protesters from moving off into a march or prevented from protesting, including use of batons); "tear gas" (gaz lacrymogène or غاز مسيل للدموع); "live ammunition" (tir à balle réelle or طلق ناري).

13. Repressive agent (*repressiveagent*): The actor responsible for repression. Most frequently one of "police" (la police or الشرطة); "national guard" (la garde nationale or الحرس الوطني); or "army" (l'armée or الجيش). On one occasion, protesters were attacked by unknown assailants and on another members of Ben Ali's ruling RCD party were identified as the assailants. When the repressive agent was not identified, the cell was left blank.

14. Killed (*killed*). Binary variable recording whether anyone was identified as having been killed at the protest. It should be noted that for the present paper, the data provided by the Bouderbala Commission was used in place of data on killings provided by newspaper reports.

15. Number killed (*noofkilled*): The number killed during the protest. Ocassionally reports of numbers killed would differ. In these instances, I opted for the more conservative report. In any case, as above, the data provided by the Bouderbala Commission is used in place of the data provided by protest reports.

16. Arrested (*arrested*): Binary variable recording whether anyone was identified as having been arrested at the protest.

17. Number arrested (*noofarrested*): The number arrested during the protest. Ocassionally reports of numbers arrested would differ. In such instances, I opted for the more

conservative report. In some cases, reports would be of "large numbers" arrested, which was coded as 11, while "several" was coded as 3.

18. Violence (*violence*): Binary variable recording whether violent forms of protest took place. This differs from reports of repression. Repression assumes no response from protesters. In numerous cases, however, reports would be of "clashes" (affrontement or مواجهة) with police. In such cases, protesters fought back. This was also the case when there was a report of stones being thrown (lancer des pierres or رشق بالحجارة) or police stations being set on fire (incendier or احراق).

19. Source (*source*): Source of the protest report (e.g., names of Facebook group, newspaper, radio station etc.).

20. Facebook (*facebook*): Binary variable coded 1 if one of sources includes a Facebook page.

A2.5 Ecological data sources

- For the development index used in the main event history analyses, I assemble data from the Comparative Study on Tunisian Regional Development (*Étude comparative en terme de développement régional de la Tunisie*) conducted by the Tunisian Competition and Quantitative Studies Institute (*Institut Tunisien de la Compétitivité et des Études Quantitatives*), a subsidiary of the Ministry of Planning and Regional Development (*Ministère du Développement Régional et de la Planification*). An example overview of the index and its measures (for the Beja governorate) can be accessed here: `http://www.mpci.gov.tn/tn/Gov/indica/beja.pdf`. The study was conducted in order to provide a composite delegation-level index of regional development (IDR). This in view of the considerable regional disparities that exist in Tunisia, particularly between the interior and the Sahel. The index ranges from 0-1, with 1 representing the most developed and 0 the least developed. The index was constructed using principal components analysis on twenty-six separate variables.

  The index comprises infrastructural measures (proportion roads classified; percentage households connected to sanitation system; percentage households connected to clean water; distance to nearest port/airport; distance to each of Tunisia's main city hubs (Tunis, Sousse, Sfax)); health measures (number of doctors per 1000 residents; number of pharmacies per 1000 residents; number of hospital beds per 1000 residents) social measures (number of families "in need" per 1000 residents; poverty rate; dependency rate) demographic measures (average population growth 2008-2012; net migration); education measures (percentage educated population (secondary and higher); illiter-

acy rate; BAC admissions rate) economic activity measures (placement rate; number of private enterprises per 1000 residents); and labour market measures (employment demand and opportunity; average size of private enterprises; percentage labour force employed in private enterprises; unemployment rate). A full list of measures used for the construction of the index, as well as links to further information, where available, is provided in Table A5. As should be clear, the vast majority of these measures are taken from the period predating the revolution. A few are taken in 2012, in the year immediately after the revolution.

Table A5: Sources and measurements of IDR data

Variable	Source	Measurement	Further information
Proportion roads classified (2010)	Direction générale d'infrastructure	proportion of roads (in Kms) classified over total Kms of road in delegation.	
Distance to city hubs	Direction générale d'infrastructure	distance between delegation and each of Tunisia's main three city hubs (Tunis, Sousse, Sfax).	
Distance to nearest port	Direction générale d'infrastructure	distance between delegation and nearest port/airport.	
Agricultural labour force (2004)	2004 Census	percentage individuals employed in agriculture denominated by total active population aged 15 or over.	http://nada.ins.tn/index.php/catalog/8
Sewage connection (2004)	2004 Census	percentage households connected to sewage system.	http://nada.ins.tn/index.php/catalog/8
Drinking water (2004)	2004 Census	percentage households with clean drinking water.	http://nada.ins.tn/index.php/catalog/8
Number doctors (2010)	Commissariat et offices, Tunisie	number of doctors per 1000 residents.	
Number pharmacies (2010)	Commissariat et offices, Tunisie	number of pharmacies per 1000 residents.	
Number beds (2010)	Commissariat et offices, Tunisie	number of hospital beds per 1000 residents.	
Number families "in need" (2011)	Commissariat et offices, Tunisie	number of individuals per 1000 residents in receipt of government assistance.	http://www.cres.tn
Poverty rate (2005)	Institut National de la Statistique, Tunisie	percentage households living below poverty rate.	http://www.ins.tn/fr/publication/enqu%C3%AAte-sur-la-consommation-des-m%C3%A9nages-2005-volume
Dependency rate (2004)	Institut National de la Statistique, Tunisie	percentage population 0-14 and 65+ denominated by total population.	http://nada.ins.tn/index.php/catalog/8
Population (2010)	Institut National de la Statistique, Tunisie	number of individuals in delegation.	
Population growth (2008-2012)	Institut National de la Statistique, Tunisie	average growth in population over the period 2008-2012.	
Net migration (2004)	Institut National de la Statistique, Tunisie	net migration over period 1999-2004.	http://nada.ins.tn/index.php/catalog/8
Educated population (2004)	Institut National de la Statistique, Tunisie	percentage population with secondary or higher education certificate denominated by total population.	http://nada.ins.tn/index.php/catalog/8
Illiteracy rate (2004)	Institut National de la Statistique, Tunisie	percentage population illiterate denominated by total population.	http://nada.ins.tn/index.php/catalog/8
Bac admissions (2010)	Commissariat et offices, Tunisie	rate of admission to the Baccalaureate (final school examinations required for university admissions).	
Labour supply (2012)	Direction générale des ressources humaines	job opportunities per 1000 residents.	
Labour demand (2012)	Direction générale des ressources humaines	job demands per 1000 residents.	
Placement rate (2012)	Direction générale des ressources humaines		
Private industry (2010)	Institut National de la Statistique, Tunisie	number private enterprises per 1000 residents	http://www.ins.nat.tn/fr/themes/entreprises
Herfindahl index (2010)	Institut National de la Statistique, Tunisie	sum of squares of (delegation-level) market shares of enterprises	
Average private business size (2010)	Institut National de la Statistique, Tunisie		
Employed in private sector (2010)	Institut National de la Statistique, Tunisie	percentage employed in private sector	
Unemployment rate (2004)	Institut National de la Statistique, Tunisie	percentage individuals aged 18-59 without employment denominated by total active population aged 18-59.	http://nada.ins.tn/index.php/catalog/8

- The variable measuring youth population was taken from the 2014 census. The measurement of each of this item, as well as several others used in supplementary analyses detailed below, are listed in Table A6.

- For a supplementary analysis, results of which below in Table A9, data at the delegation level was taken from publicly available census data from censuses conducted in 2004 and 2014. From these, I extracted, from the 2004 census, data on delegation-level illiteracy rates. From the 2014 census, I extracted delegation-level graduate unemployment rates, illiteracy, youth population, % employed in agriculture, and % internet use. The measurement of each of these items, all taken at the delegation level, is listed in Table A6.

Table A6: Sources and measurements of ecological data

Variable	**Source**	**Measurement**	**Further information**
Illiteracy rate (2004)	2004 Census	percentage illiterate individuals aged 10 or over denominated by total population aged 10 or over.	`http://nada.ins.tn/index.php/catalog/8`
Youth population (2004)	2004 Census	percentage individuals of given age bracket (either 15-19 or 20-29) denominated by total population.	`http://nada.ins.tn/index.php/catalog/8`
Graduate unemployment rate (2014)	2014 Census	percentage graduates without employment denominated by total graduate population.	`http://census.ins.tn/fr/resultats`
Illiteracy rate (2014)	2014 Census	percentage illiterate individuals aged 10 or over denominated by total population aged 10 or over.	`http://census.ins.tn/fr/resultats`
Youth population (2014)	2014 Census	percentage individuals of given age bracket (either 15-19 or 20-29) denominated by total population.	`http://census.ins.tn/fr/resultats`
Internet use (2014)	2014 Census	percentage individuals aged 10 or over who use the internet denominated by total population aged 10 or over.	`http://census.ins.tn/fr/resultats`

- There are significant time intervals between the taking of the censuses and the out-

break of the Tunisian Revolution. In order to get a handle on this, I also extracted data from a 2010 Labour Survey in Tunisia (*Enquête nationale sur l'emploi 2010*), available here: `http://www.ins.tn/fr/publication/enqu%C3%AAte-nationale-sur-l%E2%80%99emploi-2010`. Figures from 2010 are only available at the governorate level. To adjudicate between measures, I am then able to compare correlations between the 2004 and 2014 governorate-level data and that available at the governorate level from 2010. These are displayed in Table A7 below. As should be clear, most measures are highly correlated between the two measurement periods. Youth population is strikingly weak, however. It is also difficult to adjudicate between the 2004 and 2014 measures as both are in turn highly correlated, at the governorate level, with the measure taken in 2010. For each of the models in Table 2, ecological measures are taken from 2014, being more temporally proximate. Rerunning the main and supplementary analyses in Table A9 below with ecological data taken from 2004 gives identical results. The youth population measure from 2004, however, loses significance. I justify the use of the 2014 measure as it is more temporally proximate than that for 2004.

Table A7: Comparisons of ecological data

Variable	**Level of measurement**	**Years compared**	**Bivariate correlation**
Illiteracy rate	Delegation	2004 & 2014	0.97
Youth population	Delegation	2004 & 2014	0.31
Graduate unemployment rate	Governorate	2010 & 2014	0.95
Internet use	Governorate	2010 & 2014	0.68
Youth population	Governorate	2004 & 2010	0.81
Youth population	Governorate	2010 & 2014	0.81

A2.6 Survey data

The survey data used in the analysis is taken from Wave II of the Arab Barometer, a widely used set of nationally representative surveys from the MENA region. An extra battery of questions were added in 2011 for Tunisia (and Egypt) relating to participation in Arab Spring protests and their aftermath. The Arab Barometer is a joint initiative of the University of Michigan, Princeton University, and the Arab Reform Initiative. The funding for Wave II of the surveys came from the Canadian International Research and Development Centre (IDRC), the United Nations Development Program (UNDP), and the United States Institute of Peace (USIP). The fieldwork for the Tunisia survey was conducted from September 30, 2011-October 11, 2011. The Principal Researcher was Iman Mizlini of Sigma Conseil, an independent polling organization in Tunisia (see `http://www.sigma.tn/Fr/accueil_46_9`). The sample consisted of Tunisian adults aged 18 or over, stratified by governorate and urban/rural. Surveys were conducted face-to-face in Arabic. The survey used a three-stage stratification process, with delegations selected proportional to population size, sectors (within delegations) selected proportional to size, and blocks of sectors then selected at random. A block consisted of ten households. Individuals within households were then randomly selected using a Kish table. The sample is self-weighted but includes post-stratification weights to correct for age and gender imbalances.

Survey questions and codings:

- Protest participation (T902): "Did you participate in the protests against former president Zain Al- Abdeen Ben Ali between December 17th, 2010 and January 14th, 2011?"

[Yes=1, No=0].

- Timing of protest participation (T903): "If you answered "yes" to question 902 (regarding your participation in the protests): Did you participate in any of the following protests?":

  1. December 17, 2010 to January 1, 2011 [Yes=1, No=0].
  2. January 2 –January 9, 2011 [Yes=1, No=0].
  3. January 10 –January 14, 2011 [Yes=1, No=0].

  From these questions, the ordinal participation outcome measure was generated. This was coded 1 if the respondent participated from stage 1 (i.e., responded in the affirmative to item 1 of T903), 2 if the respondent protested from stage 2 (i.e., responded in the affirmative to item 2 of T903 and not to item 1), 3 if the respondent first protested at stage 3 (i.e., responded in the affirmative to item 3 of T903 and not to items 1 and 2), and 4 if the respondent participated at no stage (i.e., responded in the negative to T902). A second outcome measure, used for the multinomial logistic analysis, was coded identically except those who never protested were coded 0 and constituted the base reference outcome.

- Income (Q1014): Respondent was asked to report "Income including all wages, salaries and rent allowances". This was recorded in 2011 US dollars.

- Education (T1003): Respondent was asked to report highest level of education. Six options were offered: "1: Illiterate; 2: Elementary; 3: Preparatory/Basic; 4: Secondary; 5: BA; 6: MA and above". The variable used retained all items in an ascending six

point scale.

- Age (Q1001): Respondent was asked to report age. Recorded in years.

- Male (Q1002): Gender of respondent recorded by interviewer. [Male=1, Female=0].

- Employed (Q1004): Respondent was asked "Do you work?" [Yes=1, No=0].

- Student/Out of workforce (Q1005): Respondent was asked "Are you: 1: Retired; 2: A housewife; 3: A student; 5: Unemployed (looking for work); 4: Other (specify)". Here, a separate binary student variable was coded, a variable for being out of thr workforce (1 if retired/housewife), and a binary variable for being unemployed. The latter (unemployed) is the reference category in the full model. Only three respondents gave other categories. These were coded as missing.

- Religiosity (Q609, T6101, T6106)[50]: Composite index constructed using responses to three questions. A first (Q609) asks respondents: "Generally speaking, would you describe yourself as...? 1: Religious; 2: Somewhat religious; 3: Not religious". A second (T6101) asks respondents: "Do you pray daily? 1: Always; 2: Most of the time; 3: Sometimes; 4: Rarely; 5: Never". A third (T6106) asks respondents: "Do you listen to or read the Quran/the Bible? 1: Always; 2: Most of the time; 3: Sometimes; 4: Rarely; 5: Never". Responses were rescaled so that higher numbers indicated greater religiosity. The item was then standardized with mean 0 and standard deviation 1.

- Mosque attendance (T6105)[51]: Respondent was asked: "Do you attend Friday prayer/Sunday

[50]Note that, in the supplementary material for Doherty and Schraeder (2018), two of these variables are incorrectly referred to as "T6011" and "T6016".

[51]Note that, in the supplementary material for Doherty and Schraeder (2018), this variable is incorrectly referred to as "T6015".

services? 1: Always; 2: Most of the time; 3: Sometimes; 4: Rarely; 5: Never". Responses were rescaled so that higher values indicated greater frequency of attendance.

- Interest in politics (Q404): Respondent was asked: "In general, to what extent are you interested in politics? 1: Very interested; 2: Interested; 3: Slightly interested; 4: Not interested".

- Rural (Q13): Whether respondent district rural or not. Coded by interviewer [Yes=1, No=0].

- Friends protest (T905):[52] Respondent was asked: "Did any of your friends or acquaintances participate in the protests against former president Ben Ali between December 17th, 2010 and January 14th, 2011?" [Yes=1, No=0].

- Civil society membership (Q5012, Q5013, Q5014, Q5016). Binary variable coded 1 if respondent answered in the affirmative to any of the above when asked: "Are you a member of? A charitable society (Q5012); A professional association/trade union (Q5013); A youth/cultural/sports organization (Q5014); Q5016: A local development association (Q5016)".

- Democratic commitment index (Q516): Composite index constructed using responses to three questions gauging commitment to democracy. A first (Q5162) asks respondents to respondent to the statement: "Democratic regimes are indecisive and full of problems. 1: I strongly agree; 2: I agree; 3: I disagree; 4: I strongly disagree". A second (Q5164) offers the statement: "A democratic system may have problems, yet it

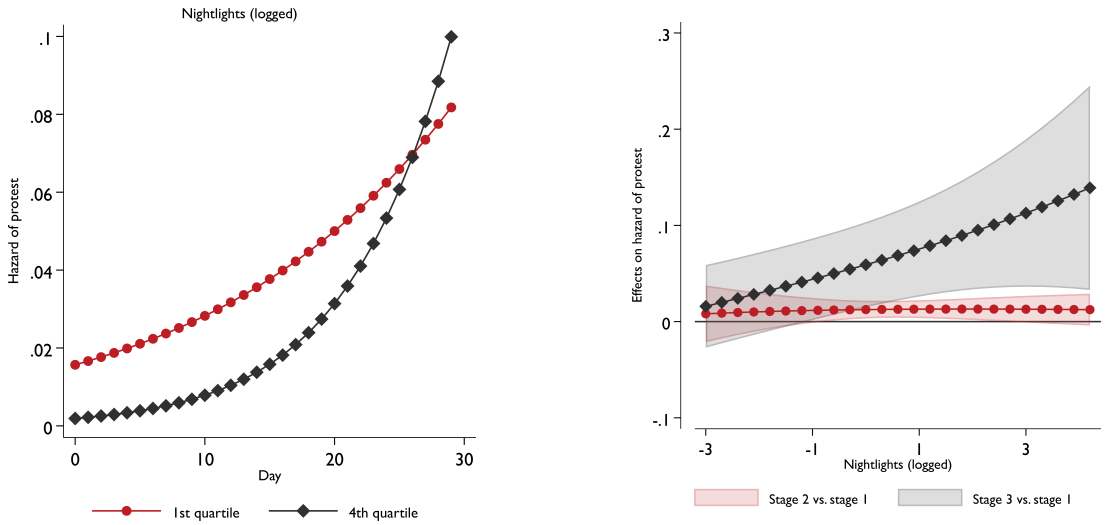
[52]Note that, in the supplementary material for Doherty and Schraeder (2018), this variable is incorrectly referred to as "Q409".

is better than other systems. 1: I strongly agree; 2: I agree; 3: I disagree; 4: I strongly disagree". A third (Q5167) offers the statement: "Democracy negatively affects social and ethical values in [Tunisia]. 1: I strongly agree; 2: I agree; 3: I disagree; 4: I strongly disagree". Items were rescaled so that higher values indicated stronger commitment to democracy. A scale of 0-4 was used, with missings recoded as the midpoint of the scal (2) in order to preserve sample size.

The alpha on this index is relatively low (0.43). Excluding question Q5164 boosts the alpha to 0.61. Including another question (Q5163) alongside Q5162, Q5164, and Q5167, which offers respondents the statement "Democratic systems are not effective at maintaining order and stability", increases alpha to 0.65. Excluding Q5164 and using just Q5162, Q5163, and Q5167 gives an alpha of 0.78. For the purposes of the main analysis, I enter the index used by Doherty and Schraeder (2018) (a variant of an additive index used by Hoffman and Jamal 2014), in order properly to replicate their results and facilitate comparison when disaggregating by time of protest participation. The alternative indices with higher alpha give substantively identical results.

A2.7 Additional outputs and robustness checks

In this section I detail several supplementary analyses of protest event data using different ecological covariates of interest and provide full outputs for the survey analysis. I first provide the full regression outputs (Table A8) for the VIIRS nighttime lights delegation-level measure of economic development with and without a time interaction. We can see that the results using this measure are substantively similar to those for the IDR measure. Including an interaction time significantly improves model fit as measured by AIC, BIC, and McFadden's R^2. Predictive margins and marginal effects of the nightlights measure over time and by stage are displayed in Figure A10.



(a) (b)

Figure A10: (a) Predictive margins of nightlights over time, upper and lower quartiles; (b) Marginal effects of nightlights by stage of uprising, with 95% CIs

For the additional supplementary event history analyses, I use the same model as in Table 2 but enter alternative ecological measures. As a more basic measure of deprivation and development, I first test a variable measuring illiteracy rates at the delegation level (%

Table A8: Discrete-time logistic regression of nighttime lights with and without time interaction, cluster robust standard errors

Variables	Model 1: Without time interaction	Model 2: With time interaction
Lagged protest	0.677**	0.347*
	(0.214)	(0.163)
Time		0.089***
		(0.015)
Nightlights	-0.099	-0.466**
	(0.058)	(0.163)
Nightlights*Time		0.021**
		(0.008)
Youth pop.	0.078	0.085
	(0.044)	(0.050)
Population (logged)	0.840***	0.888***
	(0.156)	(0.168)
Repression	0.225***	-0.020
	(0.049)	(0.066)
Constant	-13.970***	-15.808***
	(1.825)	(2.010)
Observations	5,894	5,894
AIC	1282	1245
BIC	1322	1299
McFadden's R^2	0.0720	0.101

illiterate population aged 10 or over). Given the apparent centrality of youth-led grievances relating to job opportunities, I also test a measure for delegation-level graduate unemployment (% unemployed with higher education certificate). Still others have pointed to the internet as playing a central role in the diffusion of revolutionary protest given the enhanced connectivity and new information transfer it affords (Wagner 2011; Bennett and Segerberg 2013; Howard and Hussain 2014). To test for the effects of internet connectivity on protest diffusion I include a delegation-level measure of internet usage (% households connected to Internet). These measures cannot all be included in the same model due to the high levels

of collinearity betwen them (see Table A10). They are also highly correlated with the IDR measure used in the main analysis. Including them all in a single model would thus not be meaningful and would be hindered by multicollinearity. I include them here simply in order to demonstrate that there is evidence of duration dependence when we use several different ecological covariates of interest, thereby providing additional confidence in the robustness of the headline claim of significant duration dependence. As should be clear, the inclusion of a time interaction with each of these ecological covariates significantly improves model fit and points to significant time dependencies in the data. Figure A11 displays predictive margins of each measure at upper and lower quartiles. Figure A12 displays marginal effects for each stage of the uprising.

Table A9: Supplementary event history analyses using alternative ecological covariates with and without time interactions

Variables	Model 1: Illit. rate w/o time interaction	Model 2: Illit. rate w/ time interaction	Model 3: Grad. unemp. rate w/o time interaction	Model 4: Grad. unemp. rate w/ time interaction	Model 5: Internet use w/o time interaction	Model 6: Internet use w/ time interaction
Lagged protest	0.627**	0.370**	0.633**	0.368*	0.584**	0.257
	(0.202)	(0.140)	(0.203)	(0.144)	(0.197)	(0.138)
Time		0.186***		0.219***		-0.054
		(0.029)		(0.036)		(0.032)
Ecological var.	0.018	0.095***	0.019*	0.104***	-0.001	-0.077***
	(0.010)	(0.020)	(0.009)	(0.021)	(0.007)	(0.020)
Ecological var.*Time		-0.004***		-0.005***		0.004***
		(0.001)		(0.001)		(0.001)
Youth pop.	0.089*	0.103*	0.059	0.062	0.063	0.083
	(0.045)	(0.049)	(0.042)	(0.050)	(0.046)	(0.051)
Population (logged)	0.848***	0.898***	0.845***	0.901***	0.738***	0.817***
	(0.151)	(0.160)	(0.149)	(0.158)	(0.146)	(0.157)
Repression	0.241***	-0.022	0.241***	-0.035	0.244***	-0.003
	(0.048)	(0.065)	(0.048)	(0.066)	(0.049)	(0.065)
Constant	-14.620***	-18.328***	-14.192***	-18.415***	-12.643***	-12.473***
	(1.952)	(2.172)	(1.761)	(1.967)	(1.660)	(1.825)
Observations	5,921	5,921	5,921	5,921	5,921	5,921
AIC	1288	1244	1287	1240	1291	1242
BIC	1328	1297	1327	1293	1331	1296
McFadden's R^2	0.0733	0.108	0.0741	0.111	0.0713	0.110

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

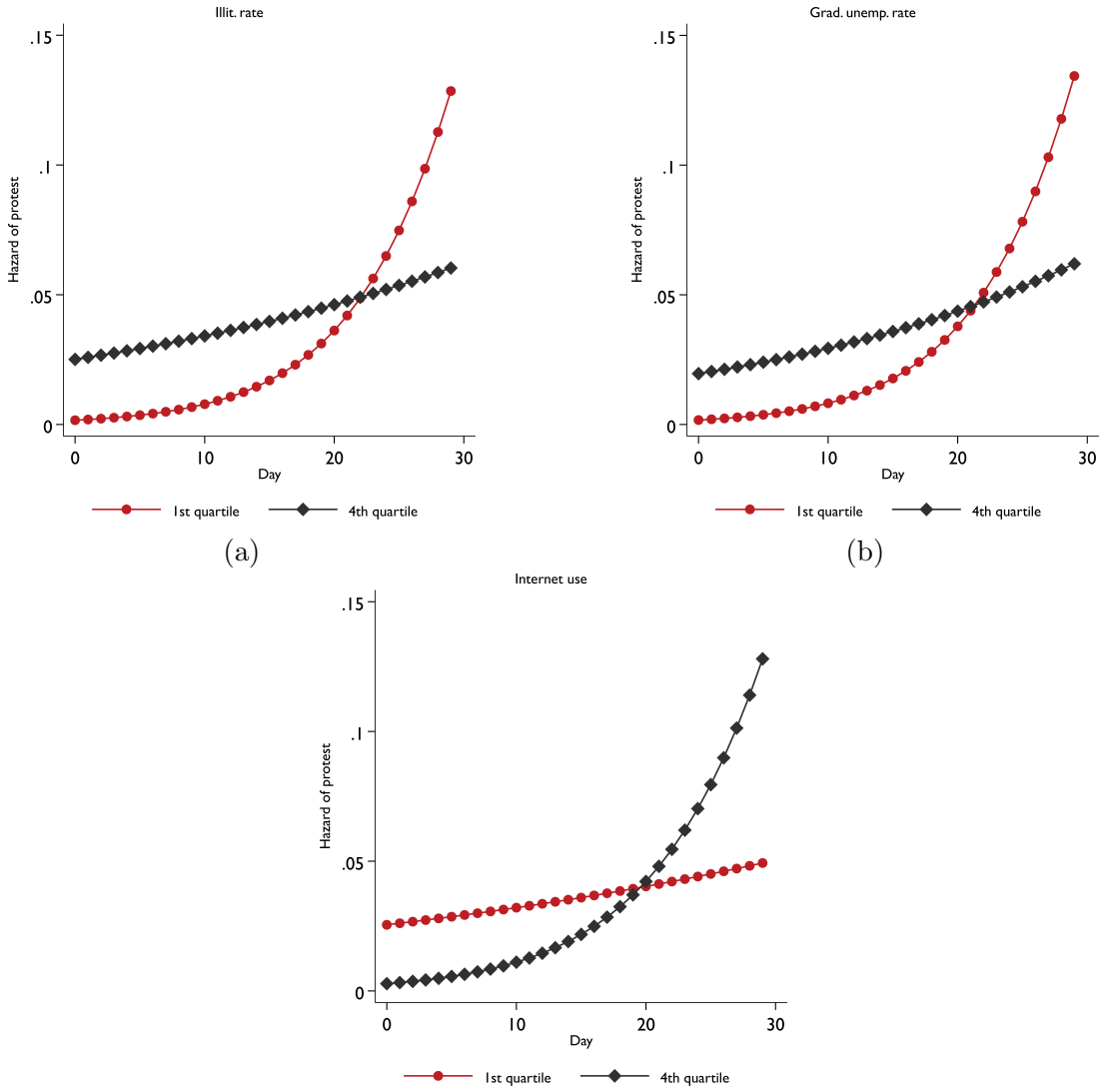


Figure A11: Predictive margins of alternative ecological measures over time, upper and lower quartiles

Table A10: Correlation matrix of alternative ecological variables

Variables	IDR	Illit. rate	Grad. unemp. rate	Internet use
IDR	1.000			
Illit. rate	-0.798	1.000		
Grad. unemp. rate 2014	-0.721	0.511	1.000	
Internet use	0.762	-0.883	-0.530	1.000

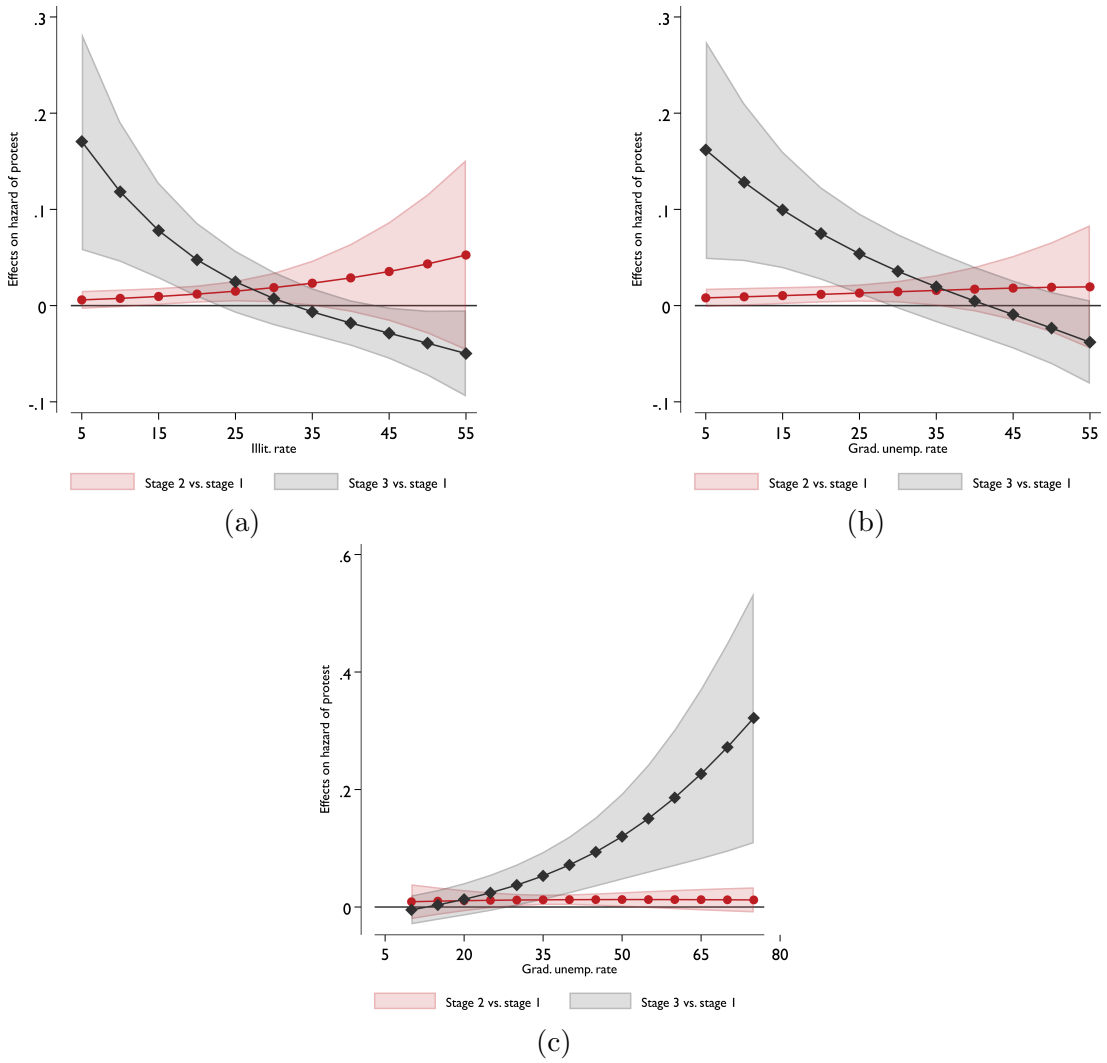


Figure A12: Marginal effects of alternative ecological measures by stage of uprising, with 95% CIs

Table A11 displays full results for the replicated analysis of Doherty and Schraeder (2018) alongside the results produced when using an ordinal outcome measure. Note that for ordinal models, cut points (not displayed here), are computed in place of a constant. Table A12 displays the full results of the multinomial logistic regression with those who never protested used as the base category.

Table A11: Logistic and ordinal logistic regression of protest participation with differently discretized outcome

Variables	Model 1: Logistic	Model 2: Ordinal logistic
Commitment to democracy	-0.052	0.083
	(0.155)	(0.158)
Income (logged)	-0.059	0.064
	(0.141)	(0.137)
Income (missing)	-0.062	-0.061
	(0.277)	(0.289)
Education	0.041	-0.034
	(0.087)	(0.082)
Age	-0.033**	0.031**
	(0.010)	(0.011)
Male	1.721***	-1.627***
	(0.283)	(0.293)
Employed	-0.038	-0.168
	(0.297)	(0.310)
Retired/Housewife	-0.859	0.757
	(0.459)	(0.508)
Student	0.219	-0.488
	(0.371)	(0.388)
Religiosity	0.453**	-0.440**
	(0.144)	(0.141)
Mosque attendance	-0.121	0.131
	(0.090)	(0.089)
Rural	-0.559*	0.518
	(0.274)	(0.293)
Interest in politics	0.284*	-0.315**
	(0.121)	(0.113)
Friend participated	2.342***	-2.516***
	(0.260)	(0.285)
Civil society membership	0.626	-0.390
	(0.344)	(0.323)
Constant	-3.406**	
	(1.227)	
Governorate indicators included	✓	✓
Observations	1,115	1,108

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table A12: Multinomial logistic regression of protest participation with differently aggregated outcome

Variables	Model 1: Stage 1 vs. 0	Model 1: Stage 2 vs. 0	Model 1: Stage 3 vs. 0
Commitment to democracy	-0.261	-0.305	0.481*
	(0.222)	(0.282)	(0.235)
Income (logged)	-0.069	-0.356	0.061
	(0.208)	(0.308)	(0.220)
Income (missing)	0.300	-0.210	-0.103
	(0.405)	(0.669)	(0.397)
Education	0.025	0.370*	-0.057
	(0.127)	(0.167)	(0.122)
Age	-0.040*	-0.044	-0.029*
	(0.016)	(0.026)	(0.014)
Male	2.060***	2.381**	1.478***
	(0.478)	(0.822)	(0.438)
Employed	0.256	0.889	-0.575
	(0.456)	(0.698)	(0.378)
Retired/Housewife	-0.307	-13.476***	-1.569*
	(0.729)	(0.910)	(0.666)
Student	0.714	1.475*	-0.672
	(0.599)	(0.683)	(0.509)
Religiosity	0.612**	0.257	0.456*
	(0.218)	(0.301)	(0.212)
Mosque attendance	-0.204	-0.263	-0.080
	(0.130)	(0.234)	(0.135)
Rural	-0.509	-1.540*	-0.340
	(0.387)	(0.755)	(0.385)
Interest in politics	0.286	0.543*	0.310
	(0.163)	(0.261)	(0.170)
Friends participated	2.933***	2.453**	2.441***
	(0.448)	(0.753)	(0.380)
Civil society membership	0.745	0.741	0.385
	(0.501)	(0.558)	(0.437)
Constant	-3.420*	-20.689***	-21.917***
	(1.664)	(2.430)	(2.220)
Governorate indicators included	✓	✓	✓
Observations	1,108	1,108	1,108

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

A2.8 Interview fieldwork

Interviews were variously conducted in Arabic, French or English and were semi-structured in format. Most interviews were recorded (and subsequently transcribed in full) unless informants desired otherwise. Names have been changed to preserve anonymity. Translations are all my own. In all, I conducted forty-one interviews. The length of interview ranged from 15 minutes to over three hours. The transcribed interview transcripts count over 38,000 words. In order to gain access to interviewees I employed a snowball-sampling procedure, all the while making sure to engage multiple entry points. In all, I used seven separate initial entry points. Interviewees ranged from members of the UGTT (13); members of student activism groups (5); members of lawyer and other civil society groups (4); journalists (2); members of the political party the PDP (2); and unaffiliated residents of Sfax, Sidi Bouzid, and Tunis (10). Some interviewees were interviewed on more than one occasion. Interviews were conducted by the author over the period February-March, 2017 and March-April, 2019.

Chapter 3

Paper Three

The Parochial Logics of Online Action: Social Media and the Tunisian Revolution

Abstract

How does information shared online contribute to protest diffusion? An influential literature argues that new information and communications technologies (ICTs) function to reduce the costs of collective action. In theory, online platforms overcome geographical constraints on information exchange and coordination. The consequences of these affordances for protest, however, have yet to receive systematic empirical scrutiny. Combining original event data with Twitter data from the Tunisian Revolution, I show that activity online has an underappreciated parochial logic. Information on protest shared online leads to protest diffusion but only locally. I bolster these findings with evidence from field interviews and a qualitative coding of over 10,000 tweets from during the revolution. The article sheds light on the sociological mechanisms linking protesting diffusion and social media. Despite the availability of new ICTs, geographical proximity and physical copresence remain central.

1 Introduction

Does online information lead to protest diffusion? What are the mechanisms linking online information and 'offline' protest? A prominent theoretical framework for understanding revolution conceptualizes the process of uprising as an "informational cascade" (Kuran 1991; Lohmann 1994). Here, so the logic goes, protest begins as an activity engaged in by a small group of committed actors who, through their public act of dissent, reveal normally undisclosed dissatisfaction to bystanders. Conceptualized this way, the spark that lights the revolutionary flame is no more than a signal of new information. Crucially, these sparks only win their place in history if the information they carry causes protest to grow.

The availability of new ICTs forces us to reappraise the dynamics of information exchange leading to protest growth.[1] Scholars have argued that the Internet, and social media platforms in particular, are making possible a form of "mass self-communication" (Castells 2015) and generating fundamentally new logics of "connective action" (Bennett and Segerberg 2013 cf. Bimber et al. 2005). This article tacks a different course. Recognizing that revolutionary cascades have a history that long predates the introduction of social media, it asks instead how new media of information exchange might inhere in processes of insurrection already familiar to us. Further, it asks not how social media might give rise to changes in mass attitudes, or contribute to movement building, but how social media functions as a tool of information exchange over the course of an uprising. This move requires shifting our analytical lens to the micro level and the early development of protest—an arena of contention

[1] In what follows, I will refer variously to "new ICTs," "new media," and "social media." The reader should understand these as synonymous.

that has received only limited attention in the literature.

This gap is an important one as social media platforms, in theory, have the capacity to overcome two geographical constraints characterizing information flow in the context of protest diffusion. These pertain to: 1) the availability of information on protest and 2) the ability of individuals to coordinate in signalling their willingness to participate. If previously both forms of information were bounded geographically, social media has the means to overcome any such constraints.

Taking as its case the 2011 uprising in Tunisia, the article brings empirical attention to this theoretical conjecture. I find evidence that social media does indeed contribute to protest diffusion but that this process remains geographically circumscribed: information shared online leads to further protest but only when that information derives from nearby regions. What is more, I find only limited evidence of online coordination leading to protest. To conduct the main analysis, I rely on a geo-referenced event catalogue of protest events over the twenty-nine day period of the Tunisian Revolution. Constructed using multiple offline and online news media, I am able to triangulate between over twenty sources and determine which protests received exposure online. Combining this event catalogue with two separate samples of Twitter data from during the revolution, I show that local online information was the strongest predictor of protest diffusion.

Testimony from field interviews, as well as a qualitative coding of over 10,000 tweets from the first two weeks of the revolution, help make sense of the mechanisms undergirding the findings. Early participants bore little resemblance to the tech-savvy cyberactivists who take center stage in the literature on "digitally networked" protest action (Bennett and Segerberg 2013; Tufekci 2017). Most did not have internet at their homes and would con-

gregate at internet cafés, or *Publinets*, in order to receive information on protest. There, discussions would take place offline during which individuals would signal their intention to protest. Protest nearby, in regions with which potential participants more closely identified, provided the strongest signal. Evidence gleaned from the Twitter data bolsters these findings: a manual coding of tweets reveals only very limited commitment signalling or protest organization, and that which did take place was concentrated in the capital city where, for most of the uprising, little protest was seen. The findings show that physical copresence and "attributions of similarity" (McAdam and Rucht 1993; McAdam et al. 2001b remain central to dynamics of informational exchange in protest. This in spite of the affordances of new communications technologies.

2 Revolutionary Cascades, New ICTs, and Mass Protest

Revolutionary cascades can be understood as informational cascades (Kuran 1991; Lohmann 1994). According to this understanding, the sparks that ignite prairie fires (Kuran 1989) do so because of the distribution of revolutionary thresholds in a population. Formally, those with low thresholds—committed inviduals or "activists"—are likely to be the first movers. In so doing, they signal their dissatisfaction and willingness to protest. And this process has the capacity to be "self-augmenting" (Kuran 1991, 19): revolutionary cascades, or "bandwagons", result when the defection of individuals to oppositions signal a change in the distribution of preferences in a population, thereby impelling the participation of higher threshold individuals who previously erred on the side of quiescence. Subsequent scholarship has refined the theory, recommending an attention to the composition and convictions of

crowds in addition to their size (Lohmann 1994; González-Bailón et al. 2011).

Whether or not we accept the formal predicates of these theories, what this article shares with them is a conceptualization of mass uprising as a *process of information exposure*. Revolutionary cascades rely on the recursive exposure to new information, which citizens use to measure their own commitment to protest against the thresholds of visible others. Uprisings of this sort are therefore inherently processual phenomena that expand over time, incorporating new constituencies as new information becomes available. A central implication of this conceptualization, then, is that revolutions begin as small population phenomena, and any effect of new information exposure operates in the short term within a fast-moving process of protest diffusion. The Tunisian Revolution is archetypal of this understanding (Lynch 2011).

Despite the central position that this conceptualization occupies in the literature, the majority of scholarship on new ICTs and protest neglect diffusion dynamics. Instead, the overarching theoretical claim of this literature holds that new ICTs lower the cost of large-scale collective action, leading to a heightened aggregate incidence of collective violence (Pierskalla and Hollenbach 2013) and collective protest (Ruijgrok 2017; Stein 2017; Enikolopov et al. 2018). A body of literature variously leveraging survey data and field interviews also finds associations between information consumption online and participation in mass protest (Tufekci and Wilson 2012; Breuer et al. 2015; Clarke and Kocak 2018). Common to these literatures is a static focus on large-scale forms of collective action.[2] However, this focus on the more spectacular, headline-grabbing, episodes of contention neglects the prehisto-

[2]A notable exception is Rød and Weidmann (2019) who recommend a focus on the tempora dynamics of protest and the differential impact of new ICTs at different stages of a protest wave's unfolding.

ries of protest diffusion crucial for understanding how social media inheres in processes of insurrection.

The Internet functions to lower the cost of collective action in two ways. First, online media make information more easily accessible, leading to new logics of both protest organization (Bennett and Segerberg 2013) and diffusion Weidmann 2015, which are loosened of previous constraints of localized information exchange.[3] Second, the Internet enables citizens to signal their willingness to participate to broad publics, and coordinate protest outside the geographical bounds of their own interpersonal networks (Tufekci and Wilson 2012; Pierskalla and Hollenbach 2013; Steinert-Threlkeld et al. 2015; Steinert-Threlkeld 2017; Tufekci 2017; Little 2016; Clarke and Kocak 2018). These twin affordances of new ICTs affect the geographies of information and coordination. If previously information was constrained by the geographical concentration of media availability and social networks (Myers 2000; Biggs 2005), new ICTs make possible the exchange of information "unrestricted by geographic distance" (Earl and Kimport, 2011, 130).

Both information exchange and coordination relate to short-term dynamics. The adoption of an appropriate level of analysis hinges on how we conceptualize the Internet as it relates to contention. A first approach sees that the Internet conditions mass attitudes or promotes movement building and resource mobilization over the longer term(e.g., Leeson 2008; Lotan et al. 2011; Tufekci and Wilson 2012; Pierskalla and Hollenbach 2013; McGarty et al. 2014; Breuer et al. 2015; Weidmann 2015; Tufekci 2017.[4] A second conceives of the

[3]Experimental literature in computational science reinforces such claims, with the finding that weak ties provide conduits of "novel" information; i.e., information to which we would otherwise not have been exposed due to the parochial character of social networks (Bakshy et al. 2012).

[4]See also Steinert-Threlkeld (2017: 382-383) on core-based mechanisms that predispose individuals to protest but are not in themselves mobilizing

Internet as a tool of information exchange and understands any information effect as relating primarily to immediate exposure (e.g., Steinert-Threlkeld et al. 2015; Steinert-Threlkeld 2017; Larson et al. 2019).[5] This second is particularly relevant for understanding the diffusion of initial protest; a process that often involves just small numbers of participants. The question we must, then, ask is whether we are interested in the Internet as a tool or as an exogenous influence on mass preferences and movement building.

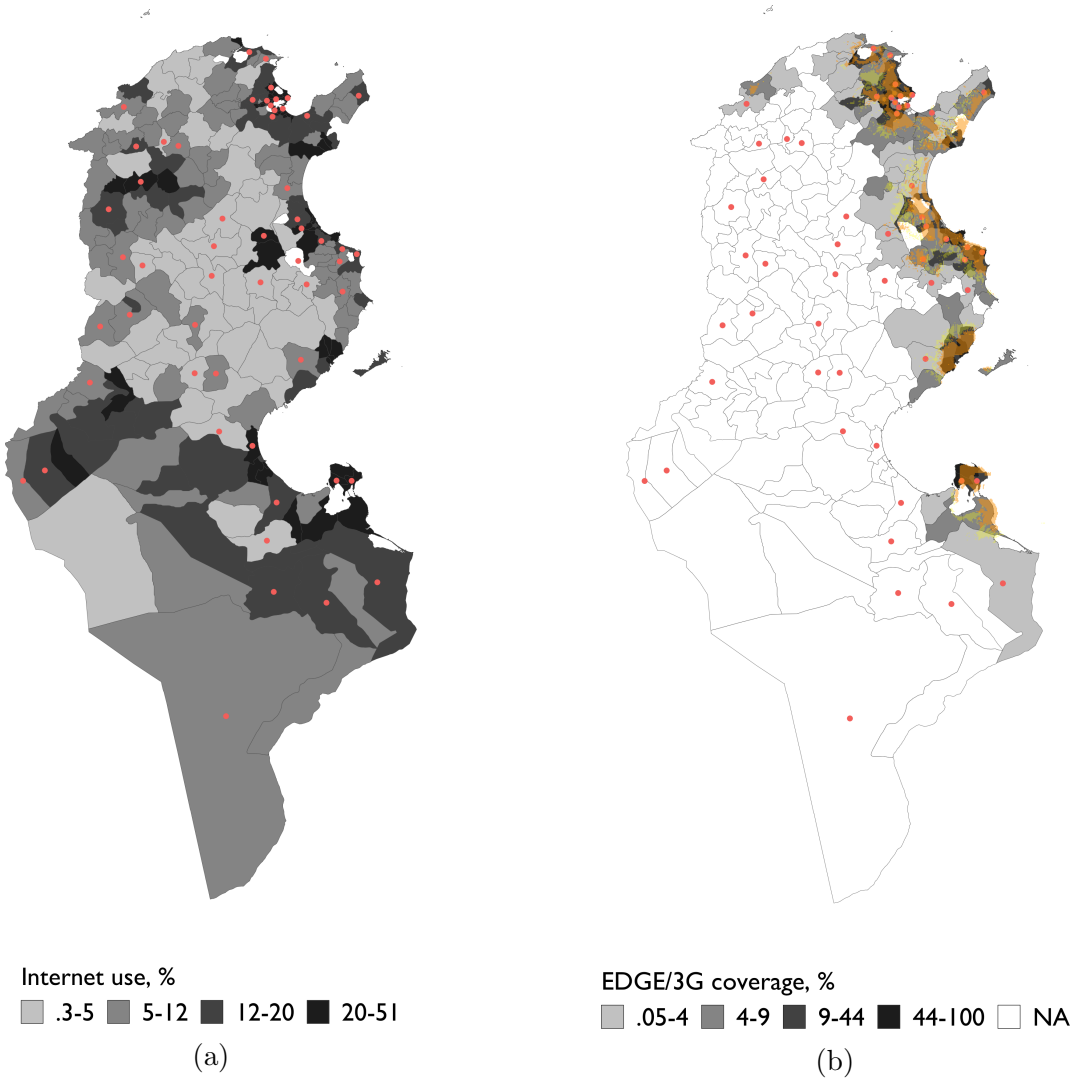
The conception of collective action favoured by the latter is better suited to forms of ecological analysis using aggregate data that operate over a longer timescale. When applied to the relatively brief and sudden protest wave that struck Tunisia from 2010-2011, we risk making faulty conclusions when relying on inferences derived from aggregate data. Figure 1 displays the locations of protest sites over district-level measures of internet (ADSL) and cellular network penetration.[6] The majority of protest over the first two weeks of the Tunisian Revolution took place in districts with low internet penetration and no 3G cellular network availability.[7] Sidi Bouzid, where the uprising began, had no 3G coverage and fell in the lowest band of Internet penetration. We might then conclude that the Internet played little role in the generation of this mass mobilization episode.

The reason we should distrust such a conclusion is directly related to the conceptualization of the Internet and revolution outlined above. If protest begins as a small population

[5]Little (2016: fn.22) makes reference to this distinction when noting that antiregime sentiment may be stable over short time periods whereas coordination involves rapid fluctuations of information availability.

[6]Data for internet penetration is imputed from the 2014 Tunisian Census. This is an admittedly imperfect measure, though governorate-level internet use in 2014 and 2010, from which values at the delegation level were imputed, are correlated at .75 indicating that any growth in internet penetration was largely consistent across governorates. 3G network coverage was extracted using GIS softwares from an online map of the Orange cellular network in July 2010. EDGE was a so-called "2.5G" network that straddled the transition from 2G to 3G. See Appendix for further details on the construction of these variables.

[7]The first fourteen days of protest is chosen as an appropriate timeframe for 'initial' protest. The first twenty-one days shows a similar picture.



(a) (b)

Figure 1: (a) Internet penetration and protest. Protest sites in red; (b) Internet penetration and protest. Protest sites in red. EDGE represented by yellow overlay; 3G by orange.

phenomenon, impelled by the participation of a group of committed individuals, we are plainly not in the realm of mass preferences or resource mobilization.[8] Nor would it be appropriate to measure information availability at an aggregate level. Consider a group of highly committed individuals who oppose a given regime. Now imagine they wish to broadcast news of a recent protest further afield. While high Internet penetration would lower

[8]Though long-term causes and how the distribution of mass preferences relates to revolutionary cascades is discussed by Kuran (1989: 54-58).

the costs of broadcasting this information, the presence of one connected computer is all that is needed to disseminate news of the protest worldwide, just as this is all that would be required to receive details of a protest. Measuring information availability, as proxied by density of communications infrastructure, would not capture this. Such a measure captures instead the likelihood of information availability generally; it does not capture actual exposure to salient information. Conceptualizing the Internet as a tool of mobilization forces us to examine information availability as it relates directly to observed protest activity. As Henry Farrell (2012: 45) notes, however, this "data on the timing and place of protests as well as the timing and point of origin of online discussions" is precisely what is missing in the current literature.

3 Data and Method

In order to overcome this gap, I triangulate multiple offline and online source materials for the construction of an event catalogue of protest events during the twenty-nine days of the Tunisian Revolution. Conventionally, researchers make use of newspaper data when building event catalogues. Practitioners in this field encourage triangulation between sources as a metric of reliability (Earl et al. 2004b). More recent scholarship has highlighted the considerable bias introduced by a reliance on English-language and machine-coded event data sources, especially when conducting analysis at a subnational level (Herkenrath and Knoll 2011; Hammond and Weidmann 2014).[9] Taking lessons from this scholarship, I choose

[9]Recent computational advances in this field point to the future possibility of employing automated coding techniques for non-English-language media (Osorio and Reyes 2017). These methods are yet to be applied to Arabic-language news media, however.

to triangulate between numerous Arabic-, French-, and English-language source material. In sum, the event catalogue relies on twenty-seven separate media sources. These are detailed in Table 1 and are described in detail below (as well as in the Appendix). Following Cook and Weidmann (2019), I provide details of the number of reports I derive from each of these sources. As I go on to discuss, the form of protest event analysis used in this paper—discrete-time event history analysis—requires data structured in "spells" wherein only information on the first day of protest in a given district is retained. This technique is designed to measure the geographical diffusion of protest over time and is thus ideally suited to the question at hand. In Table 1, I supply reporting frequency by source both for the full event catalogue (EC), as well as the event history analysis (EH) dataset used in the main analysis. Similarly, in Appendix Table A4, I provide details of first observed protests and source material for each delegation in the EH data.

A near-complete media blackout on the part of national news media in Tunisia during the twenty-nine days of the uprising meant that Tunisians took to Facebook to learn of, and report on, protest. Two of these pages (NATS and PTON) were created especially for the purposes of reporting. Another two (MAMN and Takriz) were already in existence. Each of these pages was archived and manually coded. Protests were located in one of Tunisia's 264 "delegations", and information recorded on the repertoire (e.g., protest, march, sit-in), size, start location (e.g., union office, governorate building, main road), end location, repression, and crucially, any other sources that reported the same event.[10]

While mainstream domestic newspapers were largely silent on protest, a number of dis-

[10]When size was not reported, participation numbers were imputed from the repertoire, following Francisco (2000). See Appendix for further details.

Table 1: Number of reports by source in event catalogue, full event catalogue (EC) and event history (EH) dataset.

Source	Freq. *EC*	Freq. *EH*
AFP	8	1
Al-Jazeera News	8	3
Al-Jazeera Video	18	3
Al-Badil	1	-
Al-Wasat	1	1
ANR	63	10
ANR Video	61	10
BBC	1	-
Bouderbala	29	7
BusinessNews	4	2
Chourouk	85	13
Elaph	1	-
France24	2	1
France24 Video	2	1
Kalima Tunis	343	87
Le Monde	1	-
Le Point	2	-
MAMN (FB)	33	6
NATS (FB)	195	48
Nawaat	144	35
Nawaat Video	106	27
Paris Match	1	-
Photo	25	4
PTON (FB)	193	68
Reuters Arabic	4	1
Takriz (FB)	42	22
Video	106	41

sident and humanitarian news outlets did report on protest. As with the Facebook sources, each of these were archived and manually coded. The first—*Kalima Tunis*—was a radio station that published one or multiple online communiqués daily detailing any protest. These reports were aggregated and published by `turess.com`, an online news aggregator. A second such source was *Nawaat*, a dissident blog created in 2004, which published online reports and videos of protests.[11] Two sources that postdate the uprising were also used. The first of these, the *Archive Numérique de la Révolution* (ANR), is a digital archive of photos and videos collected by Tunisian and French researchers in the aftermath of the revolution and stored at the Tunisian National Archives. The second, the Bouderbala Commission report, provided granular detail of deadly repression events, each verified with hospital records and home visits. This is the primary source of repression data but event details were also con-

[11] As detailed in the Appendix, many of these reports and videos became unavailable after the closure of hosting platform *posterous.com*. I was able to retrieve them through the Internet Archive, however.

sulted and triangulated with other media. Toward the close of the uprising, Tunisia's main national newspaper *Chourouk* began reporting on protest. Online reports were retrieved again from `turess.com` and also cross-checked against paper reports at the Centre de Documentation Nationale in Tunis. Finally, multiple international news media were used. Again, these are listed in Table 1.

The use of multiple media in the construction of this event catalogue allows us to investigate the dynamics of information exposure. The unit of analysis is the delegation-day; standard errors are clustered at the delegation level. The discrete-time logit model requires data structured in split-spell format. Here, only the first event(s) in a given delegation are retained and coded for whether a report of the protest appeared on a Facebook source; i.e., we are modelling the probability of an event occurring on a given delegation-day given that an event is yet to occur. Delegations drop out of the dataset after first occurrence. In sum, 148 of Tunisia's 264 delegations saw protest of some form during the course of the Revolution, giving 5,921 spells.

I leverage these data on protest to compare the "contagiousness" (Strang and Tuma 1993) of protests reported on Facebook to those that were not. The main independent variables account for differential exposure to information with a spatial weighting term. In order to construct these diffusion variables, I use an inverse square root distance weighted sum of nearby Facebook protest days at time *t-1*, taking the functional form:

$$Facebookinf_{it} = \sum_{\tau=t-1}^{t-1} \sum_{j=1}^{J} \frac{F_{j\tau}}{\sqrt{d_{ij}}}$$

, where $d_{ij}^{-0.5}$ represents the inverse square root distance between the centroid of delegation

i and delegation j and $F_{j\tau}$ represents a binary indicator of whether delegation j witnessed protest at time τ that was reported on Facebook. A 15km threshold distance is used; that is, I calculate an inverse square-root weighted sum of delegations witnessing Facebook-reported protest within a buffer of radius 15km.[12] Nearby protest not reported on Facebook takes the same functional form. Both measures are lagged by one day. Overall, 91 delegations had a first protest that was reported on Facebook, while 57 delegations saw first protest that went unreported on this platform. Figure 2 visualizes the over time diffusion of Facebook- and non-Facebook-reported protest.

Analyses of protest diffusion in the pre-Internet era had necessarily to account for geographic variation in the concentration of local media (see e.g., Myers 2000; Roscigno and Danaher 2001; Andrews and Biggs 2006). Facebook is theoretically free of such bias: reports of protest occurring 100km away from a given district have the same online visibility to another occurring 10km away. Our main spatially lagged variables are designed to test this conjecture. In order to parse national-level and nearby signal I also introduce the proportion of total events reported on Facebook at time *t-1*. Together, this first set of variables measure online activity as it relates to the transmission of protest information.

A second variable is taken from Twitter. Twitter was less used than Facebook in Tunisia but still played host to a large volume of online activity during the Revolution.[13] The first Twitter sample I use is a 1% random sample of tweets tagged with #sidibouzid—the hashtag used to identify tweets relating to the Tunisian Revolution. This dataset was collected during

[12]Mean distance between polygon centroids is 14.02km. The choice of a 15km buffer is therefore chosen as appropriate for capturing exposure to information on nearby protest. To generate these variables, I use the Stata module *spgen* developed by Keisuke Kondo (2017). The use of a 30km buffer gave substantively identical results.

[13]According to Wave II of the Arab Barometer, among those who use the internet, just 11% of Tunisians had a Twitter account versus 82% for Facebook.

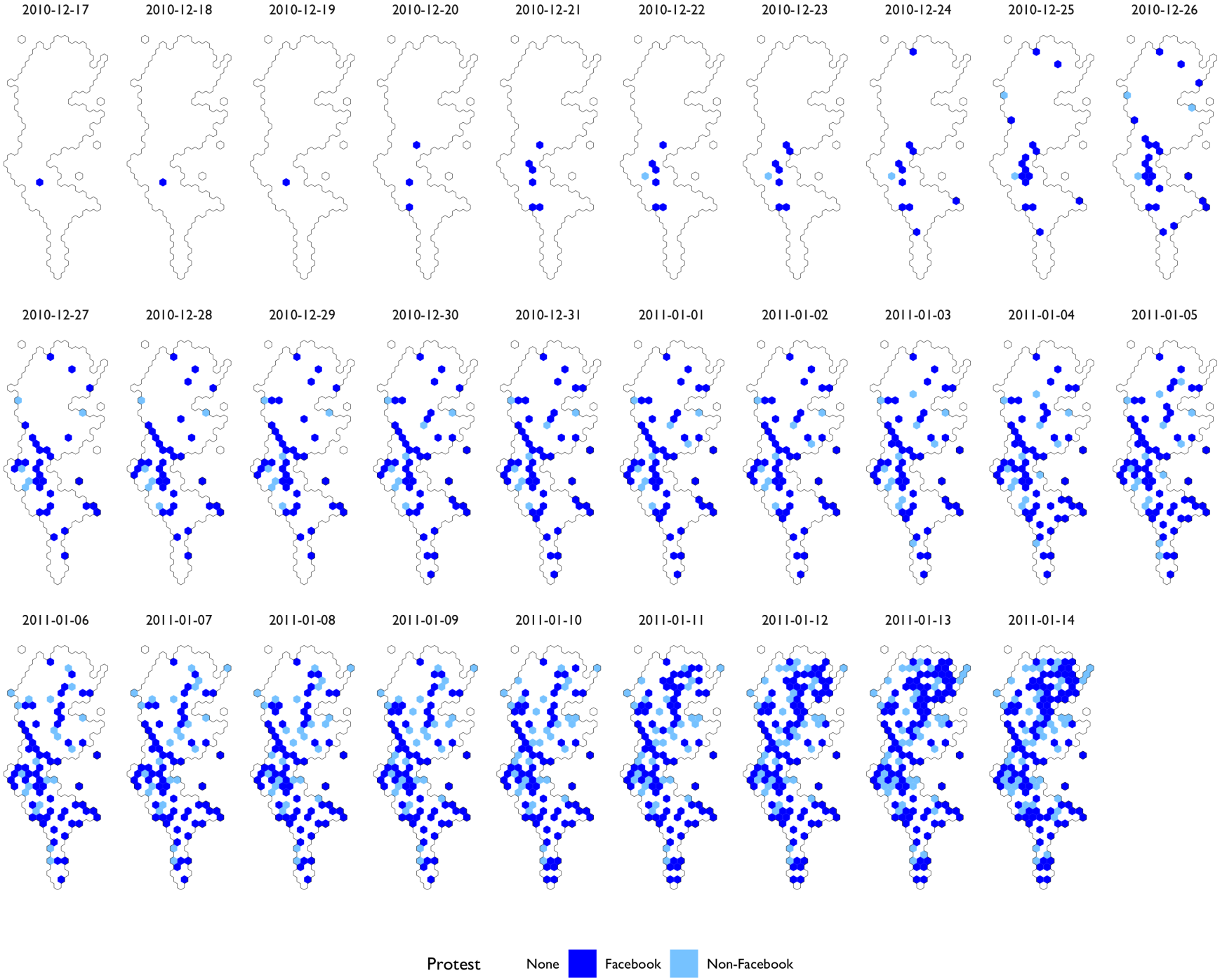


Figure 2: Diffusion of Facebook- and non-Facebook-reported protest: 17 December,2010—14 January, 2011.

the uprising itself through the Twitter streaming API and includes 87,547 tweets. [14] To capture the intensity of online communication at daily intervals, I use the lagged (*t-1*) share of tweets involving direct communication between one user and another; i.e., tweets in which one user identifies, responds to, or retweets another with their Twitter handle. In the language of network analysis, this is the number of 'directed edges' denominated by the daily sum of tweets (that were tweeted by unique user 'nodes') on a given day. It is worth stressing that this variable is silent on questions of proximity—we have no information on the location of users or the geographical relevance of tweet content. The variable is instead designed to proxy for the intensity of online communication. Online communication is conceptually distinct from online (protest) information. While the latter captures one-way transmission of information on protest, the former involves two-way communication that may or may not pertain specifically to protest.[15] While conceptually distinct, intensity of online communication is nonetheless relevant for understanding protest diffusion, and is related to online information. After all, for information transmission to exert an effect, we require an active community of receivers. It is the activity of this community of receivers that the online communication variable aims to capture. Figure 3 provides a visual representation of the construction of this variable for one day of the Revolution alongside a plot of daily first event counts from the EH dataset. Network visualization is for January 13, 2011—the day that saw the largest number of new protest events (picked out in red on accompanying time-series plots).[16]

[14] See Poell and Darmoni (2012) for previous uses and the Appendix of this article for full details of these data. It should be noted that tweet collection only began on December 18, 2010, explaining the missing values for December 17.

[15] As detailed below, tweets relating specifically to protest organization or reporting in fact constituted a minority of the tweet sample.

[16] Network visualization created in Gephi v.0.9.2.

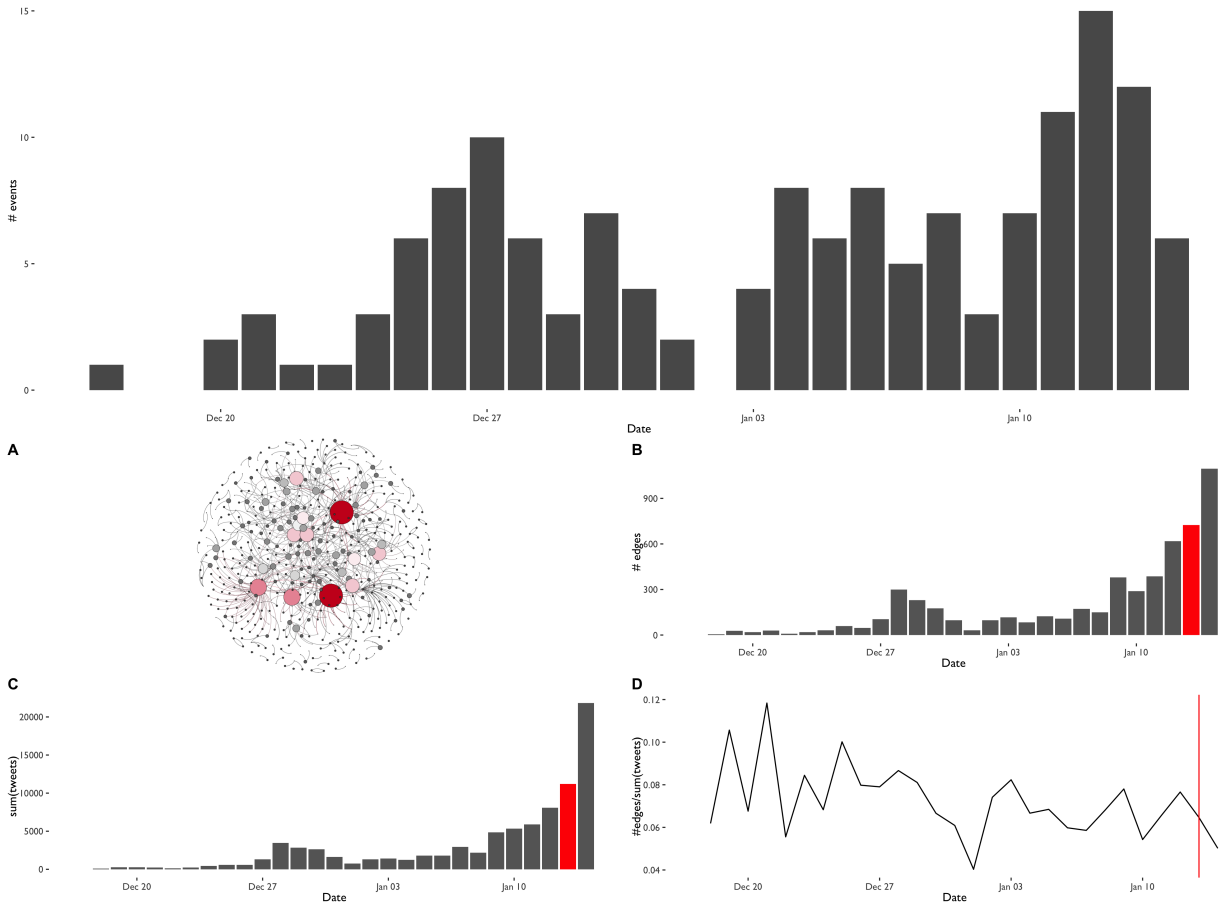


Figure 3: **Top**: Barplot of first event frequency by date from EH dataset.; **A**: Network visualization of Twitter sample for 2011-13-01. Node size scalled by in-degree.; **B** Barplot of edge counts by date. Count of edges for 2011-13-01 filled red.; **C**: Barplot of tweet counts by date. Count of tweets for 2011-13-01 filled red. **D**: Communication intensity by date. Vertical red line indicates 2011-13-01.

The theoretical and empirical literature on social media and protest makes the case for new ICTs as tools of coordination (Little 2016; Steinert-Threlkeld 2017; Clarke and Kocak 2018). In order to capture online coordination, I use data from Steinert-Threlkeld (2017). These data are taken from the Twitter 10% API: a 10% random sample of all tweets (regardless of content) published on Twitter in a given country-day. This article uses only the data for Tunisia over the period of the Revolution. I use the same operationalization for peripheral coordination as used by Steinert-Threlkeld—a daily Gini coefficient of hashtag

concentration. This is derived from the Lorenz Curve of hashtag inequality; a measure that naturally varies between 0-1, where 1 would indicate perfect inequality in the number of tweets per hashtag (only one hashtag is used), and 0 perfect equality between hashtags.[17]

If the first Twittter variable is designed to measure online communication, this second is designed to capture (peripheral) online coordination. The Twitter sampling procedures used for these respective variables helps clarify why we should treat them as conceptually distinct. The first sample includes only tweets containing #sidibouzid while the second is a random sample of all tweets. As such, while the first sample captures already engaged individuals (those using the relevant protest hashtag), the second includes information on users generally. The random nature of the second sample is key for understanding why the Gini coefficient can be understood as a measure of specifically peripheral coordination.[18] On any given country-day, thousands of unique hashtags may be used. In the context of an escalating protest wave, already engaged users will continue tweeting using the relevant protest hashtag but the Gini coefficient will remain low in the absence of broader collective attention to an individual hashtag. The Gini coefficient increases, in other words, only when previously disengaged users on the periphery begin to mobilize around an individual hashtag. It is for this reason that the Gini coefficient more properly captures peripheral coordination—a variable that is distinct from online communication by the selective sample of #sidibouzid users.[19]

[17] Formally, the Gini coefficient for hashtag coordination per day is thus calculated as: $Coord_t = \frac{2\sum_{i=1}^{n} ih_i}{n\sum_{i=1}^{n} h_i} - \frac{n+1}{n}$, where h_i represents the number of tweets observed that day for hashtag i. The location of tweets derives from either the user geocoding tweets, which are then assigned to country-unit bounding boxes (here: Tunisia) or from the user reporting location information in their Twitter "bio."

[18] "Peripheral" here therefore refers to the position of users within an online network and not to the Tunisian "Periphery", i.e., the interior of Tunisia outside of the main urban centres.

[19] The weak (.02) correlation between these two variables points to empirical support for this conceptual distinction. While this concentration variable may from some measurement error in the full cross-national

A recent literature finds that media disruption, outages, and blackouts can function to boost mobilization (Hassanpour 2014; Hobbs and Roberts 2018. Here, the argument is that censorship motivates individuals to find alternative, sometimes local, avenues of informational exchange, thereby impelling further mobilization. To try to capture this, I use Google Trends data for "proxy" searches. During the revolution, Tunisians used proxy servers, most often "Hotspot Shield," to bypass regime censorship and Internet blockages. Search volume is normalized between 0-100, with 100 indicating peak search volume.[20]

While online activity is the focus of this paper, protest has also been linked to several structural factors relating to development and deprivation. Their inclusion in the analysis is also key for understanding the role of social similarity in protest diffusion Braun and Koopmans 2010. The area-specific literature points primarily to deprivation in the interior and regional inequalities in development as a key factor in the outbreak of protest (Ayeb 2011; Hibou 2011). To measure economic development at the delegation level I therefore us the local development index (IDR).[21] A growing youth population (or "youth bulge") is also cited as a key factor in the Arab Spring protests (Campante and Chor 2012). Thus, I control for delegation-level youth population (% population aged 20-29), taken from the 2014 Census.

Two protest-specific variables are also included as controls. The first is a general diffusion variable and is measured as the (square-rooted) sum of protests nationally at time *t-1*. As a measure of repression, I use the (square-rooted) count of deaths (as recorded by the Boud-

dataset of Steinert-Threlkeld (2017), which covers a far longer time period, the Gini measure of coordination used in this paper is less likely to suffer from spurious coordination around any other event over the truncated twenty-nine day period of the Tunisian Revolution.

[20]See Appendix for further details of the Google Trends measure.

[21]Table A5 in the Appendix details the data sources used for this composite index.

erbala Commission) resulting from protest repression at *t-1*.[22] Protest is expected to take place in more populated areas and so I enter (logged) population at the delegation level.[23] Following Carter and Signorino (2010), I control for temporal dependence by introducing a cubic polynomial of time at risk.[24]

4 Results

Results of the event history analysis are displayed in Table 2, with coefficients displayed as log-odds. Model 1 includes only the Facebook variables. Protests reported on Facebook are positively associated with subsequent protest, and this effect has a significant spatial dimension: nearby protests reported on Facebook are stronger predictors of subsequent protest than those further away. Notably, protests that went unreported on Facebook do not significantly predict subsequent protest. Information shared online thus appears to play a role in protest diffusion, but with an important caveat: geographical proximity of information remains consequential. The variable measuring the overall share of protest reported on Facebook shows no significant association with subsequent protest.

Model 2 incorporates the Twitter variables. Here, we see that the intensity of online communication—a variable designed to measure the online activity of potential receivers of online information—is positively associated with protest diffusion. Our coordination measure is also positively associated with subsequent protest but does not reach statistical significance. Finally, Model 3 adds the measure for media disruption, which shows no significant

[22] See the Appendix for coding criteria and source details for the repression variable.

[23] Using population density ($\log(\frac{population}{delegationarea})$) gives substantively identical results.

[24] Interactions of time with several covariates are significantly different from zero, indicating a violation of the proportional hazards assumption.

association with protest diffusion.

Table 2: Discrete time event history analysis of protest diffusion. Coefficients expressed as log-odds.

	Model 1	**Model 2**	**Model 3**
Nearby FB protest (t-1)	0.74**	0.76**	0.76**
	(0.24)	(0.24)	(0.24)
Nearby non-FB protest (t-1)	0.30	0.28	0.30
	(0.47)	(0.48)	(0.48)
Prop. FB protest (t-1)	0.23	0.23	0.23
	(0.47)	(0.59)	(0.60)
Twitter communication (t-1)		0.15*	0.15*
		(0.07)	(0.07)
Twitter coordination Gini (t-1)		1.01	1.02
		(0.59)	(0.59)
Proxy search volume (t-1)			0.00
			(0.01)
Repression (t-1)	-0.27	-0.25	-0.26
	(0.15)	(0.15)	(0.15)
Total events (t-1, sqrt)	-0.00	-0.04	-0.02
	(0.09)	(0.10)	(0.13)
IDR	-1.53	-1.56	-1.56
	(0.94)	(0.94)	(0.94)
Youth pop.	0.09	0.09	0.09
	(0.05)	(0.05)	(0.05)
Population (logged)	0.93***	0.92***	0.92***
	(0.18)	(0.18)	(0.18)
Time polynomial	✓	✓	✓
Spells	5921	5921	5921

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

While the above estimations account for the source of protest information, they are nonetheless silent on the observed qualities of protest in nearby districts. It could be that more noteworthy protests receive attention online, and are thus more likely to spread. Facebook exposure, in this case, would be endogenous to perceived protest importance. Repression is the most obvious axis of distinction. There are nonetheless no significant differences in the percentage of protests repressed in the Facebook- and non-Facebook-reported protests

(54% versus 56%). [25] Protest size is another potentially salient characteristic but mean protest size between Facebook- and non-Facebook-reported protest (290 versus 291) also points to broad equivalence. Facebook-reported protest does, however, seem to take place in delegations with higher mean levels of internet usage than non-Facebook-reported protest (40% versus 34%). In Model 4 of Appendix Table A6, I include delegation-level internet usage as a covariate. Results remain substantively unchanged.

The above results find little support for online activity as a tool of coordination. To parse so-called 'core' and 'peripheral' coordination, Steinert-Threlkeld (2017) also includes an interaction of the coordination Gini with the percentage of hashtags produced by the "core" (users with followers at or above the 95th percentile). He then includes a number of additional variables to further isolate peripheral coordination. These are the percentage of hashtags from "mainstream media" and "online actor" accounts (taken from Lotan et al. 2011). The addition of these Twitter covariates (Table A6, Model 5) still indicates weak support for a coordination role. Here, the Twitter communication variable loses significance but the percentage of tweets communicated by the core shows a positive, and significant, association with protest diffusion, perhaps indicating that these two variables are measuring similar phenomena. Finally, given the shifting ecologies of protest over the course of the observation period, we may also want to control for time-dependence by introducing an interaction between key ecological covariates and time (as opposed to using a cubic polynomial of time). Introducing an interaction between time and local development points to significant time-dependence but does not substantively alter headlines results as they relate

[25] The same is true when we measure repression by number arrested and number killed.

to the FB exposure variables.[26]

The findings for nearby Facebook protest may be confounded by unobserved unit-, or governorate-level, heterogeneity (sometimes referred to as "frailty" in a survival context). In this case, rather than being a function of exposure to online protest information, diffusion here may simply be the result of shared but unmeasured characteristics within and between units. According to the literature, unmeasured frailty tends to produce underestimates of the "true proportionate response of the hazard" to a change in any independent variable of interest (Jenkins 2005). Advances in the multilevel modeling of survival data allow us to address these concerns.[27] I therefore use a random intercept complementary log-log model with delegations nested in governorates. The model introduces an error term to account for unobserved governorate-level correlation in the hazard of experiencing a protest event. A cubic polynomial of elapsed time by delegation is again used to account for duration dependence. Results are displayed in Table A6, Model 6, and remain substantively unchanged. The Twitter communication variable again falls below the 5% threshold of statistical significance. The coefficient for nearby Facebook protest increases in magnitude.

Can some of the parochialism of online action be explained by the Facebook "News Feed" algorithm? In other words, were users simply more exposed to more information from nearby users? To answer this question, we must look back in history to the algorithm governing the Facebook News Feed at this time. The observation period for this article predates the September 2011 introduction of the "Combined News Feed," which amalgamated group and friend activity into a single feed. The News Feed algorithm for the period of interest in

[26]The same is true when interacting time with population, internet penetration, and youth population.
[27]For overviews of these approaches see Barber et al. (2000) and Austin (2017).

this article ordered posts by popularity, as measured by level of engagement (i.e., responses, likes etc.). Group activity was separate and required navigating to the Facebook Group of interest. Thus, if users were being exposed to information from the protest news pages used in this article, there would be little algorithmic bias in exposure.[28] However, we know from recent contributions to the computational geoinference literature that our social networks remain highly localized (Jurgens 2013.[29] If friends of users were also posting information on protest, it is likely, then, that these friends were geographically proximate. Measurement of the precise contribution of the Facebook algorithm or the extent of users' networks falls outside the scope of the present article. What we can say is that information shared between users (rather than on group pages) was likely local in nature, thereby reinforcing the central claim of this article: information exposure online has an important parochial dimension.

5 Discussion

Two conclusions emerge from the foregoing analysis. First, exposure to online information contributes to protest diffusion, but with an important qualification: the strength of this signal diminishes with distance. Geographical proximity, in other words, remains central to informational cascades. Second, the coordination theory of online action—that new ICTs enable coordination at a distance—finds little support. In what follows, I seek to shed light on both findings with evidence from interviews, a qualitative coding of Twitter data, and a cache of documentary material.

[28]Though it is possible that users with friends who were members of these groups would be more likely to be exposed if their friends shared with them information on the group.

[29]We also know that we are more likely to share information from close friends (Bakshy et al. 2012).

5.1 Qualitative tweet coding

A majority of quantitative analyses of social media and protest rely on broad proxies and aggregations of online content. This is a recognized shortcoming in the literature (Neumayer and Rossi 2016). Reliance on proxy measures means such analyses are largely silent on the content of tweets. In order to address this, I conducted a qualitative coding of tweets contained in the #sidibouzid sample. Given our focus on the initiation and process of protest diffusion, the sample was restricted to the first first fourteen days of the Tunisian Revolution. The data was also purged of retweets. The final sample consisted of 10,514 tweets. Coding category assignment relied on a general inductive approach (Thomas 2006) whereby dominant themes that emerged from a reading, and rereading, of tweets were assigned a code that were subsequently recorded alongside each tweet. Two codes were permitted for each.[30] Of primary interest to the present article are the codes relating specifically to protest information and organization/coordination. Table 3 displays coding criteria and example tweets for each of the three protest-specific codes.

Approximately ten percent of tweets related specifically to the reporting of protest occurrence.[31] A far smaller share, however, related to updating of ongoing protest. What is more, these tweets were only in evidence on select days; namely, those on which protests took place in the capital city, Tunis. The emergence of this category is unlikely to be a function of protest size. Protests in Tunis only ever numbered in the hundreds during the first two weeks of the uprising, and were no larger than protests taking place elsewhere in the country.

[30] A recognized limitation of this approach is that the author was the sole evaluator for coding assignment.

[31] Note: this does not include tweets containing news articles (e.g., from Al-Jazeera, The Guardian) that describe ongoing protest more generally, which were assigned a different code.

Table 3: Assignment criteria for #sidibouzid Twitter sample.

Example tweet	Code & definition
 **Translation**: "The coastal cities are protesting again, with mobilization in Sousse, Mahdia, and Monastir #sidiBouzid"	***prepdes***: Tweets describing or reporting on protest that has taken place.
 **Translation**: "RT[@twitterhandle] RT[@twitterhandle] #djerbaprotest is starting in 10 minutes outside the trade union offices! #SidiBouzid"	***orgprot***: Tweets organizing, or containing information on the organization or whereabouts of, protest that is yet to take place.
 **Translation**: "#tunisprotest #sidibouzid everyone, there is another protest at the atfd offices, liberty street, by tijari bank"	***pupdates***: Tweets describing, or providing updates on, protest that is currently taking place.

The use of live updating is likely attributable instead to the size of Tunis relative to other cities in Tunisia (where, by comparison, scarce choice existed for protest location, making online coordination redundant) as well as the wider availability of mobile Internet (Figure 1). Protest organization was even less frequent, representing little more than one percent of tweets on most days. This tallies with evidence from the Facebook pages used in the event history analyses above. On no occasion were these groups used for the public advertising or scheduling of protest. Instead, as with our Twitter sample, the overwhelming majority of protest-related content was devoted to the simple reporting of events.

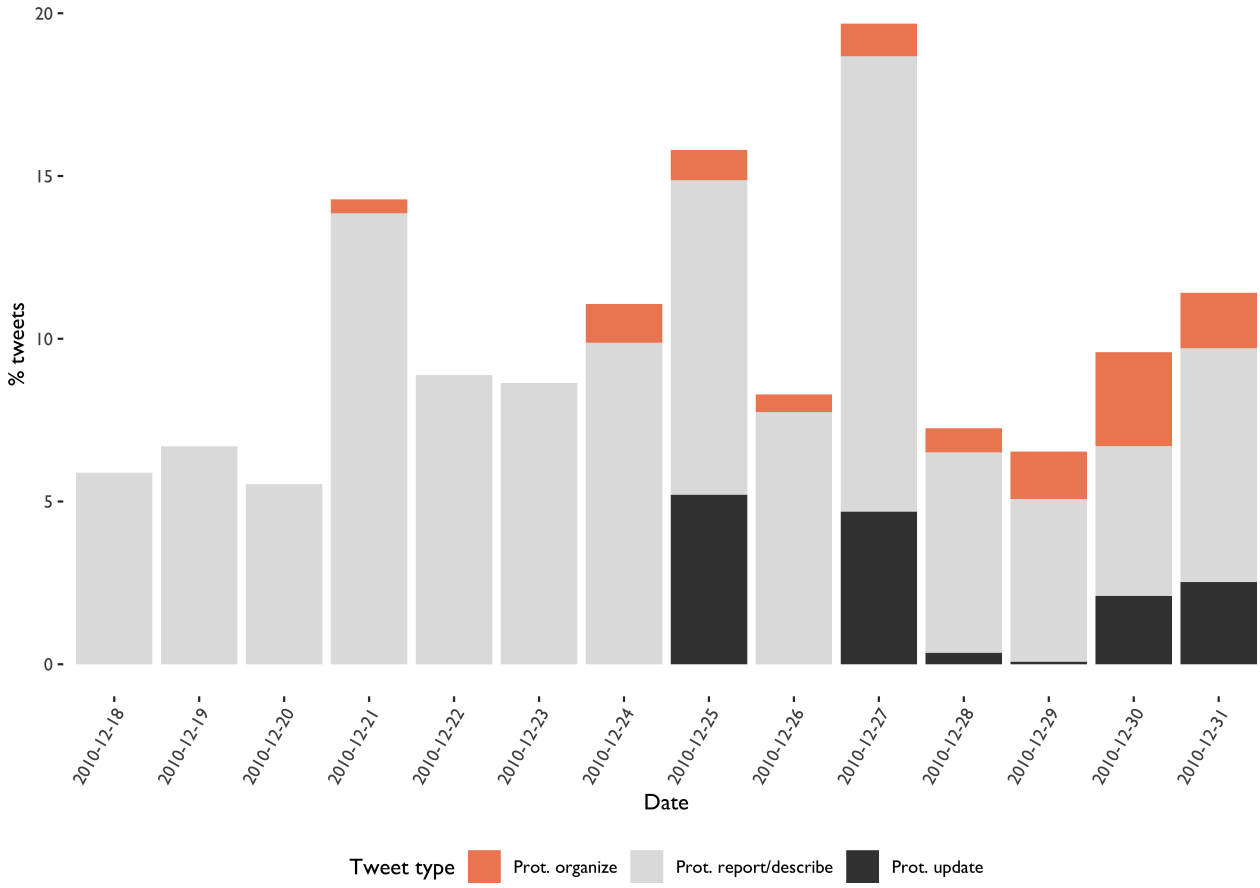


Figure 4: Tweet content by protest code category, 2010-18-12–2010-31-12.

5.2 Interview testimony

If most online activity involved the simple dissemination of information, how then did individuals make the decision to protest? Put otherwise, what links online information exposure to offline protest?

Internet penetration in Tunisia in 2011, it is important to stress, remained low. According to Wave II of the Arab Barometer Survey, conducted in September–October 2011, only 17% of Tunisians were users of the Internet "daily or almost daily." Of those who participated in the first two weeks of the uprising, just 27% were daily users.[32] A majority of participants,

[32] "Daily" refers henceforth to respondents reporting "daily or almost daily" use. Of those who reported participating at any stage of the uprising, this percentage is only slightly higher at 34%.

in other words, bear little resemblance to the archetypical, "networked," online activists who constitute the focus of much existing scholarship (e.g., Howard and Hussain 2011; Tufekci and Wilson 2012; Aman and Jayroe 2013; Tufekci 2017; Breuer et al. 2015). What, then, were the spaces inhabited by, and activities of, these participants? And was the Internet orthogonal to their participation decisions?

To investigate the mechanisms linking online information and decisions to protest, I conducted a set of over forty interviews in the spring of 2017 and 2019. Interviews were with a diverse range of participants, including former members of student protest movements, trade unionists, unaffiliated (former) school students, and members of the one semi-legal opposition party—the Parti démocrate progressiste (PDP). Interviewees were enrolled using a snowball sampling procedure, exploiting multiple entry points, and took place in Sfax, Sidi Bouzid, and Tunis—three regions that saw significant protest at different stages of the Revolution.[33]

In the absence of Internet access at home, the majority of interviewees in Sidi Bouzid—the region of the Tunisian interior where protest first began on December 17, 2010—would frequent Internet cafés, or *Publinets*.[34] Publinets were state-subsidized, but privately owned, Internet access points. The first Publinets began to appear in 1998 and were aimed at providing affordable Internet access to Tunisians (see Ben Sassi 2004). Inequalities in access nonetheless remained and coastal regions were disproportionate recipients of these new ICTs (Ben Hassine 2009). Many such "cybercafés" were not cafés per se but small shopfronts

[33]Interviews were variously conducted in Arabic, French or English and were semi-structured in format. Most interviews were recorded (and subsequently transcribed in full) unless informants desired otherwise. Names have been changed to preserve anonymity. Translations are all my own. See Appendix for further details.

[34]This insight tallies with previous ethnographic work (Lecomte 2011).

or backrooms where young, principally male, Tunisians would go to play video games and socialize:

> "there were Internet cafés in every hood... And also in the places they'd gather to play Playstation. It was a space for the youth... They don't have a special name—not Publinets—they're Playstation stores that they'd go to. It's not formal, not even legal. They were the places we'd go to play Fifa or Pes [two soccer games]." (interview Ayoub, March 2017)



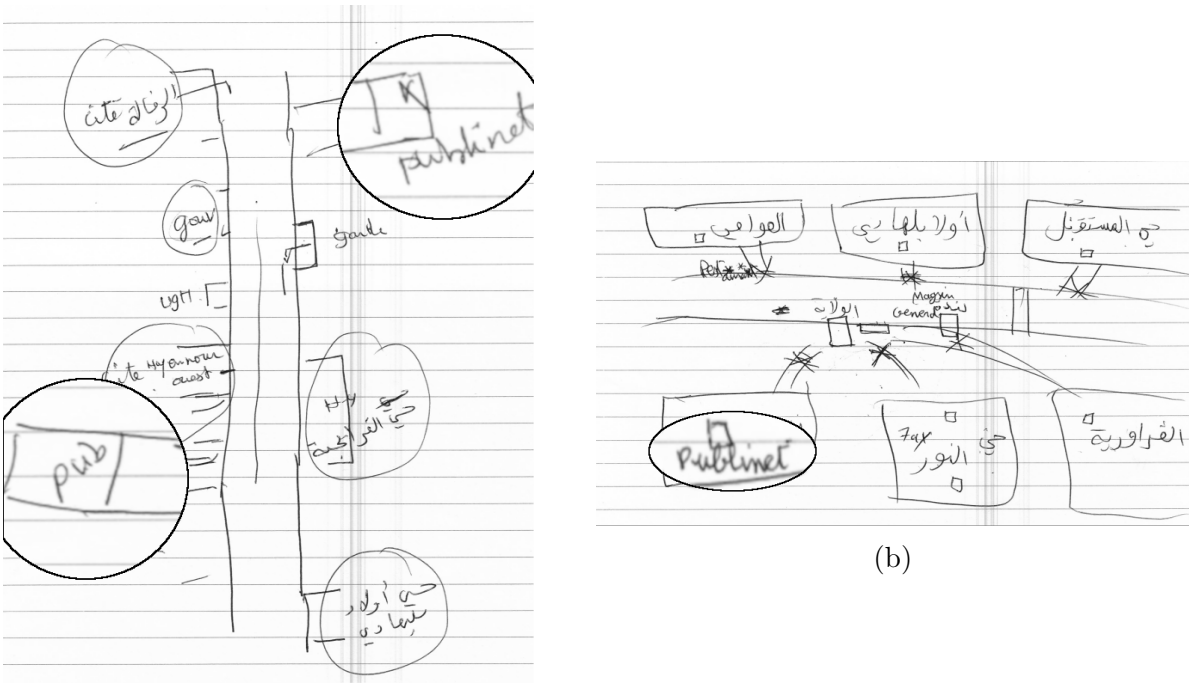
(a) Sidi Bouzid (b) Tunis

Figure 5: Publinets in Sidi Bouzid and Tunis. Source: author. Taken: March 2017

To gain some insight into the spatialities of protest observed in Sidi Bouzid, I asked interviewees to draw maps of protest sites, as well as significant locations in the immediate vicinity. Publinets were mentioned frequently during testimony and, on several occasions, interviewees opted to add reference markers to these sites on the maps (Figure 6).[35]

The circulation of information deriving from Sidi Bouzid took place "almost entirely in Publinets" (interview Lilia, April 2019). What was sent and received at these locations? Here, testimony corroborates our findings above: in the main the Internet was used as a

[35]Inspiration for this technique was taken from Petersen (2001)



(a) (b)

Figure 6: Maps drawn by interviewees in Sidi Bouzid, spring 2017. Publinet references zoomed.

means to publish or view protest information in the form of photos, videos, and reports. Live updating of protest events was not an option for inhabitants of Sidi Bouzid—few owned smartphones and cellular Internet speeds were insufficient for the uploading of content via handheld devices. Attesting to the relative paucity of online information at the onset of mobilization, interviewees were able even to tell me the name of the individual who uploaded the first video of protests in Sidi Bouzid (interview Beji, April 2019; interview Salah, April 2019). The small quantity of online content that was uploaded would often be published without comment in a bid to avoid censorship or potential repression (Lecomte 2011). Participants would use fake account names, too, publishing and viewing content either in Publinets owned by trusted familiars or, alternatively, stowing themselves in corner seats to avoid the gaze of informer proprietors (interview Lilia, April 2019; interview Salah, April

2019).

It was often in the evening, in the aftermath of protests, that individuals visited Publinets to upload photos and videos (interview Lilia, March 2017; interview Slim, March 2017). Slim would recall buying a camera-equipped cellphone on December 24, a week after the first protests, in order to begin documenting events himself: "During this period Facebook was the real media... We were in a war against the [national] media" (interview, March 2017). Rather than coordinating protest through, for example, Facebook chat, individuals were more prone to correct the record and chronicle events via Facebook news feeds and dedicated pages (interview Alaa, March 2019; interview Ayoub, March 2017). In other words, Facebook served principally as an alternative media channel, and tool of information.

The perceived horizons of this information are noteworthy. "You can write two or three words—there's a march in Sidi Bouzid. And you've got friends in Kasserine, Gafsa, Sfax who see that", Slim recalled, naming three governorates immediately neighbouring his own (interview, March 2017). Recalling how she used Facebook during the uprising, Lilia suggested something similar: "when I exchanged information it was with people I knew. I mean when I put something on my [Facebook] wall it was for everyone. But really the contact was between us in Sidi Bouzid, and in Gafsa and Kasserine" (interview, March 2019). If information exchange was regionally circumscribed, information also held distinctly regional significance. The Tunisian interior has a shared history of both underdevelopment and anti-colonial resistance (Hibou 2011; Jdey 2012); a defining cleavage relative to eastern coastal regions. Questioned on why they believed protest spread in the way it did, interviewees were quick to mention this. The "fiercest fighters" against French rule were from interior regions, Hamza said, and this history was taught at schools (interview, March 2019). In March, 2010,

another street vendor—Abdesslam Trimech—set himself alight in an act of protest in the coastal town of Monastir. His act, almost identical to that of Mohamed Bouazizi in Sidi Bouzid nine months later, sparked no wider protest. Asked their opinion why, interviewees were definitive: "the two regions [Sidi Bouzid and Monastir] are incomparable." (interview Ali and Ismail, March 2017).

Online action, then, was dedicated to reportage more than it was coordination, and this information had regional resonance. How, then, did protesters coordinate their action? Initial protests, it is worth recalling, were small. Fearing repression, an already committed core would exchange information via telephone, while some chose to come to central Sidi Bouzid from the nearby town of Menzel Bouzaienne (interview Mehdi, March 2017; interview Lilia, March 2019). Few used their real names online. Despite the affordances of online media, then, information exchange remained localized, and relied on pre-existing offline networks. Facebook groups mentioned by interviewees were also limited in their geographical reach; in Sidi Bouzid a group named "The Winter of Anger in Sidi Bouzid" counted among its hundred "Friends" mainly known associates of its founder (interview Slim, March 2017). In Sfax, a neighbouring region that saw protest later on in the uprising, students used their school Facebook groups to exchange information (interview Alaa, March 2019). Discussions and coordination of violent protest were strictly offline; oppositionists in Sidi Bouzid would speak in person, and in secret, to young men from surrounding popular quarters to plan these actions (interview Slim, March 2017). Alaa, at the time of the Revolution a high-school student in Sfax, explicitly played down the idea of online coordination: "Mostly it was in-person interaction," he remarked, echoing the recollections of another Sidi Bouzid resident when asked whether Facebook was used for organization:

> "No, [they organized] from the street... It's not like they gathered in a room and [mimics whiteboard] "you do that, you do that," like a general. It's not like that... They'd be sitting on the street like always and see people fighting the police and they'd think, let's fight them together. It was very natural. Very natural." (interview Ayoub , March 2017)

Publinets were nonetheless spaces where young men could gather or find refuge. Having suffered a double leg fracture at the hands of the police, Salah recalled finding safety in a Publinet owned by his friend in Sidi Bouzid where he would continue to watch videos of ongoing protests (interview, March 2019). The same young men who coordinated in violent protest would go to Publinets at night to publish information of their actions online:

> "It became a sort of ritual. Every night, at around 7pm, they would meet up... And here the Publinets were important too. There were lots of these... The young men would go in and then close the shutters to protect them and allow them to pass on information." (interview Lilia, March 2017)

Publinets afforded places of refuge, then, especially at night. But here the disjuncture between online and offline action is thrown into plainest relief. While online media was a tool for broadcasting and receiving information, it was plainly not a tool of coordination. Instead, coordination occurred most often in the context of contention and everyday interaction with nearby associates. Videos and photos were certainly viewed online, but meaningful discussion of their significance was conducted in person. Such discussions function as "occasions for deciding"—local arenas in which individuals are able to signal their own willingness to participate (Oliver 1989; Myers 2000; Biggs 2005). Thus, even if spurred by online media,

signals of willigness remained an offline activity. Physical copresence, in other words, long cited as fundamental to protest and social movements (Diani 2000, cf. Earl and Kimport 2011), remains a key constituent of coordination in collective action, and of the parochialism of much online action.

While theoretically translocal in reach, information also remained locally resonant. This is the second mechanism underpinning the parochial logics described above, and one again familiar to scholars of social movements—the "attribution of similarity" (McAdam and Rucht 1993; McAdam et al. 2001b). The salience and meaning of protest are "culturally constructed" (Biggs, 2005, 1690). And, crucially, these cultural constructs have geographical dimensions: social similarity is often geographically clustered (Braun and Koopmans 2010). In order that news of protest be perceived as relevant to a given population, its meaning, however derived, must resonate with a given population. In Tunisia, at the onset of the uprising at least, a shared history of resistance and common experience of underdevelopment provided the resonant rubric for mobilization.

6 Conclusion

While considerable attention has been devoted to the dynamics of online activity (e.g., Barberá et al. 2015; Kharroub and Bas 2016; Steinert-Threlkeld 2017; Freelon et al. 2018; LeFebvre and Armstrong 2018; Casas and Williams 2019), almost none of this scholarship has tried or been able plausibly to connect these dynamics to "real-world behavior" (Larson et al. 2019). The lack of granular information on actually observed protest has likely exacerbated this (albeit understandable) emphasis on the new affordances of ICTs.

By foregrounding the "tech-savvy", and spectacular episodes of mass mobilization, we fail to appreciate what is most remarkable for being unremarkable in online action.[36] The overhwelming majority of protest participants in the Tunisian Revolution were not daily Internet users. These were not, in other words, "networked" (Bennett and Segerberg 2013) activists inhabiting "thoroughly wired" (Howard and Hussain 2011) social spaces, and a digital elite was not responsible for "form[ing] the networks that initiated, coordinated, and sustained successful campaigns of civil disobedience" (Howard and Hussain 2011, 41). Rather, the activism witnessed during the initiating phases of the Tunisian Revolutiion relied on routine congregation in offline spaces, was conducted by non-elites, and was profoundly shaped by locally bounded social geographies.

Most importantly, a focus on moments of mass mobilization, the new affordances of online tools, and the activities of a small digital elite misses what is sociologically scaleable in the existing literature, just as it misses how already familiar mechanisms may inhere in online processes as well as offline. These insights are of consequence for understanding how contemporary episodes of mass mobilization will unfold. The study of that which remains should, then, be at least as worthy of study as that which is lost. Just as we have come to appreciate how "liberation technologies" might also function as tools of repression (Tucker et al. 2017), we must also appreciate how the local might continue to shape and constrain the translocal reach of online action.

[36] Schradie (2018) argues similarly that a focus on the "extraordinary" in online action neglects the class dimensions of such activism.

Appendix 3

A3.1 Event data sources

While the majority of protest event analyses derive their data from newspaper reports, this was not possible during for the twenty-nine day revolutionary uprising in Tunisia where a media blackout aimed specifically at stymieing the flow of information. I overcome this obstacle by triangulating multiple alternative sources of information. I made use first of Facebook pages, two of which were already in operation before the uprising, and two of which were created for the specific purpose of posting news of protests. The names and details of these pages are below. The pages were archived in PDF format, retaining the link structure, thereby enabling the manual coding of protest events, photos, and videos from each of them. These sources were then supplemented with multiple further sources of information, including national newspapers, international newspapers, a post-revolutionary investigatory commission, an archive of protest reports from the dissident blog *Nawaat*, as well as the *Archive Numérique de la Révolution*—a digital archive at the Tunisian National Archives devoted to the collection and archiving of photos and videos from the period of the uprising. The groups used, as well as further sources used for constructing the event catalogue for the revolutionary period, are listed below.

Tunisia event data sources for revolutionary period (17/12/2010-14/01/2011)

Facebook

- شعب تونس يحرق في روحو يا سيادة الرئيس *Chaab Tunis Yahriq fi Ruhu ya Siyyadat al-Ra'is* (Mr. President, the People of Tunisia are On Fire (PTON)). This page was set up upon the outbreak of protests, as the title of the group suggests. It went through six iterations as it was continually hijacked by unknown cyber attackers, likely linked to the Ben Ali regime.[37] When hijacked, the founders would set up a new page by the same title but with the number of the version of the group appended. The pages contained information on protest for everyday of the uprising with the exception of the period 02/01/11-08/01/11 when the page was down. Protest reports would often report on the type of protest (e.g., march, occupation, demonstration), include some mention of size (e.g. 'a group of', 'large', 'huge'), and give some mention of source (most often 'union sources'). When the report cited 'unconfirmed reports', the report was not included in the event catalogue. In total these pages provided information on 193 protest events, 140 of which were corroborated with at least one other source. Out of the 193 protest events recorded from this source, 94 could be checked against video evidence. Figure A7gives an example of a video protest report posted to this page.

- وكالة أنباء تحرّكات الشارع التونسي *Wikalat Anba' Taharrukat al-Shari'a al-Tunisi* (News Agency of the Tunisian Street (NATS)). This page was also set up upon the outbreak of protests in Sidi Bouzid and protest reports followed a similar formula to the above

[37] An interview with the founders of the page can be accessed here: `http://www.thedailybeast.com/articles/2011/01/15/tunisa-protests-the-facebook-revolution.html`, last accessed: 19/03/2018.



Figure A7: Typical video protest report from PTON. Text underneath reads: 31/12/10: Er-Rouhia—Siliana Governorate. Subsequent lines detail chants heard during the protest, including: "Don't be a coward, go out onto the street!"; "Work, freedom, national dignity!"; "Work is a right, you gang of thieves!", "No to tyranny and corrupt government!".

page. It has two iterations, after the first was also hijacked. The pages contained information on protest for the period 02/01/11-14/01/11. In total, this page provided information on 195 protest events, of which 106 could be matched with a secondary source. Out of the 195 protest events recorded from this source, 71 could be checked against video evidence. Figure A8 gives an example of a typical protest report from this page.

- ما عندي مانقلك *Ma 'Ayndi Mankolek* (I Have Nothing to Say to You). This page was already in existence prior to the revolution. It was a forum for dissident opinion and took positions against, for example, online censorship. This page was active for the



Figure A8: Typical protest report from NATS. Text reads: "Kasserine, today 06/01/2011: A large march of students, teachers, unemployed and unemployed graduates left this morning from the UGTT offices, circling the city before stopping outside the RCD office at which point the chant "Down with the Dostour Party, down with the executioner of people" was heard alongside other chants calling for work, freedom, and national dignity. Lawyers also joined in the protest as the march went past the court building, at which point the police forcefully intervened. We will keep you updated".

entire period of the uprising. In total, this page provided information on 33 protest events, 29 of which could be matched with a secondary source, and 18 of which could be checked against video evidence.

- ***TAKRIZ*** (Ball-Breaker). This page was already in existence prior to the revolution and ran alongside the now-defunct website *takriz.com*, founded in 1998. It was a forum for dissident opinion, anti-censorship activism, and often irreverent commentary on Tunisian affairs. Upon the outbreak of the revolution, its administrators began posting videos and reports of protests, encouraging their members to go out and protest at the same time. Unfortunately, the page was not available for the period 02/1/11-14/01/11. In total, this provided information on 42 protest events, of which 30 could be verified against a secondary source.

Radio/National News

- راديو كلمة تونس *Radio Kalima Tunis* (Word of Tunisia Radio). Kalima Tunis is a radio station set up in 2008 by journalist and human rights campaigner Sihem Bensedrine, and Omar Mestiri. The radio station operated from France after being banned in 2009, but still had journalists on the ground. It published multiple dispatches daily on the unfolding of protest events that have been archived by online news aggregator `turess.com`. In total, Kalima Tunis provided information on 342 protest events, of which 199 could corroborated with a secondary source.

- الشروق *Al Chourouk* (Sunrise). Pro-regime newspaper that only began to report on protest in the closing stages of the uprising. Nonetheless, it provided information on 86 protest events, of which 44 could be checked against a secondary source. Copies of these reports were obtained from `turess.com`. These articles were also checked against archived paper copies of the newspaper in the Centre de Documentation Nationale archive in Tunisia in order to check for any omissions on the `turess.com` website. No significant omissions were found.

Other sources

- Two weekly newspapers of the few oppositional parties nominally authorized in Tunisia, *Attariq Al Jadid* (of the centre-left Ettajdid party), and *Al Mawkif* (of the leftist Parti démocrate progressiste), as well as one, *Echaab* (of the national trade union federation the UGTT), were sought out from the Centre de Documentation Nationale and the UGTT's own archives to provide further information with which to cross-check the

Facebook protest reports, however these provided only limited information on protest occurrence.

Nawaat Archive

- Over the course of the revolution, *Nawaat*, a dissident blog established in 2004, reported on protest events. Most of these reports became unavailable after the shutdown of blogging host platform `posterous.com`. Using the Wayback Machine Internet Archive, however, I was able to retrieve this content. These yielded reports on 140 protest events, 127 of which could be triangulated with other sources.

Digital Archive of the Revolution

- A cache of videos and photos, collected by Jean-Marc Salmon in conjunction with archivists at the Tunisian National Archives, was handed over to the National Archives in Tunis in March 2017. Reporting on the collection can be accessed here: `https://tinyurl.com/ANRtiny`. The collection contains around 1000 photos and 800 videos. Researchers focused their efforts on Greater Tunis, Kasserine, and Sidi Bouzid meaning that documents from other regions may have yet to find their way into the archive. Nonetheless, the archive contains documents for each of Tunisia's twenty-four governorates, and nearly all photos and videos are datestamped. I searched through each date for every district in every governorate over the period of the revolution and triangulated protest reports with the event catalogue, updating e.g., protest sizes according to photo and video availability, and adding new events when omitted. The archive yielded reports on 63 protest events that could reliably be located in a delegation, and

40 of these could be triangulated with other sources.

Videos and Photos

- Videos. Videos were often posted to the Facebook groups listed above accompanied with reports on the protest itself. In total 222 videos were found, all of which were matched with a protest report. Videos were nearly all accompanied by a date in the comments under the video. Alternatively, videos would be accompanied by a comment such as "Situation today in [name of town/city]", meaning the date could then be assumed as the date of the posting itself.

- Photos. Photos were also often posted to the Facebook groups listed above accompanied with reports on the protest itself. In total 25 photos were used and matched with protest reports. Photos would also either be accompanied by a date or the date of the event could be deduced from comments in the post e.g. "Photos from protest yesterday in [name of town/city]".

International News

- International news sources were also used when available. Two of these took the form of evening news reports, archived versions of which were posted on the Facebook pages described above. The first of these is *Al Jazeera: The Maghreb Harvest* (الجزيرة: الحصاد المغربي). This was a daily news round up of events in Arab North Africa that, given the ongoing protests in Tunisia, focused primarily on Tunisian affairs over the twenty-nine days of the uprising. *France 24* (24 فرانس) also provided a daily round of news in North Africa, with a particular focus on Tunisia over the twenty-nine days

of the revolt. News articles from Arabic-, French-, and English-language news outlets were also archived when posted on the Facebook groups listed above. These included: *BBC News*, *Agence France Presse*, *Le Point*, *Le Monde*, *Reuters Arabic*, *Agence Tunis Afrique Presse*, *Business News Tunisia*. Further articles from international news media were extracted from Google News. These were then all matched against existing protest reports. In total, these sources together provided information on 53 separate protest events, all of which were verified against a secondary source.

Bouderbala Commission

- The full name of the investigatory commission, now commonly referred to after its Head, Taoufik Bouderbala, is the "Commission nationale d'investigation sur les abus enregistrés au cours de la période allant du 17 décembre jusqu'à l'accomplissement de son objet". The full report is available online here: `http://www.leaders.com.tn/uploads/FCK_files/Rapport%20Bouderbala.pdf` In this first report, the Commission looked into abuses committed from 17 December 2010 up to the first elections on 23 October 2011. Bouderbala is himself a lawyer and Honourary President of the Tunisian Human Rights League (Ligue tunisienne des droits de l'homme). The report is itself the subject of some scrutiny as it is perceived not to have gone far enough in identifying individuals responsible for the deaths of protesters. Further, the list of deaths published was described as "provisional" and the Commission has yet to publish its final version. While the existing list may only be provisional, and it does not identify police responsible, the report is nonetheless comprehensive (running to over 1,000 pages) and provides a rich source of information for the purposes of this

study. While reports of injuries contain sometimes sparse information, the Bouderbala Commission verified deaths with visits to the homes of the bereaved and checked reports against available medical records, thus providing a confident estimate of levels of repression witnessed during protests. The reports included the circumstances of the death, the date of the incident, and the institutional identity of the perpetrator. Only those that stated explicitly that the individual was killed at the hands of state security (police, national guard or army), or was killed during a protest, were included for the analysis. The report also contains information on the locations of protest, but limits its reports to the closing stages of the revolution. The information contained therein was nonetheless checked against the event data for purposes of further corroboration.

A3.2 Event catalogue codebook

The variables, and their codings, for the event catalogue are listed below. Note that not all variables are used in the abaove analysis. They are listed here for completeness. Relevant variables for the present article include: *date*; *governorate*; *delegation*; *ppart*; *noofkilled*; *source*; *facebook*.

1. Date (*date*): The date of the protest occurring. This could be deduced from the report itself and the date attached to the post in Facebook, for example, or the date of the article posted on the website of the Radio Station or newspaper. In one or two cases, protests were reported as having been ongoing for X number of days. In such cases they were backcoded to the first day of the protest based on the length of time it had been reported as ongoing.

2. Governorate (*governorate*): The Governorate (one of 24) in which the protest took place. These would normally be reported in the protest reports themselves. Otherwise, reports would include reference to the specific town or area in which the protest took place, from which one could deduce the Governorate from the list of delegations in each Governorate or by Google searching the name of the town/city. There were no cases in which the location of the protest could not be located in its Governorate. On a few cases, reports would refer to e.g. "protest across [name of Governorate]". In such cases, three protest events within the Governorate were coded.x

3. Delegation (*delegation*): The Delegation (one of 264) in which the protest took place. Normally the delegation could be deduced by Google searching the specific location

of the protest (e.g. name of school, *Wilaya* building, UGTT building) or would be specifically reported. Only 66 protest reports could not be located in their respective delegation and these were dropped from the analysis.

4. Protest participation (*ppart*): Estimated participation in the protest. Here, I employed the coding convention used in the European Protest and Coercion Dataset (Francisco 2000). Protest size is often reported in factors of ten—e.g., "tens", "hundreds", "thousands". In such cases, these are coded as "31", "301", and "3001" respectively. Protests would occasionally also be described as "large" or "huge", in such cases, participation was increased by a factor of ten. When no further information was provided "demonstration/protest" (manifestation/protestation or مظاهرة/احتجاج) was coded as "301", as was march (marche or مسيرة) and strike (grève or إضراب), while a regional general strike (grève régionale or إضراب عام محلي) would be coded as 3001 if in just one delegation and 30,001 if in an entire governorate. Blockade (bloquer la route or قطع الطريق) and attack (attaque or مهاجمة) would be coded as 31. Occupations (occupation or اعتصام) would be coded as 301 when outside and 31 when occupying the inside e.g. of a building. Sit-ins (sit-in or وقفة احتجاجية) would be coded as 31. For the purposes of the present paper, participation is not used.

5. Repertoire (*repert*): The type of protest. This was normally contained within the protest report itself or could be identified in the videos or photos of the protests. Repertoire could be one of "demonstration" (manifestation/protestation or مظاهرة/احتجاج); "march" (marche or مسيرة); "strike" strike (grève or إضراب); "general strike" (grève régionale or إضراب عام محلي); "blockade" (bloquer la route or قطع الطريق); attack (at-

taque or مهاجمة); "occupation" (occupation or اعتصام) or "sit-in" (sit-in or وقفة احتجاجية).

6. Secondary repertoire (*reper2*): The secondary repertoire of the protest. Sometimes, protests or sit-ins would e.g. break out into marches along the surrounding streets. In such cases, a secondary repertoire would be recorded.

7. Protest location (*protlocation*): The specific location of the protest e.g. outside Wilayat building or UGTT offices.

8. Starting location (*protstartlocation*): A general identifier for the start location. One of "city centre"; "govt building" (e.g. any official building such as police station, local government building, RCD (ruling party) offices); "hospital"; "main road"; "public transport" (e.g. railway/bus station); "residential street"; "saha" (square); "school" or "university".

9. Moving to (*movingto*): Where the protest moved to, if it did move.

10. End location (*protendlocation*): General identifier for where the protest ended, from among those listed in variable #8.

11. Organizer (*organizer*): Organizer of the protest. This was coded for both those specifically identified as organizing the protest e.g. "unionists" normally from the national trade union federation the UGTT, or it was coded for the principal participants e.g. "teachers" or "students".

12. Repression (*repression*): Binary variable recording whether the protest met any form of repression. Repression could take the form of "crowd control" (e.g. when police

reported to prevent protesters from moving off into a march or prevented from protesting, including use of batons); "tear gas" (gaz lacrymogène or غاز مسيل للدموع); "live ammunition" (tir à balle réelle or طلق ناري).

13. Repressive agent (*repressiveagent*): The actor responsible for repression. Most frequently one of "police" (la police or الشرطة); "national guard" (la garde nationale or الحرس الوطني); or "army" (l'armée or الجيش). On one occasion, protesters were attacked by unknown assailants and on another members of Ben Ali's ruling RCD party were identified as the assailants. When the repressive agent was not identified, the cell was left blank.

14. Killed (*killed*). Binary variable recording whether anyone was identified as having been killed at the protest. It should be noted that for the present paper, the data provided by the Bouderbala Commission was used in place of data on killings provided by newspaper reports.

15. Number killed (*noofkilled*): The number killed during the protest. Ocassionally reports of numbers killed would differ. In these instances, I opted for the more conservative report. In any case, as above, the data provided by the Bouderbala Commission is used in place of the data provided by protest reports.

16. Arrested (*arrested*): Binary variable recording whether anyone was identified as having been arrested at the protest.

17. Number arrested (*noofarrested*): The number arrested during the protest. Ocassionally reports of numbers arrested would differ. In such instances, I opted for the more

conservative report. In some cases, reports would be of "large numbers" arrested, which was coded as 11, while "several" was coded as 3.

18. Violence (*violence*): Binary variable recording whether violent forms of protest took place. This differs from reports of repression. Repression assumes no response from protesters. In numerous cases, however, reports would be of "clashes" (affrontement or مواجهة) with police. In such cases, protesters fought back. This was also the case when there was a report of stones being thrown (lancer des pierres or رشق بالحجارة) or police stations being set on fire (incendier or احراق).

19. Source (*source*): Source of the protest report (e.g., names of Facebook group, newspaper, radio station etc.).

20. Facebook (*facebook*): Binary variable coded 1 if one of sources includes a Facebook page.

A3.3 Other connectivity data sources

Construction of Internet penetration and cellphone network availability measures

- To construct the measures used in Figure 1, I used first the measure of Internet use taken from the 2014 Census conducted in Tunisia (see `http://census.ins.tn/fr/resultats`). This is measured as the percentage of households with an Internet connection at the delegation level. This measure evidently suffers from having been measured several years after the 2011 Revolution. A governorate-level measure of the same variable is available in a 2010 Labour Survey in Tunisia (*Enquête nationale sur l'emploi 2010*), available here: `http://www.ins.tn/fr/publication/enqu%C3%AAte-nationale-sur-l%E2%80%99emploi-2010`. By comparing similar governorate-level measures in 2014, I impute delegation-level values for 2010 by first denominating the delegation-level 2014 measures by the 2014 governorate-level measures (to calculate the scaling factor for each relative to the governorate average) and then multiplying this by the 2010 governorate-level measure. This was then converted to quantiles for the purposes of mapping.

- The construction of the EDGE/3G coverage % coverage map in Figure A9 required the use of GIS softwares. I used QGIS 2.18 to overlay a map of the Orange cellphone network from July 2010 on a map of Tunisia delegation boundaries. The map was retrieved originally from `https://www.leaders.com.tn/article/2230-orange-60-000-abonnes-des-le-p` last accessed: August 2019 and is displayed in Figure A10. EDGE was the name given to the cellular network 'generation' between 2G and 3G, and is sometimes referred to

as 2.75G (see https://en.wikipedia.org/wiki/2G). EDGE has a maximum transfer speed considerably higher than 2G. The measure of cellphone network penetration was then constructed as the percentage of a district covered by yellow or orange pixels. An example of a stage in the process of its construction is displayed in Figure A9a. This was then converted to quantiles for the purposes of mapping. Evidently, this is just one cellphone network but it is broadly representative of cellphone network availability across all networks at this time. 3G was yet to be introduced in most parts of Tunisis, as detailed in this article: https://www.babnet.net/rttdetail-37493.asp, last accessed: August 2019. The maps in Figure A11 give an idea of the growth of the 3G network in the aftermath of the Revolution. This expansion took place in the months after the Revolution, and 3G keys (that substituted for fixed ADSL connections) started being sold in the second half of 2011 (see e.g., http://www.kapitalis.com/conso/5270-les-tarifs-de-la-cle-3g-de-tunisie-telecom.html, last accessed: August 2019). By July 2011, 77% of the population had access to 3G, and the network was available in 21 of Tunisia's twenty-four governorates, compared to eight at the same time in 2010 (see https://www.babnet.net/rttdetail-37493.asp, last accessed: August 2019).

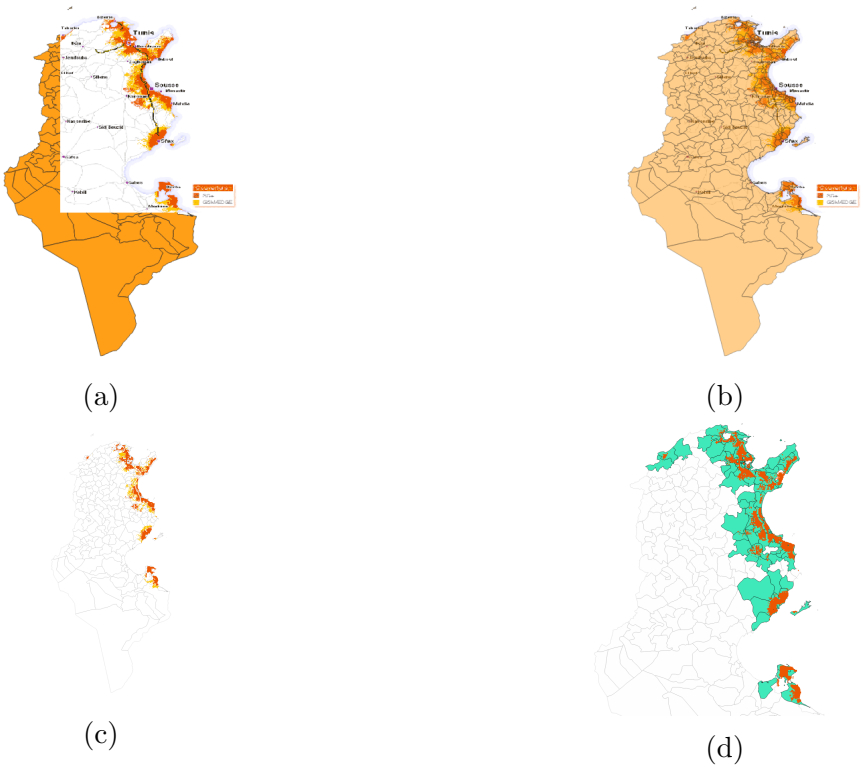


Figure A9: Construction stages of cellphone penetration measure in QGIS

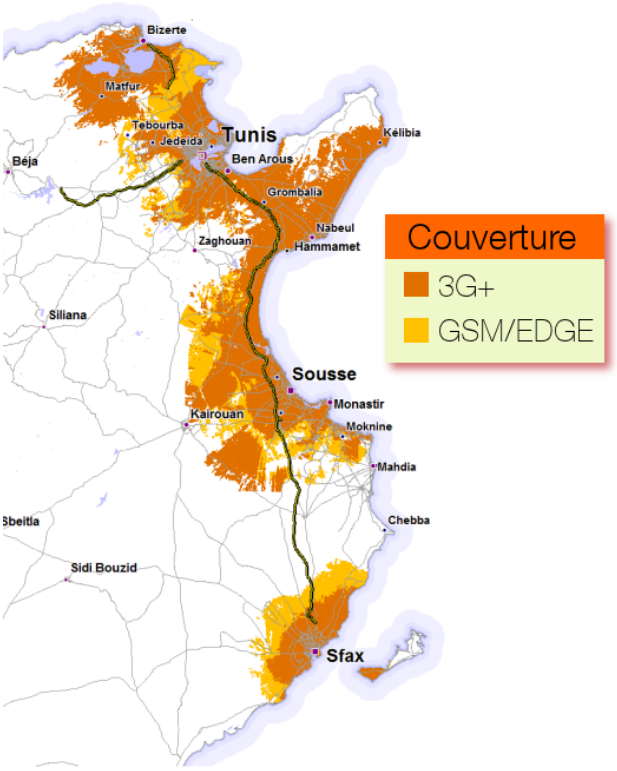
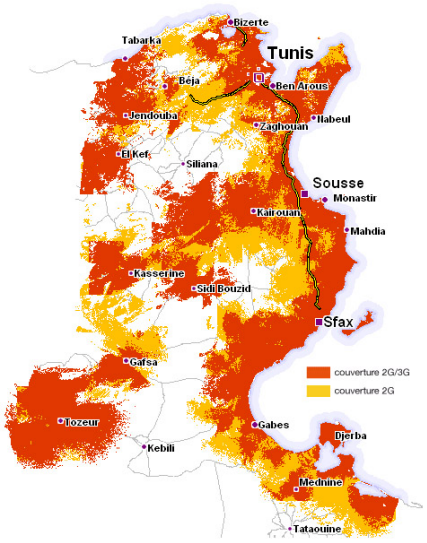
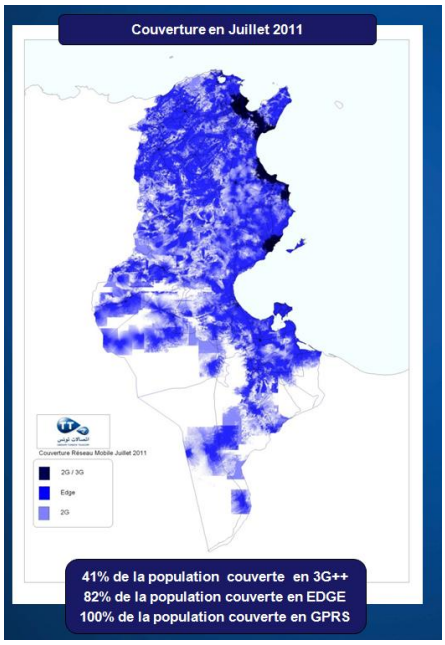


Figure A10: Original map of Orange network cellphone coverage, July 2010.



(a) Orange



(b) Tunisie Telecom

Figure A11: Maps of 3G/2G coverage July, 2011

A3.4 Details of events and sources

Sources for EH dataset

Table A4: Sources of first event-days by delegation 17/12/2011–14/01/2011

Date	Delegation	Governorate	Source(s)	# Source(s)
17/12/2010	Sidi Bouzid Ouest	Sidi Bouzid	France24Video, KalimaTunis, MAMN, PTON	4
20/12/2010	Meknassy	Sidi Bouzid	KalimaTunis, PTON, Video	3
20/12/2010	Menzel Bouzaïenne	Sidi Bouzid	KalimaTunis, PTON, Video	3
21/12/2010	Jilma	Sidi Bouzid	KalimaTunis, MAMN, Nawaat, NawaatVideo, PTON, Video	6
21/12/2010	Regueb	Sidi Bouzid	AJVideo, KalimaTunis, Nawaat, NawaatVideo, PTON, Takriz, Video	7
21/12/2010	Sidi Ali Ben Aoûn	Sidi Bouzid	KalimaTunis, PTON, Video	3
22/12/2010	Kasserine Nord	Kasserine	KalimaTunis	1
22/12/2010	Kasserine Nord	Kasserine	KalimaTunis	1
23/12/2010	Mezzouna	Sidi Bouzid	AJVideo, MAMN, Nawaat, NawaatVideo, PTON, Video	6
24/12/2010	Bizerte Nord	Bizerte	KalimaTunis, PTON, Video	3
24/12/2010	Kerkenah	Sfax	KalimaTunis, PTON, Takriz, Video	4
24/12/2010	Sousse Riadh	Sousse	Al-Wasat, Nawaat, Takriz, Video	4
25/12/2010	Bab El Bhar	Tunis	KalimaTunis, MAMN, Nawaat, NawaatVideo, PTON, ReutersAr, Takriz, Video	8
25/12/2010	Bir El Hafey	Sidi Bouzid	KalimaTunis, Nawaat, NawaatVideo, PTON	4
25/12/2010	Fernana	Jendouba	KalimaTunis	1
25/12/2010	Sbeitla	Kasserine	KalimaTunis, Nawaat	2
25/12/2010	Sbeitla	Kasserine	PTON	1
25/12/2010	Souk Jedid	Sidi Bouzid	KalimaTunis, PTON, Takriz	3
25/12/2010	Thala	Kasserine	KalimaTunis, Nawaat, PTON, Takriz	4
26/12/2010	Ben Guerdane	Medenine	KalimaTunis, PTON, Video	3
26/12/2010	Ben Guerdane	Medenine	PTON, Takriz, Video	3
26/12/2010	Cebalet Ouled Asker	Sidi Bouzid	KalimaTunis, PTON	2
26/12/2010	Djebeniana	Sfax	PTON	1
26/12/2010	Kairouan Sud	Kairouan	ANR, ANRVideo, KalimaTunis, MAMN, PTON, Takriz, Video	7
26/12/2010	Nabeul	Nabeul	KalimaTunis, PTON	2
26/12/2010	Sfax Ville	Sfax	KalimaTunis, Takriz	2
26/12/2010	Siliana Nord	Siliana	KalimaTunis, Nawaat, NawaatVideo, PTON, Takriz, Video	6
26/12/2010	Sousse Medina	Sousse	KalimaTunis	1
27/12/2010	Feriana	Kasserine	KalimaTunis, Nawaat, NawaatVideo	3
27/12/2010	Gafsa Sud	Gafsa	KalimaTunis	1
27/12/2010	Gafsa Sud	Gafsa	KalimaTunis, PTON, Takriz	3
27/12/2010	M'saken	Sousse	PTON	1
27/12/2010	Majel Bel Abbès	Kasserine	KalimaTunis	1
27/12/2010	Makthar	Siliana	Nawaat, NawaatVideo, PTON, Takriz, Video	5
27/12/2010	Medenine Sud	Medenine	Nawaat, NawaatVideo, PTON, Takriz, Video	5
27/12/2010	Oum El Araies	Gafsa	KalimaTunis, PTON, Takriz	3
27/12/2010	Redeyef	Gafsa	KalimaTunis, PTON, Takriz	3
27/12/2010	Skhira	Sfax	PTON	1
27/12/2010	Zarzis	Medenine	MAMN, Nawaat, NawaatVideo, Photo, PTON	5
28/12/2010	Bir ali Ben Kelifa	Sfax	ANR, ANRVideo, Takriz	3
28/12/2010	Fouchana	Ben Arous	KalimaTunis, Nawaat, NawaatVideo, PTON, Takriz, Video	6
28/12/2010	Kebeli Nord	Kebili	KalimaTunis	1
28/12/2010	Kef Est	El-Kef	AJNews, KalimaTunis, Nawaat, NawaatVideo, Photo, PTON, Takriz, Video	8
28/12/2010	La Medina	Tunis	PTON	1
28/12/2010	La Medina	Tunis	Chourouk, PTON	2

28/12/2010	La Medina	Tunis	AJNews, KalimaTunis, Nawaat, NawaatVideo, Photo, PTON, Takriz, Video	8
28/12/2010	Nefta	Tozeur	PTON	1
29/12/2010	Bourouis	Siliana	KalimaTunis, Takriz	2
29/12/2010	Jendouba	Jendouba	KalimaTunis, PTON, Video	3
29/12/2010	Jendouba	Jendouba	KalimaTunis	1
29/12/2010	Jendouba	Jendouba	KalimaTunis	1
29/12/2010	Jendouba	Jendouba	ANR, ANRVideo, KalimaTunis, Nawaat, NawaatVideo, Takriz	6
29/12/2010	Sned	Gafsa	KalimaTunis	1
30/12/2010	Chebba	Mahdia	PTON	1
30/12/2010	Chebba	Mahdia	ANR, ANRVideo	2
30/12/2010	Djerba Houmet Souk	Medenine	PTON, Video	2
30/12/2010	Djerba Houmet Souk	Medenine	KalimaTunis, Nawaat, NawaatVideo, PTON, Video	5
30/12/2010	Mahdia	Mahdia	KalimaTunis	1
30/12/2010	Mahdia	Mahdia	Nawaat, NawaatVideo, PTON, Video	4
30/12/2010	Monastir	Monastir	KalimaTunis, Takriz	2
30/12/2010	Sbikha	Kairouan	Nawaat	1
30/12/2010	Sfax Ouest	Sfax	PTON	1
30/12/2010	Sidi El Béchir	Tunis	Nawaat, PTON	2
31/12/2010	El Hamma	Gabes	Nawaat, NawaatVideo, PTON	3
31/12/2010	Er-Rouhia	Siliana	PTON, Video	2
31/12/2010	Grombalia	Nabeul	AFP, KalimaTunis, PTON	3
31/12/2010	Tozeur	Tozeur	KalimaTunis, PTON, Video	3
01/01/2011	El Krib		ANR, ANRVideo, Nawaat, NawaatVideo	4
01/01/2011	Zermadine	Monastir	KalimaTunis	1
03/01/2011	Belkhir	Gafsa	KalimaTunis	1
03/01/2011	Ezzouhour	Kasserine	NATS	1
03/01/2011	Gabes Medina	Gabes	KalimaTunis	1
03/01/2011	Gabes Medina	Gabes	KalimaTunis	1
03/01/2011	Mannouba	Mannouba	Nawaat, NawaatVideo	2
04/01/2011	Echrarda	Kairouan	KalimaTunis	1
04/01/2011	El Amra	Sfax	KalimaTunis, NATS	2
04/01/2011	El Hencha	Sfax	KalimaTunis, NATS	2
04/01/2011	El Ksar	Gafsa	NATS, Video	2
04/01/2011	Gabes Sud	Gabes	NATS, Video	2
04/01/2011	Ksar Helal	Monastir	NATS	1
04/01/2011	Sijoumi	Tunis	NATS	1
04/01/2011	Tataouine Nord	Tataouine	NATS, Nawaat, NawaatVideo	3
05/01/2011	Bab Souika	Tunis	NATS	1
05/01/2011	Ben Arous	Ben Arous	ANR, ANRVideo, Nawaat, NawaatVideo	4
05/01/2011	Foussana	Kasserine	AJVideo, KalimaTunis, NATS, Nawaat, NawaatVideo	5
05/01/2011	Menzel Chaker	Sfax	KalimaTunis	1
05/01/2011	Sousse Jawhara	Sousse	KalimaTunis, NATS	2
05/01/2011	Tajerouine	El-Kef	KalimaTunis, NATS	2
06/01/2011	Bou Salem	Jendouba	KalimaTunis	1
06/01/2011	Bouhajla	Kairouan	KalimaTunis	1
06/01/2011	El Ayoun	Kasserine	KalimaTunis, NATS	2
06/01/2011	El Mourouj	Ben Arous	KalimaTunis, NATS, Video	3
06/01/2011	Ghardimaou	Jendouba	KalimaTunis	1
06/01/2011	L'Ariana Ville	Ariana	KalimaTunis	1
06/01/2011	Nasrallah	Kairouan	KalimaTunis	1
06/01/2011	Souk El Ahed	Kebili	AJVideo, NATS	2
07/01/2011	Enfidha	Sousse	KalimaTunis	1
07/01/2011	Haffouz	Kairouan	KalimaTunis, Nawaat, NawaatVideo	3
07/01/2011	Kelibia	Nabeul	Nawaat, NawaatVideo	2
07/01/2011	Megrine	Ben Arous	Nawaat, NawaatVideo	2
07/01/2011	Thyna	Sfax	NATS	1
08/01/2011	Djerissa	El-Kef	KalimaTunis	1

08/01/2011	El Guetar	Gafsa	KalimaTunis	1
08/01/2011	El Menzah	Tunis	NATS	1
08/01/2011	Es-Sers	El-Kef	NATS	1
08/01/2011	Hammam Lif	Ben Arous	KalimaTunis	1
08/01/2011	Kesra	Siliana	KalimaTunis	1
08/01/2011	Ksibet El Mediouni	Monastir	KalimaTunis	1
09/01/2011	Bou Arada	Siliana	KalimaTunis	1
09/01/2011	Hidra	Kasserine	KalimaTunis	1
09/01/2011	Kef Ouest	El-Kef	NATS	1
10/01/2011	Béja Sud	Beja	Chourouk	1
10/01/2011	Béja Sud	Beja	KalimaTunis, NATS	2
10/01/2011	Carthage	Tunis	NATS	1
10/01/2011	Carthage	Tunis	NATS	1
10/01/2011	Carthage	Tunis	NATS	1
10/01/2011	Gaâfour	Siliana	Nawaat, NawaatVideo	2
10/01/2011	Hammam Sousse	Sousse	KalimaTunis	1
10/01/2011	Sakiet Eddaïer	Sfax	KalimaTunis	1
10/01/2011	Sakiet Eddaïer	Sfax	NATS	1
10/01/2011	Sakiet Ezzit	Sfax	NATS	1
10/01/2011	Tabarka	Jendouba	Nawaat, NawaatVideo	2
11/01/2011	Cité El Khadhra	Tunis	NATS	1
11/01/2011	Cité Ettadhamen	Ariana	NATS, Nawaat, NawaatVideo, Video	4
11/01/2011	Cité Ettadhamen	Ariana	ANR, ANRVideo, KalimaTunis, NATS, Nawaat, NawaatVideo, PTON	7
11/01/2011	Degach	Tozeur	Bouderbala, KalimaTunis, Nawaat	3
11/01/2011	Douar Hicher	Mannouba	NATS, PTON	2
11/01/2011	El Fahs	Zaghouan	NATS	1
11/01/2011	El Mnihla	Ariana	KalimaTunis, NATS	2
11/01/2011	El Omrane Supérieur	Tunis	NATS, PTON, Video	3
11/01/2011	Ettahrir	Tunis	KalimaTunis, NATS, PTON	3
11/01/2011	Ezzuhour	Tunis	Nawaat, NawaatVideo, PTON	3
11/01/2011	Le Bardo	Tunis	NATS	1
11/01/2011	Radès	Ben Arous	Nawaat, NawaatVideo, PTON, Video	4
12/01/2011	Bou Mhel El Bassatine	Ben Arous	PTON, Video	2
12/01/2011	Dar Châabane El Fehri	Nabeul	NATS, PTON, Video	3
12/01/2011	Douz Sud	Kebili	ANR, ANRVideo, Bouderbala, KalimaTunis, NATS, Nawaat, NawaatVideo, PTON, Video	9
12/01/2011	El Alia	Bizerte	Chourouk, Nawaat, NawaatVideo	3
12/01/2011	El Kabaria	Tunis	BusinessNews, NATS, Nawaat, NawaatVideo, PTON, Video	6
12/01/2011	El Kabaria	Tunis	BusinessNews, NATS, PTON, Video	4
12/01/2011	Hammam Chôtt	Ben Arous	PTON	1
12/01/2011	Hammamet	Nabeul	ANR, ANRVideo, Bouderbala, NATS, Nawaat, NawaatVideo, PTON, Video	8
12/01/2011	La Marsa	Tunis	NATS, Video	2
12/01/2011	Le Kram	Tunis	NATS, PTON, Video	3
12/01/2011	Mateur	Bizerte	Chourouk	1
12/01/2011	Menzel Bourguiba	Bizerte	ANR, ANRVideo, Bouderbala, Chourouk, Nawaat	5
12/01/2011	Menzel Djemil	Bizerte	Chourouk, Nawaat	2
12/01/2011	Menzel Djemil	Bizerte	Chourouk	1
12/01/2011	Mohamedia	Ben Arous	KalimaTunis, NATS	2
12/01/2011	Sidi Hassine	Tunis	KalimaTunis, NATS	2
12/01/2011	Soliman	Nabeul	PTON	1
13/01/2011	Beni khiar	Nabeul	Chourouk	1
13/01/2011	El Ouardia	Tunis	PTON	1
13/01/2011	El Ouardia	Tunis	KalimaTunis, PTON	2
13/01/2011	Korba	Nabeul	Chourouk	1
13/01/2011	La Goulette	Tunis	KalimaTunis, PTON	2
13/01/2011	La Nouvelle Medina	Ben Arous	KalimaTunis, PTON	2
13/01/2011	Menzel Temime	Nabeul	Chourouk	1
13/01/2011	Metlaoui	Gafsa	Chourouk	1

13/01/2011	Moknine	Monastir	ANR, ANRVideo, KalimaTunis	3
13/01/2011	Oued Ellil	Mannouba	ANR, ANRVideo, KalimaTunis, NATS, Video	5
13/01/2011	Ras Djebel	Bizerte	Bouderbala, NATS, Photo, PTON	4
13/01/2011	Soukra	Ariana	KalimaTunis, PTON	2
13/01/2011	Zaghouan	Zaghouan	ANR, ANRVideo, Chourouk, Nawaat, NawaatVideo	5
14/01/2011	Akouda	Sousse	Chourouk	1
14/01/2011	Douz Nord	Kebili	Chourouk	1
14/01/2011	En-Nadhour	Zaghouan	Bouderbala	1
14/01/2011	Kalaâ Kebira	Sousse	PTON	1
14/01/2011	Menzel Bouzelfa	Nabeul	ANR, ANRVideo	2
14/01/2011	Raoued	Ariana	Bouderbala	1

Sources for delegation-level controls

- **IDR**: For the development index used in the main event history analyses, I assemble data from the Comparative Study on Tunisian Regional Development (*Étude comparative en terme de développement régional de la Tunisie*) conducted by the Tunisian Competition and Quantitative Studies Institute (*Institut Tunisien de la Compétitivité et des Études Quantitatives*), a subsidiary of the Ministry of Planning and Regional Development (*Ministère du Développement Régional et de la Planification*). An example overview of the index and its measures (for the Beja governorate) can be accessed here: `http://www.mpci.gov.tn/tn/Gov/indica/beja.pdf`. The study was conducted in order to provide a composite delegation-level index of regional development (IDR). This in view of the considerable regional disparities that exist in Tunisia, particularly between the interior and the Sahel. The index ranges from 0-1, with 1 representing the most developed and 0 the least developed. The index was constructed using principal components analysis on twenty-six separate variables.

  The index comprises infrastructural measures (proportion roads classified; percentage households connected to sanitation system; percentage households connected to clean water; distance to nearest port/airport; distance to each of Tunisia's main city hubs (Tunis, Sousse, Sfax)); health measures (number of doctors per 1000 residents; number of pharmacies per 1000 residents; number of hospital beds per 1000 residents) social measures (number of families "in need" per 1000 residents; poverty rate; dependency rate) demographic measures (average population growth 2008-2012; net migration); education measures (percentage educated population (secondary and higher); illiter-

acy rate; BAC admissions rate) economic activity measures (placement rate; number of private enterprises per 1000 residents); and labour market measures (employment demand and opportunity; average size of private enterprises; percentage labour force employed in private enterprises; unemployment rate). As should be clear, the vast majority of these measures are taken from the period predating the revolution. A few are taken in 2012, in the year immediately after the revolution. Table A5 details the sources used for the construction of this index.

Table A5: Sources and measurements of IDR data

Variable	Source	Measurement	Further information
Proportion roads classified (2010)	Direction générale d'infrastructure	proportion of roads (in Kms) classified over total Kms of road in delegation.	
Distance to city hubs	Direction générale d'infrastructure	distance between delegation and each of Tunisia's main three city hubs (Tunis, Sousse, Sfax).	
Distance to nearest port	Direction générale d'infrastructure	distance between delegation and nearest port/airport.	
Agricultural labour force (2004)	2004 Census	percentage individuals employed in agriculture denominated by total active population aged 15 or over.	http://nada.ins.tn/index.php/catalog/8
Sewage connection (2004)	2004 Census	percentage households connected to sewage system.	http://nada.ins.tn/index.php/catalog/8
Drinking water (2004)	2004 Census	percentage households with clean drinking water.	http://nada.ins.tn/index.php/catalog/8
Number doctors (2010)	Commissariat et offices, Tunisie	number of doctors per 1000 residents.	
Number pharmacies (2010)	Commissariat et offices, Tunisie	number of pharmacies per 1000 residents.	
Number beds (2010)	Commissariat et offices, Tunisie	number of hospital beds per 1000 residents.	
Number families "in need" (2011)	Commissariat et offices, Tunisie	number of individuals per 1000 residents in receipt of government assistance.	http://www.cres.tn
Poverty rate (2005)	Institut National de la Statistique, Tunisie	percentage households living below poverty rate.	http://www.ins.tn/fr/publication/enqu%C3%AAte-sur-la-consommation-des-m%C3%A9nages-2005-volume
Dependency rate (2004)	Institut National de la Statistique, Tunisie	percentage population 0-14 and 65+ denominated by total population.	http://nada.ins.tn/index.php/catalog/8
Population (2010)	Institut National de la Statistique, Tunisie	number of individuals in delegation.	
Population growth (2008-2012)	Institut National de la Statistique, Tunisie	average growth in population over the period 2008-2012.	
Net migration (2004)	Institut National de la Statistique, Tunisie	net migration over period 1999-2004.	http://nada.ins.tn/index.php/catalog/8
Educated population (2004)	Institut National de la Statistique, Tunisie	percentage population with secondary or higher education certificate denominated by total population.	http://nada.ins.tn/index.php/catalog/8
Illiteracy rate (2004)	Institut National de la Statistique, Tunisie	percentage population illiterate denominated by total population.	http://nada.ins.tn/index.php/catalog/8
Bac admissions (2010)	Commissariat et offices, Tunisie	rate of admission to the Baccalaureate (final school examinations required for university admissions).	
Labour supply (2012)	Direction générale des ressources humaines	job opportunities per 1000 residents.	
Labour demand (2012)	Direction générale des ressources humaines	job demands per 1000 residents.	
Placement rate (2012)	Direction générale des ressources humaines		
Private industry (2010)	Institut National de la Statistique, Tunisie	number private enterprises per 1000 residents	http://www.ins.nat.tn/fr/themes/entreprises
Herfindahl index (2010)	Institut National de la Statistique, Tunisie	sum of squares of (delegation-level) market shares of enterprises	
Average private business size (2010)	Institut National de la Statistique, Tunisie		
Employed in private sector (2010)	Institut National de la Statistique, Tunisie	percentage employed in private sector	
Unemployment rate (2004)	Institut National de la Statistique, Tunisie	percentage individuals aged 18-59 without employment denominated by total active population aged 18-59.	http://nada.ins.tn/index.php/catalog/8

- **Youth population**: The variable measuring youth population was taken from the 2014 census and is measured as the percentage individuals aged 20-29 denominated by total population (see `http://census.ins.tn/fr/resultats`).

- **Google Trends**: Google Trends search volume is calculated as number of searches for keywords, or combination of keywords, denominated by total searches. Here, I use searches for "proxy" in Tunisia over the observation period. This is then indexed on 1-100 scale and normalized relative to the location and date range specified (here, Tunisia and 12-17-2010—01-14-2011). Thus, a value of 100 represents the day, within the specified location and date range, on which search concentration was at its peak, relative to other days in the same location. On the use of Google Trends data as a measure of online attention see Nghiem et al. (2016). Figure A12 display proxy search volume for Tunisia over the observation period.

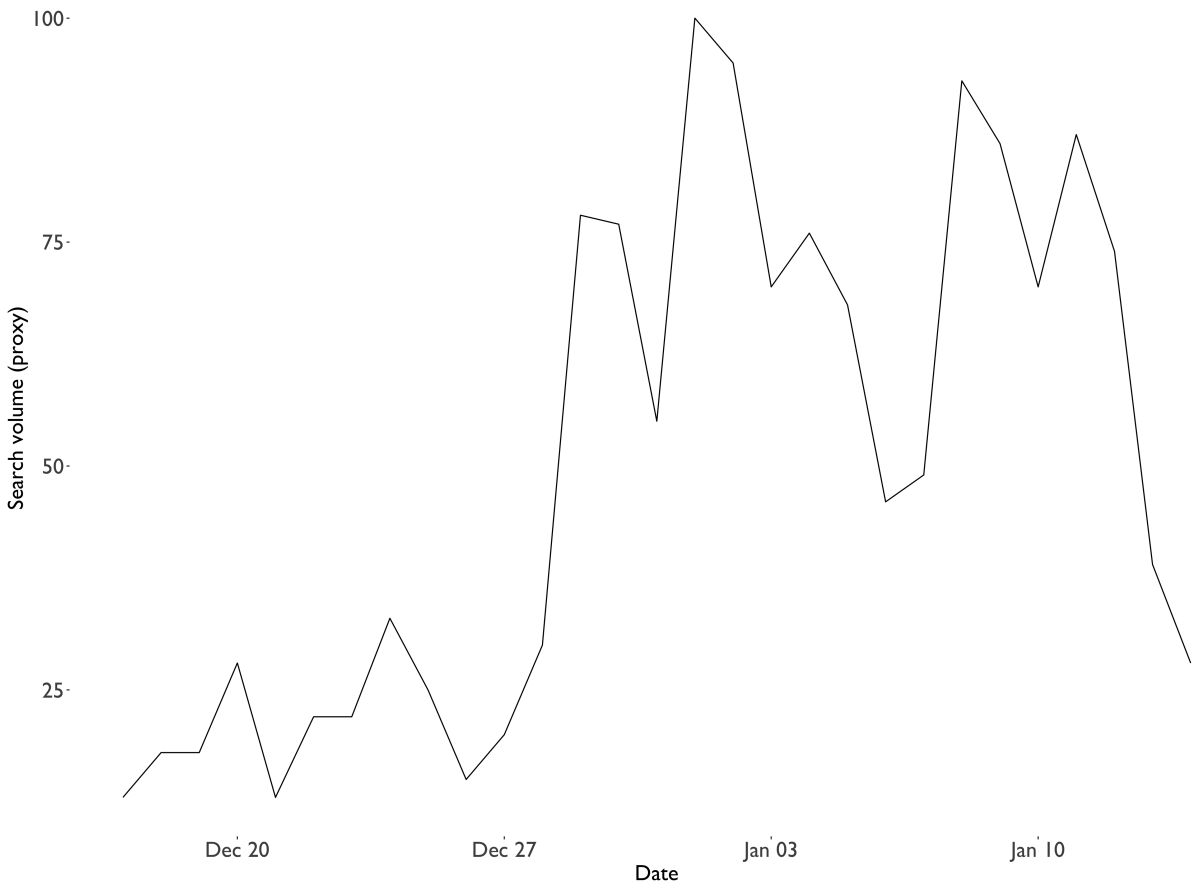


Figure A12: Search volume intensity for "proxy", 12-17-2010—01-14-2011.

A3.5 Interview fieldwork

Interviews were variously conducted in Arabic, French or English and were semi-structured in format. Most interviews were recorded (and subsequently transcribed in full) unless informants desired otherwise. Names have been changed to preserve anonymity. Translations are all my own. In all, I conducted forty-one interviews. The length of interview ranged from 15 minutes to over three hours. The transcribed interview transcripts count over 38,000 words. In order to gain access to interviewees I employed a snowball-sampling procedure, all the while making sure to engage multiple entry points. In all, I used seven separate initial entry points. Interviewees ranged from members of the UGTT (13); members of student activism groups (5); members of lawyer and other civil society groups (4); journalists (2); members of the political party the PDP (2); and unaffiliated residents of Sfax, Sidi Bouzid, and Tunis (10). Some interviewees were interviewed on more than one occasion. Interviews were conducted by the author over the period February-March, 2017 and March-April, 2019.

A3.6 Further Analyses

Results of further analyses using the additional controls employed in Steinert-Threlkeld (2017) are displayed in Table A6. These include controls for mainstream media accounts, as well as an interaction between core hashtages and the Gini cooeficient of concentration, in order better to identify the effects of "peripheral" coordination, as well as our ecological measure of internet penetration.

Table A6: Discrete time event history analysis of protest diffusion. Coefficients expressed as log-odds.

	Model 4	**Model 5**	**Model 6**
Nearby FB protest (t-1)	0.67**	0.78**	0.85***
	(0.25)	(0.24)	(0.25)
Nearby non-FB protest (t-1)	0.25	0.23	0.33
	(0.48)	(0.48)	(0.41)
Prop. FB protest (t-1)	0.22	-0.50	0.24
	(0.60)	(0.83)	(0.72)
Twitter communication (t-1)	0.15*	0.11	0.15
	(0.07)	(0.08)	(0.08)
Twitter coordination Gini (t-1)	1.01	5.07	1.02
	(0.59)	(3.94)	(0.58)
Proxy search volume (t-1)	0.00	0.01	0.00
	(0.01)	(0.01)	(0.01)
Core hashtag, % (t-1)		1.81*	
		(0.83)	
Core hashtag*Twitter Gini (t-1)		-7.46	
		(5.30)	
Mainstream media hashtag, % (t-1)		5.27	
		(7.57)	
Online actor hashtag,% (t-1)		-19.59	
		(13.55)	
Repression (t-1)	-0.26	-0.42*	-0.24
	(0.15)	(0.20)	(0.15)
Total events (t-1, sqrt)	-0.02	0.05	-0.01
	(0.13)	(0.15)	(0.12)
IDR	-2.62*	-1.55	0.49
	(1.19)	(0.94)	(1.04)
Youth pop.	0.08	0.09	0.12*
	(0.05)	(0.05)	(0.06)
Population (logged)	0.93***	0.92***	0.93***
	(0.18)	(0.18)	(0.18)
Internet use, %	0.02		
	(0.01)		
Panel variance ($\ln(\sigma_u^2)$)			-0.60
			(0.51)
Time polynomial	✓	✓	✓
Spells	5921	5921	5921

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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Concluding Notes

What conclusions can we bulld on in each of these pieces of research? I hope to have detailed in the main body of each article the principal shortcomings the analyses face. I shall spare the reader's eyes and refrain, therefore, from restating these. Instead, I set out, by way of brief conclusion, further avenues for future scholarship as well as research I envisage undertaking that builds from this thesis.

Causal identification is aided, in Paper One, by the relatively brief window of the observation period. In this short period of time, we can be confident that most of our effects can be traced back to the threat posed by the dramatic events of June 10. But here a distinction must be drawn between individual self-identification and longer-term nation-building. The historical sociological work associated with figures such as Charles Tilly and Michael Mann sees this process as operating over a protracted time period and targets institutional change as the key mechanism of changing loyalties and (re)imagined communities (Mann 1986; Tilly 1990). The twin institutional sources cited by Tilly (1990) of state coercive capacity and capital concentration, for example, are unlikely to operate in the same way in modern-day Iraq. Iraq specialists have nevertheless identified the post-2014 moment as potentially transformative. Haddad (2017, n.p.), for example, explicitly argues that the fall of Mosul, and

its aftermath, has seen a "reinvigoration of Iraqi nationalism" cutting across sectarian cleavages: "ISIS represented an enemy so cruel, so clearly identifiable, and so beyond the pale," he writes, "that [it] could serve as the same type of galvanizing foe that animated other wars of national salvation." An observable implication of the claims made in Paper One is that, in those areas that saw pronounced interethnic cooperation, we should see lasting gains in the form of renewed national loyalties. An extension of this argument would investigate the effects of direct wartime victimization on identity loyalties (see e.g., Balcells 2012) or the effects of intergroup contact resulting from wartime migration. This would require further data collection and will likely rely on future rounds of survey data.

The research contained in Papers Two and Three more obviously lends itself to a self-contained future research agenda. I intend to extend the findings of these articles and to convert them into a monograph. The prospective book asks how revolutionary coalitions for democracy form and endure. In asking this question, I will take lessons from the broader historical literature on revolution and mass mobilization generally. By expanding our lens, I have learnt from the research process to date, one begins to see what is shared between even the most ostensibily disparate instances of revolutionary uprisings. If contemporary democratic revolution is characterized by the mobilization of cross-class coalitions, so too have earlier revolutions been propelled forward by evolving coalitions of contenders. In this process, I venture, we see the essence of revolution and the reason why cross-sectional techniques are so inadequate. These are, after all, processes that are never in equilibrium but instead involve the successive incorporation of diverse and often divergent groups into loose coalitions of contenders professing common cause.

A key question, unresolved in Paper Two, will motivate the next stage of this research.

Part of the story of the Tunisian Revolution that I do not really engage in this paper concerns the defection of institutional organizations to the side of the street. If the UGTT initially distanced itself from the developing revolt, over time it would shift position and give its backing to protests. Why did this happen? And what are the characteristics of such organizations that predispose them to defection? Again, answering these questions will rely on a broader comparative and historical lens. Given that non-democratic contexts will constitute the main focus of this research, the types of organizations liable to defect will likely resemble what Ding (1994) has elsewhere referred to as "amphibious institutions;" that is, co-opted institutions which nonetheless hold out the potential for defection or "institutional conversion" as authority breaks down. These institutions are distinct from so-called "civil society," as a static version of state/civil society relations "omits and obscures precisely [this] most characteristic, dynamic and intriguing phenomenon in the devolution and disintegration of the mechanism of party-state control" (Ding 1994, 297-298). Once again, then, we are in the realm of process. This time, the process refers to the defection of party-linked elites to the side of the revolution. A second question concerns the endurance of protest coalitions in time. The literature expects the rapidly convened coalitions driving revolutionary mobilization quickly to fragment, imperilling any transition (Beissinger 2013). The rapidly mobilized coalition in Tunisia, however, remained intact and continued to influence the transitional process. Why was this possible in the Tunisian case, and what are the broader lessons it holds out?

Finally, in Paper Three, I find evidence that parochial heuristics lay beneath individual protest decisions. The article is largely silent, however, on the generalizability of these findings. Is this continued parochialism a function of the relatively low Internet penetration

in Tunisia at the time? Or can we observe decision-making that is similarly geographically circumscribed in other contemporary cases? If so, does this represent a decision calculus that has further historical reach? Evidence from a recent contribution does seem to suggest that physical copresence represents an important dimension of trust decisions even in contexts of high Internet availability. Haciyakupoglu and Zhang (2015) for example, find that, in the 2013 Gezi Protests in Turkey, being physically copresent "emerged as one of the most cited reasons for the investment of social trust" (456). One advantage, from a research perspective, of the relatively low Internet penetration in Tunisia is that we are able to determine with some confidence which protests received online exposure and which did not. This endeavour would be far more of a challenge in the present day. Testing the claims of this paper in other contexts, then, will require new, and less artisanal, techniques for the exploitation of digital trace data.

A concluding note of thanks is in order to the readers of this thesis. First and foremost to my two examiners who will have expended not insignificant energy in reaching this point—I am very grateful. Second, to the numerous individuals I list in the Acknowledgements who have read and reread countless drafts of my research over the years. I promise I'll leave some time before I send you this version too.

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