Ethno-Religious Diversity and Recovery After Conflict in Post-ISIL Iraq: A Geospatial Approach

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Abstract

After domestic conflict, why do some settlements recover faster than others? The problem of post-conflict reconstruction regularly attracts billions of aid dollars and carries hefty humanitarian and security implications, but little empirical work has focused on what causes differences in post-conflict recovery at the sub-state level. I explore the variation in recovery speed among Iraqi villages after the 2014-2017 Islamic State in Iraq and the Levant (ISIL) insurgency and focus primarily on the role of ethno-religious diversity in explaining the differences. Using satellite-observed nighttime light emissions as a proxy for economic activity, I construct an 81-month panel of economic output in 351 Iraqi settlements occupied by ISIL. This information is combined with settlement-level data on ethno-religious composition. In spatial autoregression and generalized synthetic control approaches, I evaluate the causal effect of ethno-religious diversity on post-conflict recovery across space and time. The results show that diversity has a large and significant negative influence on recovery. This result is robust to a variety of different specifications, and the magnitude of the effect grows over time. I argue that diversity slows reconstruction because it alters the local dynamics of security and cooperation and alters the strategies of local elites. Broadly, my findings support constructivist views on identity which suggest ethnic and religious identities can become “activated” in certain social conditions.
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Replication code and data

This thesis was coded in R, and data was assembled in QGIS and R. Replication code and datasets are posted at github.com/lloydlyall/LyallThesis2019.

The settlement-level IOM survey data on ethno-religious composition is potentially sensitive. For this reason it is not publicly available; I obtained written permission from IOM to use it. The parts of this dataset I use in this thesis could probably be considered public knowledge, but out of an abundance of caution, the publicly available dataset posted to GitHub excludes settlement-level ethno-religious composition information. The posted code replicates all the core empirical analysis of this thesis, but some results will be slightly different because the code excludes ethno-religious group dummies from the calculations. Users seeking to replicate specifications which include ethno-religious dummies should first obtain written permission from the IOM Iraq team to access the IOM ILA III dataset for Iraq with ethno-religious variables; I would then be happy to share the full dataset.

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Introduction and motivation

The northern Iraqi towns of Sinjar and Tal Afar are less than forty-five minutes away from each other by car. When Islamic State in Iraq and the Levant (ISIL) insurgents began capturing Iraqi territory in 2014, both towns were overrun by the militants and subjected to brutal ISIL rule. But after their liberation, they experienced drastically different recoveries. In Tal Afar, less than a year after liberation residents explained that “public services are improving, shops are reopening, people are venturing out and the security situation is improving” (al-Taie 2018). A local news outlet declared recovery efforts were “on the up and up” (Rudaw 2018). But forty-five minutes down the road, Sinjar lived a very different experience: almost three years after it was liberated, the town sat empty and silent. Reconstruction efforts were nowhere to be seen; many locals had not returned and the few who did lived “in dire conditions” (Peyre-Costa and Jenssen 2018). Why might two towns so close together rebuild so differently after ISIL occupation?

The scale of Iraq’s recovery challenge is massive. The ISIL conflict displaced 3.3 million people and destroyed $US 45.7 billion worth of infrastructure; Iraq’s government estimates it will need $US 88.2 billion to rebuild (Gordon and Coles 2018, CNBC 2018). But the need to begin reconstruction is urgent. Reconstruction allows internally displaced persons (IDPs) to return home from camps that are catalysts for conflict, disease, and trauma, and it allows locals of ISIL-occupied regions to regain the sanity of normal life and resume working in a region representing at least a fifth of the Iraqi economy. Past research shows post-conflict environments are at a high risk of entering a “conflict trap” and experiencing future war and poverty (Collier 2003). But to avoid the trap, quick post-conflict recovery is essential: Flores
and Nooruddin (2009) show that a post-conflict country’s chance of relapsing to conflict jumps from 27% to 50% if it does not recover fully in the first post-conflict year.

Iraq and the international community clearly recognize this urgency. Since the ISIL conflict began in 2014 international donors have contributed more than $US 6.4 billion towards Iraqi aid and stabilization, and at least 200 NGOs and international bodies are participating in the effort (UNOCHA 2018, NCCIraq 2018). Yet despite the obvious need for quick reconstruction and massive financial outflow, the puzzle exemplified by Sinjar and Tal Afar is repeated almost everywhere in the ISIL-affected areas of Iraq: while economic activity has returned at pace to some towns, it has been slow or entirely absent in others. The vast diversity in recovery success prolongs trauma for locals of slowly recovering areas and threatens domestic and regional stability. It has also stoked substantial disagreement about how best to organize reconstruction. The United States, for example, announced in June 2018 that it was frustrated with the inefficiency and prioritization of international funding mechanisms and that it would abandon them to directly fund reconstruction of certain Christian and Yazidi areas (Morello 2018).

Part of the failure to implement reconstruction equally and agree over aid prioritization may stem from our lack of understanding about what causes faster or slower recovery at the settlement level. The problem is bigger than Iraq: quantitative academic literature on post-conflict recovery has overwhelmingly focused on differences between states, but many of the decisions that determine the success of post-conflict strategies are made at the sub-state level. Rebuilders must decide how to allocate funds amongst different conflict-stricken towns, which strategies to use, and how interventions should vary among settlements with different characteristics and experiences. In empirical academic literature, they can currently only look to cross-country comparisons to guide them.
This thesis asks why some Iraqi settlements recover faster than others after the 2014-2018 Islamic State in Iraq and the Levant (ISIL) insurgency. Many influences surely matter, and my results provide insights for several of them. However, I focus most of my attention on the core hypothesis that ethno-religious diversity slows recovery.

Until recently, a lack of consistent settlement-level economic data in post-conflict environments has made empirical investigation of settlement-level recovery differences almost impossible. By leveraging a recent new proxy for settlement-level economic performance, this thesis supplies novel empirical evidence on settlement-level variation in recovery and hopes to begin filling the gap. Using satellite-observed nighttime light emissions as a proxy for economic activity, I construct a 81-month panel of economic output in 351 Iraqi settlements occupied by ISIL that captures activity before, during, and after their occupation. This information is combined with settlement-level survey data on ethno-religious identity, and other data on territorial control and settlement characteristics. In spatial autoregression, I quantify the importance of different factors on short-term settlement recovery, and in a second test, explore how the relative importance of these factors changes over time. I then use a generalized synthetic control strategy to focus specifically on the causal effect of greater levels of ethno-religious diversity.

The results show ethno-religious diversity has a significant negative influence on post-conflict recovery. This effect grows over time and is robust to a variety of different causal strategies, modelling approaches, and regions. I argue this evidence suggests ethno-religious diversity causes slower post-conflict recovery.

While classic literature on ethnic diversity and growth can explain some of this result, I highlight two mechanisms specific to the post-conflict setting. First, some of the recovery
problems in diverse areas may stem from differences in how ethno-religious groups were treated during conflict. Second, I suggest local elites deliberately target diverse areas when competing for influence, and that the types of elite-led competition that ensues slow recovery. The mechanisms broadly support constructivist views of identity which suggest the salience of ethno-religious identity can be “activated” in specific situations.

The thesis proceeds as follows. Chapter 1 reviews the literature on post-conflict reconstruction and argues that quantitative work at the sub-state level – and in particular, on ethno-religious diversity – can add a valuable perspective to the discussion. Chapter 2 supplies a brief historical overview of Iraqi history and the rise of ISIL, the experience of occupation and the post-conflict recovery process. Chapter 3 introduces nighttime light emissions as a proxy for economic growth. It demonstrates empirical support for the proxy in the validation literature, conducts a novel validation exercise in Iraq, and shows how the effects of ISIL occupation are clearly visible in settlement nighttime-light panels. Chapter 4 defines and operationalizes the most crucial concepts in the thesis – settlements, dates of occupation, ethno-religious diversity, and recovery - and presents descriptive statistics. Chapter 5 defines and executes a two-pronged causal strategy. It begins with spatial autoregression to describe an overall picture of influences on recovery; it then turns to a generalized synthetic control to examine the diversity result specifically. Chapter 6 interprets the findings and investigates the ethno-religious diversity result in greater detail. Chapter 7 suggests two causal mechanisms and highlights qualitative support for them drawn from Iraq’s post-conflict experience. The very brief chapter 8 identifies implications and concludes.
Chapter 1 | Literature review: diversity, growth, and post-conflict reconstruction

Post-conflict recovery encompasses many processes, from the return of economic activity to political normalization and national reconciliation. This thesis focuses post-conflict economic recovery. At the state level, this phenomenon typically follows one of two paths: some countries rise Phoenix-style from the ashes of war with dramatic post-conflict growth; others remain mired in poverty and conflict for years after conflict ends.

This chapter surveys the literature on post-conflict economic recovery with three goals in mind: to review the existing explanations for why some states bounce back while others remain destroyed, to access the degree of support for these theories, and to identify where a new contribution could be most useful. Part I describes the classic literature on post-conflict recovery, which focused on modelling and explaining the most common post-conflict growth trend. Part II surveys more recent literature that focuses on when and why the classic model fails. This review argues that the current literature has two deficiencies: many theories lack sub-state empirical support, and the role of ethnic diversity for post-conflict recovery has been understudied. In its conclusion, this chapter distills the core theory of my thesis from this gap in the literature.

Part I: The classic approach - the “Phoenix Factor”

The classic model of post-conflict reconstruction is quick and dramatic recovery: post-war countries embark on a period of short-term supra-normal growth, wherein they “catch up” to their potential GDP path. Once this recovery is complete, growth rates revert to the pre-conflict long-run growth rate.
The point of departure for this discussion is Robert Solow’s seminal 1956 model of economic growth (Solow 1956). Solow’s model posits that economic growth can be described as a function of the capital and labor stock in a country; it makes the stylized assumption that other factors – such as investment, consumption, and human capital – remain at a fixed share over time. Solow adds that there are diminishing marginal returns to capital and labor: in a labor-rich country, for example, the first few units of capital make a tremendous difference to output. Additional units of capital in a country that is already capital-rich make a far less significant impact.

Solow’s model has wide-ranging consequences for economic development, but its implications for post-conflict reconstruction are straightforward. In wartime extensive amounts of capital are destroyed – factories are attacked, bridges are bombed, and electricity grid, machinery and communications infrastructure are damaged. At the end of war, a country’s labor supply will be relatively higher than its supply of capital. The marginal return to capital will thus be enormous, and the first few investments in post-war capital reconstruction will result in tremendous economic growth. As more capital is rebuilt, the marginal return from additional capital decreases, and the recovering country’s supra-normal GDP growth levels out and eventually returns to the long-run GDP path. In the long run, conflict will have no impact on a country’s growth rate or absolute GDP level: the post-war GDP will eventually recover to its’ pre-conflict path.
Solow’s model was gradually modified to consider other factors. Ramsey (1928), Cass (1965), and Koopmans (1965) relaxed Solow’s assumptions that investment and consumption are fixed; Romer (1986), Lucas (1988), and Jones (1995) made accommodations for different levels of human capital across countries. However, the core idea remained consistent: war is destructive; it obliterates capital, human capital, and other key inputs to growth. This destruction means that returns to investment in the post-war period are extremely high; these returns spur supra-normal growth for a short time after war but eventually fade as pre-war levels of economic activity are recovered.

This theory has two implications for the post-conflict growth rate. First, it suggests that post-war economic growth is positively related to the extent of destruction: the more an area is destroyed during war, the higher the marginal returns to reconstruction and the greater the growth rate it will exhibit during recovery. Following Romer, Lucas, and Jones, “destruction” ought to be broadly conceived: it includes damage to both capital and human capital. Second, it
suggests that areas with higher growth rates in the pre-conflict period will grow faster after conflict: these cases have more work to do to catch up to their potential GDP projections.

Organski and Kugler (1977) were among the first to observe evidence of Solow’s theorized recovery in practice and dubbed it the “Phoenix factor”: Organski and Kugler examine 32 major conflicts and note that although losing countries’ economic power is at first eroded, over a 15 to 20 year period growth accelerates and the losers rise “like a Phoenix from the ashes” to recover their long-run growth rate.

The “Phoenix factor” has found robust empirical support at the state level. Chen, Loayza, and Reynal-Querol (2008) find growth is on average 2.4 percentage points higher after a war than before it in a set of 41 countries that experienced wars between 1960 and 2003. Koubi (2005) studies inter-state and intra-state wars from 1960-1989 and concludes that longer and more severe wars are associated with faster rates of post-conflict recovery.

The Phoenix factor has also gained empirical support at the sub-state level. Davis and Weinstein (2002) compare Japanese cities that were intensively bombed during World War II to other Japanese cities that were not bombed and find that the cities are virtually indistinguishable 15 to 20 years after the war ended. Brakman et. al. (2004) find a similar trend among German cities after the war. More recently, Miguel and Roland (2006) analyze post-war recovery in Vietnamese provinces subject to differential levels of U.S. bombing intensity during the Vietnam War. Miguel and Roland find that immediately after the conclusion of the war, provinces subject to greater U.S. bombing were poorer than provinces that were generally spared. However, exactly as Solow would predict, they find that the intensively bombed provinces exhibited faster growth rates than other provinces between 1992 and 2002, and by 2002, the heavily bombed provinces were indistinguishable from other Vietnamese areas.
While most scholars agree that the Phoenix effect exists in some cases, considerable debate continues over why, how, and on what timeline the effect occurs. Writing in the shadow of the two World Wars, scholars proposed a litany of explanations for supra-normal post-conflict growth. The recovery could be due to improved efficiency, governance, and industrial organization as war forces governments to become more powerful and efficient (Foch 1918, Schumpeter 1939, Organski and Kugler 1977). War might advance human capital and organizational skills that spark post-war growth (Dorn 1940). Destruction of old factories and industrial equipment may clear the way to install new state-of-the-art equipment that spurs growth (Organski and Kugler 1977), and war-affected populations might be especially motivated to work hard because they remember the pre-war status quo and want to rebuild quickly (Organski and Kugler 1977). Post-conflict countries may grow faster simply because the diversion of economic resources to domestic processes and away from the military “effortlessly” spurs growth (Gould 2013).

Part of the story could also be political: Olson (1982) argues that war can destroy “distributional coalitions” that are politically inefficient; when this occurs, the open postwar political environment increases economic competition and sparks growth. Olson therefore explains that the extent to which the pre-war political structure is destroyed is positivity associated with post-war growth. Chan (1987) finds empirical support for Olson’s theory in the post-World War 2 growth of pacific rim countries, but Kugler and Arbetman (1989) present empirics to suggest that destruction of political structures is not significant in explaining postwar growth.

Further debate centers on whether the “Phoenix Effect” is a domestic phenomenon or simply the result of post-conflict international aid. Organksi and Kugler (1977:1364) argue that
Phoenix recovery is “not because winners pick them [the losers] up and help them to their feet,” and show empirically that there is little to no association between post-World War Two U.S. aid and post-conflict growth rates. Collier and Hoeffler (2002), however, insist that reconstruction aid explains almost all the Phoenix Effect and present empirical evidence from 349 cases in 62 countries to back their claim. They argue this aid increases growth rates by diversifying post-conflict economies and boosting output growth.

**Part II: Contemporary explanations - when the Phoenix effect fails**

While the “Phoenix effect” theory provides a useful starting point for understanding variation in post-conflict recovery, not all cases are phoenixes. While some countries, cities or regions do grow quickly in the post-conflict period and catch up to their potential GDP paths, this recovery is not automatic or universal: other cases experience long-lasting negative consequences from war (Kang and Meernik 2005, Wheeler 1975).

The evidence for some countries’ failure to recover is clear: one needs only to look at post World War I Europe where peace was followed by economic depression and another war, or the list of Middle Eastern and African countries (The Central African Republic, Democratic Republic of the Congo, Afghanistan, and others) where the conclusion of civil conflict was met by decades of depressed growth or recurrent conflict. Murdoch and Sandler (2004) present data suggesting that civil war reduces country growth by 85% in the first 4 years following conflict, and that these effects persist in the long run: even 35 years after conflict, growth is still depressed by 31%. Why, then, do some post-conflict cases recover rapidly in the Phoenix-factor style, while others appear permanently damaged?
Many contemporary debates on this question begin with Collier (2007)’s “conflict trap”. Collier argues that the qualities which make states vulnerable to new domestic conflicts—such as low economic growth, poverty, and the availability of weapons—are also qualities that result from previous conflicts. Post-conflict societies are thus at a high risk of renewed conflict. If they do not rebuild quickly, they risk ensnarement in the conflict trap and a return to conflict and poverty. There is plenty of evidence that quick recovery is essential to avoid the trap. Flores and Nooruddin (2009), for example, show that a post-conflict country’s chance of relapsing to conflict jumps from 27% to 50% if it does not recover fully in the first post-conflict year. This literature clarifies that recovery must start quickly to work well, but this question leads to an equally important follow-up: why do some post-conflict cases rebuild quickly and escape the conflict trap while others do not?

Recent literature seeking to explain this variation can be broadly divided into economic, political, and social explanations. The following discussion demonstrates that while the first two
categories have been widely evaluated in the literature, empirical tests of social influences on recovery have been surprisingly absent. Additionally, in contrast to the classic Phoenix model, quantitative evidence for contemporary theories of recovery exists almost exclusively at the country level.

Economics

Contemporary economic arguments for the variation in post-conflict success cover a range of explanations. First, the relative extent of destruction between different factors may influence reconstruction. Barro and Sala-Martin (2004) argue that countries in which war resulted in relatively more intensive capital destruction will grow faster than countries with relatively more intensive labor destruction in the post-war period. Replacing labor, they argue, has a higher “adjustment cost” and therefore requires more time and energy.

Second, the level of per-capita income at the onset of peace may influence recovery success. In a country-level study of 74 civil wars, Collier et. al. (2008) show that per-capita income at the start of peace is positively and significantly associated with the duration of post-war peace. The effect size is large: Collier et. al. report that while at the mean level of income in their dataset the risk of relapse to conflict in the first decade is 40%; doubling the mean income level to twice the mean lowers this risk to 31%.

Third, the duration of conflict may drive post-conflict recovery: Collier (1999) and Koubi (2005) both present evidence suggesting countries emerging from longer conflicts grow slower after war. War duration may partially proxy for extent of destruction to physical capital – triggering Solow’s mechanism - but Collier (1999) provides a complementary theoretical perspective: war duration may drive postwar growth by capturing the status of asset and
investment flight relative to their optimal post-war levels. While in Solow-style models all capital is fixed, Collier (1999) suggests capital has both a “fixed” and “mobile” component. Investors pull their mobile capital out of a country during conflict. Hence, post-war recovery is not just about rebuilding the fixed component of capital destroyed in war; it also depends on how much mobile capital fled the country during conflict and how quickly it returns.

**Politics**

The broad conclusion of political explanations for variations in post-conflict performance is that strength trumps equity: strong and decisive governance arrangements – regardless of whether they are fair or democratic – deliver better outcomes.

First, autocracies may be better rebuilders than democracies. Collier et. al. (2008) find countries which are highly autocratic in the post-conflict period see a 27% chance of relapsing to conflict in the first postwar decade; their less autocratic counterparts see a 62% chance of relapse. Transitions to democracy are also damaging: examining 67 countries recovering from civil war, Flores and Nooruddin (2009) find that countries which democratize after conflict both take longer to recover their pre-conflict GDP per capita level and are more likely to relapse to conflict relative than states experiencing autocratic or democratic stability.

Much of the mechanism may lie in the instability and commitment problems democracy brings to post-conflict peace. One central problem is the inability of democracies to commit to credible contract enforcement and power-sharing in the post conflict period. Flores and Nooruddin (2009) find that states where conflict ends in negotiated settlements perform worse after conflict than those where conflict ends in outright military victory. They posit that democracies or messy negotiated settlements after war make it more difficult for politicians to
credibly commit to post-conflict peace; weaker credible commitments inhibit investment and slow recovery. Atlas and Licklider (1999) use a case-studies of four civil war countries to argue that negotiated settlements make return to conflict more likely.

A second source of democratic instability stems from elections. Flores and Nooruddin (2012) show that hosting elections shortly after the end of conflict – especially in new democracies – slows economic recovery and increases the likelihood of renewed violence. They suggest early elections spur division and volatility and decrease the attractiveness of post-conflict investment. Collier et. al. (2008) empirically demonstrate that post-conflict elections decrease the risk of return to violence in the year of the election but increase it in the subsequent year; they argue that opposition members shift their efforts from election work to violence.

Other explanations center on the political economy of security provision. Security is clearly an essential component of recovery: refugees will not return home until their home towns are safe; farmers and merchants will wait for safety before reopening their shops or fields; parents are unlikely to send their children to school or seek new jobs until it is safe to do so. (Feil 2002). Security is also essential to facilitating investment, re-starting economic growth and promoting national reconciliation (Muggah 2008).

But post-conflict security provision is difficult: former combatants need to be demobilized, disarmed, and reintegrated; holdouts must be quashed. The end of war leaves former combatants in the procession of weapons and with good reason to fear their own personal safety. Demobilizing former combatants thus often invokes a commitment problem: disarming former fighters have no short-run credible guarantee that the other side will similarly disarm rather than take advantage of the demobilization to secure more territory or spoils of war (Walter 1997). This commitment problem also has a political dimension: in the medium and long run,
former combatants may doubt the ability of political institutions to follow through with promises made at the end of war (Flores and Nooruddin 2009). Post-conflict security is often closely related to the ability of post-conflict arrangements to address this commitment problem; cases where a strong actor can guarantee post-conflict security and credibly commit to future promises often see more secure post-conflict environments (Flores and Nooruddin 2009).

State-level empirical evidence supports this theory; when third-parties step in the monitor the peace post-conflict stability and growth is often improved. Collier (2008) presents data suggesting external security assistance in the form of UN peacekeepers is significantly associated with extending the duration of postwar peace; Kang and Meernik (2005) similarly show that UN peacekeeper presence heightens post-war growth rates. Hoddie, Hartzell, and Rothchild (2001) demonstrate empirically that the presence of a third-party monitor to peace agreements increases the duration of post-conflict peace.

Social

What about social influences on post-conflict recovery? A robust development literature suggests that ethnic diversity slows economic growth, and work in political science has shown how ethnic and religious identities can become especially important in the wake of conflict. Yet despite these foundations, surprisingly little post-conflict work considers how ethnic diversity might impact post-conflict recovery.

The empirical link between high ethnic diversity and poor economic performance in peacetime is widely accepted. Diverse societies see reduced public goods provision (Alesina and Ferrara 2005), reduced investment (Montalvo and Reynal-Querol 2005), and slower growth (Easterly et. al. 1997). Many mechanisms have been suggested to explain this effect. Greater
diversity may lead to more polarized interest groups and worse policy (Easterly and Levine 1997), increased rent-seeking behavior (Easterly and Levine 1997), or less trust between members of society (Dinesen et. al. 2015). Miguel and Gugerty (2005) and Habyarimana et. al. (2007) have convincingly shown that increased diversity decreases the ability of societies to leverage social sanctions to encourage community contributions towards public goods. Putnam (2007) suggests that increased ethnic diversity may cause residents of a community to “hunker down” in a general sense and disengage from many faucets of social life.

In a separate literature, social scientists have shown that ethnic identities can sometimes become powerful post-conflict social cleavages. Simosen (2005) argues that conflicts that occur on ethnic lines increase the salience of ethnicity relative to other identity characteristics and cautions against post-conflict institutional designs that emphasize ethnicity. In other cases where conflicts occur on non-ethnic lines, Simosen argues that the conclusion of conflict and loss of a “common enemy” can cause ethnic tensions to resurface among groups previously united by other social or ideological characteristics. Accordingly, scholars have described how ethnic differences became aggravated after conflict in settings like Georgia (Broers 2008), Iraq (Haddad 2014), Lebanon (Kingston 2013), and many others.

The pattern of increasing sectarianism after conflict forms part of a larger debate over when and why ethno-religious identity becomes salient. Primordialists like Huntington (2000) argue that ethno-religious identities are innate, immutable, and fundamentally alter their holders’ perspectives and preferences. By contrast, constructivist views on identity suggest that individuals hold many latent identity characteristics, but certain ones can be “activated” in response to particular social political conditions.
Constructivists have detailed how ethno-religious affiliation can be situationally activated in great detail. For example, Weiss (2010) describes how the most salient social cleavage in pre-colonial Lebanon was economic class. But when French colonizers assumed administration of the country, they began to organize administration on ethno-religious lines - establishing different court systems for different religious groups and giving some ethno-religious groups special privileges. The importance of ethno-religious identity for daily activity made it the driving social cleavage. Makdisi (2000) described this shift as a “culture of sectarianism” that emerged in response to social change.

Others have shown how ethno-religious divisions become salient in response to political conditions. Bates (1983) argues that ethnic identity forms a convenient basis to build “minimum winning coalitions.” Ethnic groups are often large enough to secure benefits in political competition but small enough to maximize the per capita value of those benefits, and the use of ethnic identity makes it easy to exclude outsiders from the winnings. Posner (2002) shows that the Chewa and Tumbuka ethnic groups – which found themselves both on each side of the arbitrary colonial border between Zambia and Malawi – became political allies in Zambia but adversaries in Malawi. Posner argues this difference is due to the relative sizes for the groups in each of their countries, and the divisions that were politically expedient.

Despite the immense presence of ethnic diversity in growth literature and evidence that post-conflict circumstances can greatly increase its importance, diversity has been scarcely discussed in post-conflict empirical literature. The limited empirical work studying the impact of ethnic diversity on post-conflict recovery is confined to the country level and paints an uncertain picture. Kang and Meernik (2005) find that ethnic fractionalization has a significant negative impact on post-conflict growth rates at the country level and suggest it is probably due to the
same mechanisms that slow growth in peacetime. But the only other empirical study I am aware of disagrees: Collier (2008) finds that ethnic diversity is insignificant with respect to the duration of post-conflict peace. Even if the coefficient were to be significant, it suggests that increased ethnic diversity might *heighten* peace prospects.

**Pat III: From gaps to a theory**

This review suggests two gaps in post-conflict literature are evident. First, there is a lack of empirical support for many theories of variation in post-conflict recovery at the sub-state level. This gap is striking because many of the decisions rebuilders make that determine the success of post-conflict transitions occur at the settlement level. There are many reasons to suspect domestic reconstruction dynamics may leverage different causal mechanisms than international ones. Second, there is a lack of investigation on how ethnic diversity might affect post-conflict recovery. Although most agree that ethnic diversity slows growth in peacetime and the literature suggests ethno-religious identity may become especially important after conflict, the effect of ethno-religious diversity on post-conflict reconstruction has seen little empirical testing.

Although this thesis evaluates several influences on post-conflict economic recovery at the settlement level and provides interesting insights on many of them, I do not attempt to fully evaluate them all. Instead, I focus my attention primarily on the area where there has been the least post-conflict empirical work overall: the impact of ethno-religious diversity on recovery. My core hypothesis is that ethno-religious diversity causes slower post-conflict recovery. Chapters 3 to 5 explain how I test this hypothesis; chapters 6 and 7 interpret and explain it.
Chapter 2 | Introduction to the case: historical background, ISIL in Iraq, and post-conflict reconstruction

To test my theory, I use the case of Iraq’s recovery from the Islamic State in Iraq and the Levant (ISIL) insurgency. Between 2014 and 2017, ISIL militants following an extreme version of Sunni Islam occupied more than 300 Iraqi settlements comprising almost one-third of the country. The conflict wiped out $47.5 billion worth of infrastructure, displaced more than 3.2 million people, and inflicted immeasurable social and psychological trauma on millions of Iraqis (Gordon and Coles 2018, IOM 2018). Post-ISIL Iraq is a useful and important case study for several reasons: it is a massive reconstruction effort with large humanitarian and regional security implications; it is the target of billions of dollars in foreign aid; and high international involvement means that data and information on the recovery process is readily available.

Of course, factors which influence recovery in Iraq may not exert the same weight in other post-conflict settings. Conflicts leave distinct social legacies that shape the recovery process, and Iraq has a unique set of institutions and history other post-conflict settings do not share. In the worst-case scenario – should my conclusions be uniquely relevant to Iraq – the thesis would still be worth attempting: many domestic and international actors are involved in Iraqi reconstruction in ways that affect millions of Iraqi citizens and others touched by Iraq’s regional influence. But I will argue that this thesis’ conclusions also carry relevance for academia and practitioners broadly. This thesis is meant to begin the process of analyzing settlement-level influences on post-conflict recovery; many other perspectives could follow.

While the ISIL insurgency is a recent problem, its roots run deep in Iraqi history. This chapter seeks to describe the historical and contextual information essential to understanding the post-ISIL environment. In part I, it begins with a brief overview and history of Iraq aimed at
demonstrating how sectarianism emerged as a salient cleavage in Iraqi identity. In part II, it recounts how the Islamic State emerged from this sectarian divide and characterizes the extent, experience, and demise of its insurgency. Finally, part III describes the key dimensions of variation in settlement experience after liberation and makes an argument about how they should be viewed in context of my research question.

**Part I: An introduction to Iraq and the roots of sectarian activation**

*An overview of Iraq*

Iraq would likely not exist as it does today if its borders had not been drawn by outsiders. Present-day Iraq was part of the Ottoman Empire until World War I, when the Ottoman defeat resulted in the transfer of the Empire’s Baghdad, Basra and Mosul provinces to British control. A League of Nations decision awarded the Britain mandatory control of the three provinces on a temporary basis. They were merged to create the Kingdom of Iraq in August 1921, and Iraq gained full independence from Britain in 1932.

However, the new Kingdom of Iraq united three territories with vastly different ethno-religious, social, and political environments. Iraq’s southwest is overwhelmingly Shia Arab; Shias are the largest single ethno-religious group in the country. But the Shia south stands in contrast with an overwhelmingly Sunni Arab presence western half of the country, and a large Sunni Kurdish population in the north. More than a dozen other ethno-religious groups – including Christians, Turkmen, Yazidis, and other smaller groups – live predominately in the ethno-religiously diverse band of territory separating central and northern Iraq. Ethno-religious identity is not the only axis on which Iraqi social identity varies: the country is also home to several hundred distinct tribal groupings (Otterman 2005).
Iraq’s 1957 census is widely regarded as the last credible attempt to survey the population. It reported that 95% of Iraq’s 6.3 million inhabitants were Muslim (neither Sunni-Shia differences nor ethnic groupings were measured); Christians formed 3.3% and a smattering of smaller ethnic groups made up the difference (Government of Iraq 1957). Decadal censuses from 1967 to 1997 are all widely regarded as highly problematic, and no census has been attempted after 1997. However, a recent European Parliament research brief suggested Iraq’s population was approximately 43% Shia Arab, 26% Sunni Arab, and 12% Sunni Kurdish in 2015. The difference was comprised of a group of smaller ethno-religious groups, including Turkmen (8.7%), Christians (1.4%), Yazidi (1.4%), Shia Kurds (1.4%), Shia Shabak (0.7%), and other smaller groups (Pichon 2015).

**Figure 3: Iraq’s Ethno-religious Composition and the Area of ISIL Occupation**

![Map of Iraq's ethno-religious composition and ISIL occupation area.](image-url)
Since 2003 Iraq has been a parliamentary democracy with a popularly elected legislature in Baghdad. National elections occur roughly every five years by party-list proportional representation, and small numbers of seats are reserved for minority ethno-religious communities. Below the national level Iraq is divided into nineteen governorates; each governate is divided into several districts and each district into several subdistricts. Each administrative level elects representatives to councils which tend to local affairs. The three northernmost governorates – dominated by the Kurdish minority – form a Kurdish Autonomous Region and elect a regional parliament that enjoys a heightened local autonomy relative to other areas.

*Independence to 2003*

Sectarian identity characterizes much of the social and political organization in the contemporary Iraqi state system as well as extra-state opposition to it. But while sectarianism looms large in Iraq today, it would be wrong to assume that it has always been the most salient cleavage in Iraq. In fact, the major preceding social movement centered on an entirely different ideology: pan-Arabism emphasized the united interests of all Arab peoples, secular modernization and freedom from imperial control (Gelvin 2008). I present an incredibly brief history of Iraq from independence to 2003 to demonstrate how sectarianism was originally a latent component of Iraqi identity and slowly became “activated” in response to political events. After the 2003 US invasion, the pace of sectarian activation accelerated rapidly, and sectarian cleavages helped form the recruitment mechanism that brought ISIL to prominence.

Iraq was directly administered by the British from 1920 until 1932, when it became an independent constitutional monarchy under King Faisal I. For the next 37 years, a father-son monarchy presided over a state increasingly opposed to it: as pan-Arabist movements began to sweep through neighboring Arab countries, Iraqis became increasingly discontent with the
monarchy’s strong ties to British and American imperial influence. This discontent came to a head in 1958, when the monarchy was overthrown by a populist-inspired military faction in a Coup d’Etat.

Ten years of coups and instability that followed were put to an end in 1968 when the Iraqi Ba’ath Party staged a successful coup and seized power. The Ba'ath Party was a Sunni-dominated movement inspired by pan-Arabism and committed to secular modernization. Saddam Hussein, who began by running the party’s security apparatus, gradually amassed *de facto* power and took formal control in 1979. Though Sunnis were a minority in Iraq, Saddam’s Sunni-dominated Ba’ath party would lead Iraq for the next two decades.

In some ways, Ba’athist Iraq delivered an Arab nationalist triumph. The party nationalized Iraqi oil in 1971 and proceeded to use the revenues to facilitate a rapid state-sponsored modernization program. The country’s stock of paved roadway, schools, and hospitals doubled from 1970 to 1980, and between 1970 and 1990 Iraqi GDP grew by 54% (Blaydes 2018, World Bank 2018c). However, the Ba’ath regime was also brutal. In 1979 Saddam ordered a massive purge of his party in which hundreds of high-ranking Ba’athist officials were executed. A sophisticated state security apparatus was quick to identify and smother dissent. And in the ethnically diverse northern reaches of Iraq, Saddam embarked on increasingly blatant campaigns to forcibly displace Kurds and other minorities. He hoped to alter the ethno-religious composition of strategically important territory in favor of Sunni Arabs. As the Ba’ath party’s tenure wore on, two ill-advised conflicts with Iran and Kuwait, increasing international sanctions, attempts at ethnic engineering and simmering domestic dissent forced Saddam’s regime to gradually abandon its Arab nationalist-roots in favor of ethno-religious patrimonialism and oppression.

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Iran’s 1979 revolution left the country unstable, and Saddam sensed the potential for an easy distraction from his party’s increasing troubles. Saddam invaded Iran in 1980 expecting a quick and costless territory grab. Instead, a 9-year conflict drove Iraq into substantial debt and killed between 250,000-500,000 Iraqis (Black 2010). The western edge of Iran is populated by the same Sunni Kurdish group that populates Iraq’s north, and between 1986 and 1989, Saddam killed between 50,000 and 100,000 of his own Kurdish citizens with chemical weapons on suspicion of being enemy sympathizers (Black 1993). Just two years after the Iran-Iraq war ended, Saddam attempted to ameliorate sprawling debt and flagging morale by invading neighboring Kuwait in 1991. Shia Arabs were disproportionately harmed in this conflict (Blaydes 2018), and Iraq’s campaign was quickly wiped out by an overwhelming US-led international response.

By the end of Iraq’s defeat in Kuwait, discontent among non-Sunnis with the Ba’athist leadership was beginning to clearly register around the country. Spontaneous uprisings broke out in the Shia and Kurdish areas of the country in 1991 and were crushed by the regime. The Ba’athist administration would limp on for another decade, but enormous war debt and increasing international sanctions saddled its ability to continue the massive state development programs that had won it favor among Iraqis. State repression steadily increased, and the importance of ethno-religious identity rose.

2003 to the eve of ISIL’s insurgency

In the early morning of March 19th, 2003, Baghdad awoke to the explosions of U.S. air raids. The attacks marked the beginning of a “shock and awe” campaign opening a U.S. invasion of Iraq. Hours later, U.S. president George W. Bush took to television to announce that “at this
hour, American and coalition forces are in the early stages of military operations to disarm Iraq, to free its people and to defend the world from grave danger” (CNN 2003).

By April 12th U.S. troops had captured Baghdad, and by May 1st the U.S. had declared an end to major combat operations. The internal politics driving the American decision to invade have been hotly debated; one of the key rationales for invasion – suspicions that Iraq was developing weapons of mass destruction – was quickly proven false. However, the US invasion was at this point irreversible. Saddam was captured on December 13th, 2003, an interim administration was installed, and parliamentary elections scheduled for January 2005.

The invasion marked a watershed moment in domestic Iraqi politics. Iraq’s experience of Arab nationalism ended abruptly; in its’ place, sectarianism would emerge as the most salient organizing cleavage. Two decades of Sunni rule under the Saddam administration came to an end and Shia politicians would head Iraq’s government for the next decade. The increasing importance of sectarianism, persistent violence, and Sunni feelings of victimization under Shia administration helped set the stage for the Islamic State’s emergence a decade later.

The official end of US combat operations did not mark the beginning of peace. Instead, sectarian-driven violence began to escalate. Some Sunni Arabs, driven from power by the invasion after two decades in control, felt victimized and resisted their newly reduced status (Al-Qarawee and Hasan 2014). Former Iraqi army personnel allied with the Ba’ath regime began rioting and attacking coalition personnel as soon as the interim Coalition Provisional Authority disbanded the Iraqi army in May 2003. By 2004 major uprisings were underway in several Iraqi major cities including Fallujah, Najaf, Al-Kut and Mosul; the insurgent groups conducting attacks were increasingly organized on sectarian lines. By 2007 insurgent violence had spread
around the country and Iraq had descended into what many described as civil war (see e.g. Fearon 2007).

Party formation for the 2005 parliamentary elections saw most parties formed on ethno-religious lines. The election returned a minority government for the Shia-dominated United Iraqi Alliance, with a Kurdish-dominated party placing second. Disenfranchised Sunnis broadly failed to vote; turnout in the Sunni-dominated Anbar province was as low as 2% and the largest Sunni party won only 1.78% of the vote (Government of Iraq 2005). Shia politician Ibrahm al-Jaafari became Prime Minister, but under his first year of leadership, sectarian violence continued to deepen, and other parties became increasingly reluctant to support the government. Al-Jaafari was replaced in May 2006 by Nouri al-Maliki, another Shia politician. Maliki would continue as Iraqi prime minister for the next eight years.

Beginning in 2008, Maliki’s government slowly began to reign in sectarian violence. A military campaign in 2008 expelled local militias from the port city of Basra and restored the central government’s control of the city; similar operations elsewhere soon followed. However, the gradual decrease in violence coincided with increasing authoritarianism and government favoritism of Iraqi Shias. In the name of stability Maliki made mass arrests of Sunni citizens accused of terrorism. Many argued that the government applied de-Ba'athification reforms less strictly to Shias who were willing to shift their loyalty to support Maliki. While the violence calmed, the sectarian tensions underlying it grew (Al-Qarawee 2014).

The post-2003 era also sharpened sectarian identity among Iraq’s smaller minorities. For the Kurds, much of the contestation centered on oil. Iraq’s 2005 constitution required the oil-rich Kurdish region to cede control of its oil exports to Baghdad in exchange for transfers from the federal budget. However, Baghdad frequently accused the Kurds of selling oil independently and
cut transfers to the Kurdish region in response, and Kurdish-Sunni Arab tensions rose. Smaller minorities experienced contention as well. Christians and Turkmen alleged deliberate attempts to seize their land and limit their access to state resources; Yazidis argued their northwestern Sinjar district was being deliberately deprioritized for state assistance (Smith and Shadarevian 2017). Quantitative analysis suggests the difference in economic performance between Kurds and smaller minorities in Iraq’s north more than doubled in the decade following US invasion (Smith and Shadarevian 2017).

In Iraq’s 2010 parliamentary election, a set of Shia and Sunni leaders united to form a new nationalist coalition pitched on bridging Iraq’s sectarian divide. The new Al-Iraqia party edged Maliki’s State of Law group secure a narrow plurality in parliament, and many hoped that reconciliation was on the horizon. However, Al-Iraqia failed to deliver the reconciliation its supporters had hoped for. Maliki retained the Prime Minister’s office and limited al-Iraqiya’s attempts for reform, rejecting all the Sunni al-Iraqiya nominees for defense minister and refusing to compromise his power in a proposed new national security council (Al-Qarawee 2014). By 2013, Sunni feelings of victimization and disenfranchisement were widespread. On the eve of ISIL invasion in Iraq, only 10% of Iraqi Sunnis in the areas about to be taken over agreed their country was “moving in the right direction” (Al-Dagher and Kaltenthaler 2017).

**Part II: The Islamic State insurgency**

*The rise of ISIL*

Undercurrents of extremism had been present on the fringes of Iraqi society long before the 2003 US invasion, and some of these movements identified with Sunniism. However, the rising salience of sectarianism in Iraq provided both an opportunity and mechanism for these
extremist groups to expand their influence. After 2003, Sunni-affiliated extremists realized that disenfranchisement among Iraqi Sunnis could be weaponized into a powerful recruiting tool. Several groups began working to aggravate the sectarian divide and organize a movement to capitalize on its consequences.

The formational threads of ISIL are rooted in this beginning of this opportunistic shift among extremist groups after 2003. The story begins with Jordanian-born Sunni Abu Musab al-Zarqawi, who made his name as a high school dropout and petty criminal in Jordan before travelling to Afghanistan in the 1990s to fight in the Afghan-Soviet war. Watching the US invasion of Iraq in 2003 and growing Sunni-Shia division, Zarqawi sensed an opportunity to capitalize on the split. He travelled to Iraq and established an arm of the transnational terror group Al-Qaeda in Iraq in 2004 (Warrick 2015).

Zarqawi’s Al Qaeda in Iraq (AQI) styled itself after its parent organization, but quickly developed a reputation for unusual brutality and disrespect for its superiors. Amid an uneasy relationship with Al Qaeda central, AQI worked to deliberately inflaming tensions between Iraq’s Sunnis and Shias. It attacked shrines and markets, conducted suicide bombings, recruited intensively and spread propaganda (Warrick 2015). In February 2006, AQI members bombed the famed Shia Al-Askari mosque in in the Iraqi city of Samarra, one of Shia Islam’s holiest sites (Bush 2006).

In January 2006, AQI joined forces with several other Sunni extremist groups to create an umbrella organization dubbed the “Mujahideen Shura Council.” U.S. intelligence operatives sensed danger and killed Al-Zarqawi June 2006 airstrike, but the movement had now grown beyond Zarqawi’s personal influence. The Mujahideen Shura Council united with nine more Sunni groups in October 2006 and declared the establishment of an Islamic State of Iraq (ISI) the

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next day. Omar al-Baghdadi – who would later become ISIL’s de-facto leader – was anointed the emir of the proposed state (Warrick 2015).

The Islamic State in Iraq and its eventual result ISIL were ideologically anchored in Salafism, a branch of Sunni Islam which purports to be true to the fundamental tenets of Sunniism. Core to ISIL’s extreme interpretation of this ideology was the establishment of a Sunni Caliphate. The origins of this idea trace back to the days of the Prophet Muhammad, who in the last ten years of his life spelled out a distinct form of social organization based on the Quran. Muhammad’s immediate successors – regarded as legitimate by Sunnis but not by Shias – continued to govern major Middle Eastern metropoles such as Baghdad and Cairo for the next four centuries in line with Muhammad’s Quaran-based governance model. During this period – between 632 and 1097 – the caliphate was the most advanced and powerful polity in western Eurasia, and its cities were centers of trade and culture. The Islamic State thus aimed to reinstate the Sunni Caliphate as a mechanism to restore the glory days of Islam in modern times. ISIL saw the establishment of a caliphate as a communal responsibility and believed all Sunnis had a moral obligation to pledge allegiance to its project (Kennedy 2016).

ISIL’s extremist Salafist interpretation required several other tenets of belief. First, it saw many non-Sunnis – including Shia Muslims and several other religious other religions – as apostates. Many non-Sunnis where therefore condemned to die. Second, ISIL believed in an interpretation of Sharia and the Quran obliging offensive jihad (holy war): a continuous obligation to expand and purify the caliphate. ISIL insisted the caliph had a religious obligation to wage jihad at least once a year and was morally obligated not to strike long-term peace deals or recognize borders (Wood 2015). Third, ISIL saw itself as the fulfiller of prophecy. The Prophet Muhammad, ISIL leaders say, once prophesized that the armies of Islam would meet the
armies of “Rome” at Dabiq – a Syrian town – and the ensuing battle would trigger the apocalypse. ISIL viewed itself as the army of Islam, and believed it was acting in fulfillment of this prophecy (Wood 2015).

The ISIL interpretation of Sunni Islam is rejected by most Sunnis and disavowed by many other followers of the Salafist branch. Many religious scholars argue that ISIL selectively “cherry-picked” pieces of the Quran and Sharia law to suit its vision and ignored critical tenets of theology (Open Letter 2018); President Obama summarized the bastardization as simply “not Islamic” (BBC 2014). In fact, there is substantial debate over whether ISIL fighters believed deeply in their doctrine at all (Hasan 2015). Some argue that ISIL’s theology is better understood as a tool to unite fighters and assign coherent structure to grievances rather than a fundamental motivation itself. Many ISIL foot-soldiers were young men with limited opportunities, little income, deep grievances and relatively little religious devotion. ISIL offered them a $400 monthly salary (Suruansky 2014) and a chance for “adventure, personal power, and a sense of self and community” (Cronin 2015). However, while ISIL’s religious philosophy is a dubious textual interpretation of Salafism and of dubious religious value to its own fighters, it played a crucial part in attracting members, motivating its mission and defining its governance.

As the Islamic State of Iraq planned its imagined caliphate, it continued working to inflame Sunni-Shia tensions in Iraq. Until 2010 these efforts were severely hampered by US counterinsurgency operations. The US Iraqi troop surge in 2007 decimated the group’s leaders, and by 2010, coalition spokespeople estimated as much as 80% of ISI’s top leadership had been killed or captured (Shanker 2010). 2011, however, brought a spectacular opportunity for the struggling ISI. In neighboring Syria, popular protests erupted against Syrian president Bashir al-Assad. The situation had descended into civil war by March 2011, and Syria’s government lost
the ability to directly administer much of its territory. Baghdadi jumped on the vacuum of instability and began sending Iraqi ISI members across the border to establish an arm of his group in the Sunni Arab areas of Western Syria. This organization, the *al-Nusra* Front, quickly gained substantial following and capacity. Al-Baghdadi revealed that the al-Nusra Front had in fact been established and supported by ISI in April 2013 and announced that the two groups were now to merge under the banner of the “Islamic State of Iraq and the Levant (ISIL).” The group’s exact name has been translated inconsistently by western media and occasionally tweaked by the group itself, but this thesis uses the acronym ISIL for consistency (Warrick 2015).

ISIL immediately flexed its might by raiding prisons in the Iraqi towns of Taji and Abu Gharib in July 2013, freeing more than 500 prisoners – many of them hardened Sunni extremists (Lewis 2013). ISIL’s relationship with parent organization Al Qaeda grew increasingly strained as it grew in strength and brutality. In February 2014 Al Qaeda publicly disavowed its relationship with ISIL, leaving ISIL to become an autonomous insurgency (Sly 2014).

*Expansion, governance, and violence in the Islamic state*

With the manpower and capacity to begin seizing territory, ISIL turned its focus to the physical realization of its caliphate. ISIL’s fighting force initially entered conflict alongside the Syrian opposition forces fighting the Assad government in northern Syria. However, ISIL soon turned on its fellow opposition factions, and by January 2014, it had secured control of the Syrian city of Raqqa (Lebanon Daily Star 2014).

ISIL soon began seizing territory in Iraq. On December 30, 2013, ISIL fighters began their first Iraqi assault on the city of Fallujah, and by January 4th they had consolidated control over the city (Al Jazeera 2014a). A lighting advance by ISIL fighters over the Sunni western half
of Iraq in summer 2014 saw the group capture more than 200 settlements in a matter of weeks, and by late June 2014, the group had captured Mosul and advanced to within 25 kilometers of the Baghdad airport (Lucas 2014). ISIL leader al-Baghdadi took to Mosul’s grand mosque on June 29th to deliver a sermon and declare a caliphate. At its height, ISIL controlled over 300 populated settlements in northern and western Iraq and a third of Iraqi territory. It would control much of the territory it had gained for more than two years.

ISIL governed as a pseudo-state in much of its captured territory. The insurgent group set up court systems, prisons, and police services, collected taxes and picked up garbage. It created offices that issued marriage and birth certificates and ran a bureau that licensed new drivers. In major cities, the group set up ministries for agriculture, telecommunications, and internal revenue, and diligently taxed its population and tracked its receipts (Callimachi 2018). In Syria the group became so effective at producing power it began to strike agreements to sell electricity to the Syrian government (Cambanis 2014); across both countries, it sold oil on the black market and earned an estimated peak revenue of $50 million per month (Gusovsky 2015). In some cases, the group even improved on existing infrastructure: ISIL built covered roofs for Mosul’s Nabi Yunus market (Robinson et. al. 2017), conscripted a committee of electrical engineers in the Iraqi town of Tel Keif to install new circuit breakers to support the overloaded electricity grid, and paved a new one-mile road in Mosul to relieve traffic congestion named ‘Caliphate Way’ (Callimachi 2018).

However, ISIL occupation crippled the quality of life for Sunnis over whom it ruled. The group imposed a strict implementation of Sharia law in the settlements it governed and backed it with force. The Hisba religious police enforced an extremely strict dress code and doled out fines and imprisonment for breaches of Sharia in public (Callimachi 2018). When ISIL first took over
Mosul, its distributed leaflets instructing women to "wide, loose jilbab, stay in your homes and leave them only in cases of necessity" (Al-Aqeedi 2016). Recovered prison records show Iraqis were jailed for trimming their beards, playing cards, or listing to music. Justice was delivered in a brutal traditional fashion, and public executions, stonings, and decapitations were common (Callimachi 2018).

While Sunnis under ISIL were subjected to strict Sharia rule, other ethno-religious groups – many of whom were viewed as apostates – were subjected to horrific violence. When ISIL captured the Yazidi-dominated Iraqi district of Sinjar in summer 2014, it began wholesale slaughter and enslavement of the Yazidi population.¹ Between 2,000 and 5,500 Yazidis were executed by ISIL militants or died attempting to escape, 6,000 more were enslaved, and virtually all remaining Yazidis fled to refugee camps in northern and western Iraq (Cetorelli et al. 2017). Ethno-religious minorities elsewhere fared little better. In the Ninewa Plains, ISIL militants summarily executed Christian residents and levelled their towns. Shia Shabak and Turkmen reported similar stories of horrific violence and extermination. The United States, United Kingdom, and European Union all individually recognized ISIL’s violence towards Iraqi Yazidis and Christians as separate genocides, and violence against other non-Sunni groups was similarly horrific. ISIL occupation also triggered massive population flight from occupied areas to internally displaced persons (IDP) camps in north-eastern and southern Iraq. At the height of the ISIL occupation, the International Organization for Migration recorded more than 3.2 million displaced Iraqis (IOM 2018).

¹ Yazidis follow a distinct faith – Yazidi’ism – which is an ancient, monotheistic religion.
The global coalition and fighting back

A turning point in the ISIL insurgency arrived in August 2014 when the Obama administration decided to intervene. In August U.S. airstrikes pushed ISIL militants back from the northern city of Kirkuk and broke an ISIL siege of Yazidis on Mount Sinjar. On September 10th President Obama announced the U.S. would lead a global coalition “degrade, and ultimately destroy, ISIL.” Alongside the Iraqi army, the Kurdish Regional Government’s Peshmerga security force, and a patchwork of local militias, anti-ISIL forces regrouped and halted the ISIL advance by the end of 2014 (Quanrud 2017).

By 2015 ISIL was in retreat. As the caliphate began to lose territory, service provision in its remaining settlements began to collapse, and taxes soared. Conflicts to dislodge ISIL militants were at times lengthy and destructive. However, the slow and tedious campaign to dislodge the Islamic State ground forward, and by July 2017, coalition forces had liberated Mosul (BBC 2017a). Al-Qaim, last sizable ISIL-held settlement in Iraq, was recaptured in November 2017 (U.S. Central Command 2017).

With ISIL routed on the battlefield, its fighters turned to a guerilla-style insurgency. A smattering of militants continued sporadically attacking residents and infrastructure in the areas they used to control after the group’s military defeat. Heavy military presence in liberated areas worked to crush remaining pockets of insurgent resistance, but security concerns persisted for years after ISIL’s lost its final patch of Iraqi territory.

Part III: Aftermath - political change and post-conflict reconstruction

In the wake of ISIL’ military defeat, Iraqi found itself at the beginning of a massive reconstruction effort. Four years of ISIL insurgency wiped out $47.5 billion worth of
infrastructure in the western third of the country, displaced more than 3.2 million people, and inflicted severe social and psychological trauma on millions of Iraqis (Gordon and Coles 2018, IOM 2018).

The post-ISIL political environment in Iraq is extremely complex, and it is not useful to detail its particularities here. For now, my goal is to identify the key dimensions on which post-conflict political experience varied and argue that this variation should be treated not as independent influences on reconstruction but rather as part of the mechanism by which independent variables influence recovery. No one will be surprised to learn that fighting local security factions or deeply divisive elections slow recovery. But the assignment of these events is neither random nor exogenous. The interesting question is why political circumstances that slow recovery emerged in some settlements but not others. Chapter 7 will delve into the most important relevant mechanisms in detail, but readers need to have a general sense of the post-conflict environment and its dimensions of variation to understand the thesis’ research design. Below, I briefly summarize three key sources of variation in local post-conflict experience: security providers, elections, and the mechanics of reconstruction aid.

The first set of dimensions on which post-conflict experience varies relates to local security providers. Two professional domestic security forces – the Iraqi Security forces of Baghdad and the Pershmerga of the Kurdish autonomous region – and a patchwork of roughly 40 local militias dubbed “Popular Mobilization Forces” (PMFs) share the responsibility of local security administration in liberated territories. First, these forces differ in their levels of professionalism. While the Peshmerga and the Iraqi military are relatively well-trained and professional, some PMF groups are ill-trained and more likely to commit sectarian abuses. Second, they differ in identity: some security forces are locals who share ethno-religious and
familial ties with the population they are protecting, but others are ‘outsiders’ with little relationship to the host population. Third, forces differ in their motives: some forces are purely concerned with protecting the local population, but others are pawns of Erbil, Baghdad, or even foreign governments such as Iran. Fourth, they differ in their degree of autonomy: some forces are directly accountable to higher levels of government or foreign sponsors; others operate with little oversight. Finally, in some settlements security provision is shared between two or more groups, while in others there is a sole security provider. In situations where control is shared the level of animosity between partner security providers varies and conflict between competing “liberators” is sometimes common (Gaston and Derzsi-Horvath 2017).

Regional and national elections were held in the wake of ISIL’s defeat, and the second dimension on which post-conflict experience varies lies in the local experience of these elections. National parliamentary elections were staged in May 2018, and overall, many observers saw them as less sectarian than previous national votes (see e.g. Daragahi 2018). A relatively large number of parties ran on platforms of national unity and reconstruction, and the best performing party - Saairun - won on promises to rebuild infrastructure in areas battered by ISIL occupation, combat corruption, and fiercely oppose foreign interference from Iran and the United States. However, because the number of competing parties was so high (204) and many of them were local, the dynamics of campaigning was very different in different areas.

Two regional ballots also occurred. First, on September 25, 2017, the Kurdish Regional Government staged an independence referendum in the three northern Kurdish governorates as well as in disputed territory occupied by Kurdish Pershmerga after ISIL’s retreat. This vote was generally regarded as more ethno-religiously charged than the national election, but the experience of the campaign differed substantially from town to town. Additionally, it led to
diverse post-referendum consequences. The referendum returned a 92% landslide in favor of independence, but Baghdad was quick to brand the vote illegal and declare it would ignore the results. In response to the vote, Iraqi Security Forces advanced on territory south of the Kurdish autonomous region that had been de-facto administered by the Kurds since the defeat of ISIL. Kurdish Peshmerga forces retreated – mostly peacefully – to within the boundary of the official Kurdish autonomous region, but the local-level impacts of this control shift differed across settlements. The Kurdish region also held its own regional parliamentary election in September 2018. This vote occurred only in the three Kurdish-administered governorates and hence outside of ISIL-occupied region, but it likely impacted local dynamics in some settlements where Erbil had a presence.

Finally, post-conflict experience varies in type of reconstruction assistance provided to settlements. First, the sources and implementing partners of this aid vary. Some funding is provided by the Iraqi government, some is internationally sourced but coordinated by international organizations like the United Nations Development Program (UNDP), and some is delivered directly by international governments and third parties. Different funding sources fund different types of reconstruction projects with different implementing partners in different areas, and the competency and effectiveness of these arrangements varies.

Second, the extent to which reconstruction aid disbursement is locally versus nationally driven varies by project and settlement. Most formal funding mechanisms have hierarchical structures where donors partner with Iraqi officials at various levels of government. These mechanisms are often intended to balance input across Iraqis and foreigners and between different levels of government (UNOCHA 2019). In practice, however, the relative amounts of
influence different actors wield varies from project to project and corruption sometimes plays an important role in aid delivery (O’Driscoll 2018).

*Variation in recovery*

The political circumstances of recovery clearly vary greatly from settlement to settlement. We would expect that these differences influence recovery, and indeed, my empirical analysis quickly identifies that purely objective characteristics cannot explain all the variation in recovery performance. But as the beginning of this section explained, the experience of settlements after liberation is endogenous to their characteristics before liberation. This project seeks to understand which pre-invasion settlement characteristics make the muddled post-liberation political arrangements that slow reconstruction more likely to occur. This thesis explores a variety of pre-invasion social characteristics, but I allocate most of my effort to the most interesting one: the effect of pre-invasion ethno-religious composition.
Chapter 3 | Nighttime light as a proxy for post-conflict reconstruction

The previous chapters argued that a quantitative analysis of post-ISIL reconstruction in Iraq could add a useful perspective to understanding Iraq’s experience and post-conflict reconstruction generally. The high international interest in the conflict and extensive reconstruction effort made data on many of the covariates of interest readily available. Conflict mapping identifies when areas were invaded and liberated, survey data is available to code the ethno-religious identity of settlements, and geographic analysis can inform on many of the logistical factors which likely influence reconstruction. However, one key variable is missing: how can we measure reconstruction?

Post-conflict reconstruction literature typically uses time-series GDP data to evaluate recovery. Such data is certainly not available at the settlement level in post-ISIL Iraq and collecting it in each of the more than 300 occupied settlements would be prohibitively costly. However, a recent innovation in economic methodology provides a creative substitute: satellite–observed nighttime lighting can be used as a proxy for economic activity. Many economic processes emit light at night, and several studies show that nighttime lighting levels closely track GDP in places where GDP is known. A growing political science and economics literature has used this data to study settlement-level economic characteristics in areas of poor data quality.

In this chapter, I outline how this thesis uses satellite-observed nighttime lighting as a proxy for post-ISIL reconstruction. The chapter begins by describing the theory for nighttime light as a proxy for reconstruction. It describes the data source and goes on to summarize the literature validating it as a proxy for economic activity and some of its previous use. Finally, it
runs on a novel validation exercise to evaluate how closely nighttime lighting in Iraq has tracked economic activity.

**Part I: From nighttime lights to post-conflict recovery - the theory for the proxy**

“Post-conflict recovery” is a broad term that encompasses many distinct processes. I focus primarily on *economic* recovery, but even this term aggregates many concepts. It involves the return of inhabitants who fled ISIL occupation to their homes. It involves the physical reconstruction of damaged infrastructure, such as homes, schools, roads, and public buildings. It also speaks to a broadly-defined “return to normal life”: most observers associate recovery with workers’ return to their jobs, schoolchildren’s return to school, and the re-establishment of regular routine. How can all these processes be captured in a single measure? The literature typically defaults to GDP as a catch-all measure of recovery. Given that GDP cannot be feasibly measured over time in Iraqi settlements, I turn to proxies for GDP for help.

The theory for nighttime light emissions as a GDP proxy stems from the observation that many economic processes emit light at night. Cars driving on roads, the operation of factories and stores, the use of household appliances, and a variety of other economic processes all emit light during their use at night. The brighter the lights, the more economic activity is occurring. Since 1992, NASA satellites have captured nightly images of night-time light emissions around the globe. Christopher Elvidge first suggested this data might be used to proxy for economic activity in 1997 (Elvidge 1997), and it has been validated and used with increasing frequency since.

Light can be used to proxy for economic activity in post-conflict towns just as for settlements in peacetime. In post-ISIL Iraq, the return of nighttime lights to liberated towns
captures four components of economic recovery. First, there must be people to turn on the lights: nighttime lighting captures the return of displaced residents to their homes. Second, there must be lights to turn on: nighttime lighting captures the physical reconstruction of damaged infrastructure, because damaged buildings must be repaired before they can be illuminated. Third, there must be desire to turn on the lights. Individuals must be conducting some form of economic activity that requires nighttime lighting, such as operating a market stand, running a factory, or working at home. Finally, there must be financial capacity to turn on the lights: running gas generators or drawing grid electricity is expensive; the intensity of nighttime lighting hence reflects household and commercial income.

Dramatic changes in nighttime light emissions during ISIL occupation suggest large changes in economic activity during insurgent presence. Figure 4 shows nighttime lighting over Mosul - the largest ISIL-occupied settlement in Iraq – before, during, and after ISIL occupation. Lights dramatically decrease when ISIL invades in 2015, remain dark through ISIL occupation, and begin to gradually recover after Mosul is liberated in mid-2017.
My use of nighttime light as a reconstruction proxy requires one important qualification. Light proxies for GDP, a measure of total economic activity. For the large cities and long time periods addressed in previous reconstruction literature, GDP aligns closely with common conceptualizations of recovery. However, I apply the proxy to many small settlements over a short time horizon. In this case, it becomes more important to pay attention to the components of total economic activity. There are two key parts. First, some total economic activity consists of “ordinary” economic activity: residents operating shops, running household appliances, driving at night, and other day-to-day processes. This ordinary economic activity maps directly to the “return of ordinary life” that is the substantive outcome of interest.

A second part of total economic activity, however, consists of “reconstructive” economic activity. This is economic activity that is associated with the reconstruction effort rather than...
day-to-day regularities: for example, trucks unloading supplies to rebuild a house at night, a
NGO distributing food at night from the back of a floodlight van, or a civic works crew repairing
a power line at night will also emit light. Recovery efforts create a high temporary level of
economic activity, and later analysis will show that settlements often appear to “recover” to
higher light levels than before invasion. Readers should remember that reconstructive economic
activity is not identical to the return to normal life that is the substantive outcome of interest.
Settlements with very high levels of post-liberation light are not fully recovered in the sense that
they are fully restored, but they are enjoying more intense and effective reconstruction.

We are truly interested in the return of ordinary economic activity but can only observe
total economic activity. However, total economic activity is still a useful substitute: the part of
total economic activity which does not relate to ordinary activity today is reconstructive, and
reconstructive activity today leads to increased ordinary activity in the future. Not all brightness
is recovery, but brighter settlements are rebuilding faster.

**Part II: Introduction to luminosity**

*Description of the data source*

Nighttime lighting data has been made publicly available since 1992, and pre-processing
work by the National Oceanic and Atmospheric Administration (NOAA) makes it relatively easy
to use. Understanding the basic points of how the data is created helps contextualize my use of it
as a proxy.

From 1992 to 2013, the Earth Observation Group at NOAA’s National Geophysical Data
Center operated satellites that took daily images of the entirety of Earth’s surface between 8:30
pm and 10:00pm local time. Researchers removed images obscured by cloud cover, excessive
moonlight, or forest fires. They then merged the remaining daily images to create yearly composites and seeded them with digital numbers ranging from 0 to 62 representing the intensity of nighttime light brightness. These images – published as products of the Defense Meteorological Satellite Program (DMSP) – are openly available to the public. Each pixel on a yearly DMSP composite corresponds to approximately one square kilometer (Elvidge 1997).

As researchers began to explore DMSP data for a variety of applications, several limitations in data quality and accuracy became evident. These concerns encouraged NOAA to begin supplying a new and much-improved luminosity product from a new satellite in April 2012. Visible Infrared Imaging Radiometer Suite (VIIRS) luminosity provides monthly images of nighttime light emissions at 0.2 square kilometer spatial resolution and resolves many of the data quality challenges of DMSP data (Elvidge 2017). The VIIRS satellite takes images each night at 1:30am local time. NOAA stopped providing DMSP data after 2013, and from 2014 onwards, VIIRS satellites are the primary source of nighttime light imagery. Taken together, the DMSP and VIIRS images supply a 25-year panel of nighttime light data, available at resolutions equal or smaller to one square kilometer, across the globe.

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2 DMSP data is subject to some “bleeding” between pixels, is top-coded due to sensor saturation at the high end of its scale, and requires manual backend calibration to ensure data collected by different satellites is comparable (Elvidge 2014).

3 Like Xi et. al. (2018) and others studying luminosity in Iraq, I use VCMCFG VIIRS luminosity. The “VCMCFG” product requires more manual cleaning than it’s “VCMSLCFG” counterpart, but it more accurate and has greater temporal availability.
Light as a proxy for economic activity

Many studies have demonstrated that nighttime light closely tracks GDP in situations where GDP is known. The seminal proof-of-concept work for this relationship appeared in Henderson et. al.’s (2012) contribution to the American Economic Review. Henderson et. al. run a 20-year panel for 188 countries from 1992 to 2008, using yearly DMSP datasets to calculate growth rates at the country level. They find that growth in luminosity captures roughly 77% of the variation in growth in GDP as measured by national accounts.

Subsequent studies have replicated Henderson et. al.’s findings for DMSP data in a variety of settings. At the country level, Chen and Nordhaus (2011) compare GDP and luminosity at the country level and at the 1° latitude × 1° longitude grid-cell level for a 1992-2008 panel and find that the addition of luminosity data to national economic data improves the
quality of economic data in developing countries. Wu et al. (2013) run a similar panel for 15
years and 169 countries and find that variation in luminosity captures upwards of 90% of
variation in GDP as measured by national accounts.

Research has also validated the utility of DMSP data as a proxy at the micro level.
Mellander et al. (2015) compare DMSP luminosity with micro-level census data in Sweden;
they find moderate to strong correlations between luminosity values and wage incomes.
Weidmann and Schutte (2016) compare 34,000 village and neighborhood level luminosity
observations in developing countries with corresponding Demographic and Health Surveys
(DHS) data and find an average correlation between luminosity values and local-level wealth of
0.73. Chiovelli et al. (2018) validate DMSP against DHS survey data on household wealth in
African regions and find a strong link between DMSP and household wealth. Dai et al. (2017)
find that DMSP captures 64% of the variation in city-level GDP in 341 Chinese cities; Shi et al.
(2014) find DMSP captures 66.4% of variation in GDP in 268 Chinese cities.

The new VIIRS dataset offers a substantial improvement over its DMSP predecessor
(Elvidge 2013). In China, Li et al. (2013) find that VIIRS light observations capture 87% of the
variation in reported provincial GDP; Shi et al. (2014) recover the exact same number in a
replication study one year later. At the city level, the improvement is even more pronounced. Shi
et al. (2014) find that VIIRS captured 80.8% of variation in reported GDP at the city level in a
set of 268 Chinese cities. Working with a set of 281 Chinese cities, Ma et al. (2014) find that
VIIRS lighting captures 91% of the variation in city-level GDP. Dai et al. (2017) used a set of
341 Chinese cities and found VIIRS captures 86% of the variation in city-level GDP; their
results add that a linear relationship between VIIRS and GDP performs essentially just as well as
a polynomial or exponential fit. VIIRS data has also been proven to yield consistent estimates of
nighttime lighting even at very low light levels in very precise areas: Cao and Bai (2014) show that VIIRS data consistently captures light emissions from individual light fixtures on the San Mateo bridge and individual fishing vessels.

Previous applications in the literature

Building from the premise that luminosity data can capture economic activity, a variety of studies have used luminosity approaches to evaluate economic and political questions. Applications to development, city-level dynamics and conflict are among the most prominent.

A first group of literature uses luminosity to evaluate development questions. At the country level, researchers have used nighttime light to evaluate issues such as impact of ethnic income inequality on economic development (Alesina et. al. 2016), the relative success of autocracies and democracies in public goods provision (Min 2008), and the impact of specific social programs such as cash transfers on poverty (Villa 2014). At the regional level, researchers have used luminosity to examine patterns of regional spatial inequality within a country (Chaiwat 2016), the impact of pre-colonial institutions on African regional development (Michalopoulos et. al. 2013), and growth discontinuities at borders in Africa and Latin America (Pinkovskiy 2016, Gallego et. al. 2016). Lee (2014) uses luminosity data to evaluate the impact of economic sanctions in North Korea. Others have used luminosity at the city level to investigate the relationship between rainfall and urbanization in African cities (Henderson, Storeygard and Deichmann 2017) and the effect of intercity transport costs on income in sub-Saharan African settlements (Storeygard 2016). Some have even used luminosity to measure change in economic activity in response to specific events. Pfeifer et. al. (2018) catalog luminosity increases in neighborhoods surrounding South African soccer stadiums when World
Cup matches occurred; Roman and Stokes (2015) analyze the increase in nighttime lighting surrounding major holidays such as Christmas, New Years’ and Ramadan.

Finally, a large group of literature uses luminosity to evaluate the effects of conflict. Settlement-level analyses have used luminosity to investigate the link between economic inequality among ethnic groups and conflict (Cederman et. al. 2015) and the extent of village-level changes in wealth during violent conflict (Lopes de Fonesca and Baskaran 2015). Some have even used nighttime lights to evaluate conflict at the sub-city level: Shortland et. al. (2013) use luminosity data and geo-coded conflict data to evaluate the effect of conflict on incomes in Somalia for different socioeconomic groups, using relative location within a city to differentiate between elite versus lower-class groups.

*Luminosity in Iraq*

Iraq has struggled with a weak public electricity grid for decades, and much of the electricity infrastructure in ISIL-occupied areas was obliterated during the insurgency. Paradoxically, the weakness of the Iraqi national electricity grid makes nighttime light emissions an especially useful proxy for economic activity in Iraq. This is because the deficiencies in grid electricity forced many Iraqis to source their power from household generators and neighborhood power generation agreements. When electricity generation is hyper-local, the link between nighttime light household or business income is very direct: appliances light up when residents can afford to put gas in their generators or pay a neighbor to use electricity.

Iraq had a very high fraction of locally generated power even before the ISIL insurgency. Many households owned fuel-powered generators for personal use, and others bought electricity from private entrepreneurs who set up generators on street corners or shared generators with
neighbors (Ibrahim 2018). In 2007, a World Bank Household Survey reported that at least three-quarters of residents in each governate that would later be occupied by ISIL received at least some power from a secondary source (IAU 2010). In 2011, a joint United Nations – Iraqi Government survey found that power from secondary sources accounted for nearly half of Iraqi households’ daily power consumption: households received a daily average of 7.6 hours of electricity from the grid and generated 7 hours from generators or local networks (IKN 2011).

After battles between ISIL and coalition forces destroyed much of the formal electricity structure, local power generation arrangements likely accounted for an even larger relative share of power generation.

Luminosity is no stranger to conflict and development work in Iraq. Roman and Stokes (2015) analyze changes in DMSP light emissions over Iraq after the 2003 U.S. invasion, and find that changes in lighting can be partially explained by political and security events on the ground. Agnew et. al. (2008) use DMSP lighting over Baghdad and other major Iraqi cities to analyze the welfare impacts of the U.S. troop surge in Iraq beginning in Spring 2007. Smith and Shadarevian (2017) analyze DMSP lighting in Iraq’s Kurdish Autonomous Region from 2003 to 2013 to show that Kurdish-majority areas grew much faster in this period than areas populated by minority groups.

ISIL’s invasion of Iraq and Syria is one of the first major conflicts fully covered by the new VIIRS lights set: the earliest VIIRS monthly data begins in April 2012; ISIL took control of Fallujah – its first major Iraqi city – in December 2013 (CNN 2018). It is thus no surprise that studies evaluating VIIRS light changes during ISIL occupation have been quick to emerge. The first category of work seeks to analyze the effects of ISIL governance. The clearest finding is that when ISIL takes over towns in Iraq and Syria, the lights typically go out (Li et. al. 2015, Li
13 ISIL-occupied or contested major cities in Iraq and find that ISIL-occupied cities lost up to
90% of their pre-invasion light levels after ISIL occupation. Some researchers have also used
luminosity data to analyze more specific aspects of ISIL governance. Do et. al. (2018) analyze
VIIRS light emissions from oil refineries to estimate ISIL oil production in the areas it occupied.
Corbane et. al. (2016) use VIIRS data to identify sub-city conflict dynamics in Syria, observing
the nighttime lighting effects of barrel bombing in Damascus suburbs and comparing lights in
government versus rebel-controlled sections of Aleppo.

Others have investigated the relationship between VIIRS light emissions and the effects
of conflict. Levin, Ali and Crandall (2018) note a correlation between VIIRS values and monthly
conflict deaths in a variety of Arab Spring countries, including Iraq and Syria. They also observe
correlations between regional VIIRS light levels and the number of internally displaced persons.
Li et. al. (2014) similarly note a correlation between VIIRS levels and internally displaced
persons in Syria at the province level.

While VIIRS has begun to be leveraged to analyze the effects of ISIL governance during
occupation, this project is one of the first attempts to apply it to post-conflict reconstruction.
Perhaps the closest empirical study to this one is supplied by Li et. al. (2018), who plot VIIRS
light changes in 12 northern Iraqi cities within or on the ISIL front line and 6 southern Iraqi
“control” cities from 2012 to 2017. Li et. al. note that light generally decreases in ISIL-occupied
cities and returns when they are liberated; the “control” cities in southern Iraq do not see
decreases in light. However, Li et. al. do not analyze patterns in reconstruction or differences in
reconstruction trajectories.
Part III: Data Cleaning and preparation

The primary dataset used in this study is the VIIRS set. ISIL occupied its first major Iraqi city in December 2013 and was expelled from its last in November 2017 (Wilson Center 2018, CNN 2017), so monthly VIIRS observations from April 2012 to December 2018 provide a precise monthly panel of light levels immediately before, during, and after ISIL occupation. I at times present information from annual DMSP observations between 1992 and 2012 as supplementary contextual information, but DMSP data is not used in my core quantitative analysis. ¹⁴⁵

Both datasets must be cleaned before they can be used. Much of the initial heavy lifting is performed by analysts at NOAA, who remove extraneous light and clouds, assign numbers to pixels that represent their light intensity, and average daily observations into monthly or annual composites. However, a short set of additional cleaning steps are necessary.

First, annual DMSP data must be manually calibrated. DMSP imagery is sourced from several different satellites over two decades, and each satellite’s light sensor had a slightly different sensitivity. As a result, users need to apply calibration coefficients to each year of data to ensure they are comparable in time series (Elvidge 2013). I apply Elvidge’s (2014) calibration coefficients to each raw raster to derive a consistent panel.

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¹ Monthly DMSP data is not publicly available. It is expensive to obtain and not very important to this project, so I use only yearly DMSP data.
⁵ VIIRS and DMSP data exist at different spatial resolutions and temporal frequencies, are captured at different times of the day, and are expressed in different units that are not linearly related. Scholars that have attempted to intercalibrate the two datasets show that doing so results in substantial loss of accuracy at the pixel level. (Li et. al. 2017, Jeswani 2018) My own efforts to replicate the leading attempts in Iraq and for a set of control areas yielded pixel-level errors above 50%.

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Second, monthly VIIRS images each June are unavailable because late sunset times during these months leave lingering daylight during the satellite pass-by time, interfering with nighttime light measurements. The July 2018 data is unavailable due to a technical fault. Following the approach of Xi et. al. (2018), I interpolate data for these months using a simple linear interpolation formula.

Third, observed lighting exhibits seasonal oscillations and random error. Seasonal oscillation in nighttime lighting arises due to seasonal changes in vegetation cover and land surface reflectance (Levin 2017), atmospheric characteristics (Levin 2017), and nighttime light use patterns (Elvidge 2013). “Random” events such as short-term blackouts, programmed load shedding, or other quasi-random nighttime lighting events also introduce “random” error into time-series monthly VIIRS data. To address the seasonal and random variation in monthly observations, I use locally estimated scatterplot smoothing (“Loess”) regression to smooth the data. Each settlement has three distinct periods of economic activity: before, during, and after ISIL occupation. Settlement lighting panels in Part IV of this chapter will show that these periods are often separated by discontinuous changes in light emissions: light emissions often drop sharply on invasion day and sometimes recover sharply after liberation. For this reason, I estimate a separate Loess regression line for each of these three periods. I use this smoothed data for the core regression analysis.6

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6 I set parameter $\alpha$, which controls the degree of smoothing, to 0.5. This implies that the neighborhood of observations used to smooth a point is 50% of all data points in the period, and these points have tricubic weightings (proportional to $(1 - (\frac{\text{dist}}{\text{maxdist}})^3)^3$). Periods with fewer than 8 months do not have enough data to estimate a loess smooth with $\alpha = 0.5$, so in these cases (corresponding to during ISIL occupation periods that are shorter than 8 months) the raw data points are used. My results are not sensitive to other reasonable choices of $\alpha$. For some matching approaches I instead use a seasonal decomposition by loess (an alternate technique which uses Loess principles to isolate the “trend”, “seasonal”, and “random” components of time-series data), to help with interpretability. I mention when I use this alternate smoothing strategy and explain why when I do.
Finally, both DMSP and VIIRS data must be masked from nighttime gas flares. Nighttime gas flaring at oil wells – common in Iraq - results in enormous nighttime light emissions that are not reflective of economic activity (Elvidge 2009). I identify and exclude gas flares based on emissions in April 2012 using the identical thresholds applied by Xi et. al. (2018): pixels with light emissions greater than 500 NanoWatt/(cm2 sr) are labeled as flares, and all pixels within 10 kilometers of the flare are excluded. This results in the exclusion of a small number of ISIL-controlled settlements that would otherwise be in my sample.

Part IV: Validation in Iraq

The literature makes a compelling argument that nighttime light is a valid proxy for GDP at the settlement level generally. The work discussed earlier assumes this link holds in Iraq just as it does in other countries. I make the same assumption; however, I also run a novel exercise to validate luminosity as an economic proxy in Iraq specifically. Sub-national GDP data is not available in Iraq, but two simple exercises with closely related data help confirm that the link between luminosity and economic activity scholars have observed elsewhere holds well here.

I first examine the relationship between luminosity and GDP in Iraq at the national level over time. I plot annual national GDP values for Iraq from 2003 to 2018 against the sum of city light from all large Iraqi cities over the same period. Figure 6 shows Iraq’s GDP per capita (green; middle), against DMSP and VIIRS luminosity. Both national GDP and DMSP readings show a slight negative response to the 2008 recession, and then grow together to the beginning of ISIL occupation. Both GDP and VIIRS readings experience a clear stall and decline at the beginning of ISIL occupation, and both recover as ISIL is gradually expelled. Although there are

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some slight differences in reported GDP and the DMSP measure prior to 2008, they are small—and the VIIRS data, which used for my core empirical analysis, tracks GDP per capita movements well.

**Figure 6: GDP, VIIRS, and DMSP in Iraq: 2003 - 2018**

Second, I examine the relationship between luminosity and economic performance *cross-sectionally* across Iraq’s 17 governorates at the same point in time. Though GDP data is not publicly available for Iraqi governorates, two national household surveys in 2011 and 2012 can be used to derive estimates of monthly expenditure at the governorate level. The 2011 Iraq CSO-ILO Knowledge Network Survey (CSO 2013) and 2012 World Bank Household Socio-Economic Survey (World Bank 2015) both surveyed thousands of respondents and are representative at the governorate level. In the top two plots of Figure 7, I compare estimated monthly per capita expenditure in each governorate from the 2011 CSO-ILO and 2012 World Bank Household Socio-Economic Surveys with luminosity data.
Bank surveys against the log sum of city light (VIIRS) in that governorate during 2012. In the bottom plot, I run the same exercise, but use estimated monthly household expenditure from the 2011 ILO survey. Personal and household expenditure are imperfect measures of GDP – they are not very effective at capturing public-sector spending – and surveys are an imperfect measure of reality. However, this rough exercise still helps confirm the validity of the proxy.

**Figure 7: VIIRS Luminosity vs. Household and Individual Expenditure Survey Data at the Governorate Level in Iraq, 2011-2012**
The results suggest a clear positive correlation between luminosity and expenditure in Iraq. Baghdad and the three governorates of the Kurdish Region (Sulaymaniyah, Erbil, and Dahuk) are widely recognized to be among the richest areas in Iraq; they show up as areas with both the highest per-capita expenditure and light emissions during this period. Meanwhile, governorates such as Wassit and Ninewa – classically poorer – consistently appear in the bottom-left quadrant.⁷

**Part IV: Light during the ISIL occupation**

Settlement nighttime light panels show that lights respond acutely to ISIL occupation. Figure 8 below shows the sum of monthly night lights during period of ISIL occupation for all settlements in three Iraqi regions: the unaffected south, the northwest (territory in or near the Kurdish Autonomous region which was never occupied but near the front line), and the ISIL-occupied region.⁸ The bottom-right plot shows the sum of settlement light in all of Iraq over this time period. The region-level plots show a clear impact of ISIL occupation: the ISIL-occupied region sees a precipitous drop in nighttime lighting around 2014 when the insurgency began, and recovery in 2017 as it drew to a close. By contrast, the Kurdish north-west sees only a short stall in growth – probably the negative impact of being close to a front line – and the Iraqi south looks essentially unaffected by the insurgency.

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⁷ The apparent outlier status of Sulaymaniyah and Erbil governorates likely is explained by two factors made salient by the difference between measuring personal expenditure and outright GDP. First, these governorates are the two largest (of three) under the jurisdiction of the Kurdish Regional Government’s autonomous zone; the Kurdish regional government spends significantly more per capita resources on public services, infrastructure and administration than Baghdad does for other Iraqi governorates. This public-sector spending maps directly to GDP but is only partially captured by personal expenditure. Second, Erbil and Sulaymaniyah governorates have extraordinarily high levels of foreign investment and export-oriented manufacturing industries relative to other Iraqi governorates; this productivity also shows up fully in GDP but only partially in expenditure.

⁸ The approach used to identify settlements and ISIL occupation status is explained in the next chapter.

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Settlement trends

The effects of ISIL occupation can also be clearly seen at the settlement level. Figure 9 below shows the nighttime light trend in some major Iraqi settlements occupied by ISIL. Black vertical bars denote the beginning and end of ISIL occupation in each settlement. 9

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9 These plots show a simple loess smooth estimated through all points to emphasize the pattern of destruction and recovery. In empirical analysis, three separate loess smooths – one each for before, during, and after occupation – are used. East and West Mosul are separated here for demonstrative purposes but combined in empirical analysis.
Figure 9: Nighttime Light Trends in Select ISIL-Occupied Iraqi Settlements, 2012-2018

Al Rutba
Population: 16432

Al Qa’em
Population: 86411

Al Ramadi
Population: 412675

Fallujah
Population: 244877

Tikrit
Population: 71256

Bayji
Population: 80344

Al Haweeja
Population: 18045

East Mosul
Population: 736787

West Mosul
Population: 761796

Tal‘a’far
Population: 165207

Sinjar
Population: 15581

Al Ba’aj
Population: 7434

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The settlement panels highlight three interesting points. First, ISIL-occupied settlements experience distinct and often dramatic reductions in night-time lighting that closely correspond to the beginning of militant occupation. This observation is consistent with other research on the impacts of ISIL occupation (see e.g. RAND 2017) and directly supports Li et. al. (2015)’s findings. Second, this effect is felt consistently across all sizes of settlements. The median ISIL-occupied city with 10,000 or more residents loses 98.5% of its light during ISIL occupation; the median ISIL-occupied town with between 500 and 1,000 residents loses 93.3% of pre-invasion light. This suggests that the effect of ISIL occupation on economic activity was felt keenly even in small settlements that did not live under heavy direct ISIL administration. Third, recovery is highly heterogenous. Some settlements such as Haweeja and Tal Afar (Tala’afar) experience extraordinary recovery and appear to surpass their pre-invasion light levels in the first year. Others, such as Mosul and Tikrit, experience modest recovery. A third group – including Sinjar and Al-Baa’aj – show almost no signs of nighttime lighting for years after their liberation. This heterogeneity in post-conflict recovery motivates this thesis.

10 When ISIL began taking over territory in June 2014, the Iraqi Ministry of Electricity cut the power supply flowing into the ISIL-occupied area and turned off all ISIL-controlled substations from its central control center in Baghdad. My conversation with a former U.S. Army engineer who worked on the Iraqi electricity grid suggested ISIL could have overridden the central shutoff command at the substation level, and connected substations to power plants it controlled to create a contained electricity grid in ISIL territory. But electricity for this grid could only be sourced from power plants inside ISIL’s control, and coalition forces were quick to destroy most ISIL-controlled power plants. ISIL could also have used the substantial oil resources they controlled to power gas-fired generators, which were already abundant in the ISIL-occupied are. But In practice, ISIL-controlled areas used almost no electricity at night from any source.
Chapter 4 | Definitions, operationalizing, and descriptive statistics

This chapter defines the key variables of interest, presents descriptive information on how nighttime light emissions varied across space and time in the period surrounding the ISIL insurgency, and lays the groundwork for causal empirical analysis in chapter 5. Part I defines the sample, explains how the definition was operationalized, and presents basic descriptive information on it. Part II defines and operationalizes the key independent variable of interest – ethno-religious diversity – and shows how it is distributed across settlements. Part III defines and operationalizes the dependent variable – “recovery” – and shows how it is distributed across settlements and their diversity scores. Part IV presents some preliminary bivariate plots of diversity and recovery.

Part I: The sample

The sample includes all Iraqi settlements controlled by ISIL for at least one month, less a handful of technical exclusions detailed below. This section first explains how this definition is conceptualized and operationalized: it describes how settlements are identified, and how “control” is defined and measured. Second, it presents descriptive statistics on the sample.

Defining the sample

Unit of analysis

The unit of analysis in this study is a settlement. Settlements are simply places where people live: they may be villages, towns, or cities. Like others studying ISIL in Iraq, I am concerned only with changes to lighting on the intensive margin of settlements – the change in total lighting over time in the same fixed area (as opposed to expansion and contraction at
settlement edges). Specifically, following Li et. al. (2018) and others, I examine the sum of nighttime light emitted from the same fixed area on a monthly basis. I define settlement extents using a double threshold of population density and total population: settlements consist of areas with both a population density of at least 200 people per square kilometer and an overall population of at least 500 people.\textsuperscript{11} Population data is drawn from LandScan estimates of population in 2012.\textsuperscript{12}

500 people may seem like a very low threshold at first glance, but in reality, this definition captures the recovery experience of more than 500 people. Though only 500 people may live in the settlement core dense enough to surpass the 200 person per square kilometer threshold, many more live in suburbs, surrounding farmland, and the urban periphery. These people regularly frequent the urban core to buy and sell goods at market, attend school, visit administrative buildings, and interface with the population. Observed economic activity in urban cores thus captures the recovery experience of the geographic area for which that core is the focal point of economic activity – which almost always includes more people than live within the core itself. The 500-person minimum population threshold is used for the core analysis, but in Appendix I, I show that my core result is robust within different population brackets.

After automatic identification of settlements based on spatial data, I inspect them manually and remove a handful of identified “settlements” that are actually other built-up structures like airports, military bases, or factory complexes. Figure 10 below shows an example

\textsuperscript{11} Operationally, this means that I draw town limits around contiguous sets of 1km\textsuperscript{2} LandScan population squares where the population density in each square is at least 200 people per square kilometer.
\textsuperscript{12} LandScan is a spatial data product which combines disaggregated census counts, daytime satellite imagery of building heights and density, nighttime light emissions, imagery, elevation data, and other open and closed-source data to generate population estimates globally at 1km\textsuperscript{2} resolution (see Dobson et. al. 2000 for a full treatment of LandScan inputs). LandScan has been previously used by scholars defining urban extents for luminosity analysis, (Levin and Zhang 2017) as well as for and other scientific and social scientific research applications (Bhaduri et. al. 2002, Graesser et. al. 2012, Thakur et. al. 2018).
of the boundaries drawn by this definition (in red) around actual settlements (visible in satellite imagery) in the south-west corner of Hawija district. Each settlement’s 2012 LandScan population estimate is also shown.

**Figure 10: Example of settlement boundaries drawn by the coding rule in Hawija district**

*Example of settlement boundaries drawn by the coding rule in Hawija district*

*Legend*
- Boundary drawn by coding rule

*Population: Landscan (2012).*

*Coding dates of ISIL occupation*

Coding ISIL occupation start and end dates for each settlement is essential to identify which Iraqi settlements were occupied, and when occupied settlements were captured and liberated. I code the start date of ISIL occupation to the month in which ISIL takes control of a
settlement and the end date to the month in which the settlement is fully liberated from ISIL militants.

In this project, ISIL “control” implies that within a settlement ISIL enjoys freedom of movement, has the ability to assert coercive power, and that anti-ISIL activity in the settlement could be met with significant ISIL resistance. To be sure, ISIL did not exert the same degree of direct management over all territory it controlled. Major population centers and roads under ISIL control were often subject to a direct ISIL presence: militants set up checkpoints, patrolled the streets, and sometimes even created civic administration. These areas were often rigorously defended against anti-ISIL activity. By contrast, tiny villages deep in the western Iraqi desert did not see the same degree of day-to-day administration or vigorous defenses. However, all settlements in the ISIL-occupied area lived under the specter of ISIL influence. In an interview with The Atlantic, Bill Roggio of The Long War Journal explains:

"Iraqis in the small hamlets and villages not directly under Islamic State control know who are truly in control. Think of it like this: Americans living in the remotest areas of Alaska often see little to no government involvement, but ultimately they know the U.S. government can assert itself if it needed to (Gilsinan 2014).”

There is plenty of empirical evidence that the effect of ISIL control was tangible even in the smallest of settlements. The previous chapter showed that the median tiny village lost almost as much of its pre-invasion light (93.3%) as the median large city (98.4%), and IOM survey data shows that even small settlements saw large fractions of their population flee during ISIL control (IOM 2019a). Whether the degree of direct ISIL governance influences occupation and recovery experience is an empirical question accounted for in Chapter 5.
**Start dates**

For 48 of the larger settlements occupied by ISIL, news reports can be found reporting the start date of ISIL occupation. Regional and international news sources often reported on settlement takeovers, citing statements from local officials, reporters in nearby towns, eyewitness accounts, photos from inside occupied villages, and statements from military authorities. In these cases, I code start dates directly using these news sources.\(^{13}\) For smaller settlements where the news does not directly report invasion dates, I assign a settlement’s occupation start date to the start date for the nearest town for which a news-reported date of invasion is available. ISIL’s advance in Iraq was rapid, and towns in contiguous patches of territory were often taken over at the same time. For example, of the 48 cities with news-coded start dates, 36 were overtaken by ISIL in between June and August 2014. The error introduced into coding start dates by this interpolation method is likely to small, and often likely to be less than one month – the unit of time at which start dates are coded.

**End dates**

While ISIL’s advance across Iraq was rapid and sweeping, its removal was a slow and heterogenous process. Certain pockets of territory were liberated long before others. For example, Iraqi and coalition forces first bypassed ISIL presence in Hawija district while moving northward to liberate Mosul, leaving an “island” of ISIL-controlled territory in north-central Iraq. After the liberation of Mosul, coalition forces returned and liberated Hawija district in late 2017 (BBC 2017c). Hence, it would be ideal to augment news-sourced information on occupation end dates with a finer end-date data source.

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\(^{13}\) The sources for this coding can be found in the same location as the online replication materials.
Growing public interest in the ISIL insurgency encouraged several news and academic sources to begin publishing regular mapping data of ISIL territorial control during the conflict. While these sources do not cover the beginning of ISIL insurgency, they cover the entire period of settlement liberation and can be used to code occupation end dates. To code end dates, the first-choice method remains to use news-sourced end dates. Where a news-sourced occupation end date is unavailable, I code end dates using territorial control data from the Liveuamap project and the Institute for the Study of War. Liveuamap began producing daily shapefiles of territorial control in Iraq in 2015, using a combination of open-source intelligence and reports from the field. The Institute for the Study of War began producing maps of ISIL control in Iraq in 2015 using similar sources. These mapping sources have been used to track ISIL in Iraq and Syria by a variety of news sources, including Al Jazeera (Chughtai 2018), Newsweek (Moore 2017), The Washington Post (Karklis and Meko 2017) and others. Figure 11 below shows the number of ISIL-controlled Iraqi settlements meeting the population and density threshold by date. It shows that ISIL quickly gained many settlements in summer 2014; it then slowly lost them over the next four years.

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14 The sources for start and end dates are included in an addendum to the works cited section.
15 In the vast majority of cases, I also cross-reference this information with settlement level survey data from IOM that captures whether or not a settlement was occupied.
The sample

With a set of settlements defined and dates ISIL occupation coded, the sample can finally be extracted. All settlements meeting the above-defined threshold and occupied by ISIL for at least one month are selected for analysis. A small number of settlements are excluded because they are next to gas flares and therefore luminosity readings are obscured by other nighttime light emissions. Settlements with essentially no electricity before invasion – proxied by a median monthly light level in the 12 months before the ISIL insurgency began of less than 1 – are also excluded. After these exclusions and the omission of four outliers (to be discussed shortly), 351 settlements remain in the sample.

Figure 12 shows all the settlements included in the sample colored by their liberation date. Three characteristics of the sample are worth highlighting. First, although ISIL occupied nearly one-third of Iraq by territory, much of the ISIL-occupied region was desert. ISIL-occupied settlements are clustered along the Euphrates and Tigris rivers, and to the northern and western edges of its control. Second, while none of the ISIL settlements are in the three northernmost
governorates which form Kurdish autonomous region, some are in the “disputed” territory administered that was temporarily administered by Kurdish authorities before the Kurdish independence referendum. Finally, the distribution of settlement population is strongly right skewed. This sample includes a few major cities with large populations and many small villages and hamlets. Interestingly, my empirical results suggest that total population is not a significant influence on recovery.

**Figure 12: Settlements in the sample, colored by liberation date**
Part II: Coding ethno-religious diversity

A tool to measure ethno-religious diversity at the settlement level is essential to understand how ethno-religious diversity influences reconstruction. However, measuring diversity is not an easy task: defining ethno-religious groups requires careful attention, and ethno-religious diversity can be conceptualized in many ways. Furthermore, Iraq’s last reliable census – the 1957 count – is both too old and used groupings too broad to accurately describe the ethno-religious composition of Iraqi settlements on the eve of ISIL invasion. This section discusses this thesis’ conceptualization of ethno-religious diversity, proposes a proxy for it based on settlement-level survey data, and presents basic descriptive statistics to build confidence in the proxy.

Conceptualizing ethno-religious diversity

Diversity is a tricky concept and could be measured in many ways. Two challenges lie at the heart of the puzzle: how to identify the correct identity groupings, and how to measure diversity.

I begin with the challenge of selecting group divisions. The region of Iraq formerly controlled by ISIL is home to a mosaic of ethnic, religious, and tribal identities. One prominent Iraq ethnographer summarizes 3 broad religious groupings – Islam, Christianity, and Gnosticism [Yazdanism] – and 9 ethnic groups – Arabs, Kurds, Turkmen, Shabak, Assyrians, Chaldeans, Armenians, Yarsans, and Yazidis – in the study area (Izady 2015). In some cases, individuals have distinct ethnic and religious components of their identity. For example, some members of Iraq’s Turkmen ethnic group identify as Sunni Muslims; others identify as Shia. In other cases, ethnicity and religion go together. For example, many observers recognize the Yazidis as both a
distinct ethnic and religious group. And in addition to ethnicity and religion, many Iraqis identify with one or more of the country’s nearly 150 recognizable tribal groupings. Many of these identities exist on varying scales. The religion on Islam can be subdivided into Sunni and Shia sects, and individuals may identify with both an umbrella tribe and a smaller sub-tribe. Some divisions are more important to individuals’ conception of self-identity than others. In the face of this horizontal and vertical heterogeneity, we are left with a puzzling question: how to choose the “right” group divisions?

Given this thesis’ interest in measuring the effect of diversity, one option is to identify salient divisions between groups. As Fearon (2003) explains in his work to measure ethnic diversity:

“…the "right list" of ethnic groups for a country depend on what people in the country identify as the most socially relevant ethnic groupings… [the] objective is to include those groups that would be listed most often if randomly chosen individuals in the country in question were asked ‘what are the main ethnic (or racial or ascriptive) groups in this country?’”

In Iraq, asking this question would likely espouse answers with ethnic, religious, and tribal components. No settlement-level information on tribal identity is readily available, and I have no choice but to set this component of identity aside. However, settlement-level surveys conducted by the International Organization for Migration (IOM) as part of the post-ISIL stabilization effort make it possible to code ethno-religious composition in Iraq at the settlement level. IOM adopts an approach to ethno-religious classification broadly similar to Fearon’s “relevant groupings” approach, classifying a unique ethno-religious grouping for each commonly discussed unique ethnic and religious identity pairing. Table 1 shows the pairings.
With groups defined, how might we measure diversity? The most commonly used measure is an ethno-religious fractionalization score (see e.g. Alesina et. al. 2005), which measures the probability that two randomly selected people from a population of interest will be members of different groups. But here we have a problem: constructing an ethno-religious fractionalization score requires survey data on the exact number of individuals of each ethno-religious group present in each settlement before the ISIL conflict; IOM surveys only record the largest ethno-religious group in each settlement before the conflict. I use the IOM information to create a proxy for the ethno-religious diversity of each settlement based on its distance to settlements with different majority groups.

Operationalizing the concept

I obtained settlement-level survey data on ethno-religious composition from the IOM’s Third Integrated Location Assessment (ILA III) and used it to code the majority ethno-religious group in each settlement (IOM 2019). The ILA III survey was conducted from March 6th to May 6th 2018, and covered all ISIL-occupied areas except the northwestern Ba’ajaj district and the southern half of Sinjar district. In each location enumerators interviewed at least three representatives who could speak to the conditions of the location. Question 3.1 asked “What was

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16 For a small minority of large settlements more than one neighborhood or area was surveyed within the same settlement, and different survey points from different neighborhoods in the same settlement may report different pre-invasion ethno-religious groups. In these cases, I take the most commonly reported ethno-religious group from all surveyed locations falling within the bounds of the settlement. In a few cases, settlements do not have a survey point inside them. When this occurs, one of two things is true: the georeferenced coordinates of the survey point lie just outside the bounds of the settlement drawn by the coding rule (and the survey point is clearly intended to apply to the settlement in question), or the settlement itself is not surveyed but another extremely close by one is. In these cases, I take the ethno-religious composition of the survey point that is closest to the settlement in question. Whenever this process occurs, the distances between settlements and the coordinates of the survey point used to describe them is incredibly small: the median distance is 2.78 kilometers, 75% of interpolations are under 5.46 kilometers, and no settlement is matched to a survey point more than 13.56 kilometers away. Finally, for 7 settlements, surveyors selected the “only if the largest group cannot be determined, select a second one” option. In these cases, I use the first-listed ethno-religious group to code the majority – but it turns out that using the other group to code the majority, or excluding these settlements, hardly alters my results in any way.
the largest ethnic or religious group in this location prior to the current crisis? (Choose one, only if the largest group cannot be determined, then and only then, select a second one.” [English translation by IOM]. It allowed enumerators to select from the 15 options in Table 1. The bolded options exhaust the options selected in the formerly ISIL-occupied region.

**Table 1: Ethno-religious Groups in the IOM ILA III Survey**

<table>
<thead>
<tr>
<th>Arab Muslim Sunni</th>
<th>Kurdish Yazidi</th>
<th>Assyrian Christian</th>
<th>Kaka’i</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arab Muslim Shia</td>
<td>Kurdish Muslim Sunni</td>
<td>Syriac Christian</td>
<td>Other (specify):</td>
</tr>
<tr>
<td>Türkmen Muslim Shia</td>
<td>Kurdish Muslim Shia</td>
<td>Shabak Muslim Sunni</td>
<td>Unknown</td>
</tr>
<tr>
<td>Türkmen Muslim Sunni</td>
<td>Chaldean Christian</td>
<td>Shabak Muslim Shia</td>
<td></td>
</tr>
</tbody>
</table>

For 18 settlements in Ba’aj district and southern Sinjar district, poor security conditions during the fieldwork window prevented IOM from conducting surveys. To code the ethno-religious majority in these settlements, I used Dr. Michael Izady’s Iraq Group Divisions Map (2015). I geo-referenced the map, intersected it with settlements in Ba’aj and Sinjar, and coded each settlement’s majority ethno-religious group accordingly. This region is cleanly split between only two ethno-religious groups and therefore relatively easy to code.
I then use this information to construct an ethno-religious diversity score $\theta$ for each settlement $k$ from the sum of inverse distances to the nearest five settlements with a different majority ethno-religious group:\(^{17}\)

$$
\theta_k = \sum_{n=1}^{5} \left( \frac{1}{\text{distance}_{k,n}} \right)
$$

*Where $k$ is the settlement in question and $n \{1:5\}$ are the five nearest settlements with a majority ethno-religious group that is different from the majority group in $k$.\(^{18}\)*

For example, if settlement $k$ is majority Sunni Arab, $\theta_k$ will calculate the inverse distance between $k$ and each of the nearest five settlements with a non-Sunni Arab majority and sum them.\(^{18}\)

The core assumption of this proxy is that settlements close to many settlements of a different majority ethno-religious group are likely to be diverse, while settlements which are far from settlements of a different majority group are likely to be ethno-religiously homogeneous. I further assume that the influence of a nearby settlement of different majority ethno-religious identity on the diversity of settlement $k$ decays geometrically as distance increases. This decay function is a common assumption in human geography models of spatial influence, and it makes sense in the context of Iraq. For example, consider the line that divides majority Sunni Arab and majority Shia Arab settlements just southwest of Baghdad. Sunni Arab-majority settlements just

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\(^{17}\) I use the same ethno-religious divisions as the IOM ILA III survey with one exception: I combine Chaldean Christian, Syriac Christian, and Assyrian Christian under one “Christian” label. There are only four Christian villages of any denomination in the sample and given their short ethno-religious distance relative to other groups, I chose to combine them.

\(^{18}\) The ‘five nearest settlements’ considered for the diversity score calculation may be settlements inside or outside the ISIL-occupied region. I consider all Iraqi settlements that meet my definition of ‘settlement’. 

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west of the dividing line anecdotally have relatively high Shia Arab populations and are thus relatively diverse. The size of the Shia minority in Sunni Arab settlements drops sharply as one moves west along the Euphrates river; by the time one reaches Fallujah, the Shia Arab minority is very small. The drop-off in ethno-religious diversity between settlements ten and twenty kilometers from this dividing line is likely larger than the difference in diversity between settlements ten kilometers apart in the depths of the Sunni heartland.

The use of inverse distance captures the geometric decay of the influence of a different majority settlement on settlement k’s diversity. The selection n=5 ensures a contextual approach to diversity measurements. It reflects that a settlement close to many towns with an ethno-religious majority different from its own is likely to be more diverse than a settlement close to only a few towns of a different ethno-religious composition.

This chapter is about to present descriptive information that shows θ broadly aligns with common conceptions about where diverse settlements in Iraq are located. However, one important caveat should be addressed upfront. This measure assigns settlement k’s diversity based on its distance to settlements of different majority groups. There may be some settlements in the dataset which are close to settlements of other majority groups but are themselves homogeneous. θ will code these settlements as diverse when they are actually homogeneous settlements amid diverse areas – perhaps ethnic enclaves, or homogenous settlements located on “ethnic fault lines”. It is difficult to know whether θ is capturing diversity within settlements themselves or simply settlements in highly diverse areas. As a result, θ makes it difficult to separate the effect of within-settlement diversity from the effect of homogeneity amid a diverse area or on an ethnic fault line.
At the settlement level, not much can be done. Data directly measuring ethno-religious diversity at the settlement level is not available nationally. The potential limitations of this proxy will be discussed towards the end of the thesis. However, in Mosul – Iraq’s second-largest city and home to some one-third of the occupied population – I was able to obtain data that directly measures ethno-religious diversity at the neighborhood level. In Part IV of Chapter 6, I take advantage of this data to run a neighborhood-level matching analysis in Mosul that tests the effect of diversity on neighborhood recovery using a direct measure of ethno-religious diversity. This strategy cannot inform on whether ethnic enclave or fault-line status have an additional negative effect on recovery, but it does show that diversity directly affects recovery. This increases our confidence that the results achieved using $\theta$ are driven at least significantly (if not entirely) by ethno-religious diversity itself.

The diversity score $\theta$ originally takes on values in the sample settlements from 0.011 to 1.340, with higher numbers representing greater predicted ethno-religious diversity. To aid in interpretation, I standardize the index so that it instead takes on values between 0 and 1. 0 represents the least diverse settlement in the sample and 1 represents the most diverse settlement. Figure 13 shows the distribution of the diversity score across settlements. The distribution is right-skewed: many settlements are relatively homogeneous; a small number of settlements are highly diverse.
Figure 14 shows all the settlements in the sample shaded by their diversity index scores and overlaid on regional ethno-religious composition. White settlements are the least diverse, black are the most diverse, and the shades split settlements into 5 quantiles. This figure shows that the ethno-religious diversity index closely tracks common expectations about where Iraq’s most diverse settlements are located: settlements in the belt of “disputed territory” below the Kurdish Autonomous Region’s border are often diverse; settlements deep in Iraq’s western Sunni heartland are often homogeneous.
Table 2 reports the number of settlements of each ethno-religious group in the sample (excluding Mosul), along with their median population sizes and diversity scores. Together with Figure 14, it makes it immediately clear that neither ethno-religious majority nor the diversity score is evenly distributed across other settlement characteristics. Sunni Arab-majority settlements make up the largest group in the sample and dominate the south-west corner of Iraq, and no Shia Arab-majority settlements are in the sample. Only 68 of the 351 settlements have non-Sunni Arab majorities, and most non-Sunni Arab settlements are clustered in the northernmost ISIL-occupied districts or south of Tuz Khurma. Accordingly, the diversity index suggests that a randomly selected Sunni Arab settlement is less likely to be diverse than a

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settlement of any other group, and that the most diverse settlements lie in the northernmost and westernmost reaches of ISIL’s former territory. The spatial correlation among diverse settlements also means they are similar on other characteristics; for example, the mean highly diverse settlement was liberated sooner and occupied for a shorter time than the mean highly homogeneous settlement.

**Table 2: Number of settlements by ethno-religious group in the dataset**

<table>
<thead>
<tr>
<th>Ethno-religious group</th>
<th>Number of settlements</th>
<th>Pct. of total population</th>
<th>Pct. of total population (exc. Mosul)</th>
<th>Median settlement pop.</th>
<th>Median settlement diversity score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arab Sunni Muslim</td>
<td>288</td>
<td>86%</td>
<td>81.2%</td>
<td>1,356</td>
<td>0.119</td>
</tr>
<tr>
<td>Christian</td>
<td>4</td>
<td>1.4%</td>
<td>1.9%</td>
<td>5,468</td>
<td>0.571</td>
</tr>
<tr>
<td>Kurd Sunni Muslim</td>
<td>12</td>
<td>1%</td>
<td>1.3%</td>
<td>1,488</td>
<td>0.424</td>
</tr>
<tr>
<td>Kurd Yazidi</td>
<td>24</td>
<td>3.8%</td>
<td>5.1%</td>
<td>3,782</td>
<td>0.324</td>
</tr>
<tr>
<td>Shabak Shia Muslim</td>
<td>12</td>
<td>0.8%</td>
<td>1.1%</td>
<td>887</td>
<td>0.624</td>
</tr>
<tr>
<td>Shabak Sunni Muslim</td>
<td>3</td>
<td>0.1%</td>
<td>0.2%</td>
<td>1,232</td>
<td>0.942</td>
</tr>
<tr>
<td>Turkmen Shia Muslim</td>
<td>5</td>
<td>6.6%</td>
<td>8.9%</td>
<td>1,234</td>
<td>0.584</td>
</tr>
<tr>
<td>Turkmen Sunni Muslim</td>
<td>3</td>
<td>0.2%</td>
<td>0.3%</td>
<td>2,046</td>
<td>0.251</td>
</tr>
</tbody>
</table>

Mosul is coded as a Sunni Arab settlement by the coding rule and accounts for nearly 1/3 of the total ISIL population. I show the percentage of total population breakdowns with and without Mosul to give readers a better sense of the variation. Mosul is included in empirical analysis.
Part III: Defining recovery

Dependent variable

The third major setup question this chapter tackles is the construction of the dependent variable. Luminosity panels for individual cities need to be operationalized into a dependent variable capturing post-conflict recovery. But how to define “recovery”? 

The literature has typically treated recovery as the return of economic activity and focused on the long run. Previous scholars have compared post-conflict per-capita growth rates (Davis and Weinstein 2002, Koubi 2005), the ratio of post-war GNP growth to pre-war GNP growth (Kugler and Arbetman 1989), a selection of key welfare indicators defined on a per-capita basis at a fixed time period after peace onset (Miguel and Roland 2006), and the amount of time required for war-affected countries to return to their pre-conflict GDP per capita (Flores and Nooruddin 2009).

I choose to focus on short-run post-conflict recovery. This choice reflects the availability of data (only the first year is available at the time of writing), a desire to add to an unfilled niche in the literature (most post-conflict reconstruction studies are long run), and acknowledgement of arguments suggesting the first year of post-conflict recovery is the most essential. Flores and Nooruddin (2009) note in their dataset that in states which reached a definitive end to the post-conflict period in the first year (recovery or relapse to war), 45 cases recover and 15 cases relapse to war. Of cases that reach a definitive conclusion later, however, the odds of recovery and relapse to war are equal: 18 cases recover and 18 descend into conflict.
The focus shift from long-run state-level recovery to short-run sub-state-level recovery calls for a novel dependent variable. I use the **fraction of pre-invasion light recovered by December 2018.** The *pre-invasion light level* is calculated as the light level in November 2013, the month before ISIL began its Iraq insurgency. The *amount of light recovered* is the monthly VIIRS observation in December 2018, exactly one year after ISIL was expelled from its last settlement in Iraq. The dependent variable is then simply the ratio between the December 2018 light level and the pre-invasion level. For example, if the December 2018 light level is 80 and the pre-invasion light level is 100, the dependent variable for this settlement takes on the value of $80 / 100 = 0.8$.

The discussion in the previous chapter demonstrates how individual VIIRS monthly observations are subject to some level of random “noise”; for this reason, I use the trend line obtained by the multiple loess smooths approach in the previous chapter to calculate these values. To help address a strong right skew in recovery, I log the dependent variable. I thus arrive at the final dependent variable:

$$Fraction \ of \ pre-\ invasion \ light \ recovered = \log \left( \frac{December \ 2018 \ light \ level}{November \ 2013 \ light \ level} \right)$$

The left histogram of Figure 15 shows the distribution of the dependent variable across all settlements before logging. It shows a strong right skew in recovery, and that four settlements are extreme outliers at the high end of recovery. I remove these four outlier settlements for the core analysis, although my results are robust to their inclusion. The right histogram shows the distribution of the dependent variable after logging and exclusion of the four outliers.

---

20 These outliers are four small villages from Heet district clustered together on the banks of the Euphrates, with populations ranging from 786 to 1393. I am unsure what is happening in these settlements, but it is possibly measurement error.
Of the 351 settlements remaining after the four outliers are dropped, recovery is highly heterogenous. 141 of 351 settlements (40%) recovered between 0 and 100% of their pre-invasion light level by December 2018. A further 122 (35%) recovered more than 100% but less than double, and the remaining 83 settlements (25%) recovered more than double their initial light level. Why do so many settlements appear to have more economic activity by December 2018 than they did before the conflict? Much of this post-conflict light relates to reconstructive activity: many settlements – host only to modest levels of economic activity before invasion – have seen massive influxes of aid, construction, and NGO operations in the year after their liberation. This can result in levels of total economic activity that are higher than before the occupation.

This phenomenon draws attention to the difference between my measure – based on the total level of economic activity – and the return of pre-invasion quality of life. Chapter 3 explained that the observed total level of economic activity includes both “ordinary” economic activity (typical day-to-day processes such as operating stores and factories), and
“reconstructive” economic activity (such as clearing landmines and rebuilding damaged buildings). A post-conflict level of economic activity that is higher than the pre-conflict period thus does not imply that the settlement has fully rebuilt and is now experiencing an economic boom in excess if it’s pre-conflict level. Rather, it suggests that the economic activity generated by reconstruction efforts amounts to more total activity than was seen in the economy beforehand. Much of this “boom” is probably in reconstructive economic activity such as rebuilding infrastructure. Quality of life in the settlement may very likely still be worse than it was before conflict, and the “normal” component of the economy may not yet have fully returned.

The recovery of the ordinary component of the economy is this thesis’ substantive outcome of interest and I would measure it directly if I could. Given that this is impossible, however, observing total economic recovery is a useful and interesting substitute. First, observed total economic recovery directly captures ordinary recovery because ordinary recovery is one of its two constituent components. Second, reconstructive activity today leads to increased ordinary economic activity tomorrow. Even if light does not directly measure economic activity, it does measure reconstruction.

Visualizing recovery

The construction of a dependent variable makes it possible to view village recovery in map form. Figure 16 maps all 351 settlements meeting the definition and shades them according to their dependent variable value. Brighter colors correspond to greater recovery; the five shades are assigned by equal quantiles (the 70 settlements with the slowest recovery take the darkest color, etc.). The map highlights the heterogeneity in post-conflict recovery, and identifies some
areas where recovery is processing quickly (such as Hawija and Tal Afar) and others where it is occurring slowly (like Sinjar and Qaim).

**Figure 16: Settlement recovery across space by December 2018**

![Map showing settlement recovery by December 2018](image)

**Part IV: Putting it all together?**

Information on settlement locations and occupation dates, ethno-religious diversity, and recovery can be combined for a first pass “descriptive” analysis of the relationship between ethno-religious diversity and recovery. Figure 17 shows a bivariate plot of the recovery dependent variable against the ethno-religious diversity index. The plot suggests a moderately strong negative relationship with highly diverse settlements tending to be associated with slower recovery.

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Recovery can also be examined through the trends of settlements at different diversity levels rather than relying on the dependent variable. Figure 18 shows the luminosity trend over time for three groups of settlements representing different diversity score quantiles: the most homogeneous third of settlements (in blue, \( \theta < 0.1 \)), the middle third (in red, \( 0.1 < \theta < 0.25 \)), and the most diverse third of settlements (in green, \( \theta > 0.25 \)). For each month, the trend line for each group reports the median luminosity value among all settlements in that group. Settlement light levels are normalized to November 2013 = 1 to facilitate comparisons. The figure shows that the light trends of the three groups – which were similar before ISIL occupation – stack up roughly in line with their diversity scores in the post-conflict period. The most diverse settlements (green) are associated with the worst median performance; the most homogeneous settlements (blue) are associated with the best median performance.
The plots above establish that there is a negative correlation between ethno-religious diversity and recovery. However, so far nothing can be said about whether ethno-religious diversity causes slower recovery. As the discussion concluding Part II of this chapter noted, ethno-religiously diverse settlements are different from homogeneous settlements on a variety of characteristics in addition to their diversity. Determining whether diversity – rather than any of these confounders – causes the observed failure to recovery requires a more sophisticated design.
Chapter 5 | Causal strategy and empirical results

The descriptive analysis of Chapter 4 may tell us how recovery varies from settlement to settlement, but it cannot tell us why. The core issue is the fundamental problem of causal inference: we cannot observe how settlements would have recovered had they been of a different level of diversity but otherwise identical. Comparing averages will not do the trick: although Figure 17 and Figure 18 show that there is some variation in recovery across settlements of different diversity levels, these settlements also vary on many other dimensions which could influence recovery – like their length of ISIL occupation and the difficulty of accessing them. The settlements of north-western Sinjar district, for example, are notable for their extremely slow recovery. Many of these settlements are diverse, but they are also far from major cities and historically poor compared to the rest of Iraq. Sinjar’s settlements are recovering slowly, but we cannot yet say whether this is because they are diverse or because of other logistical concerns such as the difficulty of accessing them.

This chapter explains this thesis’ causal strategy and presents its results. Although my empirical analysis yields insights on many influences on reconstruction, I concentrate my efforts on discerning the causal impact of the most interesting one: ethno-religious diversity. Part I explains the rationale for a two-pronged causal approach, comprised of spatial autoregression and generalized synthetic matching. Parts II and III present core results from the two respective strategies. Part IV delivers the Mosul neighborhood matching analysis promised in Chapter 4 using a direct measure of ethno-religious diversity. It helps confirm that the diversity results in Parts II and III are driven at least substantially (if not wholly) by true ethno-religious diversity.
Part I: The causal strategy

Threats to inference

As with any causal project, the core threat to causal inference here is omitted variable bias. The basic problem is straightforward. A straight comparison of ethno-religious groups and recovery cannot deliver causal claims, because settlements of different ethno-religious groups also differ on a basket of other outcomes that may influence recovery. The age-old solution to this problem is to control for all the relevant confounding variables in multivariate regression. But this strategy can be risky: if a variable that is correlated with both recovery and ethno-religious identity is left out, the causal effect the results attribute to ethno-religious identity may instead be due to the omitted variable.

Two twists make this problem particularly tricky in this context. First, we must be conscious of post-treatment bias. Controlling for aspects of settlement experience that occur after liberation in regression creates a problem, because the assignment of these characteristics may be endogenous to treatment with pre-liberation settlement attributes. The post-treatment variable thus “soaks up” part of the causal effect that should be attributed to the pre-invasion treatment of interest and biases causal estimates (Montgomery et. al. 2018). For example, consider the independent variable I am most interested in - ethno-religious diversity – and the potential inclusion of a post-liberation control capturing whether control over a settlement after liberation is shared between two or more security providers. Higher levels of ethno-religious diversity are empirically associated with a greater likelihood of shared control after liberation, and as I argue in Chapter 6, shared control may in fact be a consequence of ethno-religious diversity. If the

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21 I show this in Chapter 7.
shared control variable is included, some of the causal point estimates of ethno-religious
diversity on recovery will be absorbed by the shared control point estimate.

In fact, post-treatment bias formalizes the concerns voiced at the end of Chapter 2. I
argued then that the vast degree of variation in post-liberation security forces, elections, and aid
dispersion should be viewed as parts of the mechanism by which independent variables influence
reconstruction rather than independent variables themselves. It is not surprising that (say)
disruptive and inconsistent aid delivery would slow recovery; we want to know what pre-
liberation characteristics make poor post-liberation political arrangements more likely. Post-
liberation controls need to be diligently excluded from any causal framework.

Second, we must pay attention to spatial correlation in the dataset. This project deals with
settlements across space, and events in a given settlement influence other settlements close to it.
This means two things. First, if meaningful variables are omitted, they are likely to also be
spatially correlated: ordinary least squares (OLS) regression will consistently overpredict
recovery in some areas and underpredict it in others, and errors will be spatially correlated.
Second, it threatens the independence assumption critical to multivariate regression. One crucial
assumption of simple OLS requires that outcomes for a given unit be independent of outcomes in
any other units. However, settlement recovery speeds are not independent of each other:
settlements are likely to be affected by “spin-off” effects of recovery in nearby settlements. A
quickly recovering settlement A may provide more residents willing to buy goods from
settlement B, assist directly with settlement B’s recovery, and word of settlement A’s recovery
may make settlement B’s displaced population more likely to return.

The presence of spatially interdependent outcomes and spatially correlated errors in this
data can be confirmed statistically. The Moran’s I test is a standard test for general spatial

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dependency in data: if units are not spatially dependent, the test should return a value not significantly different from zero. Unsurprisingly, the Moran’s I test on my dependent variable returns a statistic that is both positive (26.65) and significantly different from 0 (p < 0.001). Moran’s I tests for residual spatial dependency on simple linear regressions consistently show that simple linear models cannot fully capture this spatial dependency. Confounding influence must be addressed in the causal design, and simple OLS regression will not be enough to combat it.

Causal strategy

Two strategies are available to confront these challenges. First, we can tweak the OLS regression framework to attempt to statistically control for these concerns. This strategy is attractive in that it can simultaneously capture many influences on recovery and quantify their relative importance. However, it relies on the assumption that all relevant variables have been captured and all spatial dependency is accounted for. Alternatively, we can do away with regression entirely and look for or simulate “natural experiments” that allow us to compare recovery of settlements with different ethno-religious groups but otherwise identical characteristics. This strategy offers an easily interpretable picture of causality and is less vulnerable to the concerns above. It also allows us to access how the differences in recovery of different ethno-religious settlements changes over time. However, this approach can only investigate one influence on recovery at a time: it makes it difficult to understand how the size of ethno-religious effects compares to other influences on recovery.

I use both strategies in a two-pronged approach to evaluate the effect of ethno-religious identity on recovery. First, I implement spatial autoregression - an adapted version of OLS regression that controls for spatial effects – to gain an overall picture of the relative importance
of various influences on reconstruction. Second, I use a matching approach to further investigate causality for the most politically interesting finding: that ethno-religious diversity appears to cause settlements to rebuild slower. In a generalized synthetic control strategy, I use a statistical model to estimate how observed recovery trends for highly diverse settlements would have differed had those settlements instead been homogeneous but otherwise identical (Xu 2017).

**Part II: Spatial autoregression**

I begin with regression to gain an overall picture of causal influences on reconstruction. Researchers often use multivariate regression to control for confounders, but spatial dependency among Iraqi settlements violates the independence of outcomes and random error assumptions these models rely on. One strategy to address spatial dependency concerns in multivariate regression is the use of spatial autoregressive models. My preferred choice, the simultaneous spatial autoregressive (SSAR) model, accommodates for both the influence of neighboring settlements’ outcomes ($\rho$) and the influence of spatially correlated errors ($\lambda$) on recovery in the settlement in question.

I select a SSAR model for regression because it takes one of the most precise and conservative approaches to spatial dependency concerns. If results are significant in SSAR models, they are likely also significant in other, looser approaches to accommodating spatial dependency. In Appendix I, I show that my results are robust to other standard modelling approaches to address spatial correlation such as cluster-robust standard errors at the district level, district fixed effects, and autoregressive lag and error specifications.

SSAR models attempt to control for spatial dependence of outcomes and errors by extending simple multivariate regression to add two variables that capture and control for these
two influences. \( \lambda \) represents the degree to which the errors of a given settlement are correlated with the errors of nearby settlements. \( \rho \) represents the degree to which recovery in nearby settlements influences recovery for the settlement in question. After controlling for the effect of the outcomes and errors of nearby settlements, we can be more confident that the identifying assumptions of independence and random errors are restored.

The simultaneous spatial autoregression approach proceeds in two steps. In the first step, values for \( \lambda \) and \( \rho \) are estimated through a maximum likelihood procedure.\(^{22}\) In the second step, \( \lambda \) and \( \rho \) each inserted into a model of the form below, and all other variables are estimated by generalized least squares. The SSAR model takes the form:

\[
y = \rho Wy + X\beta + u, \quad u = \lambda Wu + \varepsilon
\]

Where \( W \) represents a matrix defining and weighting the “neighboring” settlements to each settlement in the dataset, and \( X\beta \) represents the variables and coefficients of all other independent variables already present in the model. The remaining two right-hand side terms - \( \rho Wy \) and \( u = \lambda Wu + \varepsilon \), account for the influence of nearby recovery and nearby errors respectively. To address the influence of neighbors’ recovery, \( \rho \) is multiplied by the matrix of neighbor weights \( W \) and the outcomes of those neighbors \( y \). The resulting term \( \rho Wy \) “controls” for the impact of recovery in neighboring settlements on recovery of the settlement in question. Similarly, to account for the influence of nearby errors, \( \lambda \) is multiplied by the matrix of neighbor weights \( W \) and their errors \( u \). The resulting term \( u = \lambda Wu + \varepsilon \) “controls” for the effect of the

\(^{22}\) This is a machine learning approach that maximizes the likelihood that the process described by the model produced the results which were observed. For a detailed mathematical explanation, see Arbia (2014).
non-random component of error – common regional characteristics that matter for recovery but are not in our regression – on recovery (Ward and Gleditsch 2018).

I consider the five nearest settlements to be the set of neighbors of the settlement at hand (k=5). Since the impact of neighboring settlements on a given settlement is almost certainly related to distance, I adopt the standard approach of weighting the influence of neighboring settlements on the target settlement by inverse distance. The results are not sensitive to other reasonable choices of k. To address post-treatment bias concerns, I only include independent variables that capture settlement characteristics before ISIL invasion.

**Independent variables**

My approach to modelling is progressive. In specification 1, I begin with only the independent variable capturing diversity and spatial controls. The model suggests a negative effect of diversity. In specifications 2 through 7 I gradually add different groups of controls to test whether this result is robust to controls for other influences on recovery and how its effect size compares to them. As controls are added, the diversity penalty gradually becomes larger and more significant. Some variables are logged to account for skewed distributions. Histograms of the distribution of each independent variable before and after selective logging are included in Appendix I.

**Ethno-religious diversity**

I begin by assessing the relationship between ethno-religious diversity and reconstruction without any controls other than the spatial corrections. In specification (1) I include only a variable capturing settlement-level ethno-religious diversity (calculated using the approach detailed in Chapter 4) and spatial controls.
Occupation severity and length

Some settlements experienced harsher ISIL occupations than others. More extensively destroyed settlements require more reconstruction to return to their pre-invasion levels; in specification (2) I add two controls to capture this concept.

Fraction of pre-invasion light remaining during occupation

While some ISIL-occupied settlements saw continued (albeit reduced) economic activity under ISIL occupation, others experienced near-complete population flight or were flattened by militants. Chapter 2 argued that night-time light emissions are a proxy for economic activity. Although electricity supply flowing in to ISIL-controlled territory was severed by the Iraqi government, there were plenty of other ways ISIL could light its settlements. ISIL-controlled oil wells produced as much as 56,000 barrels of oil per day (Do et. al. 2017), and ISIL-occupied areas already had a high prevalence of gas-powered generators and cars before militants arrived. My conversation with a former U.S. Army engineer who worked on the Iraqi electricity grid suggested the caliphate could also have used substation-level manual overrides to create local electricity circuits among settlements and power stations it controlled. The nighttime light emissions from settlements during ISIL occupation can thus act as a proxy for the level of economic activity in settlements during occupation. I calculate the median monthly light level during a settlement’s period of occupation as a fraction of the pre-invasion light level and introduce it as a control. Since this variable is right-skewed, I log it. Since some settlements have 0% if pre-invasion light remaining during occupation, I add 1 to all values before logging.

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23 Interview with David Ensign, February 1st, 2019. Mr. Ensign also confirmed that the Iraqi government deliberately shut off power supplies flowing into the ISIL-controlled region.
Duration of occupation

Second, the length of ISIL occupation is important. The longer ISIL occupies a settlement, the more residents are likely to flee. Those that have fled may travel farther from their homes, and IDPs are more likely to seek out longer-term displacement arrangements that heighten the minimum security conditions they will expect to see before returning home. Longer control periods also gave militants more time to install land mines and build defensive positions, which can lead to more destructive liberation battles and more intensive de-mining before reconstruction can resume. I calculate the number of months between ISIL capture of a settlement and its liberation and introduce it as a control.

Access and logistics

Places that are more difficult to access are more difficult to rebuild, and places that were liberated earlier should be farther along in the process. In specification (3), I add three controls to capture this concept.

Date of liberation

My measure of reconstruction captures the fraction of pre-invasion light recovered by December 2018. However, some settlements were liberated as early as 2015, and others as late as December 2017: some settlements have been rebuilding for longer than others. I expect settlements that been rebuilding for longer to have a greater fraction of recovery complete by December 2018, so controlling for the date of liberation is essential. I introduce a control capturing the month of liberation, where months are numbered and increase linearly from month 0 (the month of the first settlement liberation) to month 68 (the month of the final settlement liberation).
Driving distance to closest reconstruction center by road

Baghdad, Kirkuk, and Erbil are the three major Iraqi cities from which post-ISIL reconstruction efforts are coordinated. All are just beyond the extreme extent of ISIL occupation, and home to the government authorities, NGOs, suppliers and central communications centers that drive the reconstruction process. Longer distances between liberated settlements and centers of reconstruction implies that more time and funding is necessary to move people and resources to the liberated settlement. Additionally, longer driving routes increase the chance that vehicles will be interrupted by security disruptions along the road or be slowed by damaged roadway. Settlements further from reconstruction centers likely rebuild slower. I calculate the distance in kilometers along the shortest driving route from Baghdad, Kirkuk, or Erbil (whichever is closest) to the settlement in question. Iraqi road network data is obtained from The Humanitarian Open StreetMap team and is current to October 1, 2018. Since this variable is highly right-skewed, I log it.

Driving distance to closest major highway

I also expect the distance from a major transit artery to be important. The quality of Iraqi roads decreases dramatically between major highways and other types of roads: while major highways are paved and priorities for rehabilitation, secondary access roads are almost always dirt or gravel. They are substantially less fuel efficient to traverse and require much more driving time per unit roadway. As a result, settlements closer to major highways are substantially easier targets for resource delivery. Settlements closer to major highways should rebuild faster than those further away. I calculate the distance in kilometers along the shortest road route from a settlement to the nearest major highway, again using Open StreetMap data from October 2018.
Pre-invasion population characteristics

Pre-invasion population characteristics might influence reconstruction: they predict the type of local infrastructure, provide for scale returns to reconstruction, and proxy for urban-rural divides. In specification (4), I introduce two variables to control for density and size.

Overall population

Overall population could theoretically influence reconstruction in both directions. On one hand, major population centers could be prioritized for post-conflict reconstruction aid because of their symbolic and economic importance. The delivery of reconstruction assistance to large numbers of people in close quarters introduces increasing returns to scale on reconstruction expenditures. Rural villages and areas may be left behind. On the other hand, the symbolic importance of large cities often encouraged ISIL to fight longer and harder for them, leaving more extensive destruction in the wake of militant expulsion. I calculate overall population in 2012 using LandScan data and introduce it as a control. This variable is highly right-skewed, so I log it.

Population density

Population density is important for two reasons. First, it is a proxy for infrastructural quality: densely populated areas are likely to have more sophisticated electricity grids, better roads, and better sanitation – all of which are important to reconstruction. Second, high population density suggests increasing returns to scale in repair efforts: fixing the power line supplying power to an apartment building in Mosul may allow fifty people to turn on the lights; reconnecting a farmer’s shack in a rural village to the grid may only add one light per night. I
introduce a control for population density, using 2012 LandScan population per square kilometer. Again, this variable is highly right-skewed, so I log it.

**Pre-invasion economic characteristics**

Pre-invasion economic characteristics might also be important: rich places might rebuild differently from poor ones, and settlements that grew quickly before conflict might recover faster after it. In specification (5), I introduce two variables to capture these ideas.

**Historical growth**

I introduce a variable for historical growth to account for the possibility that faster-growing villages before conflict may recover faster after conflict: perhaps the same political and economic networks and structures that facilitated rapid pre-conflict growth can be leveraged to facilitate speedy reconstruction. To measure pre-invasion growth, I calculate the median monthly growth rate from the 12 months immediately preceding the beginning of ISIL insurgency in December 2013.24

**Per capita wealth before invasion**

Independent of growth, wealthier cities before conflict may rebuild faster after conflict: these individuals may have access to greater political capital, expanded ability secure basic resources, and heightened capacity to finance speedy reconstruction. To account for this possibility, I calculate the per capita luminosity value for all settlements. The pre-conflict luminosity value the same value used in the dependent variable: the VIIRS value from November

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24 In the very small number of cases where a settlement monthly observation is 0 in this period, the growth rate between this month and the next cannot be calculated. In these cases, I drop the monthly growth rate that cannot be calculated and calculate the average monthly growth rate instead using the 11 (or 10) remaining months.
2013, the month before the ISIL insurgency began. Population numbers are calculated from LandScan data in 2012. Since this variable is highly right-skewed, I log it.

**Ethno-religious identity**

Finally, it is important to isolate the effect of ethno-religious diversity from the effect of ethno-religious group labels themselves. Chapter 2 explained how some Sunni groups were governed by ISIL while others were exterminated; the difference in ISIL’s treatment of different groups under its control surely influenced the severity of occupation and the ease of reconstruction. Additionally, there may be political bias in the post-conflict period against some ethno-religious groups *as a group*. In specification (6), I introduce a binary dummy that evaluates to 1 if a settlement is majority Sunni or 0 otherwise. In specification (7), I replace the binary dummy with a set of dummies that record whether a settlement is majority ethno-religious group \( X \) for all ethno-religious groups \( X \) in the ISIL-occupied region that are majorities in at least one settlement. The point estimates for these dummies capture the effect of each non-Sunni Arab ethno-religious group on recovery *relative* to Sunni Arabs. This results in insertion of binary dummies for Sunni Kurds, Sunni Turkmen, Shia Turkmen, Yazidis, Shia Shabak, Sunni Shabak, and Christians. I refer to this final specification in future pages as the “preferred specification”.

**Spatial autoregression results**

Table 3 presents the results of models 1-7. While the results of the spatial autoregression will be analyzed fully in the next chapter, one result is immediately striking: all else equal, ethno-religious diversity appears to slow recovery. The ethno-religious diversity coefficient is negative and highly significant in every specification. Furthermore, its point estimate is large: specification (7) suggests that if the most homogeneous settlement in the region instead became
the most diverse settlement but was otherwise identical, it would recover more than four times less than it did.

Appendix I shows that this result is statistically robust to different sizes of settlements, regions, to only Sunni Arab settlements, and to different approaches to control for spatial dependence. It also holds within smaller brackets of diversity: when I run the preferred specification on only the most diverse settlements (or only the most homogeneous settlements, etc.) it is still always negative and often significant. Appendix I also presents added variable plots for all independent variables in the preferred specification (Model 7), and histograms showing the distribution of each variable.
**Table 3: Core Spatial Autoregression Results**

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
</tr>
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<tbody>
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***p < 0.001, **p < 0.01, *p < 0.05, p < 0.1
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<tr>
<th>Ethno-religious group dummies</th>
<th>Model 1</th>
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<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
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</table>

***p < 0.001, **p < 0.01, *p < 0.05, .p < 0.1
Can we say anything about the change in the relative importance of these influences over time? In a second test, I isolated the set of 244 settlements that were liberated before June 2017 and analyzed how the relative importance of different variables changed over time. In the models of Table 4, I use the identical specification (the preferred model) of independent variables on the identical set of settlements but vary the dependent variable: in the first specification it measures the percentage of pre-invasion light recovered by June 2017; in the second specification it measures the percentage of light recovered by September 2017; in each subsequent specification it measures recovery by a date three months forward in time through to December 2018. This effect is to estimate the same model on the same settlements in repeated cross-sections at progressively later points in time. One other methodological tweak is necessary: Since some early recovery fractions are 0, I am forced to add 1 to all values of the dependent variable before logging. This makes the point estimates difficult to interpret precisely, but the results give a general sense of the influences on recovery over time.

25 Descriptive statistics on this isolated set are available in Appendix I
Intentionally blank
TABLE 4: PREferred SPECIFICATION ON THE SAME GROUP OF SETTLEMENTS AT DIFFERENT POINTS IN TIME AFTER LIBERATION

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<td>(intercept)</td>
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<td>(0.701)</td>
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<td>-0.743***</td>
<td>-0.946***</td>
<td>-1.157***</td>
<td>-1.195***</td>
<td>-1.076***</td>
</tr>
<tr>
<td></td>
<td>(0.149)</td>
<td>(0.173)</td>
<td>(0.187)</td>
<td>(0.199)</td>
<td>(0.207)</td>
<td>(0.209)</td>
<td>(0.222)</td>
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<td></td>
</tr>
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<td>rho</td>
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<td>0.327***</td>
<td>0.253***</td>
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<td>0.195**</td>
<td>0.171*</td>
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<tr>
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<td>(0.069)</td>
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<td>(0.074)</td>
<td>(0.075)</td>
<td>(0.074)</td>
<td>(0.077)</td>
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<tr>
<td>lambda</td>
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<td>0.446***</td>
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<td>(0.059)</td>
<td>(0.054)</td>
<td>(0.052)</td>
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</tr>
<tr>
<td>log(frac. light during occupation + 1)</td>
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<td>0.540***</td>
<td>0.279</td>
<td>0.105</td>
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<td>-0.312</td>
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<td>(0.138)</td>
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<td>(0.187)</td>
<td>(0.194)</td>
<td>(0.196)</td>
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<td>-0.009**</td>
<td>-0.009**</td>
<td>-0.009**</td>
<td>-0.008*</td>
<td>-0.007*</td>
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<tr>
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<td>(0.003)</td>
<td>(0.003)</td>
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<td>-0.387***</td>
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<td>-0.460***</td>
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<td>0.032</td>
<td>0.030</td>
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<td>(0.030)</td>
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<td>(0.048)</td>
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*** p < 0.001, ** p < 0.01, * p < 0.05, p < 0.1
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<td>0.740***</td>
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Num. obs. 246 246 246 246 246 246 246
Parameters 21 21 21 21 21 21 21
Log Likelihood 15.619 -19.119 -44.736 -61.469 -68.564 -70.099 -90.310
AIC (Linear model) 129.268 218.569 213.263 229.328 240.421 238.413 277.504
AIC (Spatial model) 10.762 80.239 131.471 164.937 179.127 182.199 222.619
LR test: statistic 122.506 142.331 85.792 68.391 60.215 58.885
LR test: p-value 0.000 0.000 0.000 0.000 0.000 0.000 0.000

***p < 0.001, **p < 0.01, *p < 0.05, p < 0.1
Table 4 returns several interesting results. They will be discussed fully in the following chapter, but for now, I focus on the diversity variable. It is insignificant initially, but as many other influences on recovery hold steady or fade over time, the influence of diversity grows. By November 2018, the negative effect of diversity on this group of settlements is large and highly significant.

**Part III: Matching with a generalized synthetic control**

The striking ethno-religious diversity result deserves further investigation. Do higher levels of ethno-religious diversity really cause settlements to rebuild slower, and does this gap truly increase over time? I use a matching approach with a generalized synthetic control (GSC) to focus specifically on the difference in recovery caused by ethnreligious diversity (Xu 2018). The theory for matching as a causal strategy is straightforward. We want to compare highly diverse settlements to other settlements that are less diverse but otherwise similar. Given that ethno-religious diversity is the only characteristic differentiating this set of settlements, we can infer that observed differences in recovery are caused by differences in ethno-religious diversity.

Before implementing the more sophisticated GSC matching approach, I begin with a simple hand-matching exercise to build intuition. In Figure 19, I contrast the average light trends of homogeneous and diverse settlements within the same district or area, in the four areas with the highest variation in ethno-religious diversity levels among settlements. In each of the four plots below, the blue line represents the median light level of the most homogeneous third of settlements in that area, and the red line represents the median light level of all other settlements.
(which we will call “diverse”). For each settlement, light levels are normalized such that the November 2013 light level (the month before ISIL’s Iraqi insurgency began) is equal to 1.²⁶

The x-axis in all four plots represents the date; these plots make no attempt to account for different timings of liberation for different settlements within the same district. Nor do they make any attempt to control for different covariate characteristics. Instead, the assumption is that settlements located close to each other should be relatively similar in terms of other non-ethno-religious characteristics that might influence recovery. In general, the performance of diverse and homogenous settlements is very similar before and during occupation. But in all four regions, homogenous settlements outperform their diverse counterparts in the post-conflict period.

²⁶ In this exercise, I use the same multiple loess smooths approach to data preparation used earlier.
**Generalized synthetic control**

Figure 19 is a useful first pass at the difference in recovery among diverse and homogeneous settlements, but it leaves open questions of confounding variables - not all settlements in a district are identical on all confounding characteristics - and cannot quantify an average effect across all settlements. In a generalized synthetic control approach, I subject this result to a more rigorous matching test.
The high-level intuition behind statistical matching approaches is to apply the crude district-level design of Figure 19 precisely at the settlement level. Each diverse settlement is matched to a homogeneous settlement with identical characteristics except for its level of diversity. Since the settlements of each pair are identical except for their diversity levels, any observed differences in their recovery can be attributed to the only difference between them – diversity.

Yiqing Xu’s generalized synthetic control (GSC) approach takes this classic strategy several steps further. Given the relatively small number of settlements in this sample, finding perfect homogeneous matches for each diverse settlement is difficult. GSC provides a novel way to facilitate better matches. For each diverse settlement, it uses information about how homogeneous settlements with similar pre-liberation light trends performed after liberation to construct a synthetic counterfactual trend representing how the diverse settlement would have recovered had it instead been homogeneous but otherwise identical.

The process has three key steps. First, it estimates an interactive fixed effects model using only homogeneous settlements. This iterative estimation process results in the identification of a fixed number of time-varying coefficients (“latent factors”) that best describe different light trends over time in homogeneous settlements. Second, it estimates unit-specific intercepts (“factor loadings”) of the factors for each diverse settlement using information on light trends in diverse settlements before they were liberated. Finally, it estimates a synthetic counterfactual for each diverse settlement using the factors and factor loadings. The average difference between the observed performance of diverse settlements and their synthetic counterfactuals is thus the average treated effect on treated units – the causal quantity of interest.
The GSC approach has two major advantages. First, it allows us to easily examine how the performance of diverse settlements relative to their synthetic homogeneous counterparts changes over time. Second, it eliminates by design many of the omitted variable bias concerns that the earlier regression approach attempted to accommodate statistically. The difference-in-difference design eliminates the need for time-invariant controls, because it matches settlements with counterfactuals that responded identically in the pre-treatment period.

The data preparation work for the GSC analysis is very similar to the preparation for the regression analysis. An almost-identical set of ISIL-occupied settlements and the same approach to coding liberation dates and ethno-religious diversity applied to the regression analysis is used here. No other controls are needed. However, I make three small changes. First, I choose to smooth light values using a Loess-based seasonal decomposition (Cleveland et. al. 1990). This method helps address seasonal variation in lighting – a nice feature – but I primarily prefer it because the multiple loess smooths strategy used in regression results in lighting values of zero at points in this panel. This would necessitate adding 1 to all values before logging them, making the results much more difficult to interpret. Second, light levels are normalized to the April 2013 level to help facilitate comparisons, and then logged. Third, for this analysis I exclude 19

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27 The number of post-liberation observations for different settlements varies. Although all settlements have at least one year of post-liberation data, at the time of writing some have more – as much as three years of post-liberation data – while others have less. This is because settlements were liberated at different times. To estimate the ATT beyond the first liberation year, the GSC uses a matrix completion approach that imputes likely outcomes for settlements with no data at time \( t \) using the outcomes of settlements with data at time \( t \) weighted by their degree of similarity to the settlement missing data. As time goes on the number of settlements with data decreases and the number of imputed settlements increases; the 95% confidence interval grows steadily in the ATT plot below to reflect this uncertainty. However, the negative causal effect of diversity on recovery is so large that it diverges entirely from 0 even as it grows in width – suggesting that although the point estimate is more uncertain, we can still be confident that it is significantly different from and lower than 0.

28 I show the results of a generalized synthetic control test that uses the multiple loess smooths approach applied to regression (with log+1) but is otherwise the same in Appendix I; the results look similar but are less readily interpretable.

29 These light levels show the same skew as the recovery variable, so I log them for the same reason.
settlements (5.4% of all settlements) that had near-zero light levels in April 2013 – probably because they were experiencing blackouts when images were taken – because relative light levels appear artificially enormous when calculated relative to a blackout.30

Using Yiqing Xu’s gsynth package in R, I implement a generalized synthetic control. The treatment group are “diverse” settlements (in the top third of diversity scores); the control group from which synthetic controls are estimated are their homogeneous counterparts (in the lower two thirds of diversity scores). For each diverse settlement, the model constructs a synthetic control representing how the settlement would have recovered if it was homogeneous, using information from the recovery of homogeneous settlements weighted by their degree of similarity to the diverse settlement in question before and during ISIL occupation. “Treatment” applies at liberation, and we observe how the paths of diverse settlements and their homogeneous synthetic controls diverge. To address time-variant confounders I allow the algorithm to choose the optimal number of factors from the first-stage interactive fixed effects model,31 and to improve handling of time-invariant confounders I run the algorithm with unit-specific fixed effects.32

30 The inclusion of these settlements does not change the point estimates of the model, but it dramatically widens the confidence intervals and obscures the otherwise high degree of confidence that exists around the remaining 332 settlements. Light levels probably appeared near-zero in April 2013 in these settlements because they were experiencing blackouts – a common event in Iraq – that were later fixed.
31 The gsynth package includes a built-in cross-validation procedure to select the optimal number of latent factors from the first-stage interactive fixed effects estimation. I allow the algorithm to search between 1 and 10 factors; it chooses 10 as optimal. This of course means that the optimal number of factors is bounded against the high end of the search radius (and perhaps it is not the overall number of optimal factors), but the improvement in model fit between 9 and 10 factors is small and settlement-level plots show that the pre-liberation model treatment is tight, so in the interest of limiting computational intensity I use the 10-factor solution. Appendix I shows plots of the 10 latent factors estimated by the interactive fixed effects model and the loadings of the four most important ones across diverse and homogenous settlements.
32 This is a conservative choice. Running the model without unit-specific fixed effects returns an even larger divergence between homogenous and diverse settlements.
The first plot on the next page shows the observed lighting trends of diverse settlements (in black), and the estimated lighting trends those settlements would have experienced had they instead been homogeneous but otherwise identical (in blue). The second plot shows the average treatment effect on treated units (ATT): the estimated penalty caused by ethno-religious diversity in diverse settlements. The black line in this plot shows the ATT; the grey band shows the 95% confidence interval on the estimated treatment effect on individual settlements. The first plot must be viewed in context of the second one: the blue synthetic control line bounces violently towards the end of the panel, but the bottom plot shows we are also very uncertain of its position at this point. There are very few settlements liberated early enough that they have more than three years of post-conflict data available and can be used to build synthetic estimates more than three years after liberation. Like any model, readers should compare the point estimates of this model with the uncertainty surrounding them.
FIGURE 20: GENERALIZED SYNTHETIC CONTROL RESULTS

**Estimated causal effect of high diversity**

- **Log (relative light level) (April 2013 = 1)**
- **Months relative to liberation (0 = liberation)**
- **Treated Average**
- **Estimated Y(0) Average**

**Estimated causal effect of high diversity (ATT)**

- **Log (relative light level) (April 2013 = 1)**
- **Months relative to liberation (0 = liberation)**
- **Treated Average**
The generalized synthetic control analysis returns two important results. First, it confirms the existence of a diversity penalty on reconstruction suggested by the core SSAR regressions in Table 3. Un-logging the point estimates reveals that by the second post-liberation year, diversity appears to cause the average diverse settlement to have less than half economic activity than it otherwise would. By this point the entire 95% confidence interval has diverged from zero, suggesting this result is statistically significant.

Second, the GSC analysis supports the finding of Table 4 suggesting the diversity penalty grows over time. In the beginning of first post-conflict year, there is essentially no difference between diverse settlements and their synthetic controls. But a wedge between diverse settlements and their homogeneous counterfactuals quickly begins to emerge. Un-logging the point estimates, in the twelfth post-liberation month, diversity appears to cause on average a 42% decrease in economic activity. By the sixteenth post-conflict month this number has grown to 58%, and by the end of the second post-conflict year diverse settlements would have enjoyed double the economic activity they actually experienced if they were homogenous but otherwise identical. By three years the effect is massive: diverse settlements would see nearly nine times more economic activity if they were homogenous. This very large penalty suggests that homogenous settlements are essentially “taking off” in reconstruction and leaving diverse settlements behind. This result is striking on its own: not only does diversity matter for reconstruction, but its importance increases over time.

**Part IV: Mosul neighborhood matching**

One last concern must be put to rest. Chapter 4 discussed how the ethno-religious diversity proxy  used for my core analysis – based on the distance of settlements to others of
different ethno-religious majorities – may capture ethnic enclave or “ethnic fault line” effects in addition to ethno-religious diversity. Settlements that are ethnic enclaves or lie on ethnic fault lines will appear highly diverse in $\theta$ even if they are themselves homogeneous, and if these characteristics affect recovery, the estimate on ethno-religious diversity may be biased. At the national level no settlement-level data directly measuring ethno-religious diversity is available. However, within the city of Mosul, I was able to obtain neighborhood-level data that directly measures ethno-religious diversity before the ISIL conflict. Mosul is Iraq’s second-largest city (home to nearly one-third of the entire occupied population), was occupied by ISIL from June 2014 to July 2017, and is made up of a mix of ethno-religiously diverse and homogeneous neighborhoods. I use a neighborhood-level matching strategy in Mosul to confirm that ethno-religious diversity has a direct impact on recovery. This exercise cannot rule out independent effects of ethnic enclaves or fault lines, but it can bolster our confidence that the diversity results above are driven at least substantially by effects attributable to diversity itself.

Dr. Michael Izady (2010)’s ethno-religious mapping of Mosul codes neighborhoods as either “mixed” or populated by a specific ethno-religious group in 2010. I use the Izady mapping to identify 17 pairs of adjacent neighborhoods, where one neighborhood is Sunni Arab (which I call “homogeneous”) and the second is “mixed”. Although the ethnic composition of Mosul neighborhoods has shifted somewhat in the wake of ISIL occupation, I assume that homogenous neighborhoods before the conflict are also relatively more homogenous than their “mixed” counterparts in the reconstruction period. The neighborhoods range in population from around 1,000 to around 24,000 inhabitants in 2012, but paired neighborhoods are of similar size and population. Since paired neighborhoods are directly adjacent to each other, I assume with some confidence that other covariates that might affect recovery such as extent of destruction,
liberation timing, and experience of occupation are similar between them. Figure 22 shows the selected pairs. Neighborhoods with the same number are matched; blue denotes the homogeneous neighborhood of the pair and red denotes its mixed counterpart.

**Figure 22: Matched pairs of Mosul neighborhoods selected for neighborhood analysis**

Luminosity is calculated and normalized for this exercise in using the same technique as the GSC analysis above. The one important difference is that because outcomes in Mosul neighborhoods are relatively similar, I can and do avoid logging the dependent variable. Figure 23 shows the results. The black line shows the estimated average treatment effect (ATE) - the average difference between diverse neighborhoods and their paired homogeneous counterparts.
The accompanying gray band shows the 95% confidence interval on this trend. There is little difference between diverse and homogeneous neighborhoods before and during ISIL occupation. But after liberation, diverse neighborhoods recover much slower than their homogeneous counterparts – on average, the average diverse neighborhood had less than half the economic activity of a homogeneous neighborhood across the street by December 2018. By July 2018, the entirety of the confidence interval had dipped below zero – suggesting the diversity penalty is statistically significant. These results help confirm that ethno-religious diversity does have an independent causal effect on recovery. The plot also shows that the decline coincides closely with the 2018 Iraqi election – a point that will become important in the discussion of causal mechanisms in Chapter 6.

**Figure 23: Estimated effect of diversity in diverse Mosul neighborhoods**
Chapter 6 | Interpretation

The core result from chapter 5 suggests that all else equal, ethno-religiously diverse settlements appear to recover slower than homogeneous ones - and that the penalty to diversity grows over time. The primary goal of the remaining two chapters is to understand and explain the importance of ethno-religious diversity in post-conflict recovery. I start with a discussion of the influences on recovery broadly and gradually narrow my focus to ethno-religious diversity. This chapter focuses on interpreting the results of Chapter 5, with specific attention paid to ethno-religious diversity. Chapter 6 embarks on an extensive qualitative investigation to identify the causal mechanisms driving this result.

Part I of this chapter interprets the results of Chapter 5 and explains how they fit together to paint an overall picture of the most important influences on recovery across space and time. Part II delves into the diversity result in depth. It investigates the robustness and geography of support for diversity result and contextualizes it against national patterns.

Part I: Describing the trend

Interpretation begins with an attempt to understand the landscape of different influences on recovery at a high level. My objective in presenting this information is not to unpack each mechanism driving each unique influence on recovery – explaining everything is well beyond the scope of this thesis. Rather, I present an overview of the landscape to convey a sense of which influences are relatively more or less important, to help explain my decision to focus on ethno-religious diversity, and to show how its importance compares to other influences on recovery.
This discussion begins with the cross-section of recovery described by the core SSAR regressions in Table 3. The preferred specification suggests about 48% of variation in settlement recovery is due to local characteristics and case-specific circumstances that cannot be systematically modelled. The remaining 52% of variation has a systematic component. About one-fifth of this systematic variation surfaces as “spatially correlated error”: regional characteristics that systematically impact recovery but are not directly captured by the model, and are instead held constant by the spatial coefficient \( \lambda \). But remaining four-fifths of this systematic variation – 40% of the total variation in recovery – is both systematic and can be directly explained by the model. Unpacking this 40% of total variation is the focus of the coming discussion. While logistical and economic components of this variation are not unexpected, but the social influences on recovery are surprising.

Figure 24 shows the proportion of the total variation in recovery among settlements explained by each predictor in the preferred SSAR specification. Variables that speed recovery as they increase are colored in green; variables that slow recovery are colored in red. The results can be grouped into four major themes: logistics, pre-invasion characteristics, the experience of occupation, and social identities.
The first theme of these results is “logistics” influences, and logistics loom large in reconstruction. About 13% of total variation in recovery can be explained by a settlement’s distance from major highways and the driving distance to a major non-occupied city (2% and 11% of the story, respectively). A 1% increase in the driving distance to major non-occupied city slows recovery by 0.92%, and each additional kilometer of distance to the nearest major highway cuts recovery by 1.4%. Neither of these outcomes is unexpected. Aid and reconstruction material flows from major non-occupied cities to rebuilding settlements; the longer and more difficult the drive, the more expensive the transport, the longer journeys take and the greater the likelihood convoys will be interrupted by security incidents. Ease of access to a major non-occupied city also often
means that residents who have fled are still nearby; the return process is much longer and more difficult when the home to return to is far away.

Spatial coefficient ρ, which captures the influence of nearby settlements’ performance on the settlement in question, explains about 6% of recovery and is positive and significant. There is no clear substantive interpretation of the point estimate for ρ because of the nature of the SSAR model, but the positive value suggests that rapidly recovering nearby settlements speed recovery of a settlement in question. This is no surprise: as suggested in earlier chapters, quickly-rebuilding settlements likely confer “spillover” benefits on others nearby. These “spillovers” could be increased local trade activity, a larger number of returnees from a similar region telling IDPs conditions are safe to return, or any number of other local effects.

The second group of results address pre-invasion economic and demographic characteristics, where results are mixed. The pre-invasion per-capita light level accounts for about 7% of total variation in recovery; higher levels of per-capita light before conflict are negatively and significantly associated with post-conflict recovery. Since light proxies for GDP linearly (see Chapter 2), the results suggest a 1% increase in GDP per capita before conflict is responsible for a 0.25% decrease in recovery. This result is consistent with Bozzoli et. al. (2012), Serrano (2009) and others who have argued that IDPs without the financial resources to remain in displacement are forced to return home earlier while their richer counterparts can afford to wait for conditions to improve.\footnote{In line with this argument, the ILA III survey in post-ISIL Iraq shows that 37% of returnees cite a lack of financial resources as one of the main drivers for their decision to return.} The pre-invasion median monthly growth rate, however, is not a significant influence on post-conflict recovery. Population density is 2% of the story; a 1% increase in population

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density leads to a 0.28% decrease in recovery. This result could be reflective of more intensive destruction in highly urban areas. Population itself is a statistically useless predictor of recovery: all else equal, big cities recover no faster or slower than small villages.

Third, we turn to the experience of occupation. The month of liberation coefficient is insignificant, suggesting the date a settlement is liberated has little bearing on how much it has recovered by the end of December 2018. A first-pass interpretation of this result is to conclude that settlements liberated later rebuild at a faster rate than those liberated earlier. Even though settlements liberated first have had a longer time period in which to rebuild, this result might suggest that late-liberated settlements grew quickly over a short time period such that they erased the deficit incurred by starting late within a year. A closer investigation reveals the effect may be more nuanced. Individual settlement lighting panels show that even if settlements liberated early do recover, they often do not start their recovery until fighting in their district has ceased. This is not surprising: residents were often discouraged or prohibited from returning home to early-liberated settlements while fighting was ongoing nearby. The start of reconstruction was often delayed until local conditions were safe, and resources were freed from combat operations to help with rebuilding. “More time to rebuild” is an empty benefit when that time cannot be used because fighting is ongoing nearby are resources are deployed elsewhere. The relative contribution of starting late versus recovering slower once recovery begins to the recovery trend of early-liberated settlements is outside the scope of thesis, but fertile ground for future research.

All else equal, neither the length of occupation nor the fraction of light lost during it are significant predictors of recovery. At first glance this suggests that the experience of occupation
does not matter much for recovery, but this claim needs to be seriously tempered. There are many dimensions on which settlement experience of ISIL occupation varied and only some are captured by occupation length and light loss. Experience-of-occupation characteristics these measures do not directly capture – such as emotional trauma – surely matter for recovery. A broad assignment criterion for quality of ISIL governance is ethno-religious identity: Chapter 2 explained how ISIL governed Sunni Arab settlements but exterminated in others. Non-Sunni settlements likely received a worse “basket” of occupation outcomes and some are not directly captured by the model. A more likely interpretation of the model output is that occupational experience does matter and that some of this effect is absorbed by ethno-religious group dummies.

This brings us to the final category of results: social influences on recovery. Ethno-religious group dummies explain about 4% of the total variation in recovery, and their point estimates map closely to what the popular press would have us expect. The average Yazidi settlement, subject to brutal ISIL genocide, carries the largest group dummy penalty and recovers 54% slower than an otherwise-identical Sunni Arab settlement (p<0.05). Christian and Shabak settlements also appear to recover slower than Sunni settlements but the point estimates are smaller than for Yazidis and not significant – probably partially because of the small number of Christian and Shabak settlements in the sample. Kurdish settlements may recover slightly faster. The Kurdish estimate is not significant, but the suggestion that it is positive also not surprising given the relatively high capacity of the Kurdish Regional Government and its security force. Turkmen settlements do best. The performance of Turkmen – especially Shia Turkmen – is somewhat surprising but given that there are very few Turkmen settlements in the sample it is difficult to say whether this benefit is a causal result of Turkmen identity. We also observe that for ethnic groups
with both Sunni and Shia denominations, the Sunni half typically recovers faster than the Shia half: Sunni Turkmen recover faster than Shia Turkmen; Sunni Shabak recover faster than Shia Shabak. If the binary Sunni – Non-Sunni dummy is used instead, the average Sunni settlement recovery recovers 24% faster than an otherwise identical non-Sunni settlement (p<0.1). This finding is consistent with ISIL’s tendency to govern Sunni settlements but obliterate non-Sunni ones.

The group dummies suggest some differences in recovery may be directly attributable to group labels, but they are not helpful in identifying the causal driver. Part of this effect could be due to bias or discrimination in the post-conflict period: Yazidi leaders in Sinjar, for example, have been quoted suggesting that they are being deliberately deprioritized for reconstruction resources (ICG 2018). However, part of the effect of group labels likely captures elements of more severe destruction in non-Sunni settlements not captured by the experience-of-occupation controls. Identifying the causal drivers for the effect of ethnic group labels is not this thesis’ priority, but the differences suggest a potentially disturbing trend in recovery.

Finally, we arrive at perhaps the most interesting result of the model: the ethno-religious diversity variable is large, negative, and consistently highly significant (p<.01 in every specification). It explains about 8% of the total variation in recovery, making it the second-most powerful explanatory variable in the model and more than twice as powerful as all ethno-religious group dummies together. The size and explanatory power of this variable is particularly notable because many of the settlements in the sample are hardly diverse at all. Among diverse settlements, diversity appears to explain a very large fraction of variation in recovery and is a large influence.
The preferred specification suggests that if the least diverse settlement in the sample were to become the most diverse settlement but remain otherwise unchanged it would recover four times as quickly. Furthermore, because the negative significance of the diversity result survives group dummy controls, we have some confidence that this effect is not simply capturing causal effects of different group labels: there is an additional and significant penalty to mixing them.

*Influences on recovery over time*

The repeated cross-section models of Table 4 give some sense of how the relative importance of these influences varies over time. Figure 25 repeats the analysis of variance exercise developed above for each of the cross-section SSAR models from Table 4. It shows how the proportion of total variation in recovery that can be explained by each model variable varies over time. In this figure, the x-axis denotes the “recovery-by” date. For example, “2017-06” denotes model results for the model where the dependent variable is “the fraction of pre-invasion light recovered by June 2016”, “2018-06” denotes the model where the dependent variable is “the fraction of pre-invasion light recovered by June 2018”, and so on. The bold light green line represents the ethno-religious diversity variable.
Two trends are clear. First, the explanatory power of the model grows as the date of cross-section grows farther from the end of conflict. The proportion of total variation that can be directly explained by model variables grows from about 21% in June 2017 to a peak of 49% by September 2018. This suggests that local contextual characteristics like the specifics of occupation in a particular village are important initially but fade over time, and the role of “systematic” influences on recovery gradually become more important.

Second, the relative importance of different influences on recovery changes over time. In the first months after liberation, practical and economic characteristics were overwhelmingly the most important influences. In the SSAR cross-sections at June 2017, per-capita light before conflict and the recovery of nearby settlements (rho) explained 4.9% and 6.8% of total variation.
in recovery respectively. A few other variables explained a small slice of variation – 2.1% of the variation can be explained by ethno-religious dummies, 2.1% by population density and 2.3% by the fraction of light remaining during conflict – but all other variables explain less than 1% of recovery variation.

As time goes on, the landscape of influences changes. Some of the change is expected: we anticipate that driving distance to a major non-occupied city increases in importance as the efforts to transport reconstruction materials and returnees to rebuilding settlements ramps up; accordingly, the total variation that can be explained by distance to a big city rises from just 0.54% in June 2017 to more than 8% by September 2018. Similarly, as poor IDPs return begin rebuilding while rich ones hold out for better conditions before returning, we expect the difference between rich and poor settlements to widen. The model shows that the proportion of variation explained by per-capita light before conflict rises from 5% to a maximum of nearly 10% over this time period.

However, the change over time in the explanatory power of one variable stands out. Ethno-religious diversity explained just 0.75% of the total variation in recovery among these 244 settlements in June 2017. But its explanatory power grows almost steadily, and by December 2018 it has increased more than ten times in power and explains 7.8% of the total variation in recovery (9.3% in September 2018). Furthermore, the explanatory power of the diversity variable relative to other variables increases markedly: by the end of the panel ethno-religious diversity is the second most important identifiable influence on recovery, and nearly a third more powerful than the next most important influence. The relative change in explanatory power between group dummies and diversity is especially important. In June 2017, dummies explained 2.1% of total variation.
variation while the diversity variable accounted for a paltry 0.75%. But by December 2018, the
relationship inverted: diversity now explained more than double the amount of variation than group
dummies did (6.7% to 2.9%). The next section digs deeper into this diversity result, and the change
in the relative explanatory power of diversity and dummies will be one topic of discussion.

**Characterizing the ethno-religious diversity result**

All the causal strategies of Chapter 5 suggest a causal diversity penalty to recovery is
negative and significant, but the size of this estimate varies slightly depending on the strategy used.
The core SSAR analysis suggests that if the least diverse settlement were to become the most
diverse but remain otherwise unchanged it would recover four times less by December 2018. The
generalized synthetic control analysis suggests the diverse settlements recover about 42% less in
the first post-conflict year than they would if they were homogenous but otherwise identical; this
figure grows to 58% by 16 months, double by the end of the second year, and a 9-fold difference
by the end of the third year.

Chapter 4 explained that it is hard to tell whether the proxy for diversity $\theta$ is capturing
diversity *within* settlements or settlements within highly diverse localized areas. $\theta$ is literally based
on distance to settlements of different majority, and it is possible that some of the settlements it
codes as diverse are situated in diverse areas but are themselves homogenous. I conducted the
neighborhood-level matching analysis in Mosul with data that directly codes diversity to gain more
insight on the role of diversity specifically. The estimate from this test was still large, negative,
and significant. By the end of 2018, homogenous neighborhoods in Mosul have on average four
times more economic activity than their diverse counterparts across the street. We still cannot say
for certain what component of the national effect is driven by diversity within settlements versus homogenous settlements in highly diverse local areas, but the Mosul exercise gives us some confidence that the observed point estimates at the settlement level are at least substantially driven by within-settlement diversity. Nonetheless, in the chapters that follow readers should remember that “diversity” might to some extent mean “homogenous settlements in diverse local areas” in addition to “diversity” itself.

Part II: What drives the diversity result?

The above discussion explains that ethno-religious diversity appears to be a highly significant influence on recovery, and that its influence increases over time. The remainder of this thesis takes a “deep dive” into this result. In the remainder of this chapter, I examine the geography of settlements that drive the and contextualize it against national patterns. This discussion lays the groundwork for the final substantive chapter, which proposes causal mechanisms.

Which settlements “drive” the diversity result?

A potential weakness in the diversity result would be to discover that it is driven by only a few settlements that are diverse and recovering slowly or homogenous and recovering quickly. If the significance of diversity is driven by only a handful of settlements – and among most others, diversity does not matter for reconstruction – the case for a diversity penalty to recovery would be weakened. I ran a series of robustness checks and investigated the data to understand the geography of support for the diversity penalty the models suggest. The results of these exercises suggest the support is remarkably robust: the significance of diversity is not driven by a specific type or set of settlements; it emerges in a wide variety of different subsets of the data.
A first concern is whether the diversity result is driven by a small collection of settlements in a certain region. Figure 19 in chapter 5 has already partially addressed this concern by showing that relatively diverse settlements recover slower than relatively more homogenous ones in the same district, but I ran an additional test. I re-estimated the preferred SSAR specification on only the 169 settlements in the “disputed” northern territories between the KRI and the central government, and again on only the 182 settlements in “uncontested” southern areas controlled by the central government. The diversity result is negative and highly significant in each case (Appendix I, Table 10). The second concern is whether the result is being driven by only a particular type of settlement. I re-estimated the preferred SSAR on only the 137 settlements with a population less than 1,000 people; I then estimated it again in the 127 settlements with population between 1,000 and 3,000 people and a third time on the 88 settlements home to more than 3,000 people. In each individual case ethno-religious diversity is a negative and highly significant (Appendix I, Table 8).

What about ethno-religious identity? Non-Sunni Arab settlements are much more likely to be diverse than their Sunni Arab counterparts; perhaps the diversity penalty is the result of being a non-Sunni group. SSAR specifications 6 and 7 have already addressed this question by showing that the diversity penalty survives controls for Sunni/Shia status (model 6) and dummies for each ethno-religious group (model 7), but I performed two additional checks. First, I re-estimated the preferred SSAR on only the 288 settlements with a Sunni Arab majority. The ethno-religious diversity coefficient remained negative and significant: even when only Sunni Arab-majority settlements are considered, all else equal, relatively more diverse Sunni Arab settlements recover
slower than relatively homogenous ones (Appendix I, Table 10). The same is true for only minorities: I re-estimated the preferred SSAR on only the 63 settlements with non-Sunni Arab majorities; the diversity penalty is negative and significant here as well (Appendix I, Table 10).

The last result is especially striking. Consider that only 63 settlements in the data set have non-Sunni Arab majorities, that the model includes dummies for all 8 ethno-religious groups, and that non-Sunni settlements are often spatially clustered. For the diversity result to survive controls for group dummies in this specification, it must be that diversity helps differentiate recovery speed even among the small number of settlements of the same minority ethno-religious group. A quick investigation confirms this is indeed the case. For example, consider settlements of Shia Shabak majorities. Only 12 settlements in the dataset are Shia Shabak, and they are all located in 450 square kilometer patch of territory west of Mosul. But even though they are all close to each other and similar on many covariates, Figure 26 shows diversity score does a remarkably good job of ordering their recovery.34 Similar plots show a negative relationship between diversity and recovery among every other minority ethno-religious group except one (the Sunni Shabak, which have only three observations).

34 Information tying the names of these settlements to their Shabak majority is easily publicly available through a simple Google search, so I show the names here.

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**FIGURE 26: BIVARIATE PLOT OF DIVERSITY AND RECOVERY FOR SHIA SHABAK SETTLEMENTS ONLY**

Diversity and group dummies

The diversity penalty seems significant and robust cross-sectionally and is large compared to other influences on recovery. But one dynamic deserves special attention: the relationship between ethno-religious dummies and ethno-religious diversity. After controlling for diversity, the causal effect attributed to most ethno-religious identities on face shrinks substantially. In a version of the preferred specification that is identical except that the diversity coefficient is removed, the model suggests ethno-religious group labels are highly significant influences on recovery. Christians, Yazidis, Shia Shabak, and Sunni Shabak labels are all associated with negative and significant *ceteris paribus* penalties to recovery compared to Sunni Arabs; Sunni Turkmen appear to rebuild significantly faster. The results seem to suggest that groups that shared the ethno-religious composition of ISIL (Sunnis) perform better than most minority groups because of their label. But when a control for diversity is added, the causal point estimates attributed to ethno-religious group labels shrinks substantially and becomes insignificant for all groups except two.
Non-Sunni settlements are also more diverse, and it may be their *diversity* more than their ethno-religious group labels themselves that are responsible for slowing recovery. The time-series SSAR supplies more evidence in support of this observation: Part I of this chapter ended by noting that the explanatory power of diversity *relative* to group identity labels increases as time moves further from liberation.

A closer look at the case of Sunni Arab settlements helps illustrate this finding. Before controlling for diversity, Sunni Arab identity appears to deliver a positive causal benefit to recovery. But when controls for diversity are added, this effect disappears. The careful reader will remember from Chapter 3 that the average Sunni Arab settlement is less diverse than the average non-Sunni Arab settlement. On closer inspection, it becomes clear that Sunni Arab-majority towns with high levels of diversity – for example, those in the Ninewa plain – recover about the same as nearby towns with similar levels of diversity but different majority groups. Sunni Arab settlements that are highly homogeneous – closer to Baghdad or up the Euphrates river – recover faster. The initially observed benefit to Sunni Arab identity is perhaps actually driven by ethnic homogeneity – a characteristic Sunni Arab settlements are more likely to enjoy than their non-Sunni Arab counterparts. But after controlling for diversity, there is nothing about the label Sunni Arab itself that significantly affects recovery compared to other groups.

To be sure, there are some differences in recovery in Table 3 attributable to the ethno-religious label that persist with a diversity control. Yazidis still recover slower; Turkmen still recover notably faster. Ethno-religious group labels still matter. But the label matters less when diversity is accounted for, and as time goes on, ethno-religious labels become *relatively* less
important compared to the effect of diversity. All of this suggests that divergence in recovery may be driven more by the diversity of groups in a location than the identity label of any given group itself. In other words, differences in recovery are perhaps less about the immutable characteristics or pre-determined futures given conflict experience of certain ethno-religious groups, and more about the tensions that arise when they are mixed together.

The national context

In advance of the 2018 national parliamentary elections, one Foreign Policy writer declared that Iraq was entering its “First Post-Sectarian Election” (Daragahi 2018). A commentator for The Atlantic heralded the “Eclipse of Sectarianism” in the Middle East (Hassan 2018). The claims were not without merit: national political and religious leaders emphasized that post-conflict elections must stay away from sectarianism (Republic of Sumer 2018, Daragahi 2018), and the 2018 federal vote ultimately produced a strikingly secular executive branch (Hubbard and Hassan 2018, Filkins 2005). A widely-cited opinion poll in April 2017 found that 53% of Sunni Arabs in areas recently liberated by ISIL agreed that Iraq was “moving in the right direction” at the helm of a Shia-led government; the first time a majority of Sunnis had responded positively to this question since 2003 (Al-Dagher and Kaltenthaler 2017).

However, my empirical analysis shows that ethno-religious diversity slows reconstruction among ISIL-occupied towns, and that the size of this effect increases over time. This result is puzzling: why does ethno-religious diversity have such a large negative influence on recovery at a time when national politics becoming historically secular? Does the empirical result make sense? One last layer of investigation into the diversity result delivers a crucial contextual insight: while
Iraqi politics after ISIL moved away from sectarianism on the national stage, my empirical finding reflects the local situations in *diverse* ISIL-occupied towns - which trended towards sectarianism.

On closer inspection, it becomes evident that national-trends towards unity are primarily driven by ethno-religiously homogeneous areas - particularly in Sunni Arab and Shia Arab regions. Because there are many more ethno-religiously homogeneous towns in Iraq than diverse ones, trends towards unity in these areas carry the national sentiment. However, the uptick in sectarianism in *diverse* areas was swift. Chapter 7 details extensive evidence of ethno-religious groups burning and looting other group’s homes and public buildings, arbitrarily detaining and executing out-group members, building physical barriers in diverse settlements, and forming ethno-religiously homogenous militias. It recounts examples of ethno-religious group leaders appealing to ethnic rhetoric at politically salient moments and shows that levels of reported trust after conflict were lowest in diverse areas. Although politics may be trending away from sectarianism nationally, they are trending towards sectarianism locally in formerly ISIL-held areas.
The increasing sectarianism in diverse settlements is a distinct break from trends away from sectarianism in homogeneous ones. Ethno-religious diversity becomes a dramatically more powerful predictor of recovery over time, and its power is consistent across a variety of different environments: diversity matters at the neighborhood level and in settlements, in small villages and large cities, and in different districts and governorates. Furthermore, it survives controls for ethno-religious group labels, and explains much of the variation that might otherwise be attributed to them. Chapter 7 supplied evidence suggesting diversity causes slower reconstruction. What can explain this finding? I argue that existing causal mechanisms for diversity and growth can only explain part of the result. Two separate but related new drivers may also be part of the story: differences in group treatment during conflict, and the strategic choices of territory-seeking elites after conflict.

Part I: How much can the classic mechanisms explain?

Identifying a diversity penalty to post-conflict reconstruction is a new contribution to political science, but a diversity penalty to growth is not. Alesina and La Ferrara (2005), Easterly and Levine (1997) and others have already explained how diversity slows economic performance in peacetime. Core to this “classic” mechanism is the claim that ethno-religious diversity and low intergroup trust make individuals less willing to contribute to public goods that spur growth. Before investigating new causal mechanisms for the post-conflict diversity penalty, we need to examine the degree to which the classic mechanisms explain it. Perhaps diverse settlements in Iraq have always been performing worse than homogenous ones, and the observed difference in post-conflict recovery is simply a continuation of this trend.
To test the plausibility of this explanation, I investigated the determinants of economic performance in the same group of settlements used in this thesis’ analysis in the two decades before ISIL invasion. If the post-conflict divergence in diverse and homogenous settlements is no more than a continuation from the peacetime trend, than it should be the case that homogenous settlements were outperforming diverse ones even before conflict began.

I obtained and cleaned annual DMSP luminosity data from 1992 to 2012 (see chapter 3) and used it to plot the economic performance of the same settlements analyzed in Chapter 5 for two decades before the ISIL invasion. The sample is not quite the same: because the DMSP data is lower resolution, I was forced to restrict this analysis to the 212 settlements with a 2012 population of at least 2,000 people to ensure accurate measurements.35 The top panel of Figure 27 below shows the normalized light value of the median settlement in the top third of diversity scores (red) and all other settlements (blue) 1992 to 2012. The bottom panel shows the difference between them.

Diversity does turn out to be a negative influence on growth in this period. However, in the five years before ISIL occupation, it was steadily becoming a less important influence on growth – and by some measures had even become a positive one. In the final years of the Saddam regime before 2003, a gap steadily opened between the performance of diverse and homogenous...
settlements. But after 2003 this gap stopped increasing, and after 2006, diverse settlements even began to show signs of beginning to close the gap with their homogenous counterparts.

**FIGURE 27: LUMINOSITY TRENDS OF DIVERSE AND HOMOGENOUS SETTLEMENTS IN THE ISIL AREA, 1992 - 2012**

![Graph showing luminosity trends of diverse and homogenous settlements](image)
SSAR regression analysis – the results of which are presented in Appendix I – shows that these observations are robust to controls for population, location, distance to major cities and other basic characteristics. In these regressions diversity is a negative and insignificant influence on the median annual growth rate from 1992 to 2002 and 2003 to 2007. From 2008 to 2012, diverse settlements actually grew significantly faster than homogenous ones. Cross-sectional regressions on per-capita income tell a similar story. During the hayday of the Saddam regime in 1997 diversity was a negative and highly significant (p<.01) influence on per-capita income. It became slightly less significant on the eve of U.S. invasion in 2002 (p < 0.05); then became more important as sectarian conflict took hold in the wake of U.S. invasion (p < 0.01 in 2007). But in 2012, the importance of diversity was only a weakly significant negative influence on growth (p<0.1), and the standard error on the coefficient had doubled from 2007. This exercise suggests that the post-conflict diversity penalty is not simply a continuation of pre-conflict trends. Diversity was steadily becoming less important for economic performance in the period immediately before ISIL; but this trend inverted, and diversity became a highly significant and growing influence on recovery after conflict.

If “public goods” can be taken to capture everything from building reconstruction to local security provision and the absence of conflict, then Alesina and La Ferrara (2005) – style trust and cooperation mechanisms may still explain a crucial piece of the diversity penalty. Recovery requires local-level cooperation, and this chapter will present substantial evidence that the inability of different ethno-religious groups to work together slowed recovery in diverse areas. The driver for this mechanism – low intergroup trust – may have been exaggerated by conflict. Indeed, IOM survey data show that diverse areas had the lowest levels of trust after the conflict (IOM 2019).
But the classic mechanism leaves two key questions for the post-conflict context. First, we want to know how this mechanism operates after conflict: diversity might retard public goods provision after conflict like in peacetime, but the reasons why may be different in the post-conflict context. Second, we want to know why diversity matters so much more after this conflict than before it. The literature does little to explain why the magnitude of a diversity penalty may vary over time, but my results suggest this variation is substantial.

The way ethno-religious diversity slows post-conflict recovery could still broadly be described as a failure to provide public goods, but I argue the specific mechanisms linking diversity to the failure to provide public goods have some important differences in this setting. I propose two: one rooted in the differential treatment of ethno-religious groups under ISIL, and a second centered on strategic choices of local elites in the post-conflict period. The theme that unites these two mechanisms also provides an answer to the second question: I argue that the increase in importance of diversity can be explained by the “activation” of ethno-religious identities. Ethno-religious identities are one of many latent identities that individuals hold, but the environmental conditions of the conflict and post-conflict environment activated their salience. In the remaining two sections of this chapter, I investigate each causal mechanism in turn.

Two literatures loom large in the background of this discussion. First, Posner (2002), Makdisi (2000), Weiss (2010), and others have already described how ethno-religious identity can be activated from latent to salient social cleavage in response to specific social conditions. Second, Alesina and Ferrara (2005), Easterly and Levine (1997), Montalvo and Reynal-Querol (2005) and
others explain how ethno-religious diversity slows economic performance when it is a salient cleavage. This thesis’ mechanisms help bring these literatures together: post-conflict conditions in Iraq activated ethno-religious diversity as a salient cleavage; this triggered the public goods provision problems that slowed recovery.

**Part II: Differences in the experience of conflict by group**

The first causal mechanism argues that the slow recovery of diverse areas is in part due to the differences in how different ethno-religious groups were treated during ISIL occupation. The short overview of this argument is as follows. The experience of ISIL occupation differed dramatically by ethno-religious group: some were governed while others were decimated. The differences in experience of conflict by group made ethno-religious affiliations salient; once this occurred; it became easy for victimized groups to view all members of other groups as complicit in ISIL’s terror. These differences were most striking, personal and visceral in diverse settlements, so the differential treatment of groups had the biggest activation effect in diverse areas. I argue that this effect than slowed recovery for two reasons: it triggered an ethnic security dilemma, and it altered the cost-benefit calculus of cooperation and revenge. The first part of this section shows how differences in the experience of ISIL occupation sharpened the ethno-religious group identity of Iraqis in occupied areas and how this effect was strongest in diverse areas. The second and third parts show how this slowed recovery by triggering an ethnic security dilemma and changing the cost-benefit revenge calculus respectively.
How differences in ISIL occupation sharpened the salience of ethno-religious identity

ISIL occupation sharpened the importance of ethno-religious identity because ethno-religious group labels were by far the most important determinant of the brutality of life under ISIL. Previous chapters have explained how in non-Sunni areas ISIL mounted mass executions of residents, flattened homes, and kidnapped locals and forced them into slavery (Cetorelli et. al. 2017). By contrast, in Sunni Arab areas ISIL aimed to govern. Sunni Arabs were neither actively exterminated nor were their homes and public spaces deliberately demolished. ISIL permitted Sunni Arabs to continue selling in markets and attending school, and even undertook civic administrative projects like road paving, electricity repair, garbage pickup, school curriculum planning, and the streamlining of land rental applications to help improve their quality of life (Callimachi 2018).

In some cases, these services for Sunnis came at the expense of other groups. A 27-page manual distributed by ISIL in Mosul and recovered by The New York Times explained that confiscation of property would be applied to every “Shia, apostate, Christian, Nusayri and Yazidi based on a lawful order issued directly by the Ministry of the Judiciary” (Callimachi 2018). The group ordered the government ministry formerly in charge of renting land to farmers to compile a list of all properties owned by non-Sunnis and seize them; Sunnis could then apply to a local ISIL office to take over the property. A new Ministry of War Spoils was set up to collect beds, tables, bookshelves, cutlery, and other valuables from the homes of non-Sunnis and reallocate them to Sunnis by application (Callimachi 2018).
Sunni “benefits” like those provided by the Ministry of War Spoils laid the groundwork for non-Sunnis to perceive that all Sunnis implicitly supported ISIL. Even though the number of Sunnis who actually joined the group was low relative to all Iraqi Sunnis (Al Jazeera 2014b), the failure of “neutral” Sunnis to actively oppose the group while it governed Sunnis and slaughtered others helped make Sunnis seem complicit through inaction in the eyes of others (Chulov 2015, Abouzeid 2018). This perception was fueled by widespread subtle Sunni signals of ISIL support. Yazidis in diverse villages in Sinjar district described seeing their Sunni Arab neighbors begin flying ISIL’s black flags as the group advanced on their villages (Ahmed 2014). In several cities Sunni administrators were conscripted to help run ISIL’s civic administration and implement schemes such as the confiscation and redistribution of non-Sunni property; when ISIL militants began redistributing seized non-Sunni property, some Sunnis queued up to receive it (Callimachi 2019). Other Sunni support was more explicit: Atran et. al. (2017) interviewed eighty Sunni IDPs near Mosul in July 2017 and reported that “almost all of those we interviewed… told us that nearly everyone among the Sunni Arab population had initially welcomed the Islamic State.” Some Sunni army generals said the same. The signals clicked with a widespread suspicion that Sunnis – who enjoyed political power before 2003 but then fell into the shadows – relished ISIL’s promise of their return to power (Gerges 2016, Atran et. al. 2017).

In practice, the true affiliations of Sunnis are much more complicated and far less supportive of ISIL than this discussion suggests. Many Sunnis signaled passive support for ISIL out of fear, coercion, or desperation and were privately horrified by the group (Abouzeid 2018). Others who initially supported ISIL shifted their allegiance after they realized the group did not keep its promises (Atran et. al. 2017) Some Sunnis did actively oppose ISIL: The New York Times
spoke to Yazidis who explained that their Sunni Arab friends had helped them cross the Syrian border to escape ISIL’s advance in Sinjar (Ahmed 2014); the deputy sheikh of the Sunni Interywit tribe recorded names and dates where his tribesmen risked their lives to help Yazidis flee to safety (Abouzeid 2018), and many Sunnis fought with coalition forces against the group. But the true motives of Sunnis whose actions appeared to enable ISIL were little consolation to ISIL’s victims. In the eyes of victimized groups, Sunnis who privately opposed the group but refused to risk their lives to stop it were cowards who enabled massacres. And though a few Sunnis did actively oppose the group, their stories became lost among the overwhelming emerging narrative of Sunni complicity through inaction (Chulov 2015).

The difference between Sunni and non-Sunni treatment under ISIL was obvious everywhere, but it was often most clear in diverse areas. In Sinjar ISIL executed and enslaved Yazidis while leaving Sunni neighbors unharmed. In settlements in the Ninewa Plains ISIL demolished Christian churches but left Sunni Mosques in the same towns standing. Residents of diverse areas could directly compare ISIL’s treatment of different ethno-religious groups simply by looking at differential levels of destruction in different homes on a street block or areas of a village.

The above discussion explains that differences in the experience of conflict activated identities and created inter-group grievances, and that this effect was strongest in diverse areas. But how did reinforced group identities and inter-group grievances lead to slower recovery? Alesina and others would argue that these effects make individuals less likely to contribute to public goods. They suggest that this could be because individuals may prefer to interact with
members of their own group, find it *strategic* to interact with their own group in the absence of strong formal institutions (Alesina and La Ferrara 2005). I agree that diversity leads to worsened public goods provision in this setting but argue the reasons *why* may be slightly different. The next two sections explain two ways sharpened ethno-religious identities led to slower recovery in diverse areas.

*Ethnic security dilemma*

The first path by which salient ethno-religious identity leads to slow recovery is through an ethnic security dilemma. My description of this mechanism builds from Posner’s (1993) seminal work on ethnic security dilemmas, but it adds some specificity on how diversity interacts with the theory.

Chapter 2 explained how after conflict a patchwork of different militias and security forces assumed responsibility for security administration in different liberated towns. One consequence of the narratives of homogenous group experience that emerged during occupation is that members of any given ethno-religious group do not trust security forces comprised of other ethno-religious groups to provide security in their neighborhoods in the post-conflict period (Ahn, Campbell, and Knoetagen 2018). In some cases, this mistrust is well-founded: many local militias are poorly trained, and “out-group” militias are often perceived – sometimes justifiably – as more likely to commit sectarian abuses (Boghani 2017).

Even if out-group security providers are behaving professionally for the time being, they find themselves facing a difficult commitment problem. Out-group militias will promise locals
that they will provide security and refrain from committing sectarian abuses. But locals know that
their out-group defenders have little personal interest in defending them, and in many cases the
militias promising defense are co-ethnics of defectors to ISIL or militias that failed to defend
settlements before ISIL invasion. Locals do not trust that out-group defenders they will continue
defending them in the face of shifting political or security conditions. Security providers are stuck:
regardless of their actual intentions, they cannot credibly commit to faithful security provision in
the future (Ahn, Campbell, and Knoetagen 2018). Yazidi-dominated Sinjar supplies an illustrative
example. In Yazidi-majority Sinjar villages, the Kurdish Peshmerga providing security fled as ISIL
militants approached – allowing ISIL to take the district with little to no resistance. Some reports
allege that Pershmerga soldiers even took weapons from Yazidis – promising to protect them – as
ISIL approached, but then abandoned Yazidis to their attackers (Ochab 2017). Now, the same
Peshmerga are back promising to provide security and competing to control the district. Yazidis
are understandably dubious.

Unable to trust the commitments of external security providers to keep the peace, ethno-
religious groups began forming local militias of co-ethnics. In the Ninewa plains, Iraqi Christians
formed the all-Christian Ninewa Plains Protection Units. Shia Shabak responded with their all-
Shia Shabak Ninewa Plains Forces, and Sunni Arabs created the majority-Sunni Ninewa Guards.
Around Tel Afar, Shia Turkmen formed the Al-Hashad al-Turkmani militia composed almost
exclusively of Shia Turkmen. Yazidis formed the all-Yazidi Lalish Regiment to operate in Sinjar.
And scores of nearly-homogenous security forces from larger groups – such as all-Shia Popular
Mobilization Forces, the Kurdish Peshmerga, and the majority-Shia Iraqi Security force – all
continued to operate in diverse areas (Ahn, Campbell and Knoetgen 2018). Shared cultural,
religious, and familial ties between these militias and the populations they defend make the defended more likely to believe that promises by the defenders to keep defending are credible. As Ahn, Campbell, and Knoetagen (2018) note:

“Ethnically composed militias provide a sense of security through their connection to the local community. The familial and cultural ties of militia members to the population make the community feel more secure, even if the actual conduct of the security forces may not meet the standards of a more professionalized force.”

As ethnically homogeneous militias emerge as the only credible security providers, an ethnic security dilemma emerges (Posen 1993). Militias generally have similar levels of technology and weaponry, so the key determinants of militia power are size and group cohesion. Ethno-religious groups try to increase the power of their respective militias by bolstering recruitment and reinforcing cohesion; to do this, they have incentives to characterize actions of other groups in ways that magnify the outside threat. Additionally, the formation of ethno-religious militias has a spiral effect: while their formation makes co-ethnics feels safer, they make others feel more in danger. These groups now must protect their own security by forming and improving and ethnically homogeneous militia of their own. Thus, the formation of ethnically homogenous militias and their attempts to gain strength increase the salience of ethno-religious identity.

None of this is particularly novel so far. Posen (1993) outlines the theory of ethnic security dilemmas in the context of state collapse, and Ahn, Campbell, and Knoetagen (2018) observe its realization in post-ISIL Iraq. But the theory as-is does not quite fit observed experience in Iraq:
many ethnically homogeneous Sunni Arab settlements are controlled by Shia-dominated Iraqi Security Forces or Popular Mobilization Units and are among the fastest-rebuilding settlements (IOM 2019). Why does an out-group controller trigger conflict and controversy in some areas but not others? I argue ethno-religious diversity influences the magnitude of the negative effects brought by the ethnic security dilemma. Diversity enters the mechanism in two ways. 

First, the experience of ISIL occupation lowers levels of intergroup trust the most in settlements that are diverse. This chapter has already explained that grievances are sharpest in diverse settlements because betrayals are most visceral and personal there; a similar mechanism applies to trust. In Sinjar district, for example, Sunni Arabs who had long lived peacefully with their Yazidi neighbors joined the ISIL militants and began killing, kidnapping, and forcibly converting Yazidis who they has previously regularly interacted with (ICG 2018). One Yazidi Sinjar resident interviewed by The New York Times described calling his “closest friend” after he had fled his village, a Sunni Arab who worked at a local shop: “when I asked him what he was doing, he told me he was looking for Yazidis to kill (Ahmed 2014).” Another displaced Yazidi told his interviewers that “we would like to go back to our village, but we will never have a relationship with the Arabs anymore… It will never be the same” (Ahmed 2014). It is no surprise that individuals with these experiences do not trust a militia of the same ethno-religious affiliation of the friends that betrayed them to provide protection in peacetime (Ahn, Campbell, and Knoetagen 2018).

That intergroup trust was lowest after ISIL in the most diverse settlements can also be shown empirically. The IOM ILA III survey asked about levels of inter-group trust in the
settlements it surveyed after the ISIL conflict. I compared this data with settlement diversity scores. The median settlement reporting that some mistrust between ethnic or religious groups is present in the community has a diversity score half a standard deviation higher than the median settlement reporting no mistrust, and this difference is statistically significant (p<0.05).\footnote{Excluding al-Ba’aaaj and Sinjar districts, where no survey data is available.} Lower levels of intergroup trust make the security provision commitment problem more severe, and thus sharpen the incentives of the ethnic security dilemma.

Second, once ethnically homogeneous militias are established and an ethnic security dilemma is in progress, diverse settlements become hotspots for contention because the division of security responsibilities along ethno-religiously homogeneous lines is difficult. Diverse settlements comprise of individuals from several different ethno-religious groups, and groups often live in enclaves speckled throughout a settlement or are mixed entirely. If locals believe that militias sharing their ethno-religious identity are the only credible security providers and others pose a threat, they will push to have their militia provide security over their neighborhood. Other groups will do the same.

Unfortunately, identifying ethnically homogeneous neighborhoods within a diverse settlement and assigning them to different controlling groups is a tall order. In many cases, it may simply be not feasible: some neighborhoods are genuinely mixed among several ethnic groups, and short of assigning a different militia to watch over each house, homogeneous resident-defender assignment is impossible. Fearon (1995) describes how indivisible territory holdings can cause bargains to avoid conflict to break down because the prize of interest cannot be split. When
settlements cannot be easily split among controllers, conflict may erupt for similar reasons. Consider the two equally unappealing options that are available.

First, one militia could be assigned to watch over the entire neighborhood. Its co-ethnics will feel secure, but others will feel in danger. Groups will anticipate this and fight over the initial assignment of security provider, and the losing group will agitate for change. Alternatively, militias could jointly patrol the same neighborhood. This leads to disputed-authority problems and the joint controllers are likely to fight when one does something the other disagrees with. Even if it is possible to divide and assign with a high degree of accuracy, different controlling militias will be operating in extreme proximity to each other. Groups see the militias of other groups as a threat, and so the proximity of ethno-religiously homogeneous security providers is likely to spark disputes and aggression. No matter which situation arises, if ethno-religious identity is the criterion for security force legitimacy, force assignment is likely to spark dispute.

An illustrative example of this problem can be found in the post-conflict experience of Tuz Khumartu, a city south of Kirkuk split between roughly 119,000 Shia Turkmen, Sunni Turkmen, Sunni Arabs, and Sunni Kurds. After ISIL was expelled from the Tuz district, control of Tuz Khumartu was split between the Sunni Kurdish Pershmerga and Shia Popular Mobilization Forces. The Sunni Kurds controlled majority-Sunni neighborhoods, the Shia PMF controlled majority-Shia neighborhoods and two mixed neighborhoods, and the two sides promptly erected concrete barriers, fortifications, and checkpoints between each other’s control zones. In each side, the minority of residents that did not share the religious identity of the controlling group quickly fled to the other side of the city for safety: the city composition shifted such that the Sunnis lived only
in the Sunni Kurdish controlled half, and only Shia Turkmen lived in the Shia PMF controlled half. Sunni Kurds and Sunni Arabs interviewed by the Global Public Policy Institute said they feared crossing into the Shia zone and been abused in the Shia-controlled central market and told not to return. The effect was most severe in the two mixed neighborhoods controlled by the Shia PMF, where Sunni residents spoke of targeted killings, abductions, and daily abuses at the hands of the Shia security providers. All but five to ten percent of Sunni residents in the two neighborhoods eventually fled to the Kurdish side (Gaston and Derzsi-Horvath 2017).

**Altering the costs and benefits of revenge**

The second path by which salient ethno-religious identity leads to slow recovery is through altering the costs and benefits of cooperation and revenge. In this section I explain my theory and present qualitative support for it.

I begin with the theory. After conflict, individuals victimized by ISIL need to make decisions about who to seek revenge on and who to cooperate with. The ideal outcome is to seek justice against former ISIL militants and cooperate with others who were victimized to rebuild. But realizing this goal is hard: identifying the extent of individuals’ involvement with ISIL is difficult and deciding what level of involvement merits punishment is somewhat arbitrary. To simplify this argument, I focus on the decision of an ISIL victim to commit a revenge attack. However, this choice could be easily substituted for other choices group members make – such as the decision to arrest an ISIL suspect or not cooperate with a neighbor. I suggest ISIL victims’ decisions of when to seek revenge and who to target are governed by two basic constraints: the level of involvement victims deem sufficient to merit retaliation, and the level of evidence
sufficient to prove involvement. The frequency of revenge attacks is a function of these thresholds, as well as the ease of revenge given a set of thresholds.

First, revenge-getters need to decide on an evidence threshold. Identifying which Sunnis joined ISIL or how directly they supported the group is incredibly difficult. Records of ISIL involvement are often incomplete or absent entirely. Personal observation is equally unhelpful: as ISIL approached settlements scores of locals fled and communications networks went down; it is difficult to know whether the absence of a neighbor was because they had fled to an IDP camp or whether they had joined the militants. In the post-conflict period, ISIL fighters or supporters have every incentive to hide or lie about the extent of their involvement. Proper investigation into alleged ISIL affiliates is expensive, time-consuming, and difficult. Victims thus need to decide what level evidence is sufficient to conclude a suspect is guilty and exact revenge. Second, victims need to decide on an involvement threshold. Everyone agrees that ISIL militants should be punished, but what about their families or friends? What about people who simply hung ISIL flags from their windows, or refused to work against them? ISIL involvement ranges from passive compliance to outright involvement, and punishers must decide what threshold of behaviour merits punishment.

The most obvious and crudest evidence threshold is to use Sunni identity to detect ISIL supporters. Using an ethno-religious group label to identify who participated in an insurgency is easy, but it leads to many false positives: many Iraqis are Sunnis but did not join ISIL. This is where the activation of group identity enters the mechanism. The previous section explained how this identity activation encouraged non-Sunnis to perceive Sunnis who did not actively join ISIL
to still be passive enablers of the group: even if these Sunnis are not guilty of fighting for ISIL, in the eyes of non-Sunnis they are probably guilty of tacitly supporting it. Perhaps they benefitted from ISIL’s property seizures, flew ISIL flags from their windows, or fed and bunked jihadists. Thus, dropping the threshold of involvement that justifies punishment helps justify dropping the evidence threshold. ISIL militants can be brought to justice, and if some non-ISIL Sunnis become collateral damage, no great harm – they were probably complicit even if they did not fight for the group and hence “deserve” punishment anyway.

Evidence of this mentality is widespread. First, non-Sunnis often used the Sunni label to identify ISIL sympathizers with little further investigation. In the Iraqi court system, Sunnis were tried and convicted of ties to ISIL in farcical trials that rarely lasted more than 10 minutes (Taub 2018). After conflict thousands of Iraqi Sunnis were held in internment camps based on uncontrollable identity characteristics like being related to an ISIL fighter or hailing from a village or tribe that featured widespread ISIL support (Taub 2018). One senior Iraqi intelligence official told New Yorker interviewers that Shia government authorities had imprisoned “hundreds of innocent [Sunnis] …because their names are similar to those of wanted people.” In Mosul the civil service refused to help residents retrieve bodies of people from Sunni towns with known high levels of ISIL supporters because they assume they are likely ISIL fighters (Taub 2018). In the face of this abuse based on the Sunni label, Sunnis began approaching Iraqi identity card offices to change their names to Shia-sounding names to avoid abuse (Chulov 2015).

Second, there is substantial evidence that non-Sunnis justified the potential “false positives” – where revenge against Sunnis took place with little evidence of their actual
involvement – on the basis that *all* Sunnis were in some way complicit. After the liberation of the mixed Sunni Arab – Yazidi Sinjar district, eyewitnesses described watching trucks of looted furniture driving out of Sunni Arab towns. “They took our possessions, now we are going to take theirs!” one Yazidi man overheard by *New York Times* reporters exclaimed (Gordon and Callimachi 2015). In the diverse Sunni-majority town of Muneria south of Mosul, houses belonging to Sunni Arab families suspected of being ISIL members were looted and torched by other village residents. Villagers told interviewers “they are the ones who brought Daesh” (Fahim 2017).

The problem, of course, is that many of the Sunnis targeted by this strategy had nothing to do with ISIL at all. In Sinjar, Yazidi militias have conducted retaliatory raids on Sunni Arab settlements – but Sunni leaders claim some of the Sunnis killed in these attacks were the same Sunnis who had *helped* Yazidis flee from ISIL in 2014 (ICG 2018). And the punishment delivered to suspects is brutal: Iraqi security forces have filmed themselves beating and whipping suspected ISIL members in ad-hoc detention sites, beheading captives, and hanging bodies from telephone poles. In October 2016, an Iraqi security unit in the town of Qayyarah filmed themselves tying the bodies of ISIL fighters to a pickup truck and dragging them through the village streets to cheers from villagers (Taub 2018). One Sunni Sheikh explained the problem to his interviews: “It’s not fair that our tribe is branded ‘Daesh’ because of these 600 people. They are less than one percent of us. It’s insulting… We understand they are in pain, but why are we paying for the crimes of others? They want and deserve justice from Daesh, but we are not Daesh” (Abouzeid 2018).
These sentiments help further enshrine in-group identity among Sunnis, leading to less inter-group cooperation. At its worst, they trigger a revenge trap where attacks on Sunnis and resulting outrage from innocent Sunni targets cyclically decreases inter-group cooperation and increases violence. The link from these effects to slow recovery is now clear. Sunnis are often prohibited from returning home or afraid to do so for fear of being targeted (Abouzeid 2018), and localized violence and revenge attacks interfere with reconstruction activity and slow returns (ICG 2018).

Almost all the examples in this section are drawn from highly diverse settlements, and this trend is no coincidence: reports of revenge overwhelmingly arise from diverse areas. The beginning of this section argued that ethno-religious identities and inter-group grievances are sharpest in diverse areas because this is where differences in treatment during occupation were most visceral. The theory just explained suggests that the frequency of revenge attacks is subject to the position of the evidence and involvement thresholds, and the ease of revenge attacks given those levels. Finally, we can explain with precision how sharpened identities and grievances in diverse settlements may lead to more revenge attacks. The heightened salience of ethno-religious identity in diverse areas both lowers the thresholds for revenge and makes the costs of revenge relatively smaller.

First, diverse settlements increase the relative benefits of revenge given a set of thresholds. The benefit of revenge is primarily a personal one: revenge-getters can avenge the loss of a loved one or personal injustice during conflict. This benefit is often higher in diverse settlements because they are where grievances are the sharpest: it is one thing when strangers from a different village
invade your home and kill your friends; it is quite another when the raiders and killers are people you know and used to trust. Individuals contemplating revenge likely perceive their personal benefit from carrying out revenge to be higher when their grievances are more severe.

The costs of revenge are lower in diverse settlements because the targets are next door rather than in a different city or province. When prospective aggressors are contemplating an act of revenge in their hometown, they can rely on their personal knowledge of other residents and local authorities to better guess at how certain acts of revenge will be received and what will be permissible. They can also carry-out smaller scale acts of revenge with less planning and greater frequency: to get back at a perceived ISIL sympathizer an aggressor can torch their car across the street, rather than driving to a different province.

Finally, the position of the evidence and involvement thresholds is lower and diverse areas. Relatively more passive forms of ISIL support – or even a failure to help non-Sunnis escape - are more devastating betrayals when the people shuttering their doors are next-door neighbors of those begging to be let in. Passive support for ISIL or a failure to combat it takes on a deeply personal dimension when the supporters are people who have lived and interacted with the victims for years. Hence, in diverse areas, non-Sunnis are more likely to think that Sunnis deserve punishment for a lower level of involvement. A lower evidence threshold follows suit: if you commit a revenge attack on a suspected ISIL militant and are incorrect, no great loss: the Sunni family probably still “deserved” to be punished.
Part III: Elite strategies for local control

The last mechanism I propose for how post-conflict conditions in diverse areas activate sectarian identity and lead to slow reconstruction focuses on the role of local political elites. Blaydes and Linzer (2012) have already shown how the rhetoric and signaling of domestic political elites can help activate latent social cleavages in the context of rising anti-American sentiment in the Islamic world, and suggested elites’ choice of rhetoric is a strategic decision made in response to environmental conditions. I suggest the signaling and strategy choices of local elites may also help explain the salience of ethno-religious identity in diverse post-conflict settlements. Levels of ethno-religious diversity influence where and how local elites compete for influence. In diverse areas, diversity incentivizes forms of elite-led territorial competition that slow recovery.

The end of the ISIL insurgency created a series of opportunities for elites to increase or defend their influence in rapid succession. Some opportunities arose at the ballot box: the Kurdish region hosted an independence referendum in September 2017 and a regional parliamentary election in September 2018; in May 2018, Iraq held a national parliamentary election. A second route lay in the streets: struggles for de-facto territorial control quickly emerged in many of the areas ISIL formerly controlled. But to win elections or control territory, local elites needed ways to recruit individuals to their security forces, convert them to voters, and buttress their claims to territory. A natural starting point is to focus on gaining control in the areas that offer the easiest pathways to consolidating influence. Hence, influence-seeking elites made two choices: they needed to strategically select the locations they contested, and strategically choose the ways they would contest them.
I argue that diverse areas were the most attractive targets for groups looking to expand their spheres of influence partially because they were diverse. Local elites could point to a slice of the population in a contested settlement that belongs to their ethno-religious group and use this “foothold” group to help make a credible claim to administer the entire settlement. But since many elites made similar calculations, control in diverse areas was more likely to be contested. This contestation slowed recovery in two ways. First, competing security providers fought each other in disputes over control and may have strategically chosen to use violence against civilians to induce local support. Second, ethno-religious identity proved to be one of the most effective recruitment tools in diverse areas, and so many elites selected it as their tool of choice to consolidate local support. This elite signaling choice raised the salience of ethnic identities and slowed recovery. The remainder of this chapter walks through this argument in detail and offers qualitative support for it.

*Elites target diverse settlements because they are diverse*

Elites looking to expand de-facto control in the vacuum of ISIL’s defeat disproportionately targeted diverse settlements. The Kurdish government staged an independence referendum in 2017 in the Kurdish region as well as in diverse south of its border. After the ballot, Shia Iraqi Security Forces “retook” diverse settlements de-facto administered by the Kurds. In mixed Tuz district, Shia PMF and Sunni Kurdish Pershmega traded control of villages. In diverse Sinjar district, post-ISIL control rotated between at least six different security providers alternately loyal to Turkmen, Kurds, Sunni Arabs, Shia Arabs, and Yazidis. Contests for control even erupted in diverse areas between the smallest of minorities. Shabaks and Christians—roughly 0.1% and 1.2% of the Iraqi population respectively (Izady 2015) - fiercely contested settlements in the central Ninewa plains
after their liberation (Kiely 2018). There is also clear evidence that this contestation was about establishing long-term influence and control, rather than simple military posturing. In Sinjar, Shia militias began to co-opt representatives on district councils and assume management of NGO registration in areas they controlled (ICG 2018). In southern Tuz district, Shia militias have begun cultivating the farms of Kurdish or Sunni Arab residents who fled. By contrast, there is little evidence of such fierce contestation in ethno-religiously homogenous areas in Iraq’s southwest.

I argue that local elites disproportionately targeted diverse settlements intentionally. Diverse settlements have an attractive quality to leaders looking to expand their influence: elites can use a minority of their group already living in a diverse settlement as a “foothold” to build a case for governing the whole settlement. It is easier for Kurds (for example) to claim they should govern a settlement that already has some Kurdish population than one entirely devoid of Kurds. This strategy is not new in Iraq: groups have long pointed to ethno-religious similarities between themselves and the population of contested settlements when making claims to control them. For example, from 1960 to 2000 the Saddam regime expelled non-Arabs from many northern Iraqi cities contested between the Kurds and Baghdad and encouraged Arabs to move in during its “Arabization” policy. It then claimed these settlements belonged to Baghdad because of their Arab population (Daponte et. al. 1997). When the Kurdish Regional Government rose in prominence after 2003, it responded with a “Kurdification” policy to increase the fraction of Kurdish residents in these areas aimed at buffering the Kurdish government’s claim to their control. It then argued they should be Kurdish administered because of the high numbers of Kurds that lived in them (Smith and Shadarevian 2017).
There is strong evidence that local elites continued to use “ethnic footholds” as tools to help buttress their claims to diverse settlements after ISIL’s defeat. In fact, this argument was so powerful that post-liberation administrators often tried to alter the ethno-religious composition of disputed settlements in their favor. There is substantial evidence that controlling militias selectively destroyed homes and barred certain groups from returning in ways that shifted the ethno-religious composition of diverse settlements in favor of the controlling elites’ group. For example, a November 2016 Human Rights Watch confirmed 20 instances of Kurdish forces destroying Sunni Arab homes in ethnically mixed Sunni Arab – Kurdish settlements in the territory south of the KRI and used satellite analysis to identify similar destruction trends in 62 additional villages it was barred from visiting. Witnesses described finding destroyed Sunni Arab buildings next to intact Kurdish ones (HRW 2016).

The ethnic engineering is not limited to the Kurds. In diverse Tuz Khumartu, Amnesty International reported that members of Shia militias, Iraqi security forces and Turkmen fighters had looted, burned, and destroyed “hundreds” of homes in Kurdish-majority neighborhoods of al-Jumhuriya and Hai Jamila. One Kurdish interviewee explained that Shia Arab and Shia Turkmen militias “knew the houses” of Kurds and selectively targeted them (Amnesty 2017). On the roads leading from the Kurdish capital of Erbil to the ethno-religiously diverse settlements of the disputed Ninewa Plains, Sunni Arab security forces kicked at the license plates of Kurdish drivers and told them they could not pass (Kiely 2018). In the Shia-controlled southern half of Tuz district, Shia militias destroyed Sunni Arab and Sunni Turkmen homes in at least 30 separate villages and began cultivating the farms of displaced Sunni residents (Gaston and Derzsi-Horvath 2017). In Hilla and Diyala, Shia-dominated paramilitary forces compelled local councils to invalidate the
property rights of Sunnis on the grounds that they supported ISIL (El-Ghobashy and Salim 2018). In August 2017, Gaston (2018) estimated Shi’a Turkmen militias had intentionally prevented 70,000 non-Shi’a Turkmen from returning to diverse areas that those militias controlled.

To be sure, ethno-religiously diverse areas in Iraq often overlap with strategically valuable and resource rich areas. Desire to control these resources and areas is surely part of the attraction of targeting diverse areas. But resources and territory alone cannot fully explain why some areas are frequently targeted for expansion while others are not. For example, diverse Sinjar’s strategic position near the Turkish and Syrian borders is similar to the value of homogeneous Al-Qaim’s strategic position near the Syrian and Jordanian borders. But while Kurds, Turkmen, Yazidis, Sunnis and Shias virulently contest control of Sinjar, al-Qaim is relatively peaceful.

*How this contestation slowed recovery*

Unfortunately, the attractiveness of diverse settlements as targets for expansionary elites may also be the reason they rebuild slowly. If multiple groups think diverse settlements are good targets, these settlements are more likely to be contested. The qualitative discussion above highlights that diverse areas were often contested between groups, but this trend can also be seen empirically. IOM’s ILA III survey asked questions about which security forces were controlling a settlement at the time of the enumerator’s visit in summer 2018. I used this information to determine if more than one group was jointly administering a settlement at the time of the survey.

---

37 In fact, these areas might be diverse partially because they are resource-rich. “Arabization” policies under the Saddam regime and counteracting “Kurdification” policy from Erbil attempted to move certain ethnic groups into strategically valuable settlements; the patchwork of ethno-religious groups living in diverse areas today is partly because different political actors moved them there to try to secure territorial control.
in summer 2018 and compared this to settlement diversity scores. The results show that settlements with joint administration had a median diversity score of 0.14 as compared to a median score of 0.1 for settlements administered by only one controlling group.

Elite contestation in diverse settlements slows their recovery in two ways. First, intra-group contestation slows recovery by triggering conflict. Security providers often clash with each other when more than one is trying to administer a settlement. When Shia Arab security forces pushed Kurdish Peshmerga out of diverse settlements, thousands of Sunni Arabs and Sunni Kurds temporarily fled north for fear of their safety (Gaston and Derzsi-Horvath 2017). In Sinjar, fighting between liberators forced extended road closures and temporary suspensions of aid activity (ICG 2018). But militias competing for control in diverse settlements also often committed violence against civilians. They have burned civilian homes (HRW 2017), fired on religious sites (Kiely 2018), and detained, tortured, and killed citizens and prisoners in retaliation for attacks they did not commit (Gaston and Derzsi-Horvath 2017).

The decision to inflict violence on civilians may also be a strategic choice by elites. While establishing military control of settlements is important for making claims to administer them, securing local support is equally valuable. If locals in a diverse settlement prefer one governing power to another, they will join its militias, welcome its control, and make it difficult for other forces to govern. This lowers the cost of administration for the benefitting controller, which can claim legitimacy because the locals “want” it there (demonstrated, for example, through a referendum result), and govern at lower cost. Kalyvas (2006) argues in the context of mass killings

38 I excluded al-Ba’aj district and the lower half of Sinjar district in this test because there is no IOM survey data there.
in civil war that the location and timing of especially violent events is strategic: opposing sides commit the worst atrocities in the most contested areas to induce local support for their side. A similar dynamic could be at play here: elites deploy the most threatening strategies in the most fiercely contested areas to induce local support.

The second way elite contestation in diverse settlements slows recovery is through the strategies elites use to compete. In diverse settlements, local elites frequently used ethno-religious arguments to amass support at politically contentious points in the post-conflict period. One clear example was the rhetoric of local elites surrounding the Kurdish independence referendum – a vote that was most contested in diverse areas. Kurdish Prime Minister Barzani had declared after ISIL’s onset that that Kurds would sacrifice their lives “fighting to the last person in Kirkuk” and that new borders would be “drawn in blood”; Sowell (2017) explains that “Barzani’s use of the language of self-defense in reference to Kirkuk highlights the assumption that Kirkuk belongs to Kurds.”39 The Iraqi Turkmen Front leader asked Turkmen to oppose the vote because “the Turkmen areas are the exclusive geography of the Turkmen” (Rudaw 2017), and a Shia Turkmen leader with the Popular Mobilization Forces penned an open letter to Arab and Turkmen tribes in Kirkuk asking them to resist “oppression” by the Kurds with force (Sowell 2017). The past chairman of the Evangelical Alliance in Kurdistan said “the [Christian] parties and their supporters do not want [Kurdish] independence because they believe it will end their hopes of a future state for Christians.” (Jackson 2017). In March 2017, a conference of some Iraqi Christian leaders demanded a Christian-administered region in the Ninewa Plain to isolate themselves from

39 Barzani also made unifying statements around the referendum. Others made relatively fewer.
“political conflicts… as well as sectarian conflicts between the various groups that make up Iraqi society” (Gombaci 2017).

Though this ethno-religious rhetoric does not directly constitute violence, it encourages violent acts from regular citizens that slow recovery. For example, in the week before the referendum a group of Kurdish gunmen opened fire on the Iraqi Turkmen Front headquarters in diverse Kirkuk; armed guards returned fire and killed one of the attackers. “Right now, Arabs and Turkmen are worried for their lives…” a spokesperson for the Iraqi Turkmen Front told The Intercept. “If they [the Kurds] start shooting at us, we will start shooting at them as well” (Miller 2017). After the referendum, nearly 30,000 Kurds temporarily fled Kirkuk for fear of reprisal at the hands of their Turkmen and Sunni Arab neighbors; Turkmen in Kirkuk celebrated by driving through the streets with Iraqi flags and firing shots into the air (Chmaytelli and Mahmoud 2017).

I argue that elites’ use of ethno-religious rhetoric in diverse areas is intentional: elites use this rhetoric because it is useful for galvanizing support. There are two reasons why. First, ethno-religious groups are cross-sectional identities in ways many other social cleavages are not. They can transcend wealth and rural-urban divides and allow rich politicians in political centers to claim they share a common identity with poor farmers in the rural hinterlands. Second, ethno-religious identity forms an attractive basis to build minimum winning coalitions. Ethno-religious groups are large enough to secure benefits in political competition but small enough to maximize the per capita value of those benefits, and they make it easy to exclude outsiders (Bates 1983).
As this discussion predicts, there is ample evidence demonstrating the usefulness of ethno-religious appeals in diverse areas. For example, ethno-religiously homogeneous local militias maintained one of the most active direct presences in Ninewa governorate after conflict because they successfully recruited co-ethnics from local communities. By contrast, when non-local militias such as the Badr Organization and Asaib Ahl Al-Haq opened recruitment offices in Mosul, they were met with little enthusiasm (Ahn, Campbell and Knoetgen 2018). Similarly, ethno-religiously charged votes seemed to drive more people to the polls than ones conduced with broad nationalist overtones. Turnout for the sectarian-charged September 2017 KRI independence referendum was 72.6% (BBC 2017b). By contrast, turnout for the 2018 national parliamentary election – where many candidates ran on secular platforms of national unity – 44.5% - was the lowest in any national Iraqi election since 2003 (Mansour and van den Toorn 2018).

**Summing up**

This chapter argued two mechanisms – differential treatment during conflict and local elite strategy selection – can help explain why sectarian identity became activated in diverse settlements and how it led to slower recovery. I by no means claim these mechanisms are exhaustive: classic explanations for diverse groups’ unwillingness to contribute to public goods are very likely at work, and other mechanisms may be important as well. But this discussion helps highlight how the explanations for why individuals in diverse settlements do not contribute to public goods may be slightly different in diverse settlements, and that the activation of ethno-religious identity can help explain the increase in salience of these characteristics over time.
Chapter 8 | Conclusions and Implications

This thesis demonstrated empirical support for a hypothesis that ethno-religious diversity slows post-conflict recovery at the settlement level in Iraq. I argued in chapter 7 that this result can be explained by differences in group experience during ISIL occupation and local elites’ strategic choices after conflict. In this very brief final chapter, I offer some thoughts on how this conclusion connects to academic literature and policymaking, reflect on the limitations of my work, and make some suggestions for future research.

Connections to academia and policymaking

For academia, this work has both substantive and methodological implications. Substantively, it offers insight on how several major theories in political science might apply to the sub-state post-conflict context. First, findings from growth and development theory that suggest diversity slows economic growth may also be applicable to post-conflict recovery, but for different reasons. The mechanisms discussed in Chapter 6 differ from the mechanisms traditionally suggested for the diversity-growth result. Instead, they draw from other literatures such as the security dilemma and identity theory. Second, my result supports constructivist theories of identity that suggest ethno-religious differences can be “activated” in response to certain environmental characteristics. This finding is in keeping with the results of constructivist identity literature, and contrasts with primordialists who argue that the salience of ethnic and religious differences are innate and unchanging.

This thesis also contributes to the methods of the post-conflict recovery literature in two ways. First, it underlines the importance of empirical work at the sub-state level on post-conflict recovery; a contrast to the overwhelming presence of state-level studies among current empirical
work in this field. I have not had the time to explore all the non-diversity results of the models in great detail, but the keen observer will notice many of them support or challenge different theories of recovery formed and tested at the state level. Since many of the most important post-conflict recovery decisions occur at the local level, testing the robustness of the current post-conflict literature at the settlement level is essential. Second, this thesis demonstrates how nighttime light emissions can be used as a valuable tool to study economic outcomes in post-conflict settings. I have shown how light trends clearly respond to settlement-level environmental changes. Given the difficulty of collecting consistent and unbiased panel data at the local level in post-conflict environments, this tool could be invaluable for new empirical work in this area.

For policymakers, my core results can help inform decisions on how post-conflict aid is prioritized among damaged settlements and the types of interventions that are pursued. At the time of writing, the debate on aid prioritization in post-ISIL Iraq centered on two options: to prioritize major population centers (the view championed by the UN Development Program), or to focus on smaller settlements of the most severely harmed ethnic and religious groups (the view held by the United States and other individual donors). But these results suggest that population is not an important influence on recovery – all else equal, big cities do not recover differently from small settlements – and ethno-religious group labels matter less than one might think. Instead, a third option could be worth pursuing: diverse settlements should be prioritized for aid. These are the areas where reconstruction will otherwise proceed the slowest. Furthermore, successful interventions in diverse areas will be those that work to diffuse the security provision commitment problem, alter elite signaling priorities and change the incentives...
for revenge. I leave the design of such interventions to future researchers, but this work helps begin to identify the problems that need solving.

Additionally, these results provide specific feedback on the policies of and options available to various governments. First, they suggest that the current American strategy of earmarking aid for specific minority ethno-religious groups could backfire. The Christian and Yazidi towns targeted by the Trump administration’s decision to fast-track aid in summer 2018 are highly diverse. The U.S. aid is earmarked for organizations such as the Catholic Relief Service and a program to provide reconciliation to “Christian and Yazidi communities” (World Watch Monitor 2018). If aid is given only or primarily to members of certain ethno-religious groups in diverse areas, the aggravating role of diversity explained in Chapter 6 could become exaggerated. Second, they suggest that the Iraqi government must prioritize building the capacity of the Iraqi Security Forces as a professional, centralized, non-sectarian force, so that ethno-religious identity does not continue to be regarded as a key criterion for the legitimacy of security providers. Third, they suggest that post-conflict elections can be recovery-deteriorating in diverse areas. Governments weighing whether to conduct elections immediately after conflict should consider that they risk making the worst-off places worse-off, even if elections are implemented relatively peacefully and constructively nationally.

Limitations and future research

My work is subject to several obvious limitations. The first major one is that both my dependent variable and key independent variable are measured through proxies rather than direct measures. Nighttime light is used as a proxy for economic activity and distance to settlements of different ethno-religious majorities is used as a proxy for diversity. I have tried hard to validate
both measures before using them, but there surely remain reasons to contest both measures’ validity. Concerns on the diversity measure could be most important: as explained earlier, the diversity measure could be capturing homogenous settlements in diverse areas as well as diverse settlements themselves. A direct measure of diversity could produce different point estimates, and the mechanisms driving recovery in ethnic enclaves or ethnic fault-line settlements could be different. Second, I have not had the time to provide any empirical support for my conclusions’ out-of-sample validity. I have argued that some of the lessons learned here might be applicable to other post-conflict environments, but the degree of truth to this statement is an empirical question that can only be answered by testing theories in other post-conflict settings. Third, while I have identified what I argue are some of the most important causal mechanisms for the diversity result and provided qualitative evidence in support of them, I have by no means undertaken an exhaustive review of causal mechanisms and much more could be done to confirm them empirically.

These limitations help define an agenda for future research. First, a valuable contribution would be to swap proxies for data. If future researchers can obtain data that directly measures economic performance or ethno-religious diversity at the settlement level over time in a post-conflict setting, my findings should be checked for robustness. Second, sub-state empirical testing of influences on post-conflict recover in other countries would be invaluable in helping to refine mechanisms, identify new ones, and confirm or disprove the robustness of these results. Third, further research on the mechanisms by which ethno-religious diversity slows reconstruction – and any work that can empirically trace their effect – would help ground the debate. Finally, there is a desperate need for research on interventions in diverse settlements. I have demonstrated the problems caused by ethno-religious diversity and begun to examine why
they occur, but I have said almost nothing about how to fix them. Identification of interventions that help ameliorate the deleterious effects of ethno-religious diversity in post-conflict settings would be an invaluable contribution to the practice of post-conflict recovery.
Works Cited

The works cited section contains three parts. Part I contains the main works cited and includes all the textual information cited in the thesis. Part II cites the datasets, imagery, mapping, and infographics used in quantitative analysis and figure creation. Part III cites the open-source software packages used in quantitative analysis and figure generation.

Part I: Academic literature, news, and reports


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Mendershausen, Horst. "The Economics of War (New York, 1943)." Ch. 4MendershausenThe Economics of War1943.


Lyall 188


Republic of Sumer 2018: https://twitter.com/Sumer_Iraq/status/992344001406799873


Weiss, Max. *In the shadow of sectarianism.* Harvard University Press, 2010.


Part II: Data

I used various data sources in my empirical analysis and google satellite imagery in the creation of some of my graphics. The data used are cited below using the creator’s preferred citation where provided, and MLA otherwise.

Control of territory data:


Sources for the manual start and end date coding are available in the online supplement to this thesis at https://github.com/lloydlyall/ LyallThesis2019

IOM survey data:


Luminosity data:


Mappings by Dr. M. Izady:


Other data:


Google satellite: citations are on the images as per Google’s request.


Landscan: Landscan data was accessed with permission from the Oak Ridge National Laboratory. The Oak Ridge National Laboratory requests that the following statement be used to cite LandScan:

This product was made utilizing the LandScan 2012. High Resolution global Population Data Set copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under Contract No. DE-AC05-00OR22725 with the United States Department of Energy. The United States Government has certain rights in this Data Set. Neither UT-BATTELLE, LLC NOR THE UNITED STATES DEPARTMENT OF ENERGY, NOR ANY OF THEIR EMPLOYEES, MAKES ANY WARRANTY, EXPRESS OR IMPLIED, OR ASSUMES ANY LEGAL LIABILITY OR RESPONSIBILITY FOR THE ACCURACY, COMPLETENESS, OR USEFULNESS OF THE DATA SET.


Part III: Software packages

This thesis used open-source programs and software packages for quantitative analysis. The programs, packages, and their authors are cited below using the authors’ preferred citation when provided, and with MLA information and a link to the CRAN repository stub otherwise.

Open-source software:


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Open-source R packages:

CRAN: https://cran.r-project.org/web/packages/Metrics/index.html
Appendix I | Supporting material for quantitative analysis

This thesis mentions a variety of figures and results which are not included in the body of the thesis. Those results are included here.

**FIGURE 28: GSC LATENT FACTORS**

This figure shows the latent factors estimated by the interactive fixed effects model in the core generalized synthetic control analysis. They broadly align with different trends of destruction and recovery, and are loaded onto various settlements accordingly.
This figure shows the loadings (weightings) of the four most important latent factors onto the control and treatment groups. It shows that common support for the factors across the control and treatment groups is roughly achieved.
**Figure 30: Histograms of Independent Variables Before Logging**

Histograms of independent variables (before logging)

- Median monthly growth rate, Nov. 2012-Nov. 2013
- Per capita light before invasion
- Population density (2012)

- 2012 population
- Length of occupation (months)
- Driving distance to closest big city (km)

- Dist. to nearest highway (km)
- Frac. light remaining during
**Figure 31: Histograms of Independent Variables After Logging**

- Median monthly growth rate, Nov. 2012-Nov. 2013
- Per capita light before invasion (LOG)
- Population density (2012) (LOG)
- 2012 population (LOG)
- Length of occupation (months)
- Driving distance to closest big city (km) (LOG)
- Dist. to nearest highway (km)
- Frac. light remaining during (LOG + 1)

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These plots show the relationship between each independent variable and recovery in the preferred regression specification holding all other variables constant.
This table presents descriptive statistics for the set of 246 settlements used in the repeated cross section SSAR models of table Table 4: Preferred specification on the same group of settlements at different points in time after liberationTable 4.

<table>
<thead>
<tr>
<th>Settlements in dataset – repeated cross-sections regression</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ethno-religious group</strong></td>
</tr>
<tr>
<td>Arab Sunni Muslim</td>
</tr>
<tr>
<td>Christian</td>
</tr>
<tr>
<td>Kurd Sunni Muslim</td>
</tr>
<tr>
<td>Kurd Yazidi</td>
</tr>
<tr>
<td>Shabak Shia Muslim</td>
</tr>
<tr>
<td>Shabak Sunni Muslim</td>
</tr>
<tr>
<td>Turkmen Shia Muslim</td>
</tr>
<tr>
<td>Turkmen Sunni Muslim</td>
</tr>
</tbody>
</table>
Supplementary regressions and modelling – robustness checks

Table 6 shows regression results from the test of determinants of economic performance in settlements during the two decades prior to ISIL occupation. These results were referenced in chapter 7. The first three models use the median annual growth rate in three different periods as outcome variables; the next four models use per capita light in four different years as outcome variables. The population numbers for the per capita calculation were always based on 2012 population figures.

Table 6 shows regression results for the preferred set of variables but with different modelling strategies: simple OLS, cluster-robust standard errors at the district level, district fixed effects (the district fixed effects output is not shown), the simultaneous spatial autoregression used in the thesis, and error SAR (only lambda) and lag SAR (only rho) models.

Table 8 runs the preferred specification on sets of villages within different population sizes. Each model lists the population size at the top of the table, and the preferred specification is run only on settlements in that population bracket.

Table 9 runs the preferred specification on sets of villages within different diversity brackets. Each model lists the diversity bracket at the top of the table, and the preferred specification is run only on settlements in that diversity bracket.

Table 10 runs the preferred specification in only certain regions and on only certain groups. The first three models run the specification on only settlements in specific regions. The “disputed” test considers only settlements in the region “disputed” between the KRI and Baghdad, with a disputed region boundary based on Smith and Shadarevian (2017). The “uncontested” test considers only settlements in territory that is “uncontested” and firmly claimed by the central government – all settlements in the sample not in the disputed region. “All settlements” considers all settlements. The final two models run the specification on only Sunni Arab settlements, and on only non-Suni Arab settlements.

Figure 33 repeats the generalized synthetic control analysis but uses the multiple loess smooths used for regressions instead of a single seasonal decomposition loess smooth.
### Table 6: Economic Performance in Occupied Settlements, 1993-2012

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(intercept)</td>
<td>0.279 (0.247)</td>
<td>0.014 (0.226)</td>
<td>0.206 (0.180)</td>
<td>0.098***</td>
<td>0.105***</td>
<td>0.092***</td>
<td>0.180***</td>
</tr>
<tr>
<td>ethno-religious diversity</td>
<td>-0.049 (0.109)</td>
<td>-0.047 (0.095)</td>
<td>0.157*</td>
<td>-0.014**</td>
<td>-0.012*</td>
<td>-0.011**</td>
<td>-0.014*</td>
</tr>
<tr>
<td><strong>Economic controls</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dist. to nearest highway</td>
<td>-0.008***</td>
<td>-0.002</td>
<td>0.001</td>
<td>-0.000***</td>
<td>-0.000***</td>
<td>-0.000***</td>
<td>-0.000***</td>
</tr>
<tr>
<td>log(dist. to nearest city)</td>
<td>-0.100**</td>
<td>-0.045</td>
<td>-0.029</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.002</td>
<td>-0.006*</td>
</tr>
<tr>
<td>log(2012 population)</td>
<td>0.024 (0.017)</td>
<td>-0.006</td>
<td>-0.014</td>
<td>0.005***</td>
<td>0.005***</td>
<td>0.004***</td>
<td>0.006***</td>
</tr>
<tr>
<td>log(2012 population density)</td>
<td>-0.003</td>
<td>0.036</td>
<td>0.015</td>
<td>-0.016***</td>
<td>-0.017***</td>
<td>-0.014***</td>
<td>-0.025***</td>
</tr>
<tr>
<td><strong>Ethno-religious group dummies</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Christian</td>
<td>-0.011 (0.111)</td>
<td>0.005</td>
<td>-0.092</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td>Kurd Sunni Muslim</td>
<td>-0.025 (0.075)</td>
<td>0.003</td>
<td>-0.016</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>-0.000</td>
</tr>
<tr>
<td>Kurd Yazidi</td>
<td>0.104 (0.055)</td>
<td>0.006</td>
<td>-0.024</td>
<td>0.002</td>
<td>-0.001</td>
<td>0.000</td>
<td>-0.000</td>
</tr>
<tr>
<td>Shabak Shia Muslim</td>
<td>-0.020 (0.100)</td>
<td>0.005</td>
<td>-0.101</td>
<td>-0.006</td>
<td>-0.002</td>
<td>-0.002</td>
<td>-0.008</td>
</tr>
<tr>
<td>Shabak Sunni Muslim</td>
<td>0.051 (0.137)</td>
<td>0.046</td>
<td>-0.212*</td>
<td>0.003</td>
<td>0.002</td>
<td>0.002</td>
<td>-0.003</td>
</tr>
<tr>
<td>Turkmen Shia Muslim</td>
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***p < 0.001, **p < 0.01, *p < 0.05, p < 0.1

Lyall 204
## Table 7: Robustness | Different Strategies for Addressing Spatial Correlation, Preferred Specification

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<th>Error SAR</th>
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**p < 0.001,  *p < 0.05,  p < 0.1

### Table 7: Robustness | Different strategies for addressing spatial correlation, preferred specification (continued)

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<th>Ethno-religious group dummies</th>
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<th>Error SAR</th>
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Log Likelihood  
AIC (Linear model)  
AIC (Spatial model)  
LR test: statistic  
LR test: p-value  

***p < 0.001,  **p < 0.01,  *p < 0.05,  p < 0.1
### Table 8: Robustness | Different Population Sizes, Preferred Specification

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<td>(0.098)</td>
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*** p < 0.001, ** p < 0.01, * p < 0.05, p < 0.1
### Table 8: Robustness | Different population sizes, preferred specification (continued)

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<th>all larger than 500</th>
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***p < 0.001, **p < 0.01, *p < 0.05, p < 0.1
# Table 9: Robustness | Different Diversity Brackets, Preferred Specification

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***p < 0.001, **p < 0.01, *p < 0.05, p < 0.1
### Table 9: Robustness | Different diversity brackets, preferred specification

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***p < 0.001, **p < 0.01, *p < 0.05, p < 0.1
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<th>Ethno-religious group dummies</th>
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| Num. obs.                  | 169                  | 182                     | 351            | 288                         | 63                            |
| Parameters                 | 21                   | 15                      | 21             | 14                          | 20                            |
| Log Likelihood             | -134.658             | -161.625                | -303.943       | -72.146                     | 10.158                        |
| AIC (Linear model)         | 316.169              | 413.346                 | 739.887        | 226.282                     | 16.273                        |
| AIC (Spatial model)        | 311.316              | 353.251                 | 649.886        | 172.291                     | 19.684                        |
| LR test: statistic         | 8.854                | 64.095                  | 94.001         | 57.991                      | 0.589                         |
| LR test: p-value           | 0.012                | 0.000                   | 0.000          | 0.000                       | 0.745                         |

***p < 0.001, **p < 0.01, *p < 0.05, p < 0.1
Figure 33: GSC with multiple loess smooths

Estimated causal effect of high diversity

Estimated causal effect of high diversity (ATT)

Log (relative light level +1) (April 2013 = 1)

Months relative to liberation (0 = liberation)

- Treated Average
- Estimated Y(0) Average