Controlling a Moving World: Territorial Control, Displacement and the Spread of Civilian Targeting in Iraq

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Abstract: How do armed actors respond to population movements during civil wars? I argue that displacement alters local balances of control between territorial rulers and challengers. Rulers have incentives to govern violently if displaced persons from opposing loyalty groups move into their territories. Challengers spoil local governance by inflicting harm on civilians if incoming supporters of a local ruler reinforce the governor's control. To test these dynamics, I use a combination of manual coding and machine learning to create a novel monthly dataset of territorial control, one-sided violence against moving populations and displacement patterns dis-aggregated by ethno-religious groups in the Iraqi civil war against the Islamic State (2014-2017). Using different count models, I find that territorial challengers and rulers distinctively respond to population movements in Iraq. The paper extends previous theories of civilian victimization and territorial control by conceptualising local populations as dynamic element that explains where fleeing civilians become moving targets.

1 Introduction

Territorial control is one of the central objectives in civil wars. Much is known about how territorial control is exercised in static populations to achieve the "exclusive collaboration of civilians" (Kalyvas, 2006) through strategic and selective civilian victimization (e.g., Arjona, 2016; Arjona, Kasfir and Mampilly, 2015; Valentino, 2014; de La Calle, 2017; Schutte, 2017).

However, countries such as Afghanistan, Syria, Nigeria and the DRC experienced massive population relocations during ongoing conflicts. For example, more than 2.2 million Iraqis were newly displaced within Iraq in 2014 because of the rapid territorial advances of the Islamic State – the largest new displacement recorded worldwide in that year (IDMC, 2019).

Despite the immense scale of population movements during civil wars, political scientists have not clearly conceptualised how the movement of people in war zones affects the dynamics of territorial control and violence in civil wars. In particular, standard models explaining when civilian victimization occurs understand local populations as immobile element within a controlled territory (Kalyvas, 2006).

Adding a novel theoretical perspective, this paper focuses on territorial control when populations are moving across the conflict zone. I extend previous models of civilian victimization by conceptualising local populations as *dynamic* element that changes incentives for armed actors to govern with violence. Specifically, I argue that displacement alters the local balance of control between territorial rulers and challengers. As strategic armed actors aim to maximise their own level of control, they react with violence against civilians if displacement threatens their grip over territory. Local rulers govern more violently if displaced persons from opposing loyalty groups move into their territory. Territorial challengers have incentives to spoil local governance by harming civilians if incoming supporters reinforce the territorial control of their enemies.

These violent reactions to population movements help to explain why civilian targeting occurs in displacement destinations and why forced migration on the local level may cause conflict contagion (Salehyan and Gleditsch, 2006). Diverging from previous models of civilian victimization, the theoretical prediction from my dynamic model of civilian victimization suggests that even if local control is stabilised in a given territory, new population movements into this territory can renew incentives for violence by either the territorial ruler or challenger. This helps explain why relatively stable areas can see a resurgence of violence due to displacement and why fleeing civilians can become moving targets.

Empirically, I analyze whether movements by internally displaced people (IDPs) of different ethno-religious groups in zones of control explain the occurrence of one-sided violence in a monthly grid-cell level regression analysis of the 2014-2018 civil war against the Islamic State in Iraq. I first determine monthly zones of territorial control on the grid-cell level

using a combination of hand-coding and machine learning. I combine this territorial control data with unique displacement data from the Displacement Tracking Matrix (DTM) by the International Organization for Migration (IOM) that is disaggregated by ethno-religious groups; and one-sided violence data from the UCDP Geo-referenced Event Dataset (UCDP-GED) (Sundberg and Melander, 2013) to estimate violence against civilians. Beyond relying on UCDP-GED, I collected a new dataset on the local victimization of IDPs by armed actors by reviewing news articles and humanitarian reports in Iraq to code when violence against *moving* individuals occurred.

I find that territorial rulers reign with more violence against civilians and IDPs in particular if IDPs that do not support their rule move into their areas. For territorial challengers, I find that they tend to victimize civilians in areas to which many supporters of the territorial ruler flee, suggesting that armed groups currently not in control of a certain area punish civilians for siding with the opponent and spoil the relative stability in those areas. I do not find, however, that territorial challengers specifically target IDPs on the move for joining opponents' territory. Overall, my focus on dynamic population movements and local violence addresses gaps in the forced migration, conflict contagion and civilian victimisation literature.

The paper proceeds by reviewing the literature on the interdependent nature of territorial control, displacement, civilian victimization and conflict contagion. I then develop a theoretical argument when and why territorial rulers and challengers respond to population movements in zones of control. I introduce a novel dataset on violent dynamics of forced displacement and territorial control for the Iraq war against the Islamic State and test my hypotheses using negative binomial count regressions. I conduct several robustness checks to demonstrate that my findings on one-sided violence by territorial rulers and challengers holds in different subsamples and across the machine-trained estimations of territorial control. I end the paper with a discussion of the implications of this research for the protection of moving populations in civil wars and for research on localised conflict dynamics.

2 Displacement, civilian victimization, and conflict contagion

Territorial control - that is the ability to control civilian life within a given territory - is a crucial aspect in civil wars. Armed parties to a civil war try to maximise territorial control to win the war (Kalyvas, 2006). Importantly, control in civil wars not only refers to the amount of territory captured by an actor - or an actor's *extensive control* - but also comprises the intensity of control over the local population. *Intensive control* describes how capable a local conflict party is to establish governance structures, remain in power, gain civilian support and extract resources - such as recruits but also revenue - from the local population (e.g. Kalyvas, 2006; Arjona, Kasfir and Mampilly, 2015; Mampilly, 2012; Balcells, 2017).

Following Kalyvas (2006), many researchers have argued that violence against civilians generally undermines the ability of armed actors to extract resources from the local population (e.g., Arjona, 2016; Arjona, Kasfir and Mampilly, 2015; Valentino, 2014; de La Calle, 2017; Schutte, 2017). Strategic armed actors have an interest in keeping ordinary people safe because they rely on civilian support for recruits, legitimacy, humanitarian aid, and other resources. Within their zones of dominance, armed actors hence generally use limited and targeted violence against non-compliant civilians to avoid backlash from indiscriminate violence (e.g. Schutte, 2017) and to gain civilian support for their peaceful governance (Arjona, Kasfir and Mampilly, 2015; Mampilly, 2012). Over time, this limited and selective use of violence leads to a socialisation process in which the local population increasingly accepts the authority and legitimacy of the ruling actor (Kalyvas, 2006).

Nevertheless, almost all actors in civil wars engage in civilian targeting at some point in time (Schneider and Bussmann, 2013). In areas of competition between armed groups, indiscriminate killings of civilians are more common (Kalyvas, 2006). Armed actors also use violence against civilians to weaken the strength of opponents (e.g. Schwartz and Straus, 2018; Valentino, Huth and Balch-Lindsay, 2004; Downes, 2006), to displace civilian supporters of the enemy (Azam and Hoeffler, 2002) and to weaken their opponents' ethnic constituencies

(Fjelde and Hultman, 2014). Beyond these general incentives, non-strategic factors also explain civilian victimization. For example, weak actors that do not have the capacity to police their own members or to provide them with revenue, may victimize local populations more strongly (e.g. Wood and Kathman, 2015).

Although the dominant strategic model has greatly improved our understanding of why civilians are targeted during armed conflict, this perspective does not explicitly accommodate the fact that civilians move in and out of territories during civil wars. The canonical studies on civilian victimization usually assume a static population without displacement.

This might be a strong assumption given the actual mobility of civilians during conflicts. IDPs in war zones do not only change the overall population density at different locations, they also shift the composition of local populations along politicised cleavages in the civil war (Balcells, 2018; Steele, 2018) and they undermine the process of socialisation with local rulers. Even if a local ruler governs relatively peacefully and dominates a specific area, the fact that new people move into the territory and others leave means that neither socialisation processes nor static territorial control are given. A clear conceptualisation of how these population movements change the strategic landscape and provoke violent responses by armed actors is missing.

This is also important because researchers studying conflict processes have highlighted that violence not only creates displacement but that forced displacement also *causes* violence through conflict contagion (e.g. Salehyan and Gleditsch, 2006; Bove and Böhmelt, 2016; Choi and Salehyan, 2013; Lischer, 2005; Lebson, 2013; Buhaug and Gleditsch, 2008; Choi and Salehyan, 2013; Böhmelt, Bove and Gleditsch, 2018). On the one hand, Salehyan and Gleditsch (2006) finds a positive link of transnational refugees on conflict spread. Bohnet, Cottier and Hug (2016)'s Large-N study shows that internal displacement increases the spread of conflict within a country. However, others find no substantial contagion effect or only conditional effects of population movements on violence (e.g. Buhaug and Gleditsch, 2008; Böhmelt, Bove and Gleditsch, 2018; Bove and Böhmelt, 2016). Fisk (2014) finds no

substantial effect of refugees on local conflict events. Zhou and Shaver (2021) find a negative effect on conflict contagion. However, one-sided violence against civilians seems to increase in areas with higher numbers of refugees (Fisk, 2018).

Overall, there are many studies linking displacement and violence but the results are mixed and there is need for further investigation of causal mechanisms that explain the correlation between displacement and renewed violence. I bring together the literature on territorial control and civilian victimisation with studies of forced migration and conflict contagion to study if and when armed actors violently respond to displacement in their territories.

3 Violence and control in displacement crises

I examine how population movements during conflicts alter incentives of rational armed actors to conduct strategic one-sided violence against civilians. I argue that conflict actors, that strategically seek to maximise control, have incentives to attack civilians in areas that experience incoming population movements. Local *rulers* of a territory use one-sided violence or the "deliberate infliction of harm" on non-combatants and civilians (Kalyvas, 2006, 19) in areas with incoming IDPs from loyalty groups of their opponents to maintain their control of territory. *Challengers* of a territory engage in one-sided violence to undermine the current ruler in light of incoming supporters to the region. This interplay between spoiling local rule by challengers and establishing control by local governors explains how population movements diffuse violence across regions.

The strategic logic of control

Conflict actors strive to maximise a duality of control by gaining new territory and establishing full control in their areas of dominance. The *local ruler*, which is currently in control of an area, tries to remain in control of their territory and they increase the intensity of their rule. Ruling rebels or the government expand governance structures, provide public goods (Arjona,

Kasfir and Mampilly, 2015) and gain civilian support (Kalyvas, 2006). When choosing between using one-sided violence or governing peacefully, local rulers only use attacks against civilians to minimise challenges to the own rule, for example by punishing dissidents.

In contrast, *challengers*, which are the armed actora that have no extensive control, aim to take over the territory in question to maximise their overall territory. Unlike for local rulers, one-sided violence is not a governance tool for challengers. When evaluating their preferences over attacking civilians or not, challengers opt for violence against civilians to undermine the rule of the local occupier (e.g. Valentino, Huth and Balch-Lindsay, 2004; Downes, 2006). They strategically use one-sided violence against non-combatants to spoil the intensive control of the opponent over the territory, to signal to the civilian population that the current ruler cannot guarantee safety, and to destabilise the area. This undermining behaviour might eventually help the challenger to take over extensive control and is a short-term strategy.

Violent interactions in displacement environments

In this interplay of establishing and spoiling control between rulers and challengers, displacement may significantly modify local balances of power and intensive control. In any area that currently experiences no or little violence during a civil war, one can assume that a balance of control in favour of the local ruler exists. While the ruler may not fully control all civilian behaviour, the risk of defection is relatively low and the level of intensive control is high enough to ensure political survival (See Status Quo in Figure 1).

These calm locations are attractive destinations for IDPs (Ibáñez and Vélez, 2008). Although IDPs generally move to areas in which they support the local ruler, their de facto choice of destination is limited. Geography, road networks, and fighting shape how IDPs can move in the conflict zone. Hence, some IDPs arriving in their flight destinations may support other conflict parties or their affiliation is unknown. While incoming supporters may reinforce the governance of local rulers, non-supporters increase the risk of civilian defection. Local rulers and challengers will react to these displacement-induced changes in the level of control.

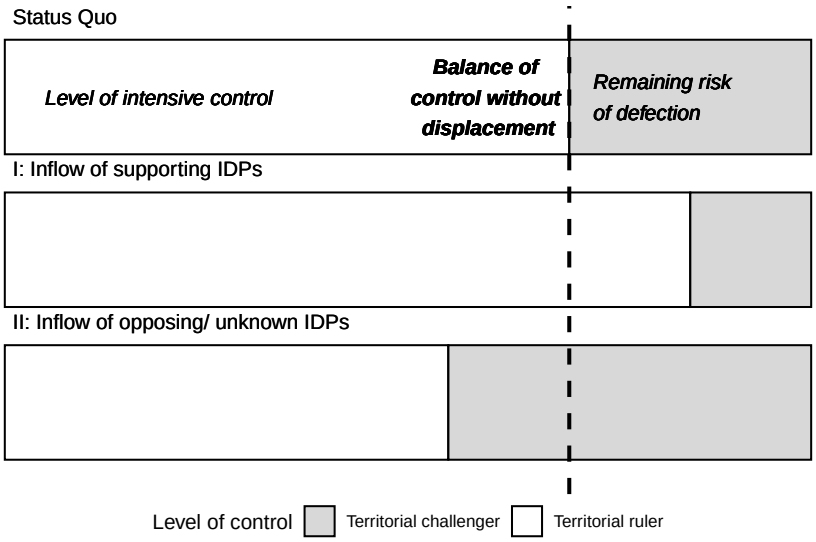

Figure 1: Theoretical expectations for ruler and challenger violence

As local ruler, incoming displaced supporters are favourable. First, IDPs that support a local ruler might be a valuable resource for recruitment as they tend to have high levels of grievances (Bohnet, Cottier and Hug, 2016). Second, they credibly inform the local population about war atrocities committed by other conflict parties (Balcells, 2018). Third, under Kalyvas (2006)'s assumption that local populations largely collaborate with conflict parties in power, supporting IDPs are also not likely to cause tensions with the local population. The absence of such tensions, that could destabilise the area and impede easy governance, allows local rulers lenience with incoming IDPs. Fourth, a high number of displaced persons in their territory may provide local rulers with international legitimacy, and sources of food and medicine through humanitarian aid (Lischer, 2008). Overall, incoming IDPs of the same loyalty group as the territorial ruler reinforce power on-site (see Scenario I in Figure 1).

However, IDPs that enter territory without belonging to the support group of the current ruler or whose loyalties are unknown to the local governor may constitute a challenge to the ruling conflict party.[1] In particular, supporters of challengers might not comply with the

[1]This framework makes the assumption that armed actors can observe the loyalty of IDPs (e.g. through markers of ethnicity or origin) and perceive civilians whose loyalties are unknown as potential threat.

local institutions built by the current ruler. Competition between loyal locals and disloyal IDPs might destabilise present institutional structures. Current occupiers also have to fear that these individuals actively undermine their rule by providing crucial information to the outside conflict party they are aligned with. As rulers cannot be sure about the compliance of individuals with no clear preference for one conflict party or with unknown war loyalties, governors will likely assume non-compliance from these groups. In sum, local rulers will expect a deterioration of their level of intensive control from an IDP entry composed of persons that do not support the ruler or whose loyalties are unknown.

Reacting to this, local governors will attempt to keep up firm governance in the increasingly contested area. Rulers can follow two strategies to preserve control that both involve an increased level of violence against civilians. First, local rulers may use coercion to enforce compliance. This involves signalling strength to the local population by violently punishing all potential dissidents or non-complying individuals. Threatening the population might also ensure that individuals with no clear preference towards one conflict actor do not dare to release information to opponents. Second, rulers may use violence to drive out non-supporters from the original population and the mobile IDP population, creating enclaves of supporters.

Violent governance in response to displacement might hit local civilians indiscriminately as IDPs often settle informally within local populations and are not always clearly distinguishable from other civilians. IDPs that merge into the local population increase Kalyvas (2006)'s identification problem. Unable to only filter out actual collaborators with opponents, insurgents or the government may increase general violence against civilians to enforce compliance, expel dissidents and ultimately mitigate losses in intensive control.

> *H1: With an increasing IDP entry of non-supporters of a local ruler, one-sided violence by the territorial ruler increases.*

The entry of IDPs may also alter incentives to locally attack civilians for territorial challenger. Challengers use civilian victimisation to manipulate the intensive control of rulers. Looking at a static situation without displacement, challengers have fewer possibilities to actively

spoil local rule as civilians in this territory may not provide the challenger with internal information and mostly comply with the local governor. Since a stable governance system is in place that extracts resources from the local population but also provides public goods such as stability in return, the control structures in favour of the ruler are consolidated.

However, displacement can disrupt this power balance to the detriment of the local ruler when incoming IDPs support the challenger rather than the ruling party (see Scenario II in Figure 1). In such a situation the external challenger profits from the local IDP entry because this slowly increases the potential influence of the invader over the territory. IDPs may provide the challenger with crucial strategic information about the increasingly heterogeneous area (Balcells, 2018), they weaken governance structures and occupy the capacities of local institutions.

While the local ruler may mitigate these effects violently, the challenging party has little incentives to use one-sided violence in these areas. If civilian victimisation is a tool for territorial challengers to undermine local governance, then these processes are already triggered by displacement and two main reasons should keep the challenger from additional violence: First, challengers do not want to risk attacking their own supporters in the area. Struggling to identify civilian supporters from opponents in the irregular settlement structures of internal displacement, the invader neither wants to attack IDPs that are aligned with it, for example through ethnic ties, nor the few supporters in the original population. Second, a non-violent approach may win the hearts and minds of the local population that is increasingly targeted by the struggling ruler. I expect that challengers will not increase attacks against non-combatants if their own loyalty group flees into this territory.

In contrast, challengers that observe the IDP entry of supporters of the local ruler might conduct attacks against civilians. With increasing clustering of opponents in an area, challengers may fear the strengthening power of the local ruler. A growing local support base for the ruler, as initiated through the displacement movement, not only suggests that conquering this particular territory becomes more difficult; it also provides the local ruler

with more resources from the local population such as additional recruits. Challengers have incentives to prevent this rise of the current ruler in a particular locality to prevent that the overall balance between the antagonising armed actors across all localities shifts to the disadvantage of the challenger.

The challenger hence uses attacks against civilians in a preventative manner to spoil positive effects for the governor (Valentino, Huth and Balch-Lindsay, 2004; Downes, 2006). The second mechanism why challenger may use one-sided violence in such locations is to punish all 'disloyal' civilians in this area that either sought shelter in enemy territory or remained in the area visibly siding with the local governor (Balcells, 2018). Thirdly, violent attacks also signal to the local population that the ruler cannot provide sufficient safety. Overall, by targeting civilians associated with the territorial ruler, "armed groups improve their odds of gaining control of contested territory" (Balcells and Steele, 2016).

H2: With an increasing IDP entry of supporters of a local ruler, one-sided violence by the territorial challengers increases.

4 Methods and Data

I assess the dynamics of one-sided violence by territorial rulers and challengers against all civilians and against IDPs in Iraq between 2014 to 2018 with the presence of IDPs and their ethno-religious composition as main predictors in a monthly grid-cell level regression analysis. The following sections first justify the selection of the Iraqi displacement crisis as my quantitative case study. Then, I specify my data sources and I present the operationalisation of my key concepts.

Case selection: Iraqi displacement crisis 2014-2018

I selected the civil war between the Islamic State of Iraq and the Levant (ISIL) and the Iraqi government from 2014 to 2018[2] for this case study because Iraq constitutes a critical case that

[2]The civil war ended in 2017 but I include 2018 as levels of local violence remained high.

provides the necessary within-case variation in displacement, territorial control and one-sided violence as the main dimensions of theoretical interest (Seawright and Gerring, 2008, 296). Iraq is the fifth most conflict-affected country worldwide in terms of fatalities (Pettersson and Eck, 2018, 537). Recurring political violence and strategic forced displacement during the Saddam Hussein regime, during the US-led invasion, and during waves of sectarian violence characterise the political landscape of Iraq. The civil war against ISIL has additionally displaced around 15 % of the entire population (IOM, 2018). This long history of violence and displacement makes Iraq a critical and policy-relevant case to analyse.

Following the rapid territorial advances of ISIL in Iraq in 2014, many Iraqis from various ethno-religious background fled to Kurdish, Sunni, or Shia areas (IDMC, 2019). The choice of displacement destinations within Iraq followed clear sectarian patterns (IOM, 2018) but at the same time, fleeing civilians were limited in their choice of displacement shelters through inhabitable desert in the west, border closures and fighting patterns. In the following months, ISIL was able to launch major offensives and to capture central cities such as Mosul. While ISIL quickly conquered large areas of Iraq, the jihadist group was also rapidly pushed back by government forces, the Kurdish Peshmerga, and Shia militias in the following years of the conflict. The Iraqi case provides high temporal and spatial variation in territorial control by different conflict parties, in IDP numbers and in ethno-religious flow compositions. See the appendix for details on the dynamics of violence and displacement in the Iraqi case.

Finally, disaggregated data on the composition of IDP flows during conflict is still scattered and not reliably available. For Iraq, efforts by the IOM to monitor which ethno-religious groups were most affected by displacement provide the unique opportunity to assess how conflict actors react to different social groups in the overall IDP population.

Units of analysis: monthly grid cells in Iraq

I use monthly PRIO-GRID cells in Iraq because they offer the advantage of a standardised resolution of units and because they are relatively large. News-based event data come with

very high spatial uncertainty and biases (Weidmann, 2015), which prevents further spatial disaggregation. I aggregate data to monthly units because of the nature of the displacement data collection.[3] The final time-series cross-section dataset entails 11,495 observations corresponding to grid cells per month from April 2014 to December 2018.

Dependent variable: one-sided violence

As dependent variable, I measure attacks against all civilians in a grid cell (broader conceptualisation) and against fleeing civilians only (narrower conceptualisation). The data for *one-sided violent events against all civilians* comes from the UCDP Geo-referenced Event Dataset (UCDP-GED) (Sundberg and Melander, 2013). Although other data sets also provide geo-referenced events of one-sided violence for Iraq, I use the UCDP-GED because the dataset covers the full observational period, reports higher precision in the geo-location of events compared to other event data collections, and provides a clear definition of one-sided violence as targeted civilian victimisation. The UCDP-GED dataset excludes collateral damage, restricts events to incidents with at least one fatality, and only records violence that can be attributed to a conflict party. Due to these coding choices, the UCDP-GED provides a conservative estimate of the amount of civilian victimisation in Iraq (477 events in total).

My second dependent variable are *one-sided violent events against moving civilians*. To capture when armed actors attack IDPs in Iraq, I collect original and geographically fine-grained data on the victimization of moving individuals and groups in Iraq. For the time period from April 2014 to December 2017, I manually coded any violent or peaceful interaction between armed groups and civilians moving from one area to the next by reviewing all news reports on fleeing civilians in *LexisNexis* and all events of violence against IDPs or refugees in the Armed Conflict Location & Event Data Project. I also coded all humanitarian reports from Human Rights Watch, Amnesty International, the Office of the High Commissioner

[3]The IDP data were collected in biweekly assessments but only 50% of the locations were updated each time and it is more appropriate to aggregate to the monthly level.

for Human Rights, the UN Assistance Mission for Iraq, the UN Office for the Coordination of Humanitarian Affairs, the UN High Commissioner for Refugees and the CCCM Cluster Management in Iraq. For details on the data collection please refer to the appendix. This novel dataset captures 289 events of violent targeting against IDPs in Iraq.

Measuring territorial control in Iraq with manual coding and machine learning

This data provides the actor committing violence but neither my hand-coded data nor the UCDP-GED data allow me to distinguish between violence committed by territorial rulers and challengers. To identify territorial rulers and challenger, the approach chosen is two-folded: I first hand-coded maps of territorial control that were published by various news sources, in particular by the Institute for the Study of War (ISW, 2019). For each grid-cell, I coded the armed actor holding the majority of the territory as the territorial ruler, distinguishing between the Iraqi government, the Kurdish Peshmerga, the Islamic State, and Shia militias. The hand-coded maps cover 29 months of the 55 months in this analysis (52.73 %).

For the remaining months, I then trained a machine learning classifier with a bagging algorithm. As features for this machine learning task, I used various spatial covariates such as distance to the capital or ruggedness of terrain, the dominant ethnic group in the area, as well as the amount of battles according to UCDP-GED. After pre-processing the data, I held back 10 randomly selected months of the hand-coded data as test set. The remaining 19 months were used to train various machine learning algorithms, to tune their parameters by means of 10-fold repeated cross-validation, and to then compare the classification performance on the held-back test data. Bagging outperformed other algorithms with an accurate out-of-sample classification of 94.69% of the test data. I then retrained the bagging classifier with the full hand-coded data and classified the zones of territorial control in Iraq for the whole time period where data is missing. Figure 2 displays the classified zones of territorial control in Iraq for the five observational years.[4] Purely descriptively, the territorial control estimates seem to

[4]I use machine learning over multiple imputation methods because the proportion of "missingness" in my data is very high to easily use multiple imputation and the data is not

capture well the decline of ISIL-held territory, the gaining in strength by Shia militia and the contest between Kurds and the Iraqi government around the 2017 Kurdish independence referendum. More details on the machine learning procedure can be found in the appendix.

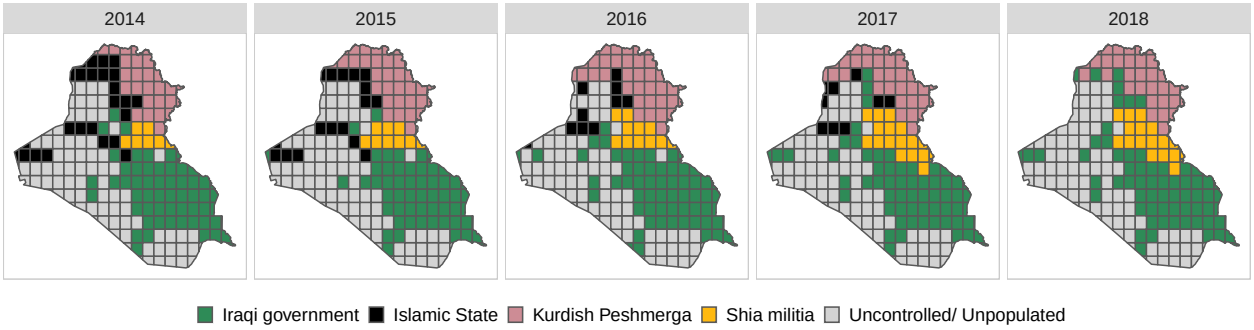

Figure 2: Territorial control in Iraq per year (most frequent actor): hand-coded and classified data (bagging)

With this territorial control data, I determined whether a specific incident of one-sided violence has been committed by an actor as territorial ruler or challenger.[5] My final dataset counts 148 events of OSV committed by rulers and 329 events perpetrated by challengers against all civilians (see location of all events in Figure 3). Focusing on violence against fleeing civilians, I identified 233 events of violence against fleeing IDPs committed by rulers and 56 victimizations of IDPs by challengers.

Independent variables: IDP numbers and composition

The main independent variables in this analysis are the total *number of IDPs families* in a grid cell and the *proportion of IDPs families supporting the local ruler* in each grid cell. In Iraq, the Displacement Tracking Matrix (DTM) by the IOM has recorded the point locations

missing at random. For machine learning, the imputation task is relatively straightforward as the algorithm only has to fill gaps between manually coded months. See information on the most influential features in the appendix.

[5]For example, if UCDP-GED reports that ISIL committed an incident of one-sided violence in a given month and location and I determined that this grid-cell was held by ISIL, I can classify this event of one-sided violence as ruler violence.

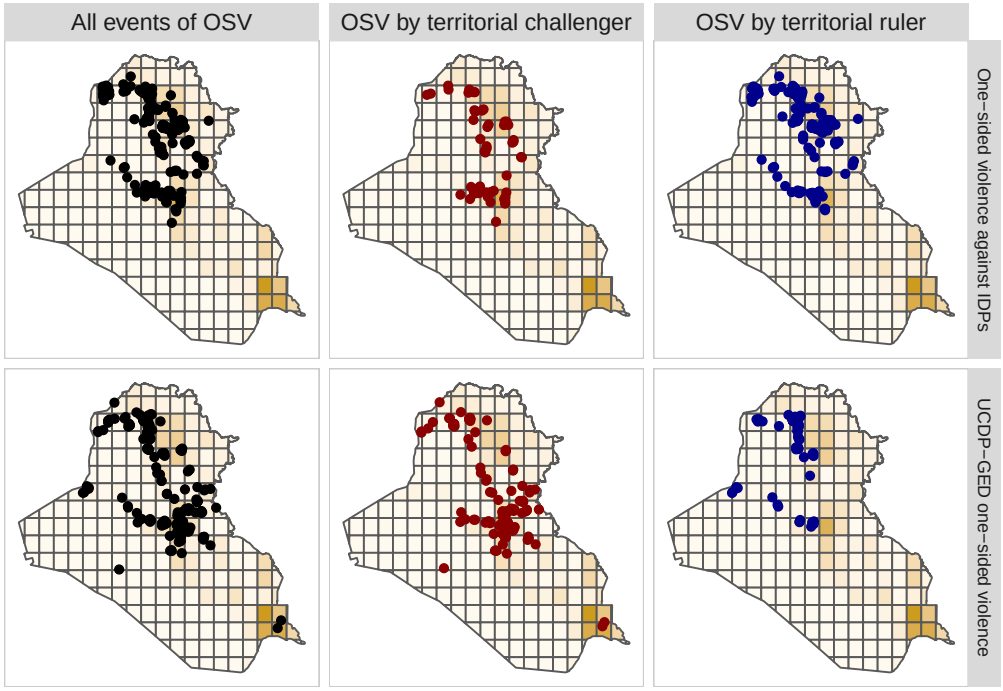

Figure 3: Events of one-sided violence in Iraq disaggregated by perpetrator of violence (dependent variables); intensity of night-time light emissions in the background

of IDPs and their numbers in these locations throughout the whole crisis in 107 assessment rounds from 2014 to 2018. Each assessment round covers an average of 3243 settlement locations with 1 to 11,450 IDP families. I aggregated this point data to months per PRIO grids.

To identify how many local IDPs supported a ruler, I use the ethno-religious composition of IDPs in each grid cell as well as information on IDPs' origin as approximation. The DTM-IOM team has recorded the ethno-religious composition of Iraqi IDPs for their point locations in three data collection rounds by means of direct observation or key informant interviews on-site. The assessments took place in August 2016, April 2017, and March 2018. I linearly interpolate between the three assessment rounds for all IDP point locations and then aggregate the very fine-grained point data to the monthly grid-cell level to generate the average ethno-religious composition in a grid per month.

Although the IOM covered the ethno-religious composition in most point locations three times (49.3%), some point locations were only assessed twice (11.8%), once (17.3%) or not

at all (21.4%). I carry the same value(s) forward and backward for locations with less than three data collections. For point location that were not assessed in any round, I impute the missing values by replacing them with the ethno-religious composition of the nearest spatial and temporal neighbour using KNN. Further details on the imputation steps and their validation as well as a map of the IDP locations can be found in the appendix.

Having generated monthly average ethno-religious compositions per grid cell, I then associate each ethno-religious or origin group in the IDP population with the conflict actor most closely associated with (see the coding scheme in Table 1). If the Iraqi government or Shia militia hold a specific territory, I approximate the proportion of IDPs supporting these actors with the proportion of Shia IDPs. If areas are sparsely populated, I also assume some level of governmental control and approximate IDP support for local rulers with the proportion of Arab Shia Muslims. In the case of territory controlled by the Kurdish Peshmerga, I approximate loyalties based on the proportion of Kurdish IDPs in a grid cell. If ISIL controls territory, I approximate support for this actor with the proportion of IDPs originating from the Anbar governorate in west Iraq. While the Islamic State is a Sunni jihadist group, few Arab Sunni Muslims in Iraq actively supported ISIL and assuming that a Sunni identity means support for the Islamic State would overestimate backing of the terrorist group in the local population. Although still imperfect and rough, I instead use the proportion of Anbari IDPs as some Sunni Arab tribes in Anbar have indeed supported the Islamic State (Dawod, 2015).

This coding assumes that ethno-religious identities are a good proxy for the *perceived* rather than the actual support for conflict parties in Iraq. Although this is a rough approximation due to data limitations, sectarianism is one of the defining political structures in Iraq since the Iraq war (Ismael, 2015), the Iraqi conflict parties speak to distinct sectarian audiences and there is qualitative evidence that the armed actors used ethno-religious group identities as proxy to target certain social groups during the fight against ISIL. For example, the Iraqi government has reportedly harassed Sunnis from Anbar in IDP camps based on alleged ties

to ISIL. Although many of these Sunni Anbaris do not support ISIL, other armed actors, such as the Kurdish Peshmerga and the Iraqi government, use their ethnicity as identifier for war loyalties. There is also evidence, further discussed in the appendix, that armed actors monitored and screened for the origin villages and ethno-religious identity of IDPs at checkpoints before letting them pass, providing further confidence that - in this specific context - ethno-religious identities are a good proxy for *perceived* support for armed actors.

Table 1: Coding scheme to approximate IDP support for local rulers

Actor controlling territory	Ethno-religious/ origin support group in IDP population
Iraqi government/ Shia militia	Arab Shia Muslim IDPs
Islamic State	Anbari IDPs
Kurdish Peshmerga	Kurdish IDPs
Uncontrolled/ Sparsely populated	Arab Shia Muslim IDPs (government support as default)

Figure 4 displays the distribution of IDP support for local rulers and the number of IDP families in the data, which constitute the main independent variables. On average, 10.29 % of the IDP population supports the local ruler, suggesting that few IDPs were able to flee to areas in which they support the local ruler.

Estimation procedure, alternative explanations and controls

I fit negative binomial count models with and without accounting for zero inflation - to reflect the over-dispersion and the high percentage of zeros in my data. The negative binomial models regress 1) OSV by the territorial ruler and 2) OSV by the territorial challenger on IDP numbers and the numbers of IDPs supporting the current territorial ruler. I use incidents of one-sided violence against all civilians and only against IDPs. The independent variables (IDP numbers and ruler support) enter the regressions as interaction effects as I want to

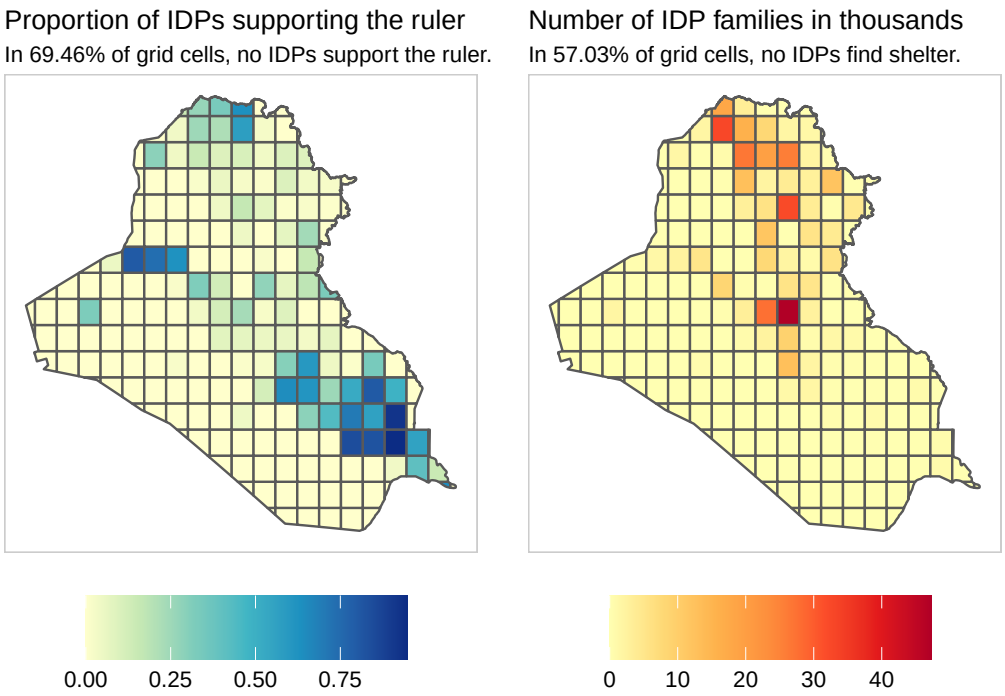

Figure 4: Distribution of IDP families and their support for local rulers in Iraq

account for the fact that a few incoming supporters may not change violent dynamics but many will make a difference.

My models should not be understood as causally identified.[6] I focus on descriptive and associational evidence because there is strong selection into displacement. I discuss in the appendix what factors predict high IDP numbers and high ruler support in the IDP population, finding that a mix of strategic (e.g. ethnicity) and unstrategic factors (e.g. urbanity) explain migration patterns. Furthermore, despite selection into displacement locations, the majority of IDPs in my data do *not* support the local ruler (Mean local ruler support: 10.29%) and they do not seem to strategically choose a territory in which they might be safer given their

[6]I report fixed effects models in the appendix: I use "arbitrary" grid cells and my units of analysis are not inherently meaningful categories to interpret in the sense of having theoretically informed unit-specific traits. Given my theoretical setup, I also cannot exclude the possibility that past treatments (IDPs) directly influence current outcomes (violence) or past outcomes (violence) affect current treatments (IDPs). In this case, fixed effects may not be the best estimate.

ethno-religious identity. This is partly because of the nature of forced displacement which limits the space to choose preferred destinations. For example, Sunnis from Anbar often had no other choice than to move to territory controlled by Kurdish, Shia, and minority forces that did not want further Sunnis moving into their areas (EASO, 2019). The regression analysis might also provide useful evidence given that switches in territorial control over time, as commonly seen in the northern part of Iraq, uproot support structures in local populations.

To account for some confounders, I include two sets of control variables in my regression analysis (see Table 2): First, I control for various geographical factors to reduce 'white noise' in the data, observations that almost certainly do not experience IDP entry or one-sided violence. A second set of control variables accounts for alternative drivers of one-sided violence and IDP relocation from previous research.[7] In the simple negative binomial count models, all these control variables are included in the regression. In the negative binomial count models that account for zero-inflation, the control variables are used to model the zero component while the main predictors (IDP families and their support for the local ruler) and the actor currently in territorial control are used in the count component.

5 Results: OSV by territorial ruler and challenger

I now turn to the main test of my theoretical hypotheses on the behaviour of territorial challengers and rulers. In Table 3, I report results when dis-aggregating civilian victimisation in Iraq into attacks committed by a local ruler (models 1-4) and by a local challenger (model 5-8). I present results from negative binomial count models that account for zero-inflation or not and I distinguish between general OSV and attacks against IDPs. I interact the absolute number of IDPs with my measure of support for the local ruler. With this interaction effect, I aim to test hypotheses 1 and 2. The intuition is that - if my theoretical argument finds associational support - the interaction term is *negative* for violence committed by the ruler

[7] In the appendix, I provide robustness checks to identify if dropping one of the control variables drastically shifts the findings of my regression analysis.

Table 2: Control variables

Control	Theoretical justification	Data & operationalisation
Geographical controls		
Population density	Relocation of IDPs most likely at places that are already populated; likewise OSV is more likely in populated spaces	Populated places in grid cell (source: IOM-OCHA data)/ Persons in grid cell (source: Tollefsen, Strand and Buhaug, 2012)
Terrain ruggedness	Mountainous and inaccessible terrain is less likely to see IDP movements into the area and OSV events	Proportion of mountainous terrain within cell (Tollefsen, Strand and Buhaug, 2012)
Theoretical controls		
Economic performance	IDPs may flee to more urban and economically strong areas; prosperity often linked to less conflict	Average measured night-time light emission; calibrated for time-series analyses (source: NGDC, 2013)
Connectivity	Allows travelling for conflict actors and IDPs; symbol of strategic value of location for IDPs and armed actors	Distance to road network (source: OCHA data), distance to capital, distance to next urban centre
Border	IDPs may flee to border regions to escape; may be contested areas	Distance to border of Iraq
Humanitarian aid	Presence of formal IDP camps and humanitarian actors might change interaction between conflict actors	Distance to next formal IDP camp (source: CCCM Cluster Iraq)
Battles	Fighting causes displacement (increases number) and is correlated with OSV	Events of state-based conflict or non-state conflict (source: UCDP-GED)
Contestation	Territorial takeovers may increase OSV and lead to IDP outflow	Change in territorial occupation compared to previous time period (source: coded data on territorial control)
Control	Actor that controls a territory may inherently be more violent towards civilians or fewer civilians may choose to move to this area	Actor in control as categorical variable (source: coded data on territorial control)
Spatial lags		
IDP families (nb)	IDPs may flee towards other fleeing civilians and may cause contagion	
OSV (nb)	Violence in the neighbourhood may explain higher IDP numbers while also implying a conflict cluster	

and *positive* for violence committed by the challenger because both respond to the distribution of war loyalties in population movements.

I first focus on violence committed by the *territorial ruler*. Overall, I find associational evidence for my hypothesis 1 when looking at all incidents of one-sided ruler violence reported by UCDP-GED: I find that the interaction of IDP numbers and ruler support is negative for violence perpetrated by rulers (Models 1+2), meaning that the entry of IDPs that support a local ruler slightly reduces the chance that this ruler will use one-sided violence against all civilians when facing high IDP numbers. This pattern can be found across negative binomial and zero-inflated models. When looking at the results for ruler violence specifically directed against IDPs and not the general civilian population, I also find negative and significant interaction terms for both negative-binomial regressions, providing support for my argument.

Using negative binomial count models, I predicted the count of one-sided violence against all civilians and report those predictions in Figure 5. The panel on the right displays the

Table 3: Regression models for one-sided violence committed by the territorial ruler (1-4) and by the territorial challenger (5-8). Negative binomial regressions (with and without zero-inflation) are reported for all one-sided violence and for violence against IDPs. For models accounting for zero-inflation, only the count model is displayed.

	Dependent variable:							
	Ruler OSV		Ruler OSV-IDPs		Challenger OSV		Challenger OSV-IDPs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IDPs x ruler support	−0.629*	−0.454*	−0.557*	−0.331*	0.813*	0.714*	−0.374	0.042
	(0.300)	(0.133)	(0.218)	(0.128)	(0.042)	(0.040)	(0.100)	(0.075)
IDP families	0.241*	−0.042	0.196*	0.140*	0.103*	0.240*	0.127	0.081
	(0.097)	(0.097)	(0.069)	(0.067)	(0.042)	(0.040)	(0.100)	(0.075)
IDP ruler support	0.403	0.751	−0.072	−0.345	−2.196*	−2.935*	−0.872	−0.404
	(0.478)	(0.469)	(0.388)	(0.428)	(0.714)	(0.782)	(0.970)	(0.790)
Controls ?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model	Neg-bin	Zero	Neg-bin	Zero	Neg-bin	Zero	Neg-bin	Zero
Observations	11,495	11,495	9,196	9,196	11,495	11,495	9,196	9,196
Log Likelihood	−222.268	−217.168	−553.386	−530.374	−586.542	−581.677	−229.037	−237.343
Akaike Inf. Crit.	482.536		1,144.772		1,211.084		496.074	
Note:							Significance threshold: * p < 0.05	

predicted count of ruler-inflicted one-sided violence as a function of IDP families and for different levels of ruler support. The shaded areas are the 95% confidence intervals. Although uncertainty around these estimates are high, we can generally observe that high IDP numbers lead to more predicted one-sided violence *if* the ruler support amongst the IDP population is low. For higher levels of ruler support, the predicted count of one-sided violence remains low. This provides some evidence in line with my theoretical argument that local rulers respond to the support structure of IDP entrys and consider IDPs as potential resource if they do not challenge their intensive control over territory. For the subset of data focusing on the victimization of IDPs (not plotted in Figure 5), I find a similar but less strong pattern.

As theoretically expected, the results are different if I regress one-sided violence by *territorial challengers* on IDP numbers and the support for territorial rulers (models 5-8 in Table 3). The interaction effect of IDP families and ruler support is statistically significant and positive for both negative binomial regressions (with and without zero-inflation) that use data on all civilian victimization. This indicates that support for a local ruler potentially increases civilian targeting by territorial challengers that do want to prevent the creation

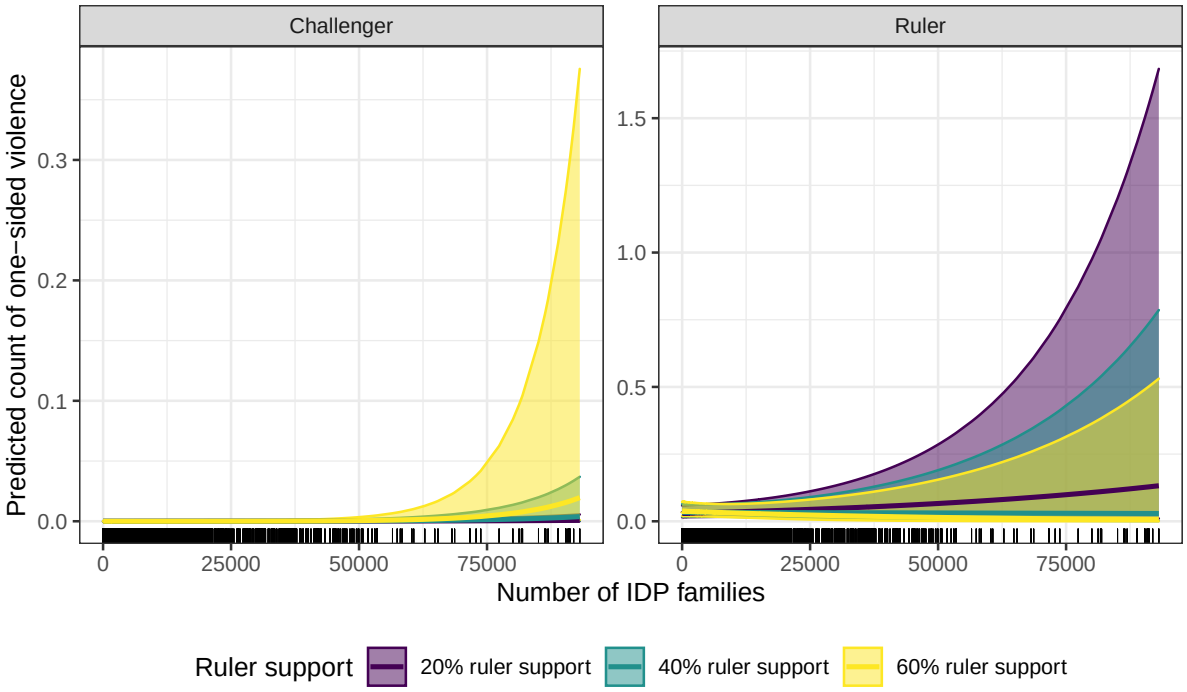

Figure 5: Predicted OSV counts by rulers and challengers as a function of the number of IDP families for different levels of IDP support for the local ruler (UCDP-GED). Negative binomial regressions. Other covariates set to mean.

of strongholds for their enemies. The panels on the left in Figure 5 show that this positive effect on violence can be found for various levels of ruler support. With higher levels of ruler support, the predicted count of one-sided violence increases. From a theoretical perspective, this provides some associational evidence that challengers indeed observe loyalties of fleeing civilians and react with more violence to weaken the territorial control of their opponents (hypothesis 2).

However, I do not find a consistent effect when I focus on violence against fleeing civilians and IDPs more specifically (Models 7+8). I find no support for the theoretical expectation that more IDP entry of ruler supporters would also lead to more specific targeting of IDPs by challengers. On a theoretical level, this could indicate that spoiling behaviour – the idea that territorial challengers spoil areas with violence against civilians to weaken strongholds of the enemy – targets civilians more broadly and not specifically IDPs. The fact that territorial challengers may have limited access, knowledge, or capacity to infiltrate enemy territory to

specifically identify IDPs and target them may also explain why I find clear results for general violence against civilians by territorial challengers but not for more targeted violence against fleeing civilians. Given my data limitations, this cannot be conclusively determined.

Given the distribution of my data, with excess zeros and few event counts, Figure 5 - showing predicted counts for different levels of ruler support and IDP families - can be difficult to interpret due to overlapping confidence intervals. In Figure 6 I hence plot the difference between the predicted count of one-sided violence for 60% of ruler support and for 20% of ruler support. I plot this difference for one-sided violence against all civilians and distinguish between challenger (green) and ruler violence (yellow). The plot shows that the difference between the predicted amount of one-sided violence by the challenger for high levels of ruler support (60% of IDPs support the ruler) and low ruler support (only 20% of IDPs support the ruler) is positive. In other words, challengers use comparatively more violence when IDPs support the local ruler while they use less violence when IDPs do not support the local ruler. In contrast, the panel on the right, displaying ruler violence, shows a negative difference. Rulers use less violence when IDPs largely support their rule (support levels at 60%) than when IDPs do not support their rule (support level at 20%).

All in all, I demonstrate that armed actors that either control or challenge a territory respond to the distribution of war loyalties in the IDP population. The results provide initial support for hypotheses 1 and 2. The intertwined local dynamics of displacement, territorial control, and civilian targeting could lead to vicious cycles of repeated flight and attacks.

Robustness checks

I have conducted several robustness checks to mitigate concerns in regards to my descriptive analysis: [8] For starters, I have limited the data to grid cells that are highly populated, have seen contestation during the conflict, have seen activity by ISIL and do not contain humanitarian camps (see Figure 7). Although I also control for those factors, I want to

[8]Further robustness checks can be found in the appendix.

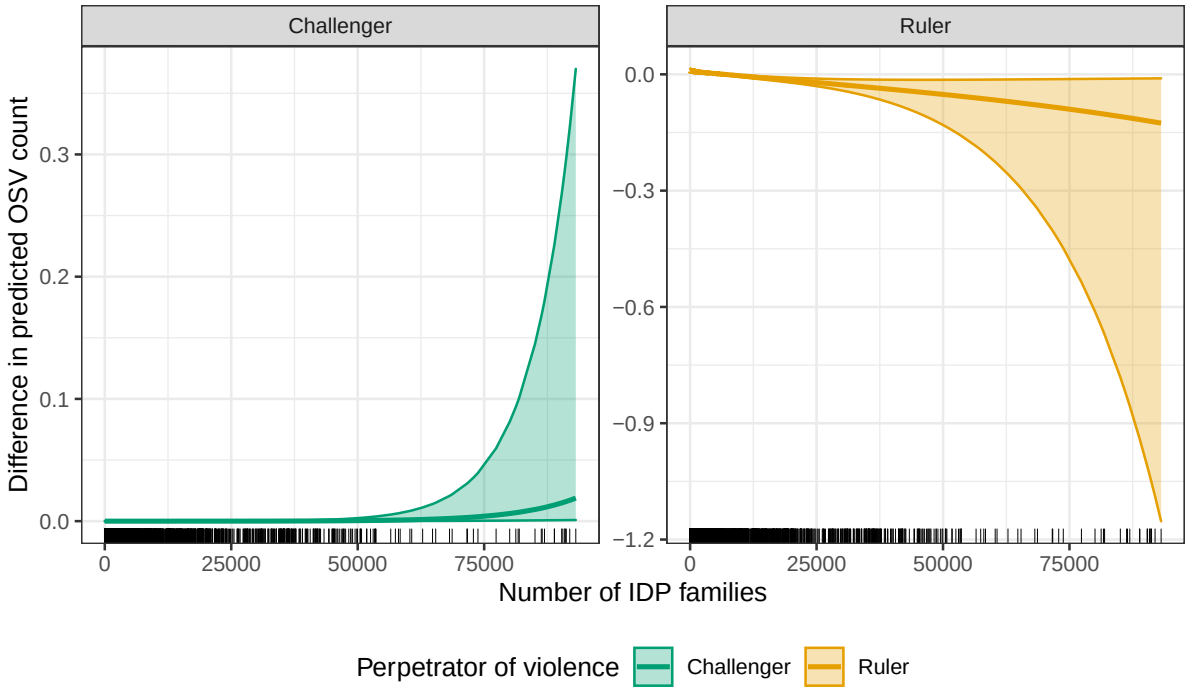

Figure 6: Difference in predicted OSV counts for 60% and 20% of ruler support given displacement. Plot shows predictions for one-sided violence against all civilians by rulers and challengers predicted with negative binomial regressions. Other covariates set to mean.

make sure that neither white noise (e.g. grid cells that are only sparsely populated), nor international actors (e.g. in camps) introduce bias in my estimates. Overall, I find that excluding grid cells that are less likely to see violence and conflict because they are only sparsely populated, they have not seen actual contestation, or they are seen as humanitarian spaces does not strongly affect my overall conclusion that territorial rulers respond differently to IDPs that territorial challengers. The robustness checks on data subsets highlight that the Islamic State is a particular violent actor. This limits the generalisability of my findings.

In a second step, I focused on methodological concerns: First, I assessed how my machine learning classification affects my results as I am concerned that areas where territorial control is unclear and prediction error is higher drive my results. To assess this problem, I first investigated if I get the same results if I only focus on months that have been coded manually. I then include more and more predicted territorial control data with lower thresholds of predicted certainty in the territorial control estimates to see if my overall estimates change (see

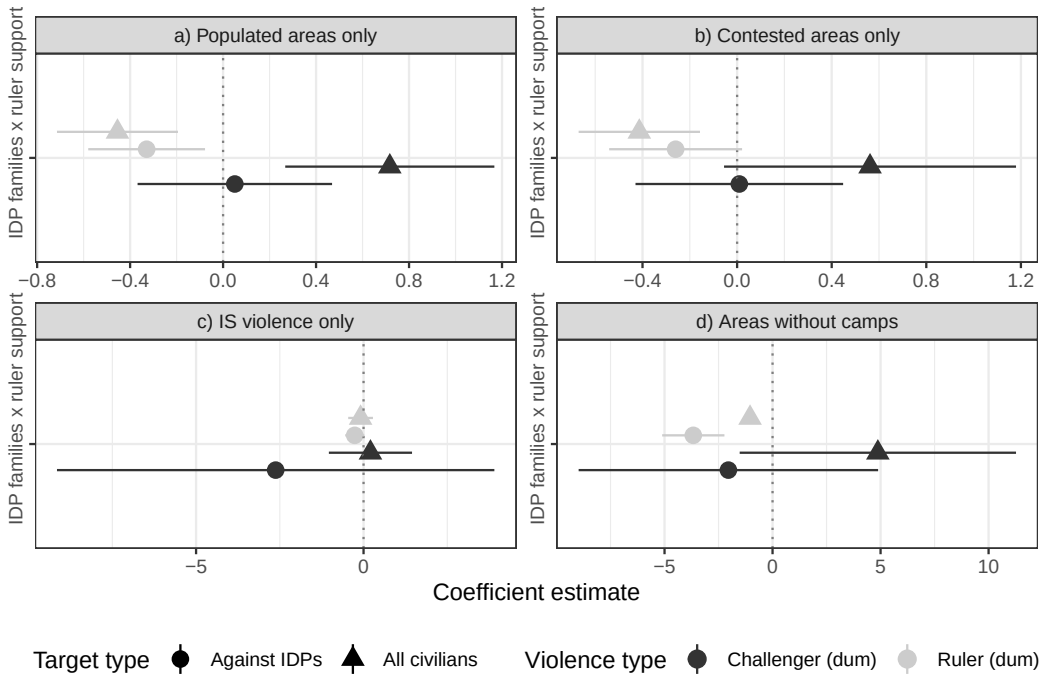

Figure 7: Coefficient plots for zero-inflated negative binomial count regressions: OSV by territorial challenger and OSV by territorial ruler. Data was limited to populated areas (panel a), to contested areas (panel b), IS violence only (panel c) and areas without camps (panel d). Only the interaction term is displayed.

Figure 8). I do not find that the uncertainty around my machine learning prediction strongly changes my general findings. I also conducted outlier analyses, dropped covariates from my models, and lagged the independent variables in time. In these methodological robustness checks, I do not find strong evidence that my results are an artefact of methodological choices.

Nevertheless, uncertainty around my estimates is high and this study only provides associational evidence. Given the structure of my data - with many time-invariant covariates, uncertainty around territorial control, and imputed proportions of ethno-religious groups in the IDP population, it seems crucial to revisit the theoretical argument when more fine-grained data on IDP characteristics and territorial control become available.

6 Discussion and conclusion

This study makes a theoretical extension to current models of civilian victimization by considering local populations as dynamic component. This dynamic parameter sheds light

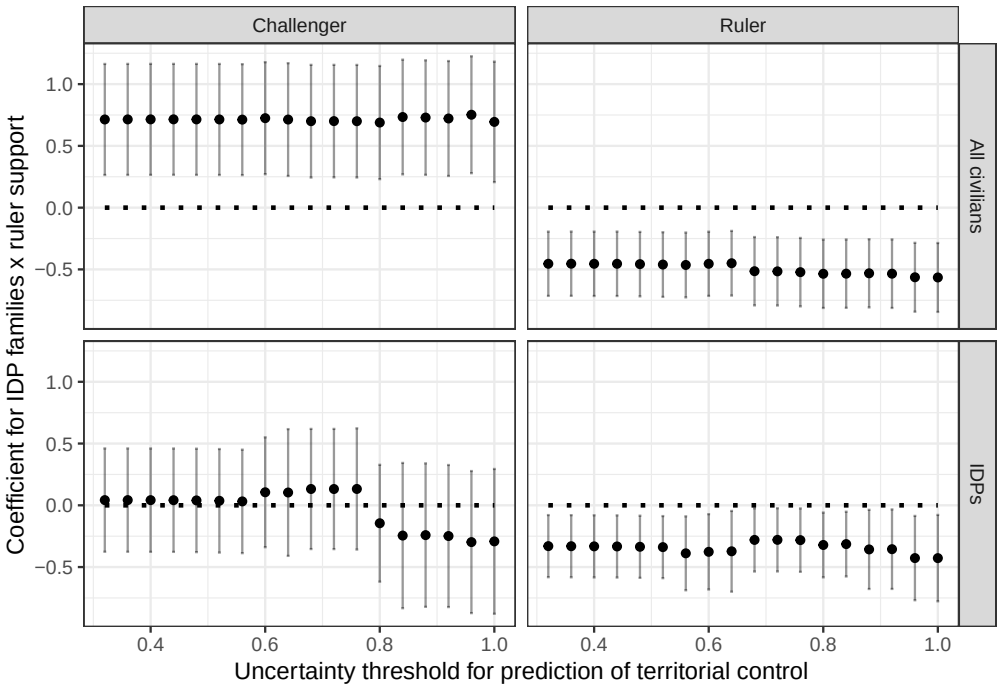

Figure 8: Coefficient plot and confidence intervals for the interaction between IDP numbers and ruler support for data restricted by thresholds of predicted uncertainty over territorial control. Zero-inflated negative-binomial models.

on different strategies to control civilians for territorial rulers and challengers and helps to identify a spoiling mechanism as war strategy of challengers. My theoretical argument explains why local population movements during civil wars can spread civilian victimisation.

I argue that population movements to more peaceful locations during civil war can cause cycles of repeated violence and secondary displacement because strategic territorial rulers and challengers have incentives to respond violently to population relocation that threatens the balance of intensive control between the warring parties. Violence against the population is used to either prevent a decrease in intensive control from the perspective of a territorial ruler that is faced with incoming non-supporters; or to undermine the intensive control of the opponent from the perspective of a challenger that observes waning influence in light of incoming supporters of the ruler. My sub-national regression analysis of grid cells in the Iraqi displacement crisis from 2014 to 2018 finds support for this argument.

The identification of these nuances in the reaction of territorial rulers and challengers to

displacement is only possible due to my extensive work to manually code maps of territorial control, to fill data gaps with machine learning algorithms, to gather and clean data on the ethno-religious affiliation of IDPs in Iraq, to collect spatially fine-grained data on the victimization of Iraqi IDPs and to combine this rich territorial control and displacement data with other data sources and spatial covariates. As such, the study not only tests a theoretical argument about violence against civilians in displacement crises, I also provide a monthly geographically fine-grained dataset of territorial control during the Islamic State insurgency in Iraq that can be used by other researchers to understand broader conflict dynamics.

However, further explorations are needed to understand how armed actors manipulate movement patterns to prevent changes in effective control, how access and knowledge constraints shape targeting patterns, and how armed actors learn about patterns of war loyalties from population movements. On a theoretical level I am largely agnostic of the movement and flow patterns of IDPs although we know that IDPs escape from violence and resettle along conflict lines and social networks (e.g. Balcells, 2018). Given the fact that I do not clearly conceptualise flows or use an exogenous shock to the distribution of IDPs in Iraq, strong causal claims are problematic and this analysis can only be seen as a first step to understand the victimisation of fleeing civilians in civil wars.

From an empirical perspective, various factors make the study of these dynamics challenging. Regarding IDP populations, the data environment is still sparse as we increasingly collect information on the location of IDPs but not on the socio-economic composition or ethnicity of IDPs. I had to rely on various imputation steps to create a time-series cross-sectional dataset that approximates IDP numbers and support for conflict actors over time. Given data limitations, my operationalisation of support for local rulers remains problematic and there is scope for future work to better measure these theoretical concepts. I also use a machine learning algorithm to estimate zones of territorial control in Iraq in the absence of fine-grained quantitative data on territorial control. Although I show in robustness checks that the uncertainty over my classification does not strongly distort my results, better data

could mitigate concerns about the biases in my analysis.

Future studies should also use smaller grid cells if event data is precise enough and should extend the analysis to well-defined spatial econometric models. This would allow to understand more clearly how migration, learning, and contagion effects affect cycles of violence and displacement. If more fine-grained data on population flows and territorial controls become available, investigating temporal dynamics while holding units constant seems crucial.

Lastly, this is a case study on the dynamics of one-sided violence in Iraq. Almost all violence recorded in the UCDP data is committed by the Islamic State, a particular brutal group that has engaged in widespread civilian targeting and killings of ethnic minorities. Whether these results transfer to other groups remains open. The described dynamics of maximising extensive and intensive control in civil wars might only apply if insurgencies are able to capture significant amounts of territory and are able to establish some long-term rule over their areas. While ISIL has taken over large areas from the government, other civil wars do not experience strong rebels that can control territory for a longer period. In other words, my theoretical argument might only apply when the scope condition of a territorial and conventional civil war applies.

Furthermore, the implicit assumption is also that the moving population can be identified as either supporters or non-supporters of conflict actors. This may be plausible in civil wars with an ethno-religious dimension, but less clear in other cases. On the one hand, massive displacement during civil wars like in Iraq is a very common feature of many conflicts such as in Syria, Colombia or Afghanistan. This stresses the importance of studying the phenomenon of population movements in times of political violence.

Despite the challenges in conducting research on forcibly displaced persons and local conflict dynamics, it is crucial to understand how repeated cycles of violence and displacement emerge and how we can protect civilians that have to flee their homes from future harm.

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Appendix for: Controlling a Moving World: Territorial Control, Displacement and the Spread of Civilian Targeting in Iraq

Contents

A One-sided violence and internal displacement in the Iraqi civil war (2014-2017)

Political violence and forced displacement have been recurring phenomena in Iraq's history. In the past, the Iraqi state has strategically used the expulsion of civilians to punish non-compliant communities, to secure access to resources, to undermine political opposition and to gain state control (Fawcett and Tanner, 2002). In the fight against the Islamic State (IS), the Iraqi society has suffered from large-scale violence and displacement by extremist groups, militias, and state agents. The civil war 2014-2017 now constitutes the worst displacement crisis in Iraq's history with around 15% of the entire population being displaced (IOM, 2018). This section provides a summary of the dynamics of violence and displacement from 2014 to 2017. I first provide some background on the ethno-religious composition of Iraq and I summarise the main belligerents and the time line of the civil war. I then describe the dynamics of displacement and give an overview of events of one-sided violence in that time period.

A.1 The Iraqi civil war: belligerents and time line

The armed conflict between the Islamic State and the Iraqi government - here referred to as the Iraqi civil war - began in early 2014 and ended in December 2017. During the conflict, the jihadist militant group was able to conquest one third of the country, exploiting sectarian and tribal fault lines to make territorial gains in western and northern Iraq (Hassan, 2014).

Modern Iraq as known today is made up of the former Ottoman provinces Mosul, Baghdad and Basra. The Iraqi state, that gained independence from the Ottoman Empire and British colonial rule in 1932, encompasses several ethnic, sectarian, and national groups. While Sunni Arabs historically inhabit the north of Iraq, the majority of Iraqis are Shia Arabs that tend to live in the south. The Kurds of Iraq, that make up around 15-20% of the population (Cordesman, 2017), enjoy autonomy in the 'Kurdistan Region of Iraq' (KRI) around Erbil. The federal status of this entity with some 8 million inhabitants is secured in Iraq's 2005 constitution. In addition, Turkmen, Armenian, Chaldean, Assyrian, Catholic, Orthodox, Jewish, Kakai and Yazidi minorities demand representation in the political system. Figure 1 displays the main settlement areas of the largest ethnic groups in Iraq. The Hashemite Kingdom of Iraq (1921-1958) that followed Iraqi independence, the subsequent Iraqi republic (1958-1968), and the rule by the Arab Socialist Ba'ath Party (1968-2003) initially consolidated power in the hands of Sunni Muslims. The first elections after the US-led invasion in 2003 brought change: a predominantly Shia government now rules Iraq (Tripp, 2002). However, the invasion of Iraq also prompted the collapse of the Iraqi state and led to brutal waves of sectarian violence between Sunni and Shia Muslims. The 2006 bombing of the Al-Askari mosque in Samarra marked the start of this wave of sectarian violence, in which state control outside of Baghdad became more and more contested and tribal and sectarian ties continued to shape Iraqi politics (Boduszyński, 2016).

The overall security situation in Iraq deteriorated over time. In May 2013 as most violent month of this period, 963 civilians were killed and 2,191 were wounded (IOM, 2018, 6). Baghdad's relations with Iraqi Kurdistan and the Sunni areas collapsed and the central government lost de-facto control over half of the Iraqi territory, creating space for militias and extremist groups (Khedery, 2015). On 30 December 2013, Iraqi forces raided a camp in Ramadi, in Anbar governorate, suspected of sheltering Sunni armed groups. The intense clashes between Sunnis and Shia following this event triggered the 2014-2017 civil war.

In the following months, the Islamic State of Iraq and the Levant (ISIL), that originally emerged as Sunni jihadist splinter group of al-Qaeda, quickly seized the majority of Anbar governorate. Local Sunni

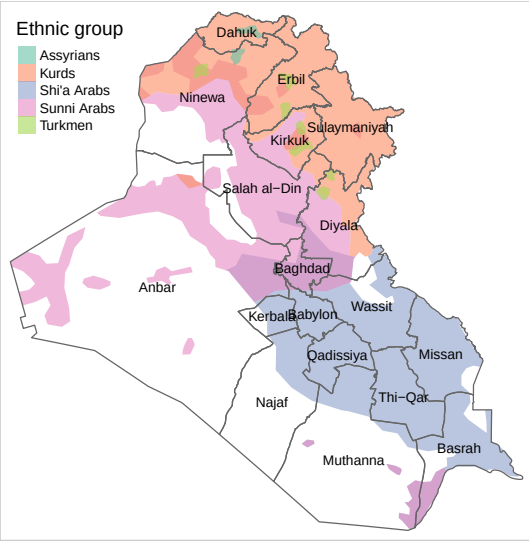

Figure 1: Ethno-religious settlement areas in Iraq (source: GeoEPR)

militia supported ISIL's campaign in the province, no longer trusting the central government in Baghdad (McCants, 2015, 125-126). Having particularly suffered from sectarian violence, many Sunni tribes joined ISIL in the hope for better and stable governance (Chulov, 2015), although some smaller tribal forces also resisted the jihadists (e.g. Tribal Mobilisation Forces). In June 2014, ISIL was successful in capturing Mosul as the second most populous city in the country (The Economist, 2014). Despite being outnumbered by government forces, ISIL was able to establish its rule in Mosul as the inhabitants vastly rejected Iraqi state authority (Ismael, 2015, 226). ISIL also captured large parts of Nineveh, Kirkuk, Diyala, and Tikrit. On 29 June, the extremist jihadist group announced the establishment of a caliphate under Abu Bakr al-Baghdadi and henceforth called itself Islamic State (Zelin, 2014).

The Islamic state not only faced resistance by the Iraqi Armed Forces that represented the Shia government in Iraq. The Kurdish Peshmerga also fought against IS. While around 35,000 Peshmerga fighters were formally incorporated into the state's forces (Beaumont, 2014), the majority of Kurdish fighters operated under the independent command of the Kurdish autonomous region of Iraq and represented Kurdish interests. The Popular Mobilisation Forces (PMF) as an umbrella organisation of more than 50 Shia armed groups also joined the Iraqi Armed Forces in their fight against IS (Gaston and Derzsi-Horváth, 2018; Di Giovanni, 2014). Many of these Shia militias are closely aligned with Iran and either newly emerged or remobilised following a 2014 *fatwa* by Grand Ayatollah Ali al-Sistani, Iraq's senior cleric. The PMF also incorporated other minority militias because various Turkmen Muslim, Assyrian Christian, Yezidi, Shabaki, and Armenian Christian forces aimed to secure their territories and to protect their sectarian support base (Gaston and Derzsi-Horváth, 2018; Gaston, 2017). Table 1 gives an overview of the main armed factions and the ethno-religious affiliation of these groups in the Iraqi population.

In August 2014, the Islamic State captured Sinjar, a predominantly Yazidi town in the north, and subjected minority communities in the area to torture, public executions, sexual slavery and forced conversion (HRW, 2014; Callimachi, 2015). In response to this genocide of Yazidis, the United States started targeted airstrikes against IS in Iraq. With this backing, Kurdish ground force were able to reconquer territories in Sinjar and around Mosul in the remaining months of 2014.

Table 1: Ethno-religious affiliation of armed actors in Iraq

Armed actor	*Ethno-religious affiliation*
Iraqi Armed Forces	Shia Muslims
Islamic State of Iraq and the Levant/ Islamic state	Sunni Muslims
Kurdish Security Forces/ Peshmerga	Kurds
Popular Mobilisation Forces (umbrella organisation of 50+ Shia militia; e.g. Mahdi Army, Hezbollah Brigades, Badr Organisation, Asa'ib Ahl al-Haqq)	Shia Muslims
Smaller armed groups and militias (partly allied with Shia militias):	
Sunni tribal forces (e.g. Tribal Mobilisation Force)	Sunni Muslims
Assyrian/ Armenian Christian forces (e.g. Ninewa Plains Protection Unit, Ninewa Plains Guard Forces, Dwekh Nawsha)	Christians
Yezidi forces (e.g. Sinjar Protection Forces)	Yezidis
Shabaki forces (e.g. 30th Brigade of the PMF)	Shabaki
Turkmen Muslim forces (e.g. Brigades 16 and 52)	Turkmen Muslims

In the following years, government troops, pro-Iranian Shia militias, and the Kurdish Peshmerga were able to further push back IS from Iraqi territory. The US-led airstrike campaign by multiple states, American and Canadian troops on the ground (Puzic, 2014), the rearmament of the Iraqi Security Forces (Alsodani and Knights, 2017), and military and logistical aid by Iran and Russia provided assistance in the fight against the Islamic State in 2015 and 2016. However, the recapturing of territory by a wide range of local, hybrid, and non-state security forces with conflicting agendas also led to a fragmentation of authority that now impedes Iraq's long-term stability under central state control (Gaston and Derzsi-Horváth, 2018).

In particular Iraqi Kurds drastically increased their military, territorial, and political importance during the civil war, gaining international attention for their successful anti-IS campaigns. On 25 September 2017, the KRI held an unofficial referendum in which the overwhelming majority voted for independence from the Iraqi government. Responding to this event, the Iraqi Armed forces launched a short offensive to recapture Kirkuk from the autonomous Kurdish government. To avoid the escalation of conflict with the central government, the KRI froze the referendum results and proposed a ceasefire. Masoud Barzani, the President of Iraqi Kurdistan, stepped down. His strategic push for independence during the civil war ended unsuccessfully with the loss of Kirkuk; and the Kurds subsequently held a weaker position than before the referendum (Kaplan, 2019).

During November 2017, Iraq captured the last strongholds of IS and on 9th December 2017 the Prime Minister Haider al-Abadi announced that IS was defeated. Nevertheless, IS continued to hold territory in the western desert of Iraq and waged low-scale insurgency campaigns against the government during 2018. Up to today, the need for reconciliation and community building remains a pressing concern in Iraq as most local communities are still strictly divided along sectarian, tribal and factional lines (OCHA, 2019).

A.2 Displacement dynamics in Iraq

The current wave of displacement due to the rise of the Islamic State in late 2013 can be described as the fourth major wave of conflict-induced population movements in modern Iraq (IDMC, 2019*b*). Under Saddam Hussain forced displacement was used to implement the regime's Arabisation policy, targeting Kurdish but also Shia individuals and communities (Romano, 2005). The US-led invasion of Iraq in 2003 led to a second wave of displacement. This period of prolonged instability and violence after the toppling of the Hussein regime displaced an estimated amount of one million Iraqis between 2003 and 2006 (IOM, 2018). Thirdly, the sectarian violence starting in 2006 created a large amount of displaced people within Iraq. Consequently, around 2.1 million people were already living as IDPs in various shelters across Iraq at the

outset of contestation between ISIL and the Iraqi state (IDMC, 2019*a*). The civil war added to this number with overall about 6 million people becoming displaced since the beginning of 2014 (OCHA, 2019).

Population movements within Iraq

Population movements were particularly high at the beginning of the armed conflict because of the almost unrestrained territorial advances of ISIL in Anbar (IOM, 2018, 11). Displacement initially occurred mostly within Anbar but IDPs started moving to the north-central areas of Iraq - reaching Salah al-Din and Ninewa - when ISIL seized Mosul. During the Mosul crisis, a clear ethno-religious movement pattern emerged: While Christians and Yazidis moved towards Iraqi Kurdistan, Turkmen Shia from Mosul moved to southern Shia-majority territories. Turkmen Sunnis of the region moved towards Kirkuk and Salah al-Din. The capturing of Sinjar and the extreme violence against non-Sunni minority groups, in particular against Yezidi, forced a high number of IDPs to flee to neighbouring governorates. Because the Islamic State moved the frontlines further eastwards, eastern governorates experienced increases in IDP numbers. In the following months, the deteriorating security situation often forced families to seek shelter in areas that were not free of violence. The International Organisation for Migration also reported that a significant proportion of IDPs in the first year belonged to minority groups in Iraq and moved towards the KRI (IOM, 2018).

Movements in 2015 were shaped by attempts to combat ISIL in Diyala, Mosul and Tikrit. The capture of Ramadi as capital of Anbar governorate by IS in the beginning of April alone caused the displacement of over half a million Iraqis. The fall of Ramadi, as the most significant city to fall to IS since Mosul, shifted the focus of the Iraqi armed forces away from retaking the north and back to Anbar governorate. Displacement also occured due to the advances of Peshmerga forces in the south of Kirkuk that caused around 60,000 new IDPs. This shows that some areas in Iraq experienced considerable high numbers of displacement although 2015 was the first year in which returns to deliberated areas were possible. At the end of 2015, 66% of all IDPs were settled in the north–central region of Iraq. 29% sought refuge in Iraqi Kurdistan due to the perceived stability of the region. Only 5% of IDPs moved to southern governorates (IOM, 2018).

In 2016, overall IDP numbers started to decrease due to the retaking of areas in Anbar . The major event causing new displacement in this year was the Mosul offensive by the government to retake the city. The campaign displaced around 300,000 Iraqis along the Mosul corridor, which constitutes about 15% of all IDPs in Iraq. In consequence, a high number of displaced individuals fled to Tikrit, Salah al-Din and Kirkuk. Furthermore, the Mosul offensive notably increased the share of IDPs in the population of Ninewa. Overall, the highest concentration of IDPs remained in the central and northern governorates (66%) but nearly a third of all IDPs were hosted in Iraqi Kurdistan. The Shia-majority governorates in the south remained comparably unaffected.

In 2017 and 2018, IDP numbers further decreased. Extensive new displacement occurred in Ninewa because of the government's efforts to retake the areas around Mosul. The handover of disputed areas from the Kurdish Peshmerga to the Iraqi Armed Forces also temporarily rose displacement figures in the end of October 2017. In total, however, return movements reduced the amount of displacement throughout Iraq. Return movements have been faster for families that return to areas where they belong to the ethno-religious majority. For Turkmen, Yazidis, Christians, and Shabak Shias, return has been much slower as they seem to fear the changes in the ethno-religious composition of their places of origin (IOM, 2018)

Table 2: Main periods of displacement during the Iraqi civil war according to IOM (2018)

Time period	*Displacement patterns*
January to May 2014	Displacement occurs in Anbar where fighting between ISIL and the government started. IDPs mostly move within Anbar or into Baghdad, Salah al-Din or Iraqi Kurdistan.
June to July 2014	Fighting spreads to Mosul and IDPs start fleeing from Ninewa and Salah al-Din to Kirkuk and Baghdad. Secondary displacement occurs. Turkmen minorities are forced to flee.
August 2014	Worst month of new displacement with around 740,000 new IDPs due to ISIL violence in Sinjar. IDPs, in particular Yazidis, flee to Dahuk and Ninewa. Erbil and Kerbala also experience an increase in IDPs.
September 2014 to March 2015	First net decrease in displaced populations due to the recapturing of territory by the state. Returns towards Diyala, Salah al-Din and Ninewa.
April 2015 to February 2016	Fall of Ramadi to IS increases outflow of IDPs from Anbar; movement towards Baghdad. Intra-governorate displacement in Kirkuk because of advancing Peshmerga forces.
March to mid-October 2016	Decrease in IDPs in Anbar, Baghdad, and Diyala. Displacement rises in Erbil, Kirkuk, Ninewa and Salah al-Din.
Mid-October 2016 to July 2017	Miliatry operations to retake Mosul city causes large-scale new displacement. Increase of IDPs in Mosul corridor despite general increase in returns in other areas.
July to December 2017	Returns outnumber IDP numbers due to the retaking of Mosul and Telefar. Returns are encouraged through policy programs.
December 2017 to December 2018	Increase in returns but protracted displacement remains pressing issue on humanitarian agenda.

Main drivers of displacement decisions

Main drivers of displacement decisions were the progression of fighting between IS, the government, Shia militias and Kurdish troops. Because most IDPs aimed to stay close to their home to monitor return possibilities, IDP numbers were particularly high in the governorates Anbar and Ninewa that have been heavily affected by fighting. Hoping for secure locations, IDPs moved to areas that were at least more stable than their habitual residence. Less important seemed the presence of formal camps that provide assistance to IDPs. 71% of IDPs in Iraq lived outside of formal camps (OCHA, 2019; IOM, 2018). In particular within the KRI and Ninewa, few IDPs could seek shelter in protected camps.

As already indicated, the population movements during the Iraqi civil war also followed clear sectarian patterns. Once displaced, IDPs in the civil war against the Islamic State overwhelmingly chose to move to areas where they would be part of the majority ethno-religious group, given that these areas also provided safety. Breaking down the population movements during the conflict by ethno-religious groups shows that the initial sectarian settlement patterns in Iraq became more consolidated over time. Sunni Arabs moved further north or into Kurdish territories. Shia moved towards the south, reinforcing Shia dominance in these areas. This overall movement pattern reversed the resettlement policies of Saddam Hussein's Arabisation strategy in which many Shia were transplanted into northern provinces (Thibos, 2014). However, this movement pattern also implies that Arab Sunni IDPs fleeing the rule of IS found themselves increasingly in Kurdish-held territory and had to come to terms with Kurdish authorities (Siddiqui, Guiu and Ameen Shwan, 2019). Minorities, in particular Christians and Yazidis, have gone to Kirkuk and Iraqi Kurdistan. The existence of these ethno-religious flight patterns resembles the previous three waves of displacement in Iraq. Forced displacement in Iraq's past and in its presence is characterised by the unmixing of people (Chatty and Mansour, 2011, 53).

A.3 Dynamics of violence against civilians

During the Iraqi civil war, civilians have suffered from widespread violence by all conflict actors. Many of these incidents of civilian casualties and war crimes can be traced back to underlying sectarian motives and strategic considerations. The Islamic State as most extreme case has used violence against civilians to exert control and instil fear. According to the UCDP Geo-referenced event dataset, IS has committed 96% of the events of one-sided violence against civilians between 2014 to 2018.[1] The armed group has strategically expelled religious minorities and Shia Muslims from their territories. The brutal expulsion of Yazidis from Sinjar, in which at least 2,000 individuals were executed and thousands abducted, is only one example for a strategy that aimed to create Sunni enclaves. Furthermore, the IS has also displaced civilians directly into zones of active fighting to shield their own jihadist fighters (Amnesty International, 2018). They executed opponents, recruited child soldiers, raped women and tortured civilians. In addition, suicide bombings in predominantly Shia Muslim areas have deliberately targeted civilians even after the civil war (EASO, 2019).

The Iraqi government has also used violence against civilians in the course of the displacement crisis. In the west Mosul campaign, the Iraqi security forces have launched a series of disproportionate attacks that killed many civilians (Amnesty International, 2018). There have also been incidents where government forces have been involved in collective punishments, unlawful killings, torture, and pre-trial detention. Amnesty International reports that thousands of men and boys were separated from their families by the government, the PMF, or Kurdish forces after fleeing IS-held territory. Many of these individuals were extra-judicially executed or they forcibly disappeared because of their origin from certain areas or neighbourhoods, their family relation to IS fighters, or for having had non-combat roles in the Islamic State (Amnesty International, 2018). The aligned Shia militias of the PMF were accused of committing serious human rights abuses and war crimes against Sunni civilian men in Baghdad and across Iraq (EASO, 2019).

Another sectarian strategy employed by conflict parties was to hinder access to their territories for incoming IDPs of other ethno-religious groups. In some government-controlled areas, such as in Baghdad, Sunni Arabs faced problems moving into Shia areas (Cordesman, 2017, 27). In Iraqi Kurdistan, IDPs required sponsorship or a specific ethno-religious profile to enter the region. Kurds, female-headed households, and women were exempted from the sponsorship requirement, but many other societal groups - in particular Sunni Arabs - were hindered in their access to the relatively stable region (DIS, 2016, 12-18).

Humanitarian actors also reported instances of deportation and violence against Arabs in the disputed areas of Iraq and within the KRI. Arabs that were accused of being IS members were arrested and camps raided to deport them out of the Kurdish areas (DIS, 2016). On 9 October 2016, Kurdish authorities in Kirkuk evicted between 3,000 and 4,000 residents of Qara Tapa village. Additionally, Peshmerga forces and Kurdish security actors have targeted political and societal opposition in their controlled territories, including attacks against human rights advocates, journalists and protesting civil servants (EASO, 2019, 22).

Even after the official end of the conflict, violence against civilians occurred and population movements remained politicized. Humanitarian agencies reported that many militias as well as the government retaliate against Sunni Arabs with perceived affiliation to IS (OCHA, 2019; IOM, 2018; Amnesty International, 2018). Conflict actors remain present in camps and informal settlements, blocking certain IDPs from obtaining civil documents and restricting their freedom of movement. They also enter and search IDP areas to arbitrarily arrest individuals (OCHA, 2019). In addition, humanitarian actors have criticised the government for forced and premature returns such as in August 2018 when the Baghdad Operations Command evicted 45 IDP families of Al Jamea'a camp on short notice (UNHCR, 2018).

[1] Data accessed on 19/06/2019.

B Data collection on armed actors' reactions to IDPs in Iraq

To focus not only on general one-sided violence against ordinary citizens in Iraq but also on specific targeted attacks against IDPs, I collected an original dataset on armed actors' reactions to IDPs in Iraq from April 2014 to December 2017. The dataset contains 713 fine-grained geo-located reactions of armed actors to displaced populations and the unit of analysis is the individual non-violent or violent reaction. The data records who reacted to displaced population, whether this armed actor was the territorial ruler or challenger, whether a specific displaced group was targeted, whether the interaction occurred in a camp setting, how many displaced persons were affected and where the event took place. Although the results in the main paper only use the violent subset of recorded reactions, the dataset can be used to answer questions such as "where did the Iraqi conflict parties harm fleeing civilians?" or "which armed actor was the most welcoming towards displaced populations in Iraq?" on different spatially and temporally aggregated levels.

B.1 Motivation for this data collection

For sub-national research on violence against civilians and conflict dynamics more broadly, it is common to use event-based datasets such as ACLED or UCDP-GED. However, those datasets come with certain caveats, such as imprecise geographical locations and media-reported bias. The following three main reasons motivated this data collection. First, this dataset concentrates on the question when armed actors induce displacement, how they respond to already moving populations in the conflict zone and how they end displacement. This focus on populations moving during civil wars narrows down the dependent variable (violence against civilians) to those individuals and groups moving during a conflict. Second, UCDP-GED focuses on violence against civilians that lead to at least one fatality. Similar to other data collections, such as ACLED, this data collection focuses on fatal and non-fatal interactions to expand the scope. Third, the UCDP-GED is heavily biased towards violence against the Islamic State. The underlying news sources for the UCDP-GED data are pre-dominantly from Western media that had a heightened interest in hearing about Islamic State atrocities. Of course, the Islamic State is the main perpetrator of one-sided violence in this period in Iraq. Nevertheless, the International Community has pointed out that Shia militia, the Iraqi government, and the Kurdish Peshmerga have all been more or less involved in human rights violations against civilians. Those instances, however, are not reflected in the UCDP-GED data and my data collection covers more variation in actors.

B.2 Data collection strategy

I manually code news-reported events or events mentioned in humanitarian reports in which armed actors engage with IDPs in Iraq. The full list of sources is:

- ACLED (only events with the specific target group IDPs/refugees)
- LexisNexis with search term Iraq AND displace OR flee OR refugee OR IDP OR fled
- Human Rights Watch: 5 reports and 255 press releases
- Amnesty International: 792 research, news and commentaries
- Office of the High Commissioner for Human Rights + UN Assistance Mission for Iraq: 11 reports on the protection of civilians in Iraq / Reports on Human Rights in Iraq
- UN OCHA: 68 Press releases/ 34 Humanitarian Bulletins/Situation Reports
- UNHCR: 69 protection updates
- CCCM Camp management files

The resulting dataset is a daily dataset from April 2014 to December 2017. The unit of analysis is the interaction/reaction level. That means, a certain event (a certain news article) can include multiple interactions between armed actors and displaced populations. I exclude reactions by international actors (e.g. humanitarians) from the data collection. My events are also restricted to events in Iraq and I omit events happening outside of the border of Iraq (for example in Syria). The data collection also excludes Improvised Explosive Devices that explode when fleeing civilians trap on them unless the underlying report makes clear that the devices were set up explicitly to target fleeing civilians. I also exclude the punishment of former ISIL members or army members that fled from the dataset as they should not be considered as IDPs/civilians.

B.3 Codebook and variables

The table below provides the full codebook and variables in the dataset.

Variable name	Content	Type
EVENT_ID	An ID identifying each event	string
INTERACTION_ID	An ID identifying a unique interaction per event	string
EVENT_DATE	The date the interaction has taken place	Date dd/mm/yyy
YEAR	The year of the interaction	integer
TIME_PRECISION	How precise the information about the date is: 1 = exact date is known; 2 = week or 2-6 day range is known; 3 = only month or two-weeks range is known	integer
EVENT_TYPE	Type of the interaction: Acceptance, Assistance/Governance, Attack, Confinement/Detainment, Denial, Evacuation, Expulsion, Harassment, Movement management, Abandonment/non-governance, Punishment, Recruitment, Screening, Strategic hiding, Human shields	string(15)
ACTOR1	The name of the armed actor reacting to IDPs (unified across dataset)	string
ACTOR2	The displaced population group: IDPs, IDPs/Refugees, Refugees	string(3)
ACTOR1_STATUS	The status of actor 1 regarding territorial rule: Ruler, Challenger. If an allied armed actor is in territorial control, this is coded as ruler	string(2)
TAKEOVER	A binary indicator whether interaction happened during a territorial takeover (1) or not (0)	integer
CONTROL	The name of the armed actor in territorial control	string
CONTROL_CODE	The level of territorial control: 1 = Territory has just been taken over/is contested; 2 = Territory has recently been taken over; 3 = Territory is in control; 4 = Territorial ruler struggles to hold control	integer

Variable name	Content	Type
CONTROL_BEFORE	The territorial ruler before the interaction has taken place (i.e. relevant if during territorial takeovers). Same as CONTROL if no change is taking place	string
VIOLENT_BIN	A binary indicator whether interaction is violent (1) or not (0)	integer
SENTIMENT	An indicator whether the interaction is welcoming to displaced populations (1), neutral (0), or not welcoming (-1)	integer
MOVE_STATUS	An indication of the movement status of IDPs: At entry, At exit, In territory, En route	string(4)
TARGET_GROUP	A description of the movement pattern of civilians: Civilians trying to flee, Civilians forced to flee, Fleeing civilians, Displaced civilians, Civilians trying to return, Civilians forced to return, Returned civilians	string(7)
TARGET_SUBGROUP	An indicator which ethno-religious subgroup of the displaced population was targeted	string
TARGET_APPROXIMATED	A binary indicator whether the information about TARGET_SUBGROUP was inferred from outside sources/based on origin patterns (1) or was contained in the original source (0)	integer
ORIGIN	The origin location (unsystematic) of the IDP population	string
ORIGIN_APPROXIMATED	A binary indicator whether the information about ORIGIN was inferred from outside sources/based on subgroup patterns (1) or was contained in the original source (0)	integer
QUOTE	A quote from the original source for illustration	string
DESCRIPTION	The description of the interaction	string
CAMP_INVOLVED	A binary indicator whether the interaction took place in or near a camp (1) or not (0)	integer
IDP_FAMILIES	The number of IDP families affected by the interaction. If IDP numbers but not family numbers are given, the figure is divided by 5	numeric
IDP_NUMBERS	The number of IDPs affected by the interaction. If only the IDP family number is known, this is multiplied by 5	numeric
FATALITIES_IDP	The number of IDPs dying in the interaction	numeric
IDP_APPROXIMATED	A binary indicator whether the information about IDP numbers and deaths affected was inferred from other sources (1) or was contained in the original source (0)	integer
SCALE	A qualitative indicator whether media attention for this interaction was HIGH, MIDDLE or LOW	string(3)

Variable name	Content	Type
DISPUTED_TERRITORY	A categorical indicator whether the area is part of the "Disputed Territory", under "Iraq federal control", or part of the "Kurdistan Region of Iraq"	string(3)
GID_ID	The PRIO-grid cell id (gid) in which the interaction took place	integer
ADMIN1	Name of the first order administrative division where the interaction took place	string
ADMIN2	Name of the second order administrative division where the interaction took place	string
ADMIN3	Name of the third order administrative division where the interaction took place	string
LOCATION	Name of the location where the interaction took place or the description of the geographical location	string
LATITUDE	Latitude (in decimal degrees)	numeric
LONGITUDE	Longitude (in decimal degrees)	numeric
GEO_PRECISION	The precision with which the coordinates and location assigned to the interaction relfect the actual interaction location: 1 = exact location of event is known at least at the neighbourhood/village level; 2 = interaction location is known on the sub-district level (point in biggest town/sub-district center); 3 = interaction location is known on the district or governorate level only (point in district/governorate capital)	integer
SOURCE	Name of the source for the interaction (e.g. news agency)	string
SOURCE_SCALE	Indicator if the source is international, regional, national or subnational	string
ACCESS_SOURCE	Name of the service through which source was accessed	string
ID_SOURCE	Additional information on the source such as the precise link to access the source, the unique identifier for the underlying dataset	string

B.4 Descriptive statistics and data visualisations

This section gives a brief overview of the variables in the final dataset by visualising key trends. Figure **??** provides the number of weekly and monthly interactions coded in the data over time, with clear peaks around key events of the Iraqi civil war, such as the Mosul offensive by the government to retake the city from the Islamic State. Figure **??** outlines how many data entries were coded for each reaction category. The figure also provides an overview of the sentiment of reactions to IDPs. For the main paper, only armed actors' reactions to IDPs that were distinctively negative (i.e. violent) were used.

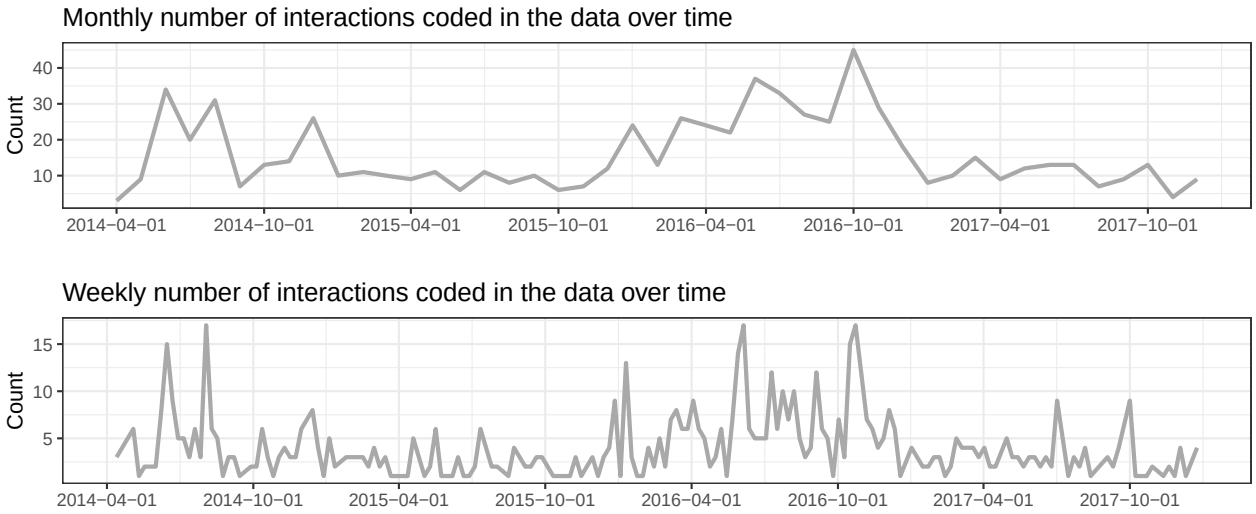

Figure 2: Monthly and weekly number of interaction with IDPs over time

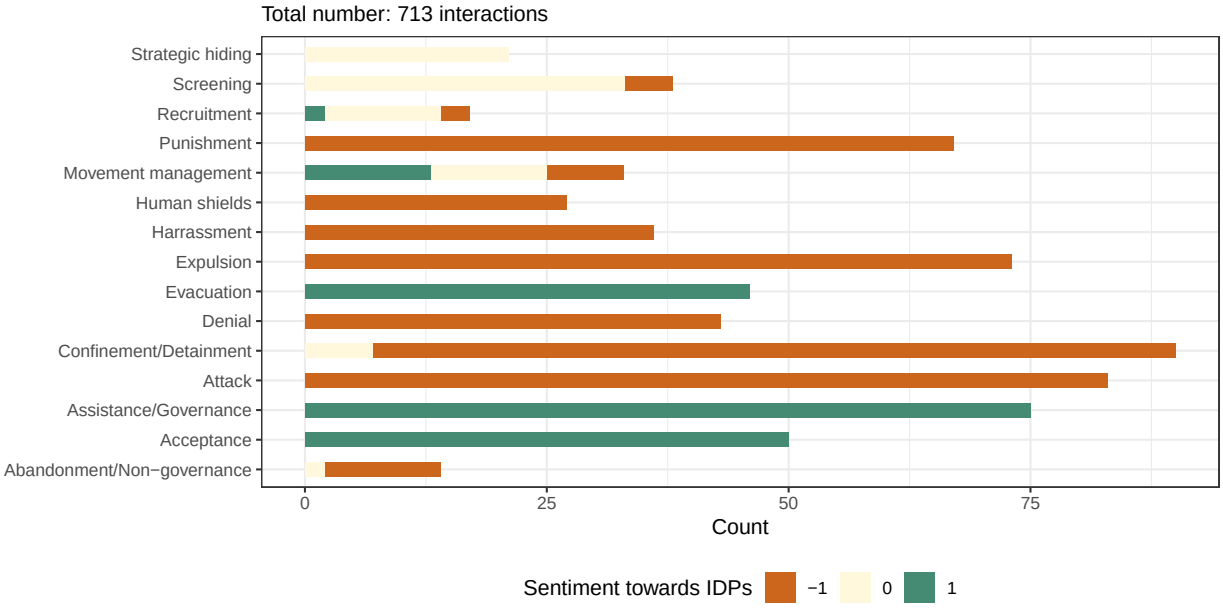

Figure 3: Distribution of armed actor-IDP interactions by type of interaction and sentiment towards IDPs. Only reactions with negative sentiment were used in the main paper

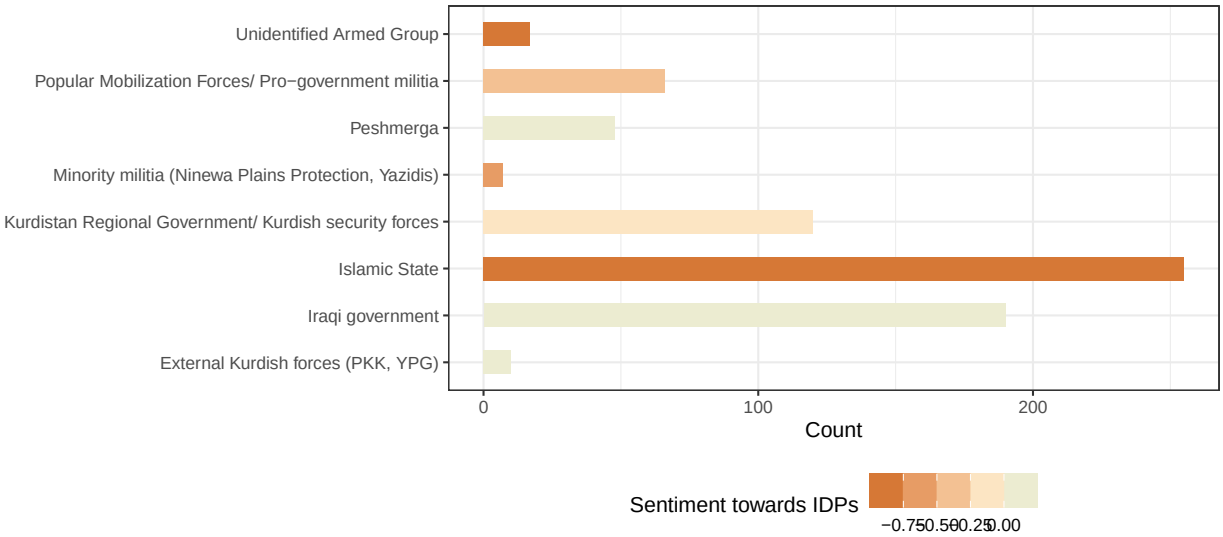

Figure 4: Distribution of armed actor in the data collection as well as their proportion of interactions with IDPs and their average sentiment towards IDPs

C Measuring territorial control in Iraq

As described in the main body of the paper, I have hand-coded maps of territorial control in Iraq on the PRIO-GRID level for the observational period if available. In a second step, I have used this data to train a machine learning algorithm that classifies the zones of control for the remaining time periods where no map data was published. This section provides the technical details for this measurement strategy.

C.1 Manual coding of maps

Various news sources have published maps on territorial control in Iraq. Most notably, the Institute for the Study of War (ISW) has published maps of Iraq on a regular basis. Other sources are the BBC, NYT, or Al Jazeera. I could identify maps for about 54.4% of my time period. Table 4 provides an overview of the map sources and time coverage. To code the data, I first manually geo-referenced the maps in ArcGIS, mapping the picture to the projection I use for the PRIO GRID shapefile (crs= 4326). Then, I have coded the actor that solely controls a grid cell or the actor that holds the biggest proportion of the grid cell. I distinguished between the Islamic State, the Iraqi government, the Kurdish Peshmerga, Shia militias, and unpopulated/uncontrolled territory.

C.2 Machine Learning approach

For the remaining months, in which I could not collect map data, I trained a classifier that predicts the categorical variable *control*. The features used for this classification task are listed in Table 5. All features were turned into dummies and numeric variables. I have also scaled all variables by substracting the mean and dividing by the standard deviation. To assess the performance of classifying zones of control, I have randomly selected 10 months of the hand-coded data as test set. The remaining 19 months are used to train 7 different machine learning algorithms and to tune parameters by means of 10-fold repeated cross-validation. Table 6 allows to compare the classification accuracy across the different machine learning approaches when parameters were tuned. Bagging performed best in predicting territorial control in the held-back test data

Table 4: Sources for hand-coded map data

Time period	Source	Link
Jul-14	ISW	http://www.understandingwar.org/backgrounder/control-terrain-iraq-july-13-2014
Aug-14	Der Spiegel	https://www.spiegel.de/politik/deutschland/waffenlieferungen-fuer-irak-bundesregierung-gibt-gruenes-licht-a-987124.html
Sep-14	ISW	http://www.understandingwar.org/backgrounder/control-terrain-iraq-september-17-2014
Oct-14	ISW	http://www.understandingwar.org/backgrounder/control-terrain-iraq-october-5-2014
Nov-14	ISW	http://www.understandingwar.org/backgrounder/control-terrain-iraq-november-20-2014
Dec-14	ISW	http://www.understandingwar.org/backgrounder/control-terrain-iraq-december-19-2014
Jan-15	BBC	https://www.bbc.co.uk/news/world-middle-east-45547595
Feb-15	ISW	http://www.understandingwar.org/backgrounder/control-terrain-iraq-february-2-2015
Mar-15	ISW	http://www.understandingwar.org/backgrounder/control-terrain-iraq-march-12-2015
Apr-15	ISW	http://www.understandingwar.org/backgrounder/control-terrain-iraq-april-3-2015
May-15	ISW	http://www.understandingwar.org/backgrounder/control-terrain-iraq-may-18-2015-0
Jul-15	ISW	http://www.understandingwar.org/backgrounder/control-terrain-iraq-july-20-2015
Sep-15	ISW	http://www.understandingwar.org/map/control-terrain-iraq-september-11-2015
Oct-15	ISW	http://www.understandingwar.org/map/iraq-control-terrain-map-october-30-2015
Nov-15	ISW	http://www.understandingwar.org/backgrounder/iraq-control-terrain-map-november-25-2015
Feb-16	ISW	http://www.understandingwar.org/backgrounder/iraq-control-terrain-map-february-9-2016
Apr-16	ISW	http://www.understandingwar.org/backgrounder/iraq-control-terrain-map-april-21-2016
May-16	ISW	http://www.understandingwar.org/backgrounder/iraq-control-terrain-map-may-23-2016
Jul-16	ISW	http://www.understandingwar.org/backgrounder/iraq-control-terrain-july-14-2016
Aug-16	ISW	http://www.understandingwar.org/backgrounder/iraq-control-terrain-map-august-25-2016
Oct-16	ISW	http://www.understandingwar.org/backgrounder/iraq-control-terrain-october-7-2016
Dec-16	ISW	http://www.understandingwar.org/backgrounder/iraq-control-terrain-december-15-2016
Mar-17	ISW	http://www.understandingwar.org/backgrounder/iraq-control-terrain-map-march-9-2017
May-17	ISW	http://www.understandingwar.org/backgrounder/isis-sanctuary-may-10-2017
Jul-17	BBC	https://www.bbc.co.uk/news/world-middle-east-45547595
Nov-17	Wilson Center	https://www.wilsoncenter.org/article/isis-after-the-caliphate-0
Mar-18	BBC	https://www.bbc.co.uk/news/world-middle-east-27838034
Oct-18	Al Jazeera	https://www.aljazeera.com/indepth/interactive/2016/08/iraq-war-map-controls-160830115440480.html
Dec-18	EASO	https://www.easo.europa.eu/sites/default/files/publications/EASO-COI-Report-Iraq-Security-situation.pdf

with an overall accuracy of 94.689 %. Bagging, as special case of a random forest when all features are used to split the tree, performed better than Naive Bayes, K-nearest neighbour, Linear Discriminant Analysis, Random trees, Random forests and Support Vector Machines and was therefore chosen as final algorithm to classify Iraqi zones of territorial control. The confusion matrix for bagging with 20 features is displayed in Table 7. Figure 5 plots the relative importance of each variable in the classification task. Substantially, this classification accuracy means that bagging classified 111 of 2090 grid-cells in the test data wrong (or on average 11.1 grid cells per month). I then retrained the bagging algorithm for the full set of hand-coded data and classified the unknown months. Figure 6 displays how many grid cells were held by which armed actor in the full dataset after classifying the data with bagging.

Table 5: Machine learning features to classify zones of control in Iraq

Feature name	*Feature*
IDP families	Number of IDP families per grid-cell
Battles all	Number of battles
Battles dum	Dummy if battle took place
Border	Dummy if border region
Camp distance	Distance to nearest formal IDP camp
Mountains mean	Average area covered by mountains
Traveltime mean	Average travel time to nearest urban center
Distance capital	Distance to Bagdad
Nightlights	Average night-time lights emissions
Population	Total population as of 2010
Precipitation	Total amount of precipitation
Settlements	Number of settlements
Road distance	Distance to nearest major road
Ethnic group	Dummy variables for largest ethnic group: Sunni, Shia, Kurds
Group prop	Proportion of grid-cell occupied by largest ethnic group
Longitude	
Latitude	
Date	

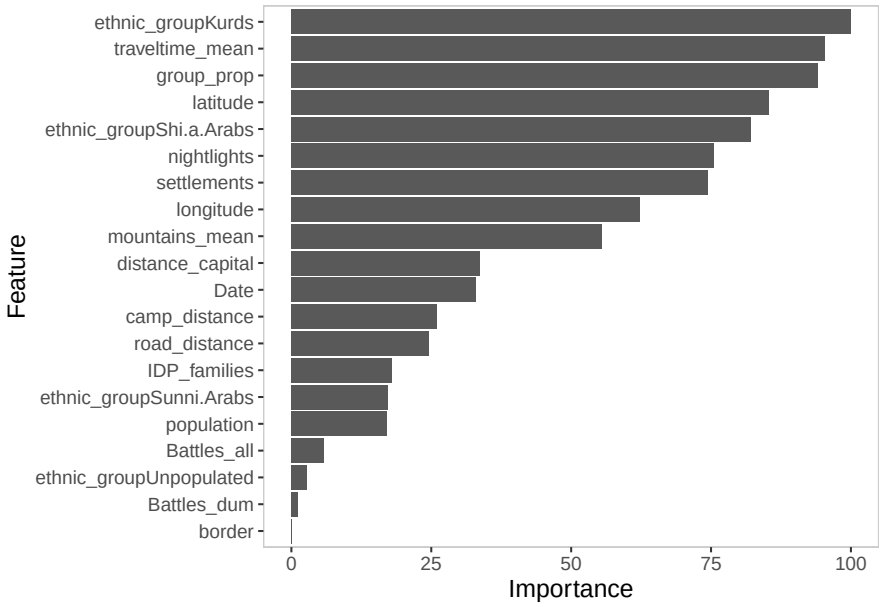

Figure 5: Importance of features in bagging

Table 6: Classification accuracy for held-back test set

Accuracy	Bayes	KNN	LDA	tree	bag	forest	svm
Iraqi government	65.135	93.661	78.922	95.087	96.197	96.038	95.880
Islamic State	51.799	66.187	28.777	48.201	70.504	69.784	63.309
Kurdish Peshmerga	94.595	94.595	94.865	95.135	95.135	95.405	87.568
Shia militia	33.858	85.827	61.417	85.827	96.063	91.339	91.339
Uncontrolled/ Unpopulated	92.710	96.112	84.933	96.719	97.205	97.327	96.841
Overall	78.421	92.488	79.713	92.057	94.689	94.402	92.344

Table 7: Confusion matrix for Bagging (on held-back test set)

	Iraqi government	Islamic State	Kurdish Peshmerga	Shia militia	Uncontrolled/ Unpopulated
Iraqi government	96.197	1.268	0.000	0.000	2.536
Islamic State	12.230	70.504	2.158	0.000	15.108
Kurdish Peshmerga	2.432	2.432	95.135	0.000	0.000
Shia militia	0.000	0.000	0.000	96.063	3.937
Uncontrolled/ Unpopulated	1.094	1.337	0.243	0.122	97.205

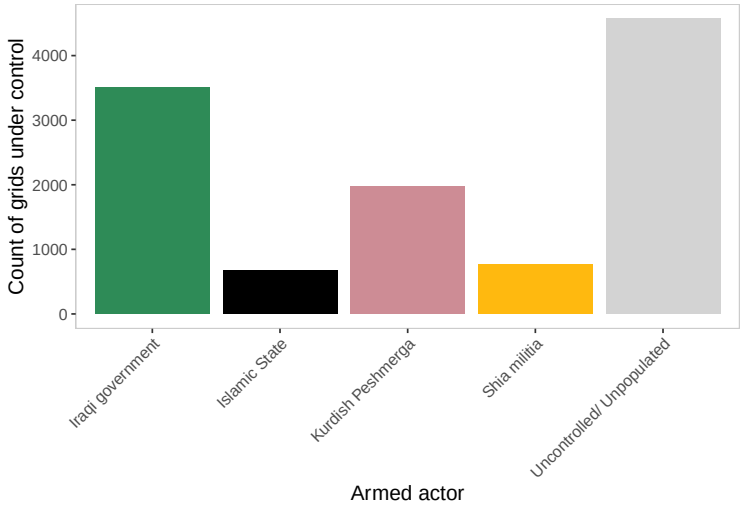

Figure 6: Distribution of control in overall data

D Imputation of ethno-religious IDP patterns in Iraq

This section summarises the imputation steps to obtain grid-cell level proportions of ethno-religious groups in the Iraqi IDP population. The IOM-DTM conducted three data collection rounds to record the ethnicity and religious identification of IDPs. On average, the IOM-DTM team assessed about 90.88% of the IDP shelters in each assessment round.[2] To impute values over the whole time period and for all IDP locations, I used the following procedure:

First, I linearly interpolated the proportions of each ethno-religious group in locations that have been assessed in at least two assessment rounds. Second, I carried values forward and backward for the time before August 2016 and after March 2018 (outside of the assessment rounds) for all locations that have been assessed at least once. After this linear interpolation, there remain locations that have not been assessed in any of the three rounds. In a third step, I therefore imputed the missing information on the proportion of ethno-religious groups within the local IDP population by using KNN imputation. Using the date, latitude, and longitude information, the KNN algorithm identifies the nearest neighbour to any location that has never been assessed and replaces the missing value with the nearest neighbour's ethnic composition. The number of neighbours k was set to 1 instead of using a weighted average over multiple neighbours because this value minimises the difference between imputed and actual proportions if data is held back (see details on validation below). Table 8 summarises the step-wise imputation.

[2]The ethno-religious composition of IDPs was recorded in 89.7% of the locations in assessment round 1 (August 2016), in 98.2% of the locations in round 2 (April 2017), and in 84.7% of the location in round 3 (March 2018).

Table 8: Steps to impute ethno-religious IDP patterns in Iraq

1. Linear interpolation between the three assessment rounds (if location is assessed at least twice)
2. Carry values backwards & forwards for time outside assessments that is before August 2016 and after March 2018 (if location is assessed at least once)
3. Imputation for non-assessed locations using KNN (k=1; features: date, latitude, longitude)

Figure 7 displays a map of the IDP locations in the last assessment round, visualising in color how often the ethno-relgious composition of a point location has been assessed. The size of the dots represents the mean number of IDP families in the recorded location.

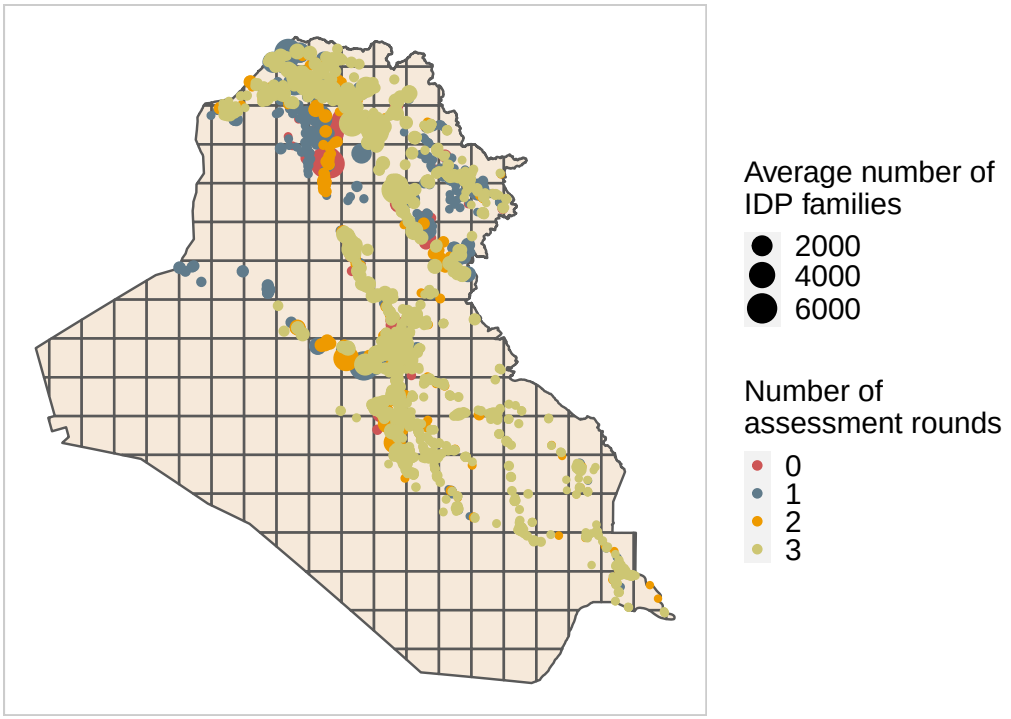

Figure 7: IDP locations and assessment rounds

To validate the number of neighbours k, I held back 300 existing data points on the ethno-religious composition of IDPs from the three IOM-DTM assessment rounds (3.15% of the existing ethno-religious data). I then imputed the values for a range of k (from 1 neighbour to 10 neighbours). The appropriate choice of the number of neighbours k is then the value that minimises the absolute difference between the actual and the imputed values. In this case, choosing k=1 minimises the imputation error for all ethno-religious groups. Figure 8 shows how k affects the imputation error for the different ethno-religious groups in the data and for the total IDP population, revealing that k=1 minimises the difference between observed and imputed values for this dataset.

Figure 9 displays a scatterplot of the actual and the imputed values of the held back test data. The graph also includes a linear regression line and the correlation between imputed and actual values, which is consistently high for the different ethno-religious groups.

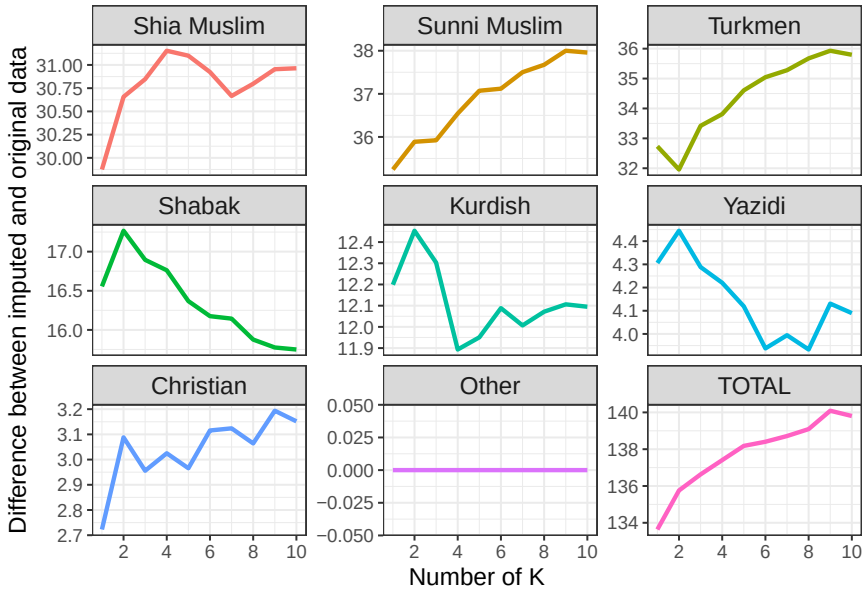

Figure 8: Validation of k with held-back data

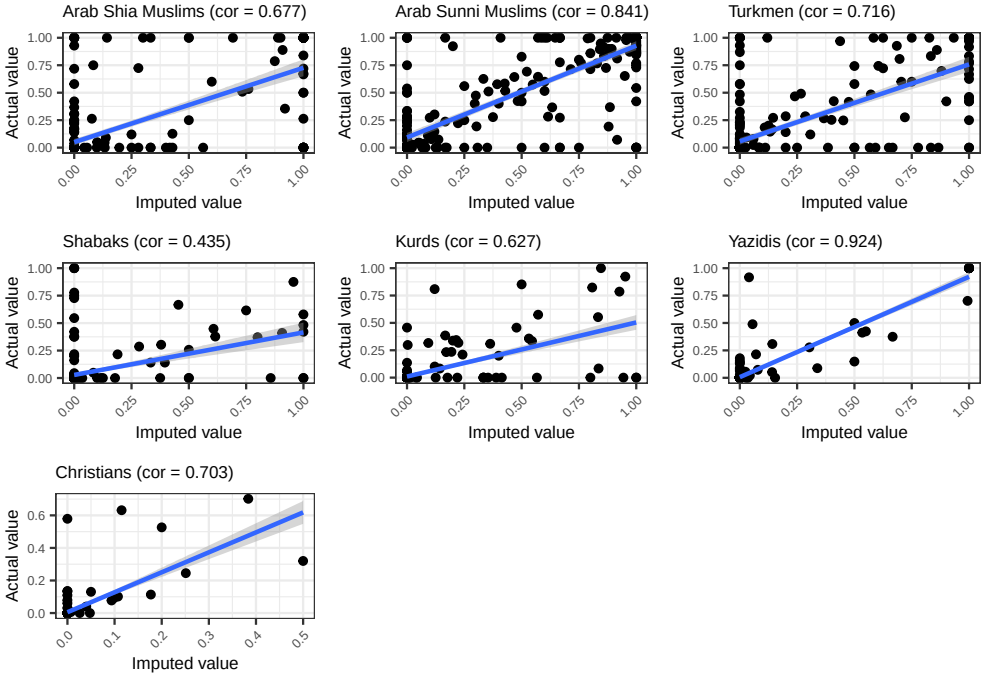

Figure 9: Imputation quality per ethnic group

E Summary statistics

Table 9: Summary statistics for numeric variables in the data

Variable	Mean	SD	Min	Max	Missing
Battles	0.000	1.000	-0.122	43.085	0
Border	0.388	0.487	0.000	1.000	0
Challenge one-sided violence (binary)	0.013	0.113	0.000	1.000	0
Challenger IDP victimization	0.006	0.095	0.000	3.000	2299
Challenger IDP victimization (binary)	0.005	0.071	0.000	1.000	2299
Challenger one-sided violence	0.029	0.405	0.000	20.000	0
Contestation	0.062	0.241	0.000	1.000	0
Distance to capital	0.000	1.000	-1.710	3.813	0
Formal camps	0.000	1.000	-0.161	13.534	0
IDP families	0.000	1.000	-0.295	12.715	0
IDP families (neighbourhood)	0.000	1.000	-0.529	6.793	0
IDP victimization	0.031	0.359	0.000	17.000	2299
IDP victimization (binary)	0.018	0.132	0.000	1.000	2299
Mountains	0.000	1.000	-0.425	2.877	0
Nightlights	0.000	1.000	-0.546	6.205	0
One-sided violence (binary)	0.018	0.133	0.000	1.000	0
One-sided violence (neighbourhood)	0.000	1.000	-0.224	15.481	0
One-sided violence (total)	0.041	0.489	0.000	20.000	0
Population	0.000	1.000	-0.457	10.680	0
Ruler IDP victimization	0.025	0.325	0.000	15.000	2299
Ruler IDP victimization (binary)	0.014	0.116	0.000	1.000	2299
Ruler one-sided violence	0.013	0.266	0.000	17.000	0
Ruler one-sided violence of ruler (binary)	0.005	0.073	0.000	1.000	0
Ruler support amongst IDPs	0.103	0.243	0.000	1.000	0
Travel time to capital	0.000	1.000	-1.320	3.586	0

F Risk of one-sided violence in displacement locations

For my main argument that rulers and challengers interact differently with displaced populations, I make the assumption that IDP destinations are indeed more prone to experiencing one-sided violence in comparison to areas that are no displacement destinations. To show that this is a plausible assumption, Figure 10 displays coefficient estimates for a regression analysis that estimates all one-sided violence (against all civilians and against IDPs) that occurred in the observational period depending on the amount of IDPs and my set of control variables. The results indicate that IDP numbers are positively associated with one-sided violence in a grid cell across model specifications. To get a better understanding of the substantial effect, Figure 11 plots the predicted counts of one-sided violence as a function of IDP numbers. The confidence intervals have been generated by using bootstrapping and predicting event counts for all IDP numbers available within the data with all other covariates set to their mean or median value.

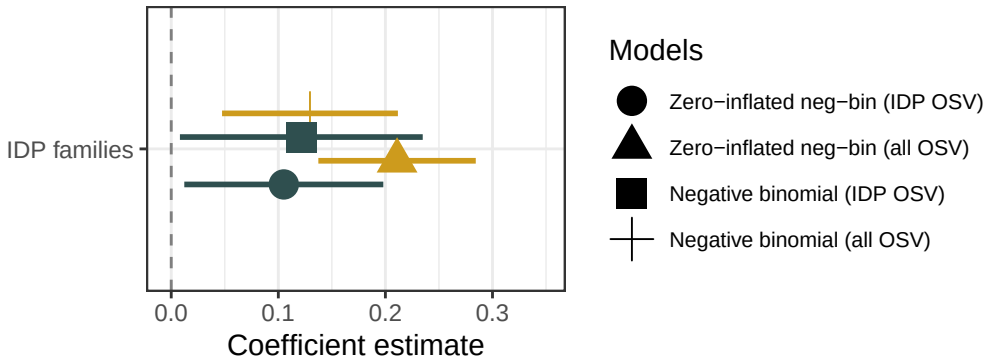

Figure 10: Coefficient plot for the total number of one-sided violence events (negative binominal count models and zero-inflated negative-binomial models for violence against all civilians (green) and against IDPs (yellow)

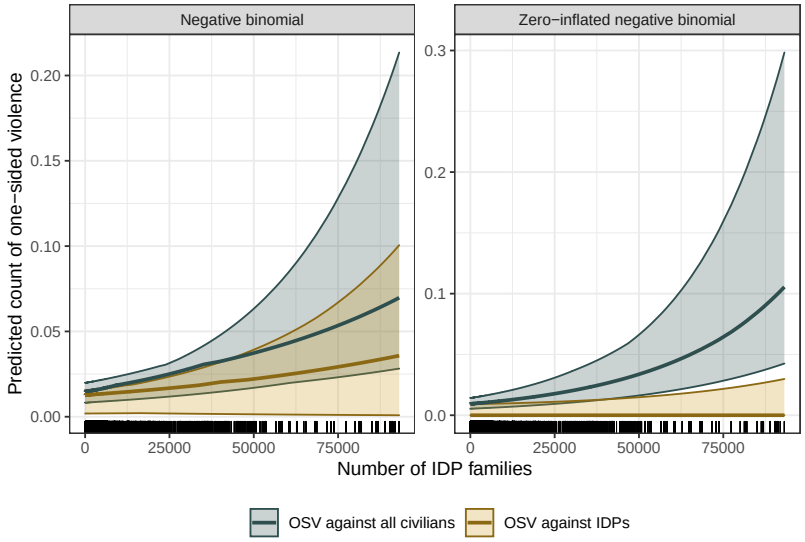

Figure 11: Predicted count of one-sided violence (all civilians and IDPs) as a function of the number of IDP families. Predictions are based on negative-binomial count models with and without zero-inflation. Confidence intervalls are generated by bootstrapping. All covariates are set to their mean or median value.

G Selection into displacement

This section discusses what factors predict high IDP numbers and high ruler support in the IDP population in my data. This is helpful to understand selection into "my treatment". For causal inference, IDP destinations are ideally random, i.e. IDPs do not strategically flee towards areas in which their "preferred" armed actor is in control. However, we know from previous research that this is not the case and IDPs do move towards areas that are inhabited by their co-ethnics and that are controlled by the actors they support. Table 10 shows that this is also the case for my data as IDPs are more likely to go to government-held areas than to areas held by the Islamic State, by the Peshmerga, or by Shia militia. The most dominant ethnic group living in a grid cell is also a significant predictor of higher IDP numbers: IDP numbers tend to be higher in Sunni and Kurdish areas. This is no surprise as these areas are the ones where the civil war took place. Previous battles, contestation and one-sided violence also explain higher/lower IDP numbers.

Table 10: Predictors of IDP numbers and patterns of ruler support (OLS regressions)

	Dependent variable:		
	IDP families	IDP ruler support	IDP families x ruler support
	(1)	(2)	(3)
Controlled by Government	0.069* (0.023)	0.049* (0.007)	−0.059* (0.006)
Controlled by IS	−0.161* (0.034)	0.353* (0.011)	0.131* (0.009)
Controlled by Peshmerga	−0.377* (0.045)	0.136* (0.014)	0.067* (0.012)
Controlled by Shia militia	−0.266* (0.039)	0.018 (0.012)	−0.021* (0.011)
Previously controlled by Government	0.014 (0.019)	0.081* (0.006)	−0.010 (0.005)
Previously controlled by IS	0.213* (0.034)	0.030* (0.010)	0.018* (0.009)
Previously controlled by Peshmerga	−0.039 (0.034)	−0.048* (0.010)	0.022* (0.009)
Previously controlled by Shia militia	−0.025 (0.037)	0.044* (0.012)	−0.025* (0.010)
Dominant ethnic group: Kurds	0.535* (0.045)	−0.007 (0.014)	−0.063* (0.012)
Dominant ethnic group: Shia	−0.195* (0.025)	0.086* (0.008)	0.001 (0.007)
Dominant ethnic group: Sunni	−0.025 (0.021)	0.005 (0.006)	−0.021* (0.006)
Battles	−0.007 (0.008)	0.001 (0.002)	0.006* (0.002)
Battles in previous month	−0.036* (0.008)	−0.008* (0.002)	−0.012* (0.002)
One-sided violence	0.264* (0.017)	−0.023* (0.005)	−0.019* (0.005)
One-sided violence in previous month	−0.135* (0.016)	−0.015* (0.005)	−0.015* (0.004)
Contested in this month	−0.059* (0.028)	−0.068* (0.009)	0.005 (0.008)
Contested in previous month	0.045 (0.028)	−0.004 (0.009)	0.018* (0.008)
Population	0.153* (0.008)	−0.004 (0.003)	−0.010* (0.002)
Terrain ruggedness	−0.050* (0.011)	0.015* (0.004)	−0.002 (0.003)
Nightlights	0.129* (0.008)	0.037* (0.003)	−0.001 (0.002)
Distance to capital	0.009 (0.008)	0.013* (0.003)	−0.003 (0.002)
Distance to road network	0.035* (0.010)	−0.013* (0.003)	0.005* (0.003)
Border	−0.053* (0.017)	−0.081* (0.005)	0.013* (0.005)
Formal camps	0.232* (0.007)	0.001 (0.002)	0.060* (0.002)
IDP families in neighbourhood	0.477* (0.009)	−0.026* (0.003)	0.042* (0.002)
One-sided violence in neighbourhood	−0.069* (0.008)	0.009* (0.003)	0.024* (0.002)
Constant	0.040* (0.019)	0.034* (0.006)	0.025* (0.005)
Observations	11,494	11,494	11,494
R^2	0.547	0.265	0.247
Adjusted R^2	0.546	0.263	0.246
Residual Std. Error (df = 11467)	0.674	0.208	0.181
F Statistic (df = 26; 11467)	533.332*	159.011*	144.837*

Note: Significance threshold: * $p < 0.05$

At the same time, however, several other factors that are not political in nature explain where IDPs seek shelter in Iraq: IDPs tend to go to more populated areas with less mountainous terrain, they tend to go to areas with a better economy (approximated by nightlights) and that are closer to roads and camps. All of these factors also explain the levels of ruler support we can find in my data (see models 2 and 3). These

Table 11: Variation explained by strategic and non-strategic predictors (Adjusted R square)

	Strategic	Non-strategic
IDP families	0.456	0.361
IDP ruler support	0.233	0.107
IDP families x ruler support	0.182	0.136

models should be interpreted with hesitation as I cannot distinguish between *incoming* and already *existing* IDPs in a given grid cell: I have no way to distinguish if IDPs are attracted to an area, have been displaced within this grid cell, or are trying to leave this particular area.

Overall, the selection into my treatment - into displacement - is driven by a mix of strategic and non-strategic incentives. I ran linear regressions to predict IDP numbers, ruler support, and the interaction of it. I did this once for all endogenous factors of a conflict (i.e. for territorial control, ethnic settlement patterns, battles, one-sided violence) that could be related to strategic self-selection and for exogenous factors (i.e. population, nightlights, terrain, distance to capital, road distance) that appear non-strategic predictors. I then compare the adjusted R-square to see which models explain more variation (see Table 11). Overall, the strategic factors seem to explain more variation for IDP numbers and IDP support for the ruler but both factors seem relevant. While this does not allow me a clear causal identification, this mixture of factor driving IDP flows and ruler support can be analyzed descriptively.

After all, the majority of IDPs in my data do not support the local ruler (10.29%) and do not seem to make a strategic choice into which territory they go. This is because the nature of forced displacement allows fleeing civilians only limited space to choose their preferred destination. For example, if fighting in Anbar breaks out, most Iraqi IDPs can only move westwards because the Syrian border and the desert in the South do not allow for other directions. As a result of this, Sunnis from Anbar must move into territory controlled by Kurdish, Shia, and minority forces. This is a common scenario in my data.

H Robustness checks

This section provides additional robustness checks. I demonstrate that neither potential outliers (Figure 12) or certain control variables (Figure 13) strongly distort my findings. In Table 12 I also assess if lagging my main independent variables affects the results. Nevertheless, uncertainty around my estimates is high and this study only provides associational evidence. Given the structure of my data - with many time-invariant covariates, uncertainty around territorial control, and imputed proportions of ethno-religious groups in the IDP population, it seems crucial to revisit the theoretical argument when more fine-grained data on IDP characteristics and territorial control become available.

H.1 Fixed and random effects models

The control variables in the main models reported in the paper do not fully account for heterogeneity across grid cells. Some grid cells are unlikely to see one-sided violence and others are more likely to be contested, such as the grid cells containing Anbar region, Mosul or Baghdad. Using either fixed or random effects could account for this heterogeneity. Table 13 reports fixed and random effects linear regressions for the count of OSV by rulers (1+2) and by challengers (3+4). Models 5 and 6 display the results when I focus on one-sided violence against IDPs committed by the ruler. The models 7 and 8 focus on challenger violence against IDPs.

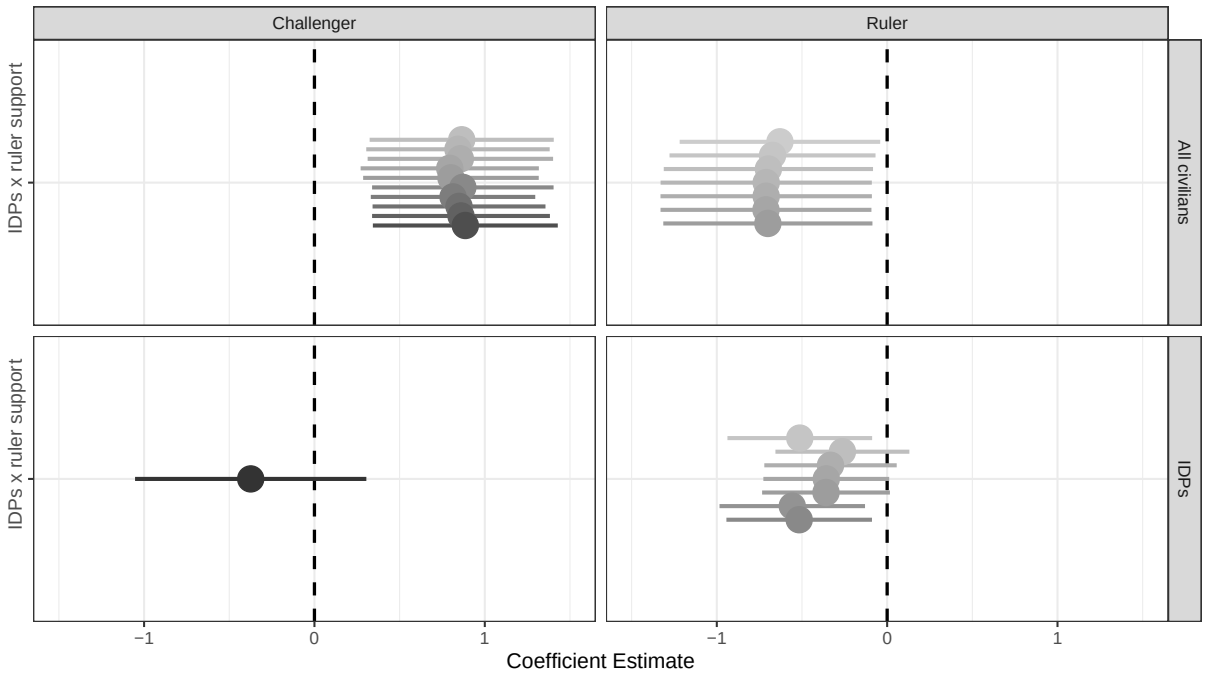

Figure 12: Outlier analysis: Coefficient estimate for the interaction between IDP families and ruler support for negative binomial regressions. The darker the color of the point estimate, the more outlier counts have been replaced by the count of one.

Table 12: Zero-inflated negative binomial regressions with lagged independent variables (IDP families and IDP ruler support).

	Ruler OSV	Ruler IDP-OSV	Challenger OSV	Challenger IDP-OSV
	(1)	(2)	(3)	(4)
IDP families x ruler support	−0.371*	0.084	0.415*	0.261
	(0.122)	(0.154)	(0.175)	(0.216)
Number of IDP families	0.004	0.154*	0.204*	0.041
	(0.097)	(0.071)	(0.039)	(0.078)
IDP support for ruler	0.486	−0.739	−2.392*	−0.241
	(0.431)	(0.459)	(0.702)	(0.837)
Controls ?	Yes	Yes	Yes	Yes
Observations	11,286	8,987	11,286	8,987
Log Likelihood	−219.149	−540.945	−572.082	−230.447

Note: Significance threshold: * p < 0.05

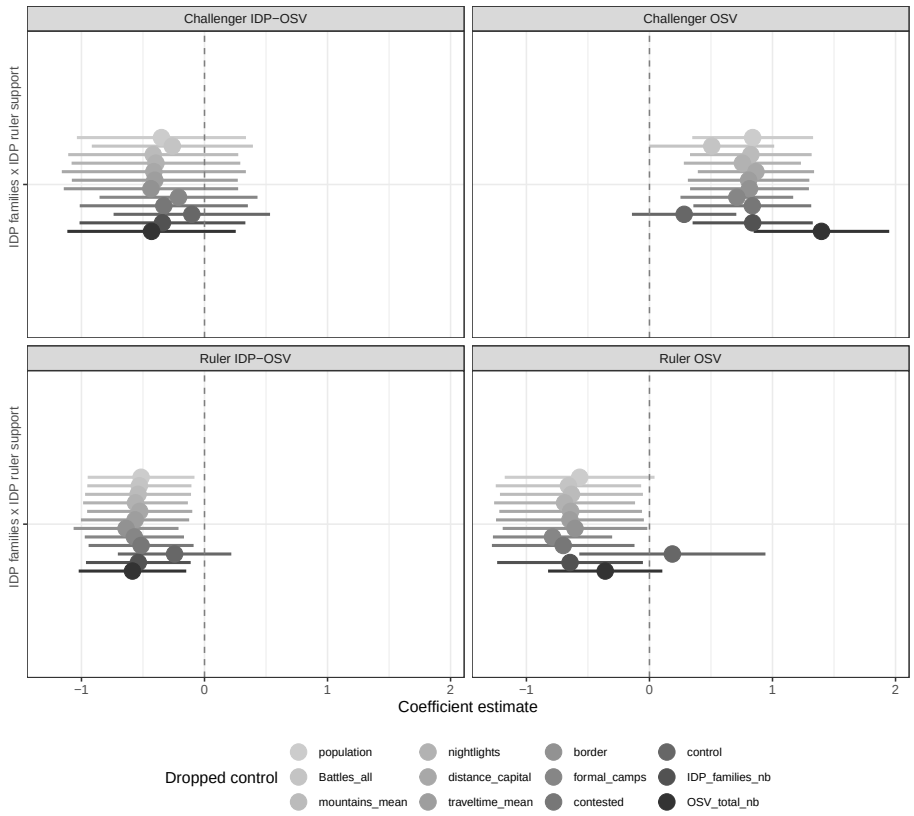

Figure 13: Coefficient plot for negative binomial count models that drop one of the covariates in each iteration. Models for violence against all civilians and against IDPs by ruler and challernger are displayed.

Table 13: Fixed and random effects linear regressions for the count of OSV by rulers and by challengers).

	Ruler OSV		Challenger OSV		Ruler IDP-OSV		Challenger IDP-OSV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IDP families x ruler support	0.014	−0.012	−0.110	−0.114	0.049*	0.025	0.004	−0.001
	(0.035)	(0.035)	(0.097)	(0.095)	(0.024)	(0.025)	(0.011)	(0.014)
Number of IDP families	−0.064*	−0.028*	0.060*	0.075*	0.008	0.011	0.005	0.004
	(0.031)	(0.011)	(0.027)	(0.029)	(0.027)	(0.017)	(0.008)	(0.004)
IDP support for ruler	−0.041	−0.032	−0.014	−0.022	0.028	0.004	0.004	−0.001
	(0.045)	(0.035)	(0.021)	(0.017)	(0.063)	(0.029)	(0.010)	(0.004)
Controls ?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model ?	Fixed	Random	Fixed	Random	Fixed	Random	Fixed	Random
Note:							Significance threshold: * p < 0.05	

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