Conflicts:
the consequences on Agriculture
Evidence from Syrian Civil War

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Abstract

We investigate the shock suffered by the primary sector in Syria, following the outbreak of the civil war in March 2011. We incorporate remote sensing dataset with machine learning (ML) to surmount the data unavailability in weak government such as Syria to evaluate the agricultural shock when the armed conflict is still under process. We split our analysis locally and at larger area. Using Staggered Difference-in-Differences (SDID) at patch level (local), we find temporary negative war effects on agricultural activities for zones directly affected by the combats, valid only in the short run (5 years). We also note anticipation effects in the form of preventive migration flows. We then adopt a *patch-donuts* strategy to quantify the spillovers in the territories indirectly affected. The externalities are persistently negative, thereby we recommend policymakers to aid both the locality receiving directly the conflict but also the adjacency. We are unable to quantify the maximal spillover effect of conflict due to our insufficient construction. Lastly, at sub-district level we run Two-Way Fixed Effects and IV (using distance to closest city as instrument) to gauge the impact embedding local equilibrium effects. There is suggestive evidence of the conflict-related damages to agriculture, especially when the Syrian State is involved in threatening military operations.

1 Introduction

Throughout the human history conflicts have evolved in multiple perspectives (technology, strategy, motivation), yet the consequential burden imposed on local communities has not changed. Demographic change (Acemoglu, Hassan, & Robinson, 2011; Boehnke & Gay, 2022), behavioral reshaping (Chiovelli, Michalopoulos, & Papaioannou, 2018; Lin, 2022), soil contamination (Mager, D., Richard, Tracy, & Carrie, 2003; Parya, Mert, Ryeol, & Ferhat, 2020; Samuelson, Awaworyi, Russell, & Trong-Anh, 2021) are just few of the most notable war-related aftermaths. Conflicts never have winners, only survivors. "Winners" occupy a territory which has lost vast socioeconomic potential and usually needs long time to start recovering, due to huge losses in human capital (deaths and displacement) and physical capital. Post-war reconstruction takes long to complete, and, unlike buildings, land regeneration is a more natural proceeding which is difficult to accelerate. Studying the devastating repercussions on agricultural productivity is paramount in emerging and underdeveloped economies, which have less "reconstruction potential" and strongly found their GDP and domestic employment on the primary sector.

Contemporary armed conflicts are more likely than the past to directly undermine land suitability and generate profound damages because of the use of intense and advanced technology. The literature analysing the war effects on soil (a detailed review is provided by (Parya et al., 2020)) underlines not only land degradation but also the subtle consequences of chemicals. This has been often found in history, such as Vietnam (Samuelson et al., 2021), Cambodia (Lin, 2022) and Laos (Riaño & Caicedo, 2024), where bombings (and unexploded mines) did affect economic development in a variety of ways. This link war-soil has always been very strict in the human history. Scorched-earth tactics are the most straightforward examples, wherein the factions at war use crop destruction as a means to hurt the enemy (Westing, 1981). First narratives date back to the 6th century BC where Herodotus described the Scythians and their military strategy[1]. Since then, scorched-earth tactics were used recursively over time by many different armies: the Hubsburg monarchy and the Tudor in the 15th century (Pálffy, 2008; Murphy, 2021), during the American Civil War (Barker, 2013), WWII (Hunt, 2014) and Gulf War (Sadiq & McCain, 2012). More notable instances are related to Russia, who adopted it during the Napoleonic wars, to counteract Nazis' operation Barbarossa during WWII and lately against Ukraine.

The Syrian civil conflict is another very recent episode which connects war to capital destruction, in particular, for agriculture. Also here scorched-earth policy has been implemented: ethnographic evidence reports intentional burning of farmland by the Islamic State after losing its territories (H. Jaafar, Sujud, & Woertz, 2022). Besides these direct effects on soil, thousands of people have been killed and millions have fled their homes in search of safety, leaving behind millions of other citizens experiencing deep food insecurity. While the context is still unclear at the time of writing, following the fall of the Assad Regime in the end of 2024, one can imagine the scale of the warfare-related agricultural shock. As of 2017, (Food and Agriculture

[1]Source: War History Online

Organization of the United Nations, 2023) estimates $15 billion financial losses in the primary sector, which are enormous considering the country's wealth and the central importance of farming in eventual economic recovery.

Despite widespread agreement on how devastating the Syrian civil war has been, there is limited work evaluating precisely the agricultural losses induced by each type of armed conflict. The main concern of researchers for this topic lies in data unavailability and potential measurement errors. Due to the ongoing combats and the weakness of the central administration, information is missing or hardly accessible. When it is, unreliability is a potential problem. Nevertheless, the emerging remote-sensing techniques make it feasible to surmount the obstacle. With the help of high-resolution satellite imagery and machine learning, we construct a panel dataset capturing the evolution of Syria since 2000, incorporating information on land, environment, demography, geography, socioeconomic outcomes and incidences of armed conflict. Additionally, to rationalize the analysis proposed, we discuss a standard Cobb-Douglas production function which models the relevant variables for the study. Besides capital (physical and labour), we decompose Total Factor Productivity and focus on state transitions, on biological and ecological determinants of land fertility, on demand covariates.

We begin by examining our treatment as a binary absorbing indicator at patch-level (a 2.1km$\times$2.1km square), that is, whether a given patch in a specific year has been directly subject to the civil conflict. By using the dynamic model of Staggered DiD (SDID) devised by (de Chaisemartin, D'Haultfœuille, & Knau, 2024), we study the time-varying war effect on alternative outcomes of socioeconomic development: Normalized Difference Vegetation Index (NDVI), whether a plot is being cultivated (called *productivity classification* for simplicity), population density and nighttime light density. This estimation gauges the direct consequences of the combats within each patch. While luminosity appears to be "immune" and actually has positive coefficients towards the end, the other variables drop significantly after the outbreak of the civil conflict in 2011. NDVI shows in particular a monotonically decreasing trend throughout the entire period, suggesting severe environmental damages produced by the combats. On the other hand, population and productivity classification start at a certain period (circa 5 years after the onset of the conflict) to recover and revert back to 0 in later periods. This result is consistent with the post-conflict recovery literature, delving into the economic rebounds of directly war-affected areas. Furthermore, we present the war effect by category of armed conflict: we re-run the SDID specification varying separately the definition of the treatment variable as indicators of (i) state-based violence, (ii) non-state violence, (iii) one-sided violence. The findings confirm that the great majority of the results is driven by state-based conflict, given the insignificance of the other two types.

Subsequently, we estimate the war indirect effects using a *patch-donuts* method. We remove the patch being directly treated and considers only the adjacent neighborhood, constructing (i) thin, and (ii) thick donuts. The former take only the outermost patches into account within a square of size 5×5 or 7×7. Hence, the study on thin donuts quantifies the maximal distance of conflict externality. Due to the maximal radius

restriction, we are unable to classify such a range. On the other hand, thick donuts consider all patches in the square apart from the central one. This approach computes instead the impact of the treatment on the whole surrounding area. As it concerns, we observe contradictory results as opposed to the direct-effect conclusions. Except luminosity (again, the relative effects are either statistically insignificant or slightly positive towards the final periods), the remaining outcomes – productivity classification, NDVI and population density[2] – are monotonically decreasing, with no sign of recovery. We argue that the armed conflict emits severe negative externality to its neighborhood while little attention being paid to the recover in adjacent area. This distinction between temporary direct effects and persistent indirect spillovers is aligned with the literature and highlights the need for tailored post-war economic policies: while war-torn regions may require reconstruction assistance, neighboring centres often necessitate long-term economic stabilization measures to mitigate economic and market shocks.
The *patch-donuts* approach enables the estimation of highly localized spillover effects, though it requires careful calibration of the spillover radius. That said, the influence of conflict often extends well beyond the spatial boundaries typically defined by these squares. We conclude the empirical strategy collapsing the dataset at *nahya* level, the third administrative layer of Syria, to capture wider equilibrium effects. The treatment variable is then continuous, measuring the number of armed-conflict incidences reported in a given sub-district and year. By using panel regressions with Two-Way Fixed Effects clustering at war zone level, we obtain suggestive evidence of the decline in productivity classification. For example, all together, the conflict incidences recorded in year 2019 caused a loss corresponding to -4.96 percentage points; vice versa, in the same year the fall is by 18.88 percentage points when we use number of civilians' deaths as measure. In accordance with the previous findings, state-based violence reports the most significant coefficients (statistically and economically speaking). Finally, we attempt an Instrumental Variable estimation to factor out any endogeneity caused by omitted variables. We use Post-Double selection LASSO to select the instruments more "objectively". We adopt only distance to closest major city: the results are valid only when clustering at war zone level. Consequently, we provide a further robustness check by partialling out the treatment from 5 chosen "LASSO covariates" and regressing the outcome on the residual variance (plus additional controls); the results are aligned with IV and outline the large shock suffered by the Syrian agriculture during the decade of warfare.

The paper is structured as follows. In Section 2 we briefly describe the context. Section 3 presents a conceptual model for food production. Section 4 describes the data and the remote-sensing technique used for gathering information. It delves into the major challenge of this article: data unavailability. In Section 5, we define the two methodologies adopted and present the corresponding results: SDID at patch level (Subsection 5.1) and Two-Way Fixed Effects at sub-district level (Subsection 5.2). To tackle potential endogeneity and omitted variable bias, we also provide an Instrumental Variable estimation and a partialling-out

[2]The war absolute effect on population density is steadily increasing in post-treatment periods. It begins to little revert only at the last two/three periods under investigation, which however should be taken with a pinch of salt given the limited number of switchers. The exact moment wherein recovery commences depends slightly on the size of the thick donut.

approach. Finally, Section 6 concludes with arguments on the implications of our findings.

1.1 Literature Contributions

We contribute to the literature linking conflict to agricultural destruction (Harvey, 1986; Brassley, Segers, & Van Molle, 2012; Yusufi, 2019) and more broadly to the environmental consequences of warfare (Jha, 2014), by focusing on Syria — a highly affected but under-researched case. While the recent war in Ukraine has dominated scholarly attention (Rexhepi, 2023; Hulich, Kharchenko, & Yemchenko, 2024; Cherevko, 2024; Nan et al., 2024), Syria has received far less causal treatment, despite the scale of its devastation. The few existing studies on Syria primarily rely on satellite monitoring of land use, vegetation, and displacement (H. H. Jaafar, Zurayk, King, Ahmad, & Al-Outa, 2015; Hazem, 2018; Abeed et al., 2021; Daiyoub, Gelabert, Saura-Mas, & Vega-Garcia, 2023), but they remain largely descriptive. This paper advances the literature by providing a causal identification strategy, leveraging a rich panel of remote-sensing and conflict data to estimate the time-varying and spatially heterogeneous effects of war on agricultural productivity and population dynamics.

The most closely related empirical article is (Xi-Ya et al., 2022), who document spatial variation in cropland degradation across Syria using fixed-effects regressions. Our paper uses remote-sensing techniques and offers a dynamic model (Staggered DiD) that uncovers temporal recovery patterns in directly affected zones, as well as persistent negative spillovers in surrounding areas — a distinction previously unexplored. By doing so, it complements prior work in other conflict zones like Rwanda (Verpoorten, 2009) and Uganda (Fiala, 2009), which emphasize long-term agricultural losses, and it reinforces the insight that war impacts extend well beyond immediate destruction.

Crucially, our paper distinguishes between types of conflict (`state-based, non-state, and one-sided violence`), discovering that only state-based violence yields significant consequences on agriculture and population. This nuance deepens the findings of studies like (Dube & Vargas, 2013), denoting that different forms of violence have varying economic effects. Moreover, by documenting potential mechanisms (such as displacement, land degradation, and loss of market access) while acknowledging the limitations of remote-sensing in identifying channels, this work sits at the intersection of descriptive monitoring and structural explanation, offering both broad empirical reach and a grounded discussion of underlying processes. In sum, our research not only fills a geographic and methodological literature gap by investigating Syria, but also adds causal precision to a largely observational field. It strengthens the connection between war and environmental-economic damage while highlighting the importance of disaggregating conflict types and considering indirect spatial effects. These insights are complementary to existing studies, pushing the literature forward in terms of both empirical depth and policy relevance.

2 Story of the Civil War in Syria

The Syrian civil war began in March 2011 as part of the broader Arab Spring movement, which saw widespread episodes of disapproval across the Middle East against authoritarian regimes. The conflict initiated with peaceful protests demanding political reforms under the regime of President Bashar al-Assad. However, following a brutal crackdown by the government on protesters, the situation escalated into a full-scale civil war, involving multiple factions and foreign powers.

Between 2012 and 2020, the war saw a large array of belligerents fighting over Syria. The Syrian Arab Armed Forces represented the Assad government and were supported by domestic forces and foreign allies such as Iran, Russia and Lebanese Hezbollah. The opposition forces included the Syrian National Army (SNA), Free Syrian militias and the militant coalition Hay'at Tahrir al-Sham (HTS). Alongside those, in the north-eastern regions a major role has been played by the Autonomous Administration of North and East Syria (AANES), made of the Syrian Democratic Forces (SDF) and the Kurdish People's Defense Units (YPG). Jihadist Organizations were also present with Al-Qaeda and Islamic State fighting in the east of the country until 2015. The conflict is therefore geopolitically complex: Figure 9 provides an overview of the different parties engaged in the combats, whether directly or indirectly.

By the end of 2020, the Syrian civil war was the second deadliest 21st-century conflict, only behind the Congo War (Encyclopaedia Britannica, 2020), with continuous human rights violations (Barnard, Hubbard, & Fisher, 2017). As of March 2024, the (Syrian Observatory for Human Rights, 2024) (SOHR) estimates that between 500,000 and 618,000 people have been killed and more than 12 million Syrians have been displaced, either internally or outside of the country, creating one of the largest refugee crises in modern history. However, the international community began holding good expectations about the future of Syria, as the war entered a phase of slower pace (described as a *stalemate* by scholars) since late 2020 with diminishing mortality rates. This situation was accurately summarized in 2023 by Vice President of the United States Institute of Peace's Middle East and North Africa Center (Mona, 2023):

> *Twelve years into Syria's devastating civil war, the conflict appears to have settled into a frozen state. Although roughly 30% of the country is controlled by opposition forces, heavy fighting has largely ceased and there is a growing regional trending toward normalizing relations with the regime of Bashar al-Assad. Over the last decade, the conflict erupted into one of the most complicated in the world, with a dizzying array of international and regional powers, opposition groups, proxies, local militias and extremist groups all playing a role. The Syrian population has been brutalized, with nearly a half a million killed, 12 million fleeing their homes to find safety elsewhere, and widespread poverty and hunger. Meanwhile, efforts to broker a political settlement have gone nowhere, leaving the Assad regime firmly in power.*

This apparent stability was totally reversed in 2024: the conflict escalated again and in November 2024 the rebel groups resumed offensives against territories held by the Assad government. In a matter of days, the rebels occupied Damascus on December 7th, overthrowing President Bachar-Al-Assad.

Farmers definitely went through a rough time and indeed thousands of them (among the 12 millions displaced) left their plots and rural areas, abandoning vast areas under cultivation. Combined with shortages of essential inputs, such as seeds or fertilizers, and with rampant poverty, the staying agricultural workers could not take advantage of larger areas (potentially) to cultivate and reduced market competition in order to increase their sales and productivity. Syria's infrastructure and economy made everything even more difficult, as a consequence of the war-related destruction. Besides the humanitarian crisis[3], estimates suggest a financial loss for the agricultural sector amounting to $15 billion because of limited production, damaged and destroyed assets and infrastructure (irrigation systems, storage facilities, and roads) (Food and Agriculture Organization of the United Nations, 2023)[4]. This is particularly true around the Euphrates Basin, which crosses the country from the south-east to the north, and is – alongside the west part of the country – the main suitable area for farming. To these material consequences, one should not forget the war effects on land by chemical contamination. As a consequence, Syrian productive capacity has fallen. Historically, the nation has relied on a strong agricultural economy, which prior to the war was self-sufficient and capable to export commodities such as cotton, fruits, and vegetables. The conflict disrupted significantly the dynamics of food imports and exports in the region. Syria has become critically dependent on food supplies and humanitarian aids. Therefore, the country's trade balance deteriorated, peaking in 2014[5], and the domestic situation got unpredictably insecure. A recent example comes from the decision of Russia to suspend supplies following the fall of Bashar al-Assad. Although the Ukrainian Agriculture Minister Vitaliy Koval has immediately responded and confirmed the intention to replace Russia in this role as Syria's supplier[6], these continuous fluctuations are detrimental.

2.1 Context

We provide an overview of the different administrative layers of Syria[7]. The nation is structured into 14 governorates, 65 districts, further divided in 272 *nahyas*, the smallest units. A visual representation for the whole country is shown in Figure 10, whereas Figure 1 zooms in and takes the example of Damascus.

The spatial pattern of pre-war wheat production across Syria's 272 nahyas, as illustrated in Figure 2b, strongly aligns with the rainfall-based agricultural stability zones depicted in Figure 2a. Specifically, high wheat yields are concentrated in the western and northwestern parts of the country, which correspond to

[3]7.6 million Syrians experienced food insecurity in 2023, as indicated by FaoSTAT, Syria: Country Profile; undernourishment has also risen from 5% before the war to more than 30% in 2021 (Cervantes-Godoy & Dewbre, 2010)

[4]This quantification holds up to year 2017, consequently it should be scaled up to include the subsequent periods.

[5]Source: Macrotrends, a nation-level database which shows information from the World Bank Development Indicators.

[6]Source

[7]`https://data.humdata.org/dataset/cod-ab-syr`

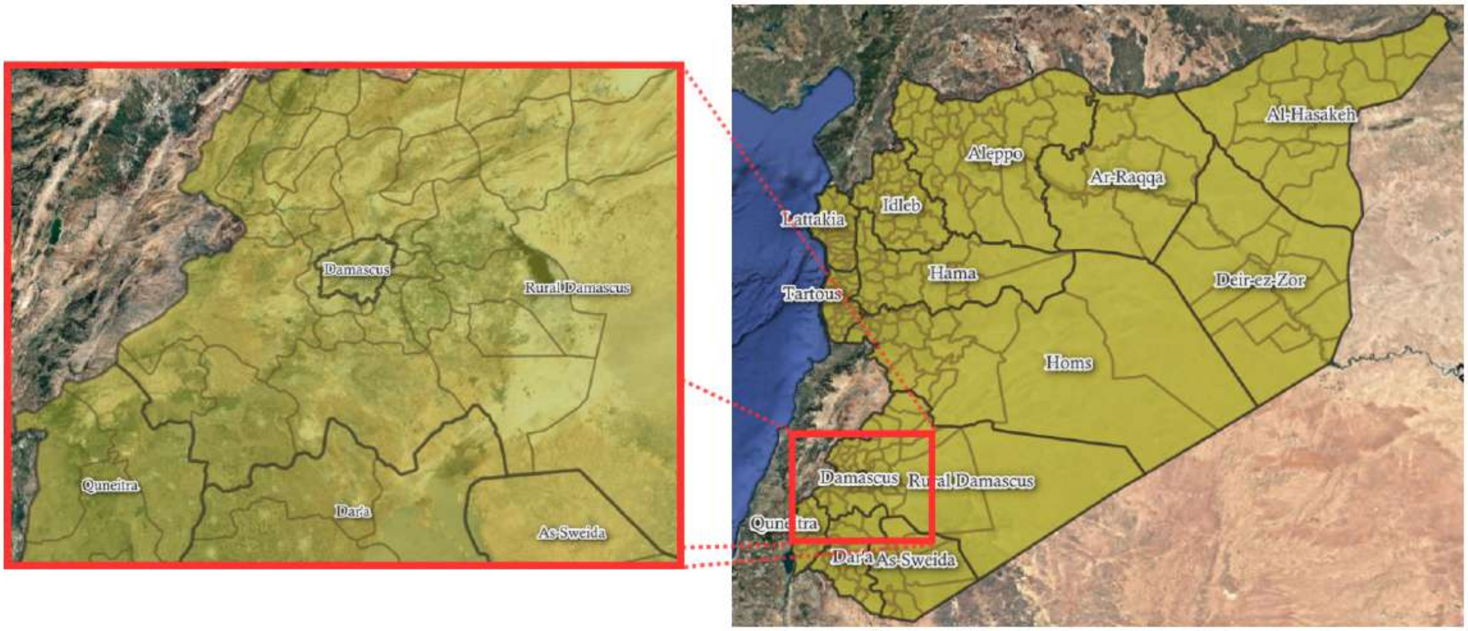
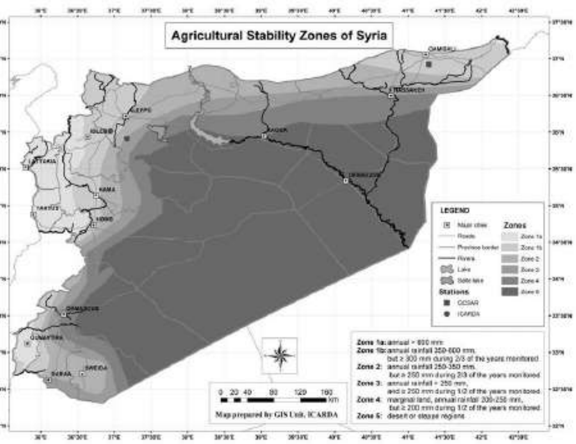


Figure 1: Administrative Levels - Example of Damascus

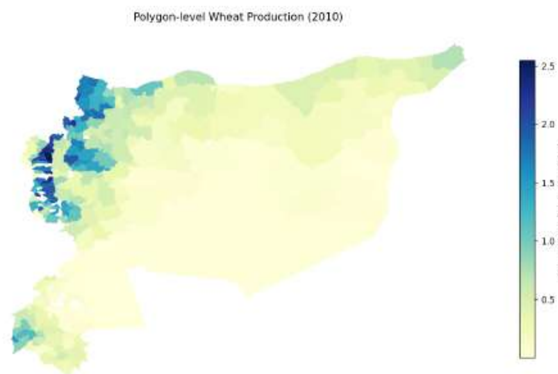
Zones 1 through 3 in the rainfall classification — areas characterized by greater and more reliable annual precipitation (Murdoch & Sandler, 2002). These zones are defined as agriculturally stable or moderately stable regions, making them suitable for cereal cultivation. In contrast, the eastern and southeastern nahyas, where rainfall is scarce and unpredictable (Zones 4 to 5), show markedly lower wheat productivity or no reported production at all. This overlap confirms the critical role of agro-ecological factors — especially rainfall stability — in shaping Syria's pre-war agricultural geography and supports the use of these areas as valid indicators of land suitability in subsequent empirical analysis. The main wheat production zone, while carrying more population and with better economic performance, receive more armed conflict treatment as described in Figure 4.

The time-series of the Syrian civil war is illustrated in Figure 3, which outlines the frequency of armed conflict events categorized into three distinct types: `state-based conflict` (blue), `non-state conflict` (green), and `one-sided violence` (red). The data, sourced from the Uppsala Conflict Data Program's (UCDP) Georeferenced Event Dataset (GED), highlights a stark increase in conflict intensity during the early years of the civil war, peaking around 2013-2014. The rapid escalation can be attributed to the intensification of battles between government forces, opposition factions, and extremist groups, coupled with increasing foreign interventions. Following this peak, the number of conflict events steadily declines, particularly for state-based violence, in alignment with the territorial gains made by the Assad government and its allies. Non-state conflicts, although fluctuating, remained at a significantly lower level. One-sided violence, represented in red in Figure 3, shows a relatively small but persistent presence throughout the period. By 2020, as the war transitioned into a frozen conflict with reduced large-scale battles, the total

Figure 2: Comparison of agricultural stability zones and wheat production in Syria



(a) Source: (Murdoch & Sandler, 2002). The map reports agricultural stability based on rainfall status in Syria. It splits Syria into 6 zones based on rainfall. Zone 5 is completely unsuitable for agricultural production.



(b) Data source from FAOGAEZ using actual production of wheat in 2010 at global scale. Production is measured in ton per hectare at *nahya* level.

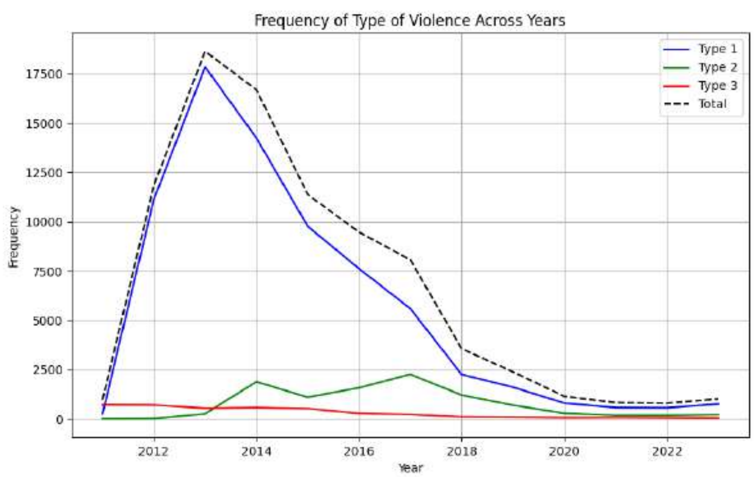


Figure 3: **Types and frequency of armed conflict in the Syrian civil war**. Figure constructed based on Uppsala Conflict Data Program's (UCDP) Georeferenced Event Dataset (GED). Type classification is based on the entry of "type of conflict". Type 1 is state based conflict, type 2 is non-state based conflict, and type 3 is one-sided conflict. The dataset covers the period from 1998 to 2023.

number of violent events decreased sharply. However, a minor resurgence in activity is visible in the following years, reflecting localized skirmishes, insurgent attacks, and sporadic clashes. Consequently, the area did initially experience fierce combats, and then saw the rise of a prolonged, lower-intensity struggle.

Figures 11 and 12 replicate Figure 3 from a geographic perspective, visualizing the spatial distribution of the three types of combats year by year. This complete gallery illustrates the shift from conventional warfare to localized insurgencies and power struggles, shaping the war's evolving landscape. The western and southwestern regions (Aleppo, Homs, Idlib, and Damascus) saw the highest concentration of state-based

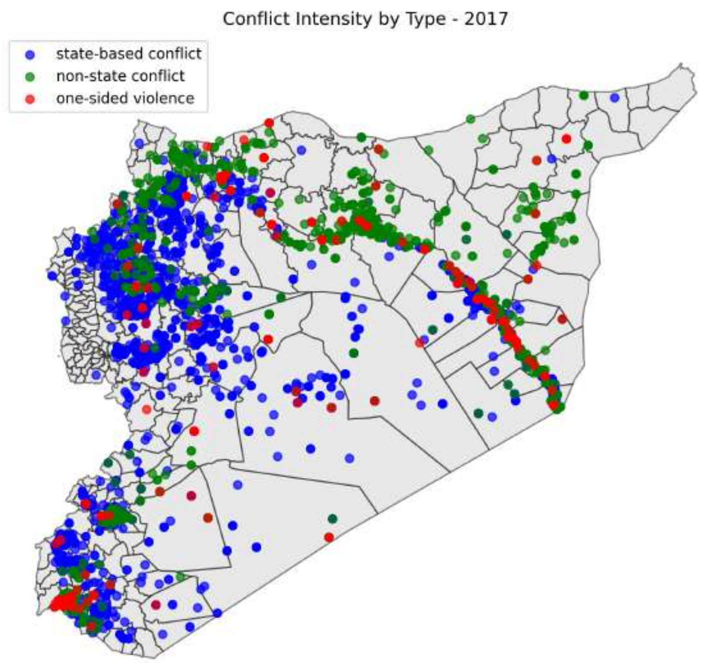


Figure 4: Conflict Map 2017. For the the full map representation, consult Figures 11 and 12. Point features are classified by the three types of conflict registered in Syria according to UCDP GED data. In blue we report state-based conflict; in green non-state conflict and in red one-sided violence. The base map is specified at nahya (sub-district) level.

conflict, reflecting major offensives between government and opposition forces. In contrast, non-state conflicts were more dispersed, particularly in northern and eastern Syria, highlighting battles between Kurdish forces, Islamic State, and other militias. One-sided violence, though less frequent, was scattered across the country, indicating targeted attacks against civilians. By 2017, fighting had become highly fragmented, with different factions controlling distinct areas. We take year 2017 as one example and report it separately in Figure 4.

One immediate implication of the spatial distribution of armed conflict is the emergence of systematic differences between nahyas that experienced conflict in 2011 (treated) and those that did not (control). To formally assess these differences, we perform a pairwise t-test comparing the mean values of key covariates at nahya level. The joint F-test confirms that they are collectively predictive of treatment status ($p < 0.01$), indicating that conflict did not occur randomly across space. For simplicity, we only report in Table 1 those variables found to be statistically unbalanced. From these results, we can derive that treated nahyas tend to be geographically closer to major urban centers like Damascus and Homs, show higher average wheat suitability scores, and exhibit higher baseline productivity in 2010. These regions are also more proximate to Egypt and are generally located further west, with slight but significant differences in ruggedness. These contextual differences underscore the need for careful attention to endogeneity concerns when estimating the causal effect of conflict on agricultural outcomes at the nahya level. Without appropriate corrections, such as instrumental variable techniques, estimates would likely conflate the effect of conflict with pre-existing

Table 1: **Balance Table**: Any conflict in 2011

	(0) Control		(1) Treated		(1)-(0) Pairwise t-test	
Variable (nahya-level)	N	Mean/(SE)	N	Mean/(SE)	N	P-value
Longitude	220	37.218 (0.106)	52	36.823 (0.130)	272	0.083*
Wheat suitability mean	220	2283.500 (131.893)	52	2967.261 (267.068)	272	0.024**
Ruggedness mean	219	0.000 (0.000)	52	0.000 (0.000)	271	0.056*
Distance to Egypt (centroid)	220	506.234 (11.593)	52	461.965 (17.777)	272	0.082*
Distance to Damascus (centroid)	220	228.674 (10.138)	52	186.670 (14.519)	272	0.058*
Distance to Homs (centroid)	220	172.573 (7.583)	52	133.502 (10.502)	272	0.018**
Distance nearest city (centroid)	220	41.776 (1.622)	52	31.546 (3.894)	272	0.008***
productivity mean 2010	220	0.118 (0.011)	52	0.161 (0.020)	272	0.071*
F-test of joint significance (P-value)						0.000***
F-test, number of observations						271

Significance: ***=.01, **=.05, *=.1. For the full set of covariates used, consult Table 9.
SE clustered at war-zone level.

geographic and agro-economic characteristics.

3 Theoretical framework: Food production

Although the main outcome of this research pertains to whether a plot is being cultivated or no more after 2011, we present a theoretical model about agricultural productivity which can be applied to the Syrian case. Indeed, understanding the capacity of this sector to feed the population has always been of utmost interest for economists. While we recognise the importance of weighting context-specific attributes, to our knowledge, there is a gap in the corresponding literature for Syrian agriculture. For this reason, we need to rely on generic theory and meta-analysis reviews, and we cross-verify the findings by means of country-specific publications. Almost all references vary in the parsimony of the structural model and in the choice of which parameters are estimated and which are imposed. A classical example is the one of state variables: institutions, trade, monetary policy and property rights have been the most selected. These variables (mostly macro) affect capital accumulation and productivity growth, as supported by the traditional Solow-Swan model (Durlauf & Quah, 1999; Durlauf, Johnson, & Temple, 2005). Therefore, this heterogeneity implies a greater difficulty of extrapolating the results and claim that they are equally valid for Syria. We attempt to alleviate this noise presenting the objectively principal factors behind agricultural productivity: we only use inputs considered *very significant* after accounting for diverse geographic location, model specification and crop. There exists the possibility of not fully reflecting the dynamics and specificity of this region. This concern is quite common in less developed countries: data about trade volumes and market prices miss or are unreliable, sometimes because of the weakness of the central government, sometimes because of the informality of the economy.

We outline the major parameters of the model, through which we specify the consequences on agricultural productivity of a big socioeconomic shock such as wars are.

3.1 Agricultural Production

We adopt a standard capital-accumulation Cobb-Douglas production function from (Solow, 1957), in which output is related to a set of inputs plus Total Factor Productivity (TFP). The latter measures technology (or efficiency) and represents the share of unexplained output variation after controlling for the other covariates. The model can be broadly generalized into:

$$Q = f(K, L, t)$$

The function is increasing and concave, satisfying Inada conditions. K denotes physical capital and is represented by equipments, livestock, fertilizers, manures, area under cultivation and tree stocks. L stands for labour capital and includes working hours, crop-management knowledge, as well as number of farmers cultivating the same plot. The empirical analysis cannot account for many of these elements because of unavailable household-level data. The problem of lack of reliably valid information is the biggest concern of this research (more on this in Subsection 4.1). Most importantly, t allows for technical change to affect agricultural capacity and its components are thoroughly disentangled below. Since the most prominent dependent variables in our empirical strategy refer to land potential for hosting farming activities, we pay attention to factors impacting on fertility and soil suitability. For clarity, this theoretical framework is uninterested in studying supply-side variations and their corresponding causes[8].

Technology A common assumption in much of the original literature was that of a homogeneous technology. In reality, producers face the practical problem of choosing which technology to employ jointly with inputs, so that technology is heterogeneous: it exists more than one function associated with the data (Mundlak, Butzer, & Larson, 2012). Understanding the role of TFP has long history given its impact on the overall level of production. Part of the literature attempts to express technology by human-capital mea-

[8] The following covariates, which the literature uses for explaining shocks to levels of agricultural supply, are not included in this model. Hence, we omit insurance and risk (Goodwin, 2001; Panda, Sharma, Ninan, & Patt, 2013; Ezdini, 2017); credit availability (Mohidul, 2020; Hardy, Charles, & Fernand, 2023; Food and Agriculture Organization of the United Nations, 2023); off-farm employment opportunities (Phimister & Roberts, 2006; Mezid & Hundie, 2014).

sures, such as average schooling. The basic idea is that higher levels of education are conducive to efficiency (Lockheed, Jamison, & Lau, 1980; Reimers & Klasen, 2011). However, results across traditional and modern research are inconsistent and we have insufficient evidence about the significance of farmers' schooling in improving agricultural performance[9].

Technical change in agriculture is not exogenous, but strongly influenced by state variables — the broader environmental, institutional, and infrastructural context in which producers operate. This aligns with the seminal insights from Marc Nerlove's dynamic supply response model (Nerlove, 1959)[10], which supports the idea of using a heterogeneous Cobb-Douglas production function that accounts for local adaptation to shocks (Mundlak et al., 2012). In our framework, the component t captures these state-dependent influences, including infrastructure, market incentives, trade access, and agro-ecological conditions. These elements collectively determine the productivity of land and modify both the baseline output level (intercept) and the marginal returns to inputs (slopes) across space and time.

One specific response to conflict-induced instability is the disruption of crop rotation practices, which are central to sustainable land management and yield stability. In peaceful settings, farmers rotate crops strategically to maintain soil fertility, control pests, and optimize nutrient cycles. However, under persistent threat, these long-term practices break down. Conflict reduces access to land, labor, capital, and reliable input supply, all of which are necessary for planning and executing effective crop cycles. As seen in Nigeria (Abro, Bello, Emerick, & Michelson, 2024) and Colombia (Ibáñez & Vélez, 2008), during wars farmers often switch to rapidly harvestable or single-season crops to minimize losses in case of sudden displacement or violence. This shift away from diverse rotations towards monoculture or shorter-cycle crops not only impacts negatively on resilience to pests and weather shocks but also accelerates soil degradation. In Syria, although we cannot directly observe specific cropping patterns due to data constraints, it is likely that the traditional rotations involving wheat, cotton, olives, and fruit trees have been significantly disrupted. These crops are input- and time-intensive, and their sustained cultivation depends on secure access to infrastructure, irrigation, and market as well as macro stability — factors which have been severely compromised since 2011.

At the same time, the destruction of infrastructure during conflict exacerbates these production shocks in uneven and long-lasting ways. Infrastructure is not uniformly targeted; its damage is shaped by the type of violence and strategic intentions of combatants. To attack the rebels indirectly, the State frequently targets key assets — roads, irrigation canals, power grids — as part of efforts to control territory or disable local economies (Buhaug, Gleditsch, & Ward, 2010; Grosjean, 2014). In contrast, non-state and one-sided violence may prioritize civilian terror or symbolic destruction, leading to more diffuse and less systematic damage (Gates, Hegre, Nygård, & Strand, 2012; Valentino, 2004). These patterns matter: (Esposito & Martelli, 2021) show that road damage in Syria disproportionately undermined rural market access, cutting farmers off from input supplies and consumer demand. Similarly, (Bozzoli, Brück, & Wald, 2013) found that in

[9] An additional concern is the one of reverse causality: *are land and farms more productive because of better education of the labour force? Or does crops' productivity push education via increased wealth?*

[10] The Nerlovian framework was later advanced by Indian agricultural economists (Krishna, 1963; Maji, Jha, & Venkataramanan, 1972; Cummings, 1975), who emphasize how farmers adjust inputs and technology in response to evolving constraints.

Sierra Leone, villages with more severe infrastructural damage faced significantly slower recovery. Thus, while population displacement and behavioral shifts are immediate outcomes of conflict, the infrastructure gap produces a deeper, longer-term inequality, inhibiting recovery and reinforcing productivity loss. Recognizing this heterogeneity is crucial for post-conflict policy, which must address not only human security but also the structural rebuilding of agricultural capacity and land management systems.

Henceforth, we examine the civil war not only focusing on its trend over time and geospatial distribution, but also decomposing the heterogeneous types of combats that have occurred in Syria since 2011. Different intensities, factions, targets, weapons and military strategies cause different consequences to the agricultural sector. The model here proposed guides our choices in the subsequent empirical approach. Firstly, we introduce a development indicator built upon nighttime light density, which picks up the effect of public goods, such as infrastructure and research. It also captures to a broad extent constraints and political stability, which play a fundamental role and are compromised by wars. Plus, despite a discussion in the Appendix about price insensitivity, we consider prices, as well, to index farmers' incentives to produce. In particular, price variability reflects the level of sectoral risk, and possibly has an indirect effect on the area allocation decision through the changes in the incremental profit ratio (Deshpande, 1996). Given the paucity of market data for Syrian crops at a fine level (spot prices, transactions, imports and exports), we control for them by using typical demand inputs, through which production capacity is affected[11]. For instance, trade and, more in general, access to the market or relative market size trigger notably positive effects by raising demand and reallocating factors of production to regions with higher returns. For this reason, we include distance to closest city and population density, which control for social interactions (ideas and exchange of knowledge), too. Finally, the conditions of the physical environment are paramount: land-suitability variables, such as ruggedness, water availability, rainfall variability (which has also a time dimension) are among the agreed parameters to include in models for agricultural productivity (Deshpande, 1996; Coelli & Rao, 2005). To summarize, the production function can be minutely expressed as follows:

$$Q = f(K, L, \text{Demand}, \text{Suitability}, \text{Stability}, t_\epsilon)$$

where *Demand* wants to group all the factors (price, trade, market, local development) which impact indirectly on farmers' cultivation decisions via change in demand. *Suitability* contains the territory-specific natural, geographic and biological characteristics. *Stability* refers to the macro and household-level conditions enabling continuity and predictability in the agricultural activities, although we omit the role of governmental policies (Antle, 1999) which are discontinuous during geopolitical crises. t_ϵ is the residual technical change after controlling for *Demand*, *Suitability* and *Stability*. Our identification strategy is therefore built on the above-mentioned inputs (whose detailed description is provided in Subsection 4.2).

[11] A thorough investigation of these inputs is presented in the Appendix.

The underlying research question is what effects the war-related instability cause on the agricultural sector. While we qualitatively describe in general terms how the conflict relates endogenously to the other inputs (Appendix), the research focuses intensely on quantitatively testing our hypothesis of serious productivity contraction leveraging the exogenous variation induced by the combats. However, this theoretical model and the analysis in Section 5 are inconsistent on the measured outcome: while Q is notably cultivation levels, the estimates we next propose pertain to whether a land is cultivated or not (in addition to other outcomes). The drawback is due to the impossibility of obtaining granular information on crop yields.

4 Data

4.1 Data Unavailability

Studying Syria hangs metaphorically a Damocles' sword over our heads, namely, measurement errors. Being a developing country fighting a civil war since 2011, administrative data at a very fine level are not collected. Indeed, the only variables we obtain externally are population density at nahya level and armed-conflict events. However, these data alone are insufficient to perform a careful empirical strategy: the setting provides inherently deficient indicators to do microeconometrics. Nonetheless, recent engineering developments allow to tackle this great concern - common in war zones - and obtain relatively reliable information. Satellite-borne sensors take images which can be converted into rich data. The potential of remote sensing based on machine-learning classification algorithms has been highlighted by many scholars to do academic research. Not only it offers the opportunity of collecting repeatable and standardized pictures on the biodiversity of an area, but also it can compensate for the paucity of information which can feature a specific region.

We take advantage of this technique and we include in our dataset measures for geography, natural resources and location. Likewise, we construct an index of economic development with satellite nighttime light density and land degradation. Most importantly, we "fill" the missing micro-level data about our major outcomes: productivity classification (whether an arable plot is cultivated) and NDVI. If not handled properly, the digitization of the Syrian map, especially for the initial years of the New Millennium, may be imprecise, causing in turn measurement errors to the constructed variables. Therefore, we use machine-learning techniques to carefully address potential problems. While retrieving information from the satellite images, we account for data noise, blooming, temporary light sources and cloud cover. We perform conservative adjustments to gain in reliability.

4.2 Dataset

For the identification strategy, in accordance with the theoretical framework elaborated in Section 3, we use the following set of geographical and socioeconomic variables. The summary statistics aggregate the values at patch and nahya levels (Tables 10 and 11), corresponding to the layers at which the empirical strategy is performed. Table 9 provides a thorough description of these measures with the associated name in the database.

Map of Syria We employ the Syria map from (Humanitarian Data Exchange, n.d.) which reports 272 nahya (sub-district) administrative boundaries[12], that remained invariant from 2000 to 2020.

Conflicts data We use Uppsala Conflict Data Program's (UCDP) Georeferenced Event Dataset (GED) (Davies, Engström, Pettersson, & Öberg, 2024). This dataset is globally recognized and systematically curated. It provides detailed, spatially and temporally disaggregated information on organized violence recording georeferenced conflict points associated with precise timing, reportage, and post-conflict mortality on each side[13]. A total number of 86,751 armed conflicts were recorded in Syria between 2011 and 2023, whose spatial distribution is displayed in Figures 11 and 12.

Agricultural productivity classification Due to historical and development reasons, there is very modest chance of directly obtaining agricultural outputs in Syria[14]. We use predicted yield in (Xi-Ya et al., 2022) to address this limitation. (Xi-Ya et al., 2022) implements Random Forests to classify cultivation status over NDVI[15] for every patch covering the national map of Syria. Hence, this important dependent variable is constructed as a binary 0/1 for whether the plot is cultivated or not. To ensure the representativeness and accuracy of the training, the authors rely only on high resolution image plus regularly cultivated area.

Population density A relevant control variable, as well as intermediate channel (war-induced migration flows determine spatial labour reallocation), is represented by local population density (Naumenko, 2021). The primary source we rely on is (WorldPop & CIESIN, Columbia University, 2018) (data from 2000-2020) with, approximately, a resolution of $1km$[16]. The alternative measures are (Bright & Coleman, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020). The LandScan dataset has the same resolution as (WorldPop & CIESIN, Columbia University, 2018) but provides additional information such as: actual population count and ethnic group-specific population count at the patch level on a global scale.

Luminosity We exploit two different sources for luminosity: VIIRS (Visible Infrared Imaging Radiometer Suite) (Elvidge, Baugh, Zhizhin, Hsu, & Ghosh, 2017) and DMSP (Defense Meteorological Satellite Program)

[12]This is also the smallest administrative level, generating a complete Syria map with no missing units that leave parts of the nation unclassified. It is accessible via Overpass API (Overpass Turbo, 2024).

[13]Each side means two sides intervened in the conflict plus the civilian mortality due to the combats.

[14]A list of motivations spans: (i) Syria has no centralized political power to manage a productivity accounting at nahya level; (ii) armed conflicts are still ongoing in the north-east and north-west for which we cannot rely on the federal government measure, since a uniquely recognized government does not exist; (iii) local governance has strong incentive to understate the local production (Olken, 2006) due to institutional problems.

[15]Normalized Difference of Vegetation Index

[16]The dataset's resolution is 30 arc, which is approximately 1km at the equator.

(Ghosh et al., 2021). VIIRS dataset is retrieved from NASA for accessing high-resolution and accurate (15-arc second, roughly 500 meters) nighttime lights information. VIIRS also has better performance than other comparable databases as concerns reducing artifacts and capturing smaller-scale variations in luminosity. However, it is available since 2012. For the previous period, we adopt DMSP which is a data source acquired from US Air force. The resolution is 30 arc second ($\tilde{1}$km at the equator), with grids spanning -180 to 180 degrees longitude and -65 to 75 degrees latitude. Images are derived from 6 different satellites: we choose the satellites which start to operate and end their mission the latest, to ensure that we acquire the information we need. As a result, we choose: F15 for year 2000-2003, F16 for 2004-2009, F18 for 2010 and 2011.

Geographical controls We use air temperature and precipitation (Funk, Peterson, Landsfeld, Pedreros, & Verdin, 2015), and terrain ruggedness (Shaver, Carter, & Shawa, 2019). As more thoroughly explained in the Appendix, air temperature, precipitation, and terrain ruggedness are confounders affecting both conflict incidence and agricultural productivity. On one hand, extreme temperatures and erratic rainfall can reduce crop yields, exacerbating resource scarcity and increasing the likelihood of disputes over land and water. On the other hand, rugged terrain can serve as a natural refuge for armed groups, influencing the spatial distribution of conflict while also limiting the expansion of large-scale agricultural activities.

5 Empirical strategy and Results

This Section delves into the econometric analysis we implement to study the conflict in Syria and how severe the consequences have been thus far on the land, consequently on agriculture. We examine our treatment (i.e., civil war and its incidence) in three separated cases: a binary conflict indicator at patch level, a conflict incidence indicator corrected for war zone and number of conflict incidences at nahya level. Hence, we shift from a canonical definition of the treatment 0–1 to a continuous version.

5.1 Patch-level analysis

To estimate the direct and indirect effect of the war, we firstly introduce the finest level of measurement at patch level: the treatment is coded as whether a conflict incidence happened in one given patch. It is an absorbing treatment, that is, once it switches from 0 to 1 the variable does not vary any longer. While the conflict per se may affect a specific area in alternate years, we prefer to adopt this format: deriving accurate non-absorbing state would require really reliable data for all periods, which is improbable during war times.

To construct the treatment variable, we split Syria into 147 grids of size 50×50 km^2 each. Then we cut the entire grid into patches roughly of size 2.1×2.1 km^2. We project the armed-conflict data onto the base map of Syria, then cover it with the full list of patches. For each patch and type of violence, the earliest year wherein there are some combats is defined as the first treated year. Given that we categorically consider the treatment variable as state-based conflict, non-state-based conflict, and one-sided violence, the absorbing treatment is defined in 3 different approaches accordingly. Furthermore, since the civil war contaminates soil and induces local labor shock, we also estimate spillover effects by using a *patch-donuts* method. To build the donuts, we remove the patch being directly treated and take only the adjacent neighborhood. We specify two types: (i) thin and (ii) thick. The former donuts take only the outermost patches into account, while the latter include all patches but the central one. Figure 5 provides an illustration of this construction. For the sake of symmetry, we only take odd numbers in constructing the size of the big square, whose edge is 3, 5, 7 times the length of single patches. Thus, since the squares have the following sizes ($3 \times 3,\ 5 \times 5,\ 7 \times 7$), we study spillovers over a surface of $6.3 \times 6.3,\ 10.5 \times 10.5,\ 14.7 \times 14.7$ km^2.

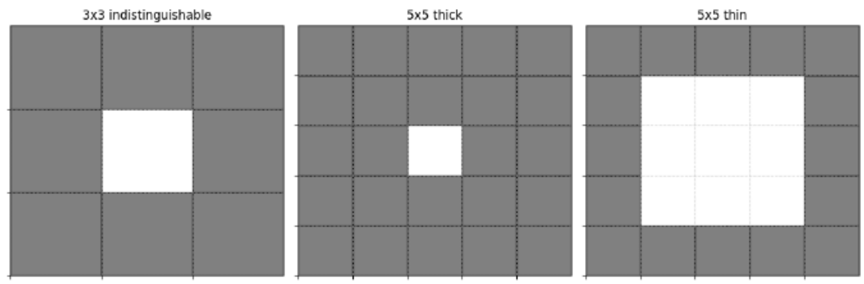


Figure 5: Illustration of indistinguishable, thick and thin donuts. The 'indistinguishable' square is 3×3, while the others are of size 5×5

We conduct the analysis using varying spatial bandwidths, where the bandwidth is defined as the radius of the smallest thin donut — that is, the maximum geographic distance from the center patch that is directly exposed to armed conflict. Based on this setup, the corresponding inner thick donut captures the broadest spatial extent of indirect (spillover) effects caused by the conflict, excluding the directly treated area.
To better understand our strategy, we introduce these notations:

$$
\begin{aligned}
E_g = &\text{ The period that group g firstly get treated} \in \{2011,\ 2012,\ 2013,\ 2014,\ 2015,\ 2016,\ 2017,\ 2018, \\
&2019,\ 2020,\ 2021,\ 2022,\ 2023\} \\
D_{igt} = &\mathbf{1}\{t \geq E_g\}
\end{aligned}
$$

Our main causal-inference method is Staggered DiD, precisely, the dynamic model in (de Chaisemartin et al., 2024), which allows to set continuous as well as non-absorbing treatments. Though, our analysis sticks to a classic binary and absorbing treatment variable. Valid causal inference relies on the following equation:

$$
Y_{igt} = \sum_{\tau=-4,\ \tau\neq 0}^{8} \gamma_\tau^{ES} \mathbf{1}\{\tau = t - E_g\} + \Lambda Rain_{igt} + \alpha_i + \alpha_t + \epsilon_{igt}, \tag{1}
$$

We add patch and time fixed effects. The variable Y_{igt} is the outcome at patch i, of group g, and at time t. We use different dependent variables: (i) population density from Landscan dataset, (ii) luminosity, (iii) Normalized Difference Vegetation Index and (iv) a productivity classification for whether land is being cultivated. Besides fixed effects, we control for the annual sum of monthly precipitation deviation (called *Rain*), which is the only covariate being both patch and time variant. This equation estimates precisely the cultivation shock in the same patch being subject to war-related violence (or not)[17]. One big reason for which we discard the canonical event study and use instead a staggered roll-out design is that the former has been proven to be biased (Goodman-Bacon, 2021; Roth, 2022) when the treatment is not assigned at one time. Indeed, the coefficient is a weighted average of pairwise comparisons and wrongly contrasts late adopters – treated group – against early adopters – control group.

It is relevant to highlight that the various outcomes Y_{igt} differ in the total number of periods for which the aggregate effects can be computed. To uniformize and compare pre-trend and no-anticipation-assumption tests, as well as the measures for the impact of the war, we take as range of the event study $[-4, 8]$ for which there exist all the dependent variables (note $\sum_{\tau=-4,\ \tau\neq 0}^{8}$ in Equation 1). Additionally, we fix the effect to be zero exactly at the last period before the war breaks out in Syria: any finding is interpreted in relation to this moment.

5.1.1 Identification assumptions

The SDID model is identified when the following assumptions are valid. Firstly, the group-specific one-period difference as-if-not-treated (i.e., in the absence of conflict incidence) is consistent across different groups (i.e. classified by the first period receiving treatment) on average. This corresponds to the parallel trends assumption for agricultural productivity. In other words, patches receiving conflict treatment for the first time in the same year have constant one-year difference, which is equal to the one-period difference of patches receiving treatment for the first time in alternative year, on average. Secondly, the outcome in untreated periods is not affected by future episodes of war. Individuals residing or cultivating on patch i should not anticipate the advent of armed conflict prior to its actual occurrence. Displacement likely induces negative bias when estimating the shock on agricultural productivity since the post-period effect is contaminated by the anticipation effect. In addition, we also need SUTVA to perform causal inference on our SDID analysis. Namely, the patch-specific outcome is independent of how the conflict treatment affects the other units. Consequently, there are no spillovers or local equilibrium effects.

The first concern we have about these restrictions is the violation of SUTVA due to capital and labor reallocation, as well as understatement of warfare intensity. As mentioned in (Xi-Ya et al., 2022), agricultural zones in conflict regions have a more flexible boundary. Consequently, adjacent land productivity will increase: despite being less fertile, these areas are unaffected by the war. To address this issue, we propose additional checks using war-zone only observations and off-war-zone sample to examine the differential path of treatment effects and recovery. For completing the classification of the year-specific war zones in Syria we use the GeoHD package (Yan, 2024). The method splits the whole map into grids and extracts the most distinctive feature within each of them. Then, the most distinctive characteristic is subtracted by the

[17] With Staggered DiD the pre-trend condition is wrong due to post-treatment contamination (Sun & Abraham, 2021; Roth, 2022). The pre-trend test is performed separately as described in (Borusyak, Jaravel, & Spiess, 2024).

value of itself and the algorithm conducts reselection until convergence of the adaptive Gaussian kernel. The package converts the representativeness into density rasters and transforms the density rasters into contour maps. To make the original classification algorithm applicable to our case, we readjust the resolution and contour approximation[18]. The output consists of a collection of contour maps, whose densities capture the point-specific intensity for certain Syrian regions. Figure 6 provides a visual example. The red points represent georeferenced conflict incidences; the purple contour captures the set of uncountably many points with identical conflict intensity. The variable war zone is coded as the largest feasible contour[19] with non-trivial conflict density. To capture migration dynamics and identify the cutoff between war-affected and war-free land, we use different sizes of *thick donuts* surrounding the patch being studied (2.1×2.1 km^2). We reorganize each patch into a square consisting of 9, 25, and 49 grids, with the central one being directly treated by the conflict. We compute the mean of the dependent variable in the remaining patches: for thick donuts we remove only the central, while for thin donuts we use the outer ring excluding all non-boundary patches.

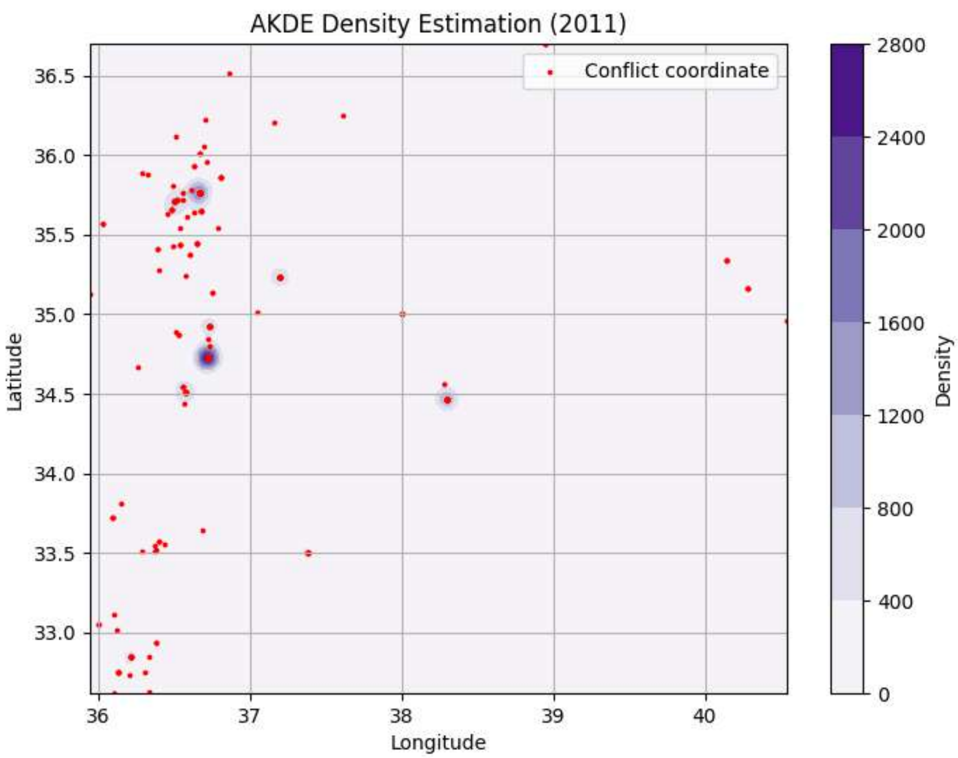


Figure 6: Adaptive kernel density estimation. The red points represent conflict events in 2011, and the purple region captures the corresponding hot zone. The plot size is fully determined by the max and min coordinates of conflict point features each year, therefore the plot size varies over time.

[18]The default resolution setting is 1000 and we make the expansion rate of contour by 0.1 (10 times as large as the default setting).

[19]By feasible contour, we mean the demarcation line between 0 density and positive density.

The construction of the war zone allows us to (i) run a pre-trend test without including the post treatment terms to avoid contamination (to test more robustly the identifying assumptions); (ii) estimate the staggered Differences-in-Differences for different subsamples (to address heterogeneous treatment effects); (iii) implement a *donut* SDID at diverse thickness levels (to study potential migration issue); (iv) in Subsection 5.2 cluster appropriately the findings. Nonetheless, one crucial concern of the war-zone sample splitting is the imbalancedness of the panel. Since the war-zone is constructed using geo-hotspot, it does not label value in a repeated cross-sectional way thereby an imbalanced panel. (De Chaisemartin & d'Haultfoeuille, 2024) notices the requirement of balanced panel for fair comparison. The sample estimation, therefore, is valid only over the patches surviving the intersection of all war-zones over all periods. The remaining sample is restricted. Consequently, our differential trend derived from sample splitting provides just suggestive rather than indicative evidence.

5.1.2 Direct effects

We begin our estimation focusing exclusively on the patch receiving conflict directly. In this first approach, we rule out any local equilibrium effect. We run Equation 1 four separate times, changing the treatment from any type of conflict to the three categories of conflicts: *state-based violence, non state-based, one-sided.* Table 2 presents the baseline results of SDID. Except for population density measured by Landscan, we reject the assumption of no anticipation: the first pre-war period shows a significantly negative coefficient relative to the reference group. This is visually evident in Figure 7 where we present the corresponding event studies[20]. This violation of the anticipation assumption leads to an understatement in the treatment effect estimation, since the subsequent periods incorporate the negative anticipation effect.

The dynamics obtained for population density confirm the pre-trend and provides some suggestions about the potential violation of SUTVA due to cross-patch spillovers. The coefficients monotonically increase in absolute value and are significant from period 1 to 5 (they range from -0.082 to -0.018 where the first value corresponds to period 5 and the second extreme is the impact in period 1). Presumably, local communities migrated from the patches where conflict had occurred to other areas following the rising intensity of the war. Being the variable measured as the number of residents per m^2, the causal effect of any type of conflict in period 1 is a drop of 0.018 individual per square meter. Interestingly, the outcome partially recovers after $t = 5$, potentially reflecting return migration. Studies on post-conflict settings, like in Japan (Davis & Weinstein, 2002) and Germany (Brakman, Garretsen, & Schramm, 2004) following WWII, discuss these population flows: previously bombed areas may experience partial re-migration due to reconstruction efforts and economic opportunities. However, this process is often slow and incomplete, depending on conflict severity, governance, and resource availability.

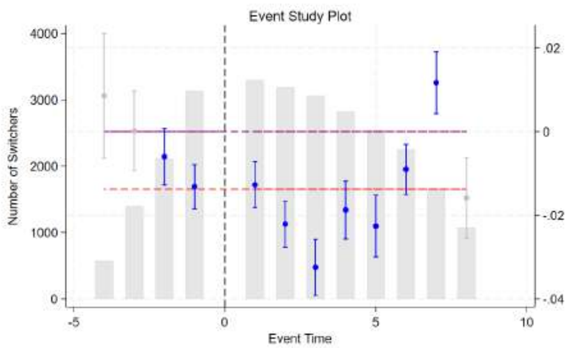
As discussed in Subsection 5.1, an additional concern pertains to heterogeneous trends for different regions:

[20]In the Appendix, specifically in Figures 13, 14 and 15, we display dynamics for the treatment effects of the three categorical variables of armed conflict. We outline that the vast majority of the results is driven by state-based violence, given the insignificance of the other two types of combats.

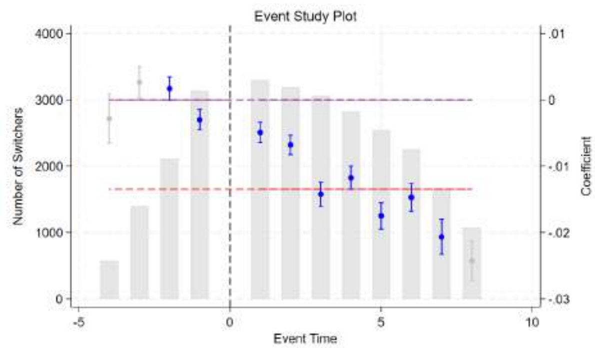
Table 2: Summary of Staggered DID Estimations with 95% Confidence Intervals

Outcome Variable	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	p-value
Productivity Classification	-0.0127	-0.0221	-0.0324	-0.0187	-0.0226	-0.0090	0.0117	-0.0158	0.000
95% CI	[-0.018, -0.007]	[-0.028, -0.017]	[-0.039, -0.026]	[-0.026, -0.012]	[-0.030, -0.015]	[-0.015, -0.003]	[0.004, 0.019]	[-0.025, -0.006]	
Luminosity	203.6	-181.7	-259.3	-488.7	-337.9	-298.0	584.9	1175.2	0.000
95% CI	[94.9, 312.3]	[-320.9, -42.6]	[-413.7, -105.0]	[-648.4, -328.9]	[-523.2, -152.6]	[-498.5, -97.6]	[376.3, 793.6]	[901.3, 1449.2]	
Landscan Pop	-0.018	-0.024	-0.045	-0.075	-0.082	-0.063	-0.049	-0.026	2.45e-11
95% CI	[-0.034, -0.003]	[-0.054, 0.006]	[-0.075, -0.016]	[-0.107, -0.042]	[-0.116, -0.047]	[-0.099, -0.027]	[-0.089, -0.010]	[-0.070, 0.017]	
NDVI	-0.005	-0.007	-0.014	-0.012	-0.017	-0.015	-0.021	-0.024	0.000
95% CI	[-0.006, -0.003]	[-0.008, -0.005]	[-0.016, -0.012]	[-0.014, -0.010]	[-0.019, -0.015]	[-0.017, -0.013]	[-0.023, -0.018]	[-0.027, -0.021]	
Placebo Tests (Parallel Trends Assumption)									
Productivity Classification	-0.013	-0.006	0.000	0.009	–	–	–	–	4.45e-08
95% CI	[-0.019, -0.007]	[-0.012, 0.001]	[-0.006, 0.006]	[0.002, 0.017]	–	–	–	–	
Luminosity	-448.2	13.54	-139.2	-398.1	–	–	–	–	4.44e-16
95% CI	[-602.5, -293.8]	[-105.3, 132.3]	[-275.1, -3.2]	[-579.2, -217.0]	–	–	–	–	
Landscan Pop	-0.007	-0.005	-0.007	-0.021	–	–	–	–	0.2627
95% CI	[-0.017, 0.003]	[-0.015, 0.005]	[-0.018, 0.004]	[-0.035, -0.007]	–	–	–	–	
World Pop	-0.086	-0.155	-0.175	-0.172	–	–	–	–	2.22e-16
95% CI	[-0.118, -0.055]	[-0.199, -0.111]	[-0.226, -0.124]	[-0.225, -0.118]	–	–	–	–	
NDVI	-0.003	0.002	0.003	-0.003	–	–	–	–	4.20e-09
95% CI	[-0.007, 0.001]	[-0.002, 0.006]	[-0.001, 0.007]	[-0.007, 0.001]	–	–	–	–	
Average Cumulative Effect per Treatment Unit									
Productivity Classification	-0.017								5.07 periods
Luminosity	-77.61								5.11 periods
Landscan Pop	-0.048								4.37 periods
World Pop	0.654								4.82 periods
NDVI	-0.013								5.07 periods

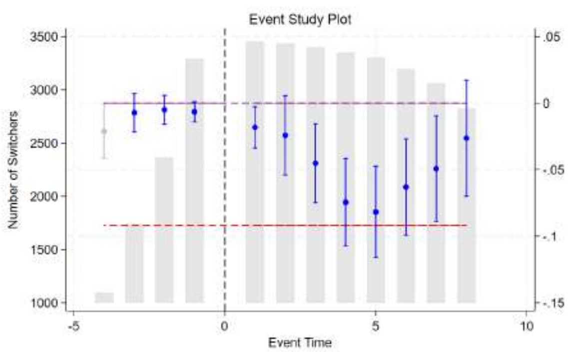
Notes: This table presents the estimated treatment effects from an event-study design using Staggered DiD over the **full sample**. Each coefficient represents the estimated impact of treatment on the outcome variables at different time periods. The rows correspond to different measures of economic activity: Productivity classification, Luminosity, Landscan Population, and NDVI. The first section presents the **event-study effects** across eight periods after treatment initiation. The second section reports **placebo tests**, which assess whether significant treatment effects exist before the treatment occurs. The final row reports the **Cumulative Treatment Effect** over all periods. Confidence intervals are reported in brackets. Statistical significance: *p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01.



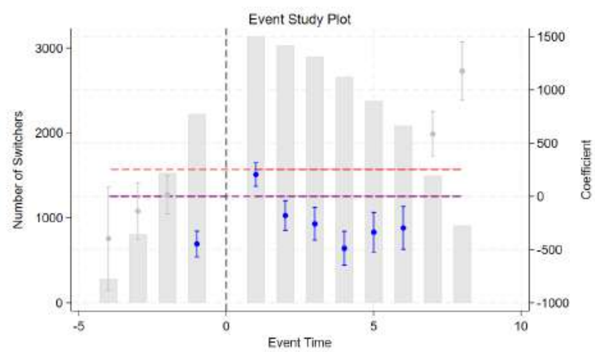
(a) Productivity Classification



(b) NDVI



(c) Landscan Population



(d) Luminosity

Figure 7: Staggered Difference-in-Differences for the **full sample**. This figure presents event-study estimates with pre-trend tests across several dependent variables: productivity classification, NDVI, Landscan population density, and nighttime luminosity.
To ensure a consistent time frame across plots, we include 4 pre-treatment periods and 8 post-treatment periods, omitting period 0 (the last period before treatment) as the reference category. Brackets show 95% confidence intervals. Treatment is defined as a binary indicator for any conflict event within a patch.
Following (De Chaisemartin & d'Haultfoeuille, 2024), we highlight in blue the periods (including placebo and post-treatment) that meet the criterion of having at least as many switchers as half of ones period 1; remaining periods are shown in gray. The bar graph (left y-axis) displays the number of treated units ('switchers') per period. The red dashed line marks half the number of switchers in period 1, and the purple dashed line indicates the zero-effect benchmark on the right y-axis.

areas enduring long-lasting combats tend to be pre-informed and able to anticipate conflict advent. On the other hand, the off-war-zone regions may not manage to predict subsequent episodes of fighting, thereby fulfilling better the SDID assumption of no anticipation. Furthermore, war-zone territories are likely more devastated, generating stronger disadvantages and frictions for migrants to move back. To account for these issues, we re-run the SDID specification varying the sample: we condition on (i) within war zone and (ii) out of war zone. Tables 3 and 4 show the corresponding results. The event studies (Figures 16 and 17) are provided in the Appendix. The results we find are analogous to the full sample, with only population density from Landscan going through the joint test of pre-trends.

5.1.3 Spillover effects

In order to examine spillover effects, we use Staggered Difference-In-Differences (the model in Equation 1) firstly on thin donuts, for which we specify two scales: 5×5 and 7×7. We then study the impact of a war episode on the borders of its spatial band (i.e. the maximum distance at which outcomes are still correlated). Table 5 shows the estimates for each dependent variable; Columns (16) and (24) represent, respectively, the outermost patches of a 5×5 and of a 7×7 square. Columns 5 and 6 present the treatment effects of any type of conflict on population density in adjacent area. The treatment effects over 5×5 thin donuts align with that of 7×7 square with slightly smaller coefficients for the bigger square (but no statistical significance between the two). There is sufficient evidence to argue that the conflict shock affects surrounding population settlement by causing residents to migrate out of the war zone. However, we acknowledge that the "ring" size is not big enough to detect overall migration consequences. Plus, it does omit any contribution from the bordering patches. Hence, these spillovers are considered as a lower bound.

After capturing an underestimation of the maximum spillover effects by using thin donuts, we switch approach and leverage thick bands to analyze the impact of the civil war on the whole surrounding region. Figure 8 reports the event studies for the different sizes of the square: 3×3, 5×5, 7×7. Except luminosity, positive anticipation effects are obtained for NDVI, population density, and productivity classification. Given that the treatment effect remains negative across all post-treatment periods for these variables, the anticipation generates a positive bias, leading to an understatement (in absolute magnitude) of the true negative impact of conflict. The significance of anticipation effects suggests that individuals in conflict zones receive early warning signals, shaping their expectations about the likelihood of subsequent combats and prompting preemptive migration to peripheral regions. Simultaneously, when local communities relocate, they find better opportunities (e.g. lower degree of threat) to set up farming activities, which explains the rise in cultivation during the pre-war periods. These findings align with observed displacement patterns in Syria, where IDP settlements formed within 30–50 km from active conflict zones, rather than dispersing widely across the country (UNHCR, 2023). However, as our estimates reveal, this relocation does not persist throughout the post-treatment period, suggesting either a return migration or a stabilization of conflict expectations over time.

Table 3: Summary of Staggered DID Estimations (War Zone Sample) with 95% Confidence Intervals

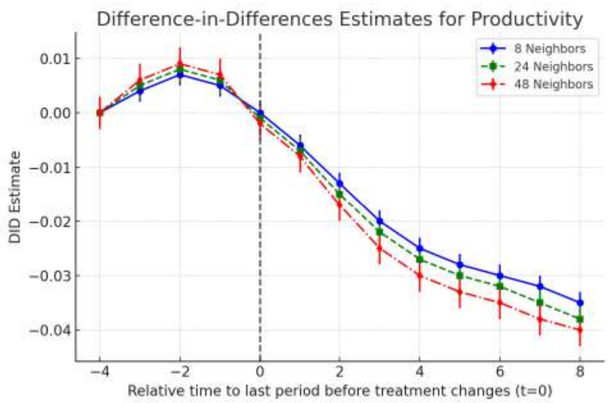
Outcome Variable	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	p-value
Productivity Classification	-0.0122	-0.0230	0.0119	-0.0156	0.0196	0.0238	0.0658	-0.0701	0.0012
95% CI	[-0.0306, 0.0062]	[-0.0428, -0.0032]	[-0.0110, 0.0348]	[-0.0456, 0.0144]	[-0.0083, 0.0474]	[-0.0170, 0.0645]	[0.0234, 0.1083]	[-0.1132, -0.0270]	
Luminosity	44.91	-575.10	-345.60	-35.90	464.74	-466.34	-1563.43	-2272.30	1.12e-07
95% CI	[-197.90, 287.72]	[-932.42, -217.79]	[-894.07, 202.87]	[-682.62, 610.82]	[-421.21, 1350.69]	[-1453.69, 521.02]	[-2521.35, -605.51]	[-3407.13, -1137.48]	
Landscan Pop	0.0180	0.0287	0.0722	0.1422	0.2278	0.2363	0.2462	0.0815	0.00006
95% CI	[-0.0201, 0.0562]	[-0.0518, 0.1093]	[-0.0225, 0.1668]	[0.0383, 0.2460]	[0.0121, 0.4435]	[0.0686, 0.4039]	[0.0176, 0.4748]	[-0.0254, 0.1883]	
NDVI	-0.0025	-0.0025	-0.0018	-0.0070	-0.0072	0.0001	0.0145	-0.0129	0.0171
95% CI	[-0.0063, 0.0012]	[-0.0078, 0.0028]	[-0.0084, 0.0048]	[-0.0137, -0.0004]	[-0.0154, 0.0010]	[-0.0101, 0.0103]	[0.0025, 0.0265]	[-0.0222, -0.0035]	
Placebo Tests (Parallel Trends Assumption)									
Productivity Classification	-0.0120	-0.0119	-0.0355	–	–	–	–	–	4.45e-08
Luminosity	-28.84	106.86	-282.45	–	–	–	–	–	4.44e-16
Landscan Pop	-0.0436	-0.0826	-0.3766	-0.3902	–	–	–	–	0.2627
NDVI	0.0016	0.0060	0.0031	–	–	–	–	–	4.20e-09
Average Cumulative Effect per Treatment Unit									
Productivity Classification	-0.0045								5.72 periods
Luminosity	-332.12								5.72 periods
Landscan Pop	0.0982								4.76 periods
NDVI	-0.0029								5.72 periods

Notes: This table presents the estimated treatment effects from an event-study design using Staggered DiD conditioning on the **war-zone sample**. Each coefficient represents the estimated treatment impact on the outcome variables at different time periods. The rows correspond to different measures of economic activity: classification for agricultural productivity, luminosity, Landscan population density, and NDVI. The first section presents the **event-study effects** across eight post-treatment periods. The second section reports **placebo tests**, which assess whether significant treatment effects exist before the treatment truly occurs. The final row reports the **Cumulative Treatment Effect** over all periods. Confidence intervals are reported in brackets. Statistical significance: *p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01.

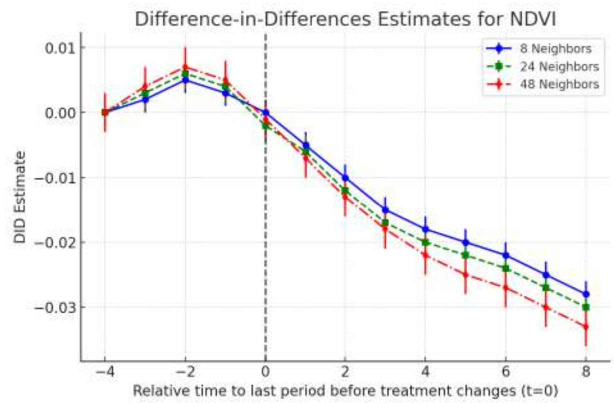
Table 4: Summary of Staggered DID Estimations (Off War-Zone Sample) with 95% Confidence Intervals

Outcome Variable	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8	p-value
Productivity Classification	-0.0115	-0.0220	-0.0302	-0.0223	-0.0278	-0.0179	0.0185	-0.0005	0.0000
95% CI	[-0.0181, -0.0048]	[-0.0289, -0.0151]	[-0.0383, -0.0222]	[-0.0308, -0.0137]	[-0.0370, -0.0186]	[-0.0253, -0.0104]	[0.0085, 0.0285]	[-0.0174, 0.0164]	
Luminosity	101.18	-409.71	-561.39	-601.99	-135.56	-559.42	145.12	111.06	0.0000
95% CI	[-26.15, 228.50]	[-574.82, -244.60]	[-739.97, -382.82]	[-786.36, -417.63]	[-367.15, 96.02]	[-822.00, -296.83]	[-132.87, 423.10]	[-339.08, 561.19]	
Landscan Pop	-0.0086	-0.0016	-0.0171	-0.0341	-0.0392	-0.0250	-0.0081	0.0089	0.00009
95% CI	[-0.0243, 0.0072]	[-0.0296, 0.0263]	[-0.0427, 0.0085]	[-0.0601, -0.0081]	[-0.0657, -0.0127]	[-0.0561, 0.0060]	[-0.0437, 0.0275]	[-0.0402, 0.0581]	
NDVI	-0.0055	-0.0060	-0.0122	-0.0092	-0.0158	-0.0123	-0.0107	-0.0104	0.0000
95% CI	[-0.0074, -0.0037]	[-0.0078, -0.0041]	[-0.0144, -0.0100]	[-0.0113, -0.0071]	[-0.0182, -0.0134]	[-0.0149, -0.0097]	[-0.0142, -0.0071]	[-0.0154, -0.0054]	
				Placebo Tests (Parallel Trends Assumption)					
Productivity Classification	-0.0078	-0.0041	-0.0051	0.0197	–	–	–	–	0.00145
95% CI	[-0.0144, -0.0012]	[-0.0122, 0.0040]	[-0.0155, 0.0053]	[0.0028, 0.0367]	–	–	–	–	
Luminosity	-294.88	-92.77	-338.47	-869.41	–	–	–	–	0.00001
95% CI	[-428.82, -160.94]	[-285.94, 100.39]	[-632.05, -44.89]	[-1471.96, -266.87]	–	–	–	–	
Landscan Pop	-0.0032	0.0055	0.0128	-0.0042	–	–	–	–	0.02477
95% CI	[-0.0110, 0.0046]	[-0.0038, 0.0148]	[-0.0009, 0.0264]	[-0.0319, 0.0235]	–	–	–	–	
NDVI	-0.0014	0.0012	0.0028	-0.0013	–	–	–	–	0.00692
95% CI	[-0.0033, 0.0005]	[-0.0008, 0.0032]	[0.0001, 0.0054]	[-0.0054, 0.0027]	–	–	–	–	
				Average Cumulative Effect per Treatment Unit					
Productivity Classification				-0.0183					5.31 periods
Luminosity				-300.54					5.36 periods
Landscan Pop				-0.0166					4.67 periods
NDVI				-0.0098					5.31 periods

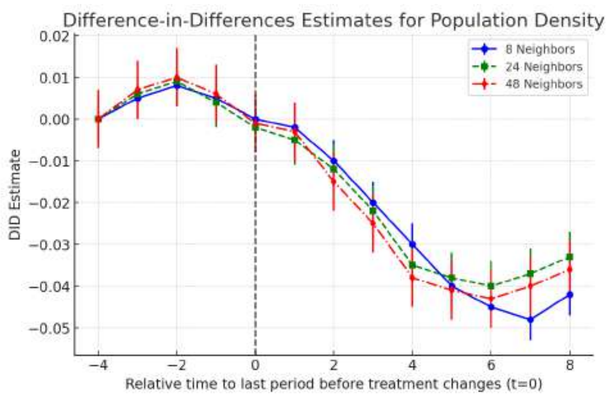
Notes: This table presents the estimated treatment effects from an event-study design using Staggered DiD conditioning on the **off war-zone sample**. Each coefficient represents the estimated treatment impact on the outcome variables at different time periods. The rows correspond to different measures of economic activity: classification of agricultural productivity, luminosity, Landscan population density, and NDVI. The first section presents the **event-study effects** across eight post-treatment periods. The second section reports **placebo tests**, which assess whether significant treatment effects exist before the treatment truly occurs. The final row reports the **Cumulative Treatment Effect** over all periods. Confidence intervals are reported in brackets. Statistical significance: *p $<$ 0.1, **p $<$ 0.05, ***p $<$ 0.01.



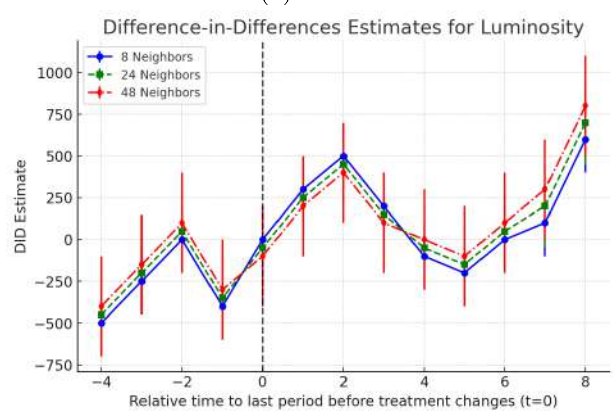
(a) Productivity Classification



(b) NDVI



(c) Landscan Population



(d) Luminosity

Figure 8: Staggered Difference-in-Differences event-study plots for four outcome variables: population density, nighttime luminosity, NDVI, and productivity classification. Each figure corresponds to a different outcome with a different neighborhood size used to define spatial treatment exposure (8, 24, and 48 units – the radius or thickness of the treatment donut). (De Chaisemartin & d'Haultfoeuille, 2024) recommends excluding the periods with fewer than half the number of individuals switching treatment status in period 1. Thus, for each dependent variable we do not materially consider the following periods: (a) $(+8) \rightarrow$ Productivity Classification; (b) $(+8) \rightarrow$ NDVI; (c) $\emptyset \rightarrow$ Landscan Population; (d) $(+7, +8) \rightarrow$ Luminosity.

Table 5: Estimation of Treatment Effects

Period	NDVI		Population Density		Luminosity		Productivity Classification	
	(16)	(24)	(16)	(24)	(16)	(24)	(16)	(24)
Treatment Periods								
Period 1	-0.0049***	-0.0053***	-0.0140***	-0.0151***	230.426***	215.672***	-0.0139***	-0.0127***
	[-0.0062, -0.0037]	[-0.0067, -0.0039]	[-0.0207, -0.0073]	[-0.0223, -0.0080]	[127.97, 332.88]	[120.45, 310.32]	[-0.0189, -0.0088]	[-0.0171, -0.0092]
Period 2	-0.0074***	-0.0081***	-0.0244***	-0.0267***	-157.113**	-148.297**	-0.0235***	-0.0221***
	[-0.0086, -0.0062]	[-0.0093, -0.0066]	[-0.0355, -0.0133]	[-0.0379, -0.0156]	[-288.44, -25.79]	[-270.55, -28.14]	[-0.0285, -0.0186]	[-0.0274, -0.0175]
Period 3	-0.0136***	-0.0148***	-0.0375***	-0.0402***	-243.594***	-233.982***	-0.0362***	-0.0349***
	[-0.0151, -0.0121]	[-0.0165, -0.0132]	[-0.0516, -0.0235]	[-0.0550, -0.0253]	[-389.05, -98.14]	[-370.33, -105.41]	[-0.0423, -0.0302]	[-0.0415, -0.0293]
Period 4	-0.0114***	-0.0125***	-0.0449***	-0.0471***	-442.086***	-427.321***	-0.0196***	-0.0184***
	[-0.0129, -0.0099]	[-0.0139, -0.0108]	[-0.0606, -0.0291]	[-0.0632, -0.0320]	[-590.01, -294.16]	[-570.23, -312.12]	[-0.0260, -0.0133]	[-0.0250, -0.0126]
Period 5	-0.0171***	-0.0183***	-0.0442***	-0.0467***	-348.987**	-335.672**	-0.0259***	-0.0243***
	[-0.0187, -0.0155]	[-0.0198, -0.0167]	[-0.0604, -0.0280]	[-0.0622, -0.0312]	[-521.17, -176.81]	[-508.12, -180.41]	[-0.0325, -0.0193]	[-0.0311, -0.0189]
Period 6	-0.0159***	-0.0174***	-0.0399***	-0.0423***	-325.277**	-312.098**	-0.0128***	-0.0117***
	[-0.0176, -0.0143]	[-0.0189, -0.0157]	[-0.0570, -0.0229]	[-0.0598, -0.0245]	[-512.33, -138.22]	[-500.12, -140.55]	[-0.0182, -0.0074]	[-0.0173, -0.0069]
Period 7	-0.0192***	-0.0205***	-0.0341***	-0.0368***	639.105***	615.232***	0.0103***	0.0118***
	[-0.0214, -0.0171]	[-0.0227, -0.0183]	[-0.0524, -0.0157]	[-0.0551, -0.0184]	[439.47, 838.73]	[430.11, 800.25]	[0.0037, 0.0167]	[0.0049, 0.0183]
Period 8	-0.0231***	-0.0247***	-0.0410***	-0.0441***	1243.086***	1200.543***	-0.0132***	-0.0121***
	[-0.0255, -0.0207]	[-0.0271, -0.0223]	[-0.0642, -0.0179]	[-0.0675, -0.0206]	[980.68, 1505.49]	[950.45, 1400.34]	[-0.0225, -0.0040]	[-0.0211, -0.0038]
Placebo Periods								
Placebo 1	-0.0035***	-0.0038***	-0.0006	-0.0009	-450.677***	-432.908***	-0.0131***	-0.0124***
	[-0.0047, -0.0022]	[-0.0052, -0.0027]	[-0.0052, 0.0040]	[-0.0061, 0.0034]	[-561.91, -339.44]	[-550.12, -320.47]	[-0.0179, -0.0084]	[-0.0168, -0.0077]
Placebo 2	0.0015*	0.0012*	0.0039	0.0043	-15.588	-18.741	-0.0051	-0.0047
	[0.0002, 0.0029]	[-0.0003, 0.0025]	[-0.0041, 0.0119]	[-0.0044, 0.0128]	[-179.20, 148.02]	[-175.23, 140.67]	[-0.0112, 0.0011]	[-0.0104, 0.0012]
Placebo 3	0.0027	0.0024	0.0011	0.0015	-125.206	-120.098	0.0010	0.0008
	[0.0009, 0.0045]	[0.0007, 0.0041]	[-0.0074, 0.0097]	[-0.0079, 0.0109]	[-375.22, 124.80]	[-360.54, 121.13]	[-0.0078, 0.0099]	[-0.0072, 0.0091]
Placebo 4	-0.0022	-0.0025	-0.0057	-0.0062	-332.475**	-320.781**	0.0052	0.0048
	[-0.0049, 0.0006]	[-0.0054, 0.0004]	[-0.0170, 0.0055]	[-0.0179, 0.0057]	[-783.64, 118.69]	[-750.98, 112.11]	[-0.0079, 0.0184]	[-0.0072, 0.0176]
Average Treatment Effect (ATT)								
ATT	-0.0125***	-0.0134***	-0.0347***	-0.0358***	-56.738	-52.311	-0.0190***	-0.0183***
	[-0.0136, -0.0115]	[-0.0145, -0.0123]	[-0.0486, -0.0209]	[-0.0499, -0.0217]	[-144.19, 30.72]	[-140.88, 28.11]	[-0.0228, -0.0153]	[-0.0220, -0.0148]

Notes: This table presents the estimated treatment effects from an event-study design. Each coefficient represents the estimated impact of treatment on the outcome variables at different time periods. The columns correspond to different measures of economic activity: Productivity classification, Luminosity, Landscan Population, and NDVI. The first section presents the **event-study effects** across eight periods after treatment initiation. The second section reports **placebo tests**, which assess whether significant treatment effects exist before the treatment occurs. The final row reports the **Average Treatment Effect on the Treated (ATT)**, which represents the averaged treatment effect over the treated over all periods. Confidence intervals are reported in brackets. Statistical significance: *p* $<$ 0.1, **p** $<$ 0.05, ***p*** $<$ 0.01.

Although Figure 8 illustrates that the war effect on NDVI and productivity classification was stronger and stronger (in absolute terms), indicating a persistent decline in agriculture, the impact on population density starts reducing a bit during the last periods under investigation. However, the maximum impact is significant: every conflict event, regardless of its type, induces a 0.03–0.045 capita-per-square-meter drop in population density. These numbers are undervaluing the consequences due to positive anticipation[21]. Interestingly, we do not observe any consequential underdevelopment: starting from 2011, the effect on economic output, as measured by nighttime luminosity, is either insignificantly different from zero or even positive.

Additionally, we observe that the estimates (in absolute terms) are larger on 14.7×14.7 km^2 areas. This fact suggests again that we are still not capturing aggregate externalities, as the value increases in spatial band: widening more the "perimeter" would allow to include additional effects. Indeed, (Dodds, 2021) and (Kerner, Gutiérrez, & Bentzen, 2023) find in other settings that most refugees and IDPs tend to relocate within 50–100 km from their original homes. We tackle this aspect in Subsection 5.2. Nonetheless, for the scope of this approach at a very fine level, we limit the size to a more contained surface of 216.09 km^2. If we compare the results between the direct effect (Table 2) and the indirect effect (Figure 8), we observe that areas receiving direct treatment experience a severe short-term negative effect (e.g., period 3 shows a

[21] The same logic applies to NDVI and productivity classification: a 0.028–0.033 drop in the NDVI index per conflict event in the long run and a 0.033–0.042 decrease in the likelihood of arable land being cultivated. Both interpretations serve as an upper bound for the actual treatment effect due to positive anticipation.

coefficient of -0.0324 for productivity classification, albeit with a negative bias due to a slightly significant anticipation effect in period -1). However, these territories tend to recover in the long run, as treatment coefficients revert back to 0 in later periods. This is what the post-conflict recovery literature argues: direct war-affected zones often experience economic rebounds due to reconstruction aid and investment (Cerra & Saxena, 2008). On the other hand, the positively biased spillover effects exhibit a monotone trend over time, meaning that long-run shocks in indirectly treated regions eventually surpass the short-term effects in the directly affected patches. This outcome is supported by empirical evidence on civil-conflict externalities: neighboring locations likely suffer from sustained economic and market disruptions due to refugee inflows, security concerns, and capital flight (Maystadt & Verwimp, 2014; Becker & Ferrara, 2017; Alix-Garcia, Artuc, & Onder, 2022). Some studies on the local setting confirm that border regions in Jordan and Turkey suffered the war effects for longer, whereas Syria's conflict-affected cities exhibited partial economic recovery (Verme et al., 2016; Fallah, Krafft, & Wahba, 2019). This distinction between temporary direct conflict effects and persistent indirect spillovers highlights the need for tailored post-war economic policies: while war-torn areas may require reconstruction assistance, neighboring centres often necessitate long-term economic stabilization measures to mitigate spillover shocks (Murdoch & Sandler, 2002; Cerra & Saxena, 2008).

5.2 Nahya-level analysis

Subsection 5.1 provides first evidence of the agricultural shock, outlining a differential trend between directly affected patches and neighbouring territories. Notwithstanding these findings, we decide to provide an additional analysis at sub-district level (*nahya*). The patch-level strategy is indeed agnostic about local equilibrium effects: "lit" patches where some sort of violence is occurring are surely unsuitable for living and for proper cultivation; farming will be contaminated as well at adjacent patches (close enough and not too far). The *patch-donuts* approach in Subsection 5.1.3 addresses this aspect, though it still focuses on a very fine level since conflict effects extend much beyond the largest ring analysed. Therefore, we take a broader view and implement the analysis aggregating the information at the *nahya* level, the third administrative layer of Syria. We drop years prior to 2003 and after 2019 because some crucial outcomes or controls are missing and we would lose much precision in the estimation. We construct an Ordinary-Least-Squares model, followed by panel regression with Two-Way Fixed Effects (Subsection 5.2.1). To exclude to study spurious relationships and to derive a causal interpretation, we adopt Instrumental Variables in Subsection 5.2.2 using distance to nearest city as instrument. We support the analysis by implementing a partialling-out approach which reports very close results.

Additionally, we need to properly reflect on how to cluster the analysis. In a civil conflict where over 12 million Syrians are displaced inside the country[22], clustering at the nahya-level is inadequate for two reasons: (i) the treatment is not assigned at this administrative layer; (ii) the events happening within a sub-district do produce external equilibrium effects. Migration and displacement reduce the population and labour force of

[22]Source: UNHCR.

one area at war, possibly increasing human capital in other regions. In order to account for spatial correlation and contemplate the location of the multiple conflicts fought in the country, we use robust-clustered standard errors at three levels: war zone, war zone-nahya and war zone-district. The first specification takes fighting as an *if-random event* at war zone level, managing to tackle the challenge of defining the extent of the treatment assignment according to the fact it does not have well-defined boundaries. The two alternatives denote a two-way clustering, which accounts for correlation within the first dimension, the second dimension and the intersection of the two (J. B. Cameron A. Colin and. Gelbach & Miller, 2011; Abadie, Athey, Imbens, & Wooldridge, 2017). By doing so, we appraise possible cross-district interactions. Despite having at least 50 units for all the three levels (considered to be the cutoff for avoiding largely biased variances (A. Cameron & Miller, 2015)), we acknowledge that this amount is still insufficient for achieving consistency, since the number of clusters should be high enough to permit an asymptotic convergence. Another potential criticism is that nahyas or districts' boundaries do not englobe all the spillovers, and one could argue that Syria as a whole should be the level at which treatment and outcome are spatially correlated. However, this choice would not capture how the war hits the different territories heterogeneously. Ideally, one may adopt randomization inference to compute Fisher's exact p-values. This technique, which requires a full understanding of the assignment mechanism, is complicate to implement in this setting. It is challenging to delineate with adequate precision the reasons for which some areas are affected by the civil war while others are not, especially because the intensity of the combats and their spatial distribution vary over time (notwithstanding ideological reasons and the involvement of foreign forces). Future research can try to extend our empirical strategy and alleviate these limits.

5.2.1 Pooled OLS and Two-Way Fixed Effects

To quantify the sum of direct and spillover effects, we start from a baseline OLS specification which introduces as covariates a full list of controls (see Table 9). We pool together all years from 2003 to 2019. We use a set of geography and natural resources variables, such as `latitude, longitude, nahya size, wheat suitability, precipitation`. We compute the distance to each major urban area and to the closest city. Likewise, we compute the distance to the closest border of Egypt, Turkey and Iraq and to the closest foreign nation. The latter measures are introduced considering that Egypt was the origin country for the Arab Spring movement (i.e., the spark for the civil war), Turkey has intervened largely in the combats, Iraq border is the location of various territorial disputes (some of them were even born in Iraq and subsequently extended to Syria). Additionally, we include the pre-war economic conditions: we take `population density, luminosity and productivity` measured in 2010, one year prior to the outbreak of the conflict. The estimated functional form is the following:

$$Y_{nt} = \alpha + \tau_1 D_{nt} + \theta X_n + \Lambda Rain_{nt} + \epsilon_{nt} \tag{2}$$

Y_{tn} is either average Normalized Difference Vegetation Index (NDVI) or share of arable land cultivated in nahya n in year t. The latter dependent variable is built summing over the results of the patch-level productivity-classification algorithm, and is unrelated to yields. D_{nt} defines the total number of conflicts recorded in nahya n in year t. Crucially, D_{nt} - labelled *Treatment 1* in the respective results - is no longer a canonical binary indicator, but a nahya-specific continuous variable (zero until 2011). X_n is the set of controls about 2010 socioeconomic status, geography, distance and location; it would include Rain_{nt}, but we keep these two notations apart as the former is fixed while the latter is time-varying.

Furthermore, we estimate the analogous regression separately by alternative definitions of the treatment, on the basis of the category of armed conflict incidences (`state-based conflict, non-state and one-sided`) and of the combats' mortality (number of deaths for each faction fighting, plus civilians). For notational synthesis, the following functional form includes all the treatment versions, even though they are evaluated per se:

$$\begin{aligned} Y_{nt} = \alpha + \tau_2 State_{nt} + \tau_3 NonState_{nt} + \tau_4 OneSided_{nt} + \\ + \tau_5 DeathsA_{nt} + \tau_6 DeathsB_{nt} + \tau_7 DeathsCivilians_{nt} + \theta X_n + \Lambda Rain_{nt} + \epsilon_{nt} \end{aligned} \tag{3}$$

Overall, we test the general treatment and 6 additional specifications. The OLS results provided in Table 12 in the Appendix are based on Equations 2 and 3. We adopt a unique clustering approach, with robust clustered standard errors at the war zone level. We also vary the set of controls included in the model, and, once all the covariates are plugged in, the coefficients of interest are insignificant, especially for share of land cultivated. This finding would contradict the reasoning that the civil conflict had a direct effect on agricultural activities. However, if we reduce the dimensionality of the controls, we attain strong statistical significance, in particular when civilians are involved (*one-sided violence* and *civilians' deaths*). This latter result is consistent with the population-displacement argument analyzed in patch-level Figures 7 and 8.

To improve on the precedent model and possibly consider the presence of time-varying and nahya-specific attributes, we implement a Two-Way Fixed Effects using nayha and time fixed effects. The former englobe almost all covariates, since geography, location and distance do not change across years. The only control left out is Rain_{nt}, which is nahya and time-dependent. The regression is the following:

$$Y_{nt} = \tau D_{nt} + \lambda_t + \phi_n + \Lambda Rain_{nt} + \epsilon_{nt} \tag{4}$$

where λ_t and ϕ_n are respectively year and nahya fixed effects. The estimation is iterated changing the definition of the treatment D_{nt} (in accordance with Equations 2 and 3) and the level of clustering for the robust standard errors (`war zone, war zone-nahya and war zone-district`). Table 6 reports the major findings (standardized size). In the Appendix we display the unstandardized estimates (Table 13) and the within R-squared for each combination of treatment-cluster (Table 14).

Table 6: **Standardized effect sizes: Two-Way Fixed Effects at nahya level**

Cluster	War zone		War zone-Sub district		War zone-District	
Outcome	(1) Share Land Cultivated	(2) Mean NDVI	(3) Share Land Cultivated	(4) Mean NDVI	(5) Share Land Cultivated	(6) Mean NDVI
Treatment 1	-0.029	-0.003	-0.029*	-0.003	-0.029**	-0.003
Total conflicts	(0.00630)	(0.00538)	(0.00486)	(0.00415)	(0.00418)	(0.00439)
Treatment 2	-0.023	-0.000	-0.023*	-0.000	-0.023*	-0.000
State-based conflict	(0.00618)	(0.00546)	(0.00447)	(0.00408)	(0.00386)	(0.00454)
Treatment 3	-0.030	-0.011	-0.030	-0.011	-0.030	-0.011
Non-state conflict	(0.00898)	(0.00631)	(0.00599)	(0.00443)	(0.00624)	(0.00464)
Treatment 4	-0.022	-0.030*	-0.022	-0.030*	-0.022	-0.030*
One-sided violence	(0.00690)	(0.00507)	(0.00541)	(0.00462)	(0.00525)	(0.00484)
Treatment 5	0.002	-0.015	0.002	-0.015	0.002	-0.015
Side A deaths	(0.00485)	(0.00412)	(0.00472)	(0.00249)	(0.00508)	(0.00251)
Treatment 6	0.007	0.023	0.007	0.023**	0.007	0.023***
Side B deaths	(0.00503)	(0.00433)	(0.00528)	(0.00239)	(0.00532)	(0.00214)
Treatment 7	-0.049**	-0.028	-0.049***	-0.028*	-0.049**	-0.028*
Civilians' deaths	(0.00647)	(0.00516)	(0.00514)	(0.00420)	(0.00539)	(0.00387)
Nahya-year FE	✓	✓	✓	✓	✓	✓
Outcome mean	0.1136	0.3658	0.1136	0.3658	0.1136	0.3658
Observations	600	600	600	600	600	600

Standardized beta coefficients. Robust Clustered Standard errors in parentheses. Each row of the table corresponds to a specific treatment variable adopted, thus, each value refers to a separate regression (different treatment, outcome and clustering method).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We focus all our attention on share of arable land being cultivated, whose coefficients become relevant when clustering considers wider spatial correlation (cluster at the larger possible level: war zone-district). Observing Column (5) of Table 6, the values signal a great heterogeneity in the effect of the war on land according to the different types of the conflict. While *non-state war* and *one-sided violence* seem to not correlate with agricultural performance, *state-based conflict* (i.e., where one of the two sides involve the Syrian government) is significant, likewise *total conflicts*. The former form is sufficiently violent to cause agricultural damages through the devastation of land. The war-induced consequential decrease in the area cultivated in a given nahya is confirmed by narrative sources, documenting the *strategy of destruction* implemented by the Syrian government[23]. The TWFE results match the precedent Ordinary Least Squares: as a whole, they provide evidence that the civil war has much hit the agricultural sector, especially via *state-based fighting*. This hypothesis is reinforced by comparing the incidence of civilians' deaths as opposed to militias/fighters/soldiers': the effects on cultivated land hold only for the former treatment definition (and with a very high degree of significance). The intuition of this by-product is immediate: deaths limit work force, thus, agriculture; similarly, the "deadliest" areas (i.e., battlefields where most side-A and side-B fighters die) are definitely unsuitable for continuing any economic activity.

While because of clustering the standard errors vary, the interpretation of the estimates is identical. Looking at Column (5) of Table 13, the (indistinct) conflict shrinks the likelihood of previously cultivated land being still cultivated by 0.00252 percentage points, on average. An increase in the conflict index by 10 SD leads to a reduction of the outcome by 0.3 SD, in accordance with Table 6. The impact may not appear at first glance economically relevant; however, we provide a more interpretable measure to illustrate its concreteness. By the end of the Syrian civil war, in 2019 the nationwide cultivated land for wheat was approximately 1.26 million hectares[24] over a total arable surface of 4.66 million hectares[25]. Only in that year more than 1,500 conflict incidences took place, leading to an estimated $1968 \times 0.0000252 \times 100 \approx 4.96$ percentage-point decline in the probability of one arable area being cultivated. The impact of this loss on the aggregate wheat production ($3,085,096$ tons in 2019) is considerable, especially because related to one of the 'least intense' periods of the civil war (Figure 3). Likewise, the probability of a plot being cultivated at time *t+1* and "surviving" the war decreases by 0.00183 percentage points per civilian perished (1 SD more reduces `productivity classification` by 0.049 SD). One could use a similar approach to measure the nationwide productivity shock. For example, deceased civilians in 2019 amounted to 10317, implying a decline in the likelihood of cultivating one plot by $10317 \times 0.0000183 \times 100 = 18.88$ percentage points. These rough estimations should be taken with a pinch of salt in terms of exact findings, yet they gauge the large-scale agricultural shock and

[23] This tactic, which is sometimes defined as 'Surrender or starve', entails multiple actions against the rebels to challenge their physical and mental resilience. Unfortunately, most of these violences hurt civilians, too, and are classified as war crimes: bombardments to schools and hospitals, interrupting food and medicine supplies, ... We also single out several *scorched-earth* operations, which are prominent to our research question and they were likely inherited from the intervention of Russia since 2012 in support of Bashar al-Assad. This strategy is an evident cause of agricultural losses. Source: Amnesty International (2017)

[24] The data is accessible in the FAO Special Report (2019).

[25] The data is accessible at Macrotrends, which uses country-specific FAO reports as sources of information.

its overall magnitude.

As concerns the effect on plant health and vegetation density, the point estimate is counterintuitively positive for the specification of *side-B deaths*. As recently found by (Zhang, Ding, Zhao, Liu, & Pereira, 2023) in Afghanistan, often conflicts cause land abandonment, which in turn leads to vegetation recuperation. These considerations may possibly explain a positive result; though, nearly all functional forms presented thus far at patch and nahya levels report a negative and statistically strong result, which suggests conversely that the war has caused environmental damages and not benefits.

5.2.2 Tackling endogeneity

The pre-war economic characteristics affect the likelihood for warfare to happen. Balance Table 1 shows the differences in observables between nahyas exposed and not exposed to any conflict in 2011, the first year of the combats. One may see why, in line with the strong rejection of the hypothesis of balance, in Subsection 5.2.1 we conditioned on several variables to make the treatment assignment akin to randomization. Despite trying to rule out potential selectivity, we cannot exclude the presence of omitted variables bias given the paucity of indexes we are constrained to work with. There are several aspects that we cannot consider with the information at disposal, yet they may play a role, such as culture (Nunn, 2009; Alesina, Giuliano, & Nunn, 2013), ideology (Carlton, 1990; Sanín & Wood, 2014) and religion[26], which are particularly valid in Syria, given the rebellion induced by the Arab Spring movement, the Islamic State (ISIL) participating in the conflict and the "cold-war kind" dispute between Russia and United States (respective allies of the national government and of the democratic forces).

Another problem springs from reverse causality: the causal link between state capacity and intra-group conflict could go either way around[27]. Developing countries are more exposed to shocks because of volatile prices of agricultural products, thus unstable supply (Jacks, O'Rourke, & Williamson, 2009; J. Chen, Kibriya, Bessler, & Price, 2018). This concept of conflict trap where "war is development in reverse" (Collier et al., 2003) complicates our attempt to identify causation. Phases of alternating conflict intensity, the presence of multiple factions and the intervention of external forces feed the civil war and exacerbate the socioeconomic status. This loop between warfare, food insecurity and impediments to agriculture has carried on for more than a decade and is a clear symptom of reverse causality. These endogenous aspects prompt us to isolate the effect of warfare by using two diverse approaches: Instrumental Variable estimation and partialling-out.

Two-Stage Least Squares By adopting Two-Stage Least Squares (2SLS), we try to identify strongly relevant and exogenous instruments that determine a variation in cultivation and agricultural productivity

[26] It is important to distinguish the persistent divine justification of war and religious influence as opposed to the specific Islam case being largely debated in recent times. Besides *jihad* motives, people might consider the *puzzling Islamic-Violence case* (i.e., contemporary civil wars have hit mostly Islamic states) a good piece of evidence for relating Islamism to propensity to fight. (Karakaya, 2015) fully denies any corresponding reasoning. (Klocek & Hassner, 2019; Polinskaya, James, & Papadogiannakis, 2024) must not be neglected for explaining armed-group behaviour and military strategies.

[27] Poverty, inequality and famine are determinants of civil disorders (Koren, Bagozzi, & Benson, 2021; Grasse, 2022; Sova, Fountain, Zembilci, & Carr, 2023). Former U.S. Senate Agriculture Committee chair Pat Roberts said in a 2015 speech, *"Show me a nation that cannot feed itself, and I'll show you a nation in chaos"* (Source).

only through the civil conflict. For their choice we rely on Least Absolute Shrinkage and Selection Operator (LASSO). To do so, we need to normalize the variables prior to LASSO estimation such that the weights automatically assigned by the algorithm are equal. In addition, we partial out *nearest city distance*, which we believe to be an appropriate IV for our study (a thorough discussion of the relative identifying assumptions is provided Appendix). The machine-learning technique keeps other measures of distance, though only in some specifications. Hence, we take a conservative decision and adopt only distance to the closest city as IV in our exactly identified model. Econometrically, we run:

$$\text{First Stage}: D_{nt} = \gamma + \beta \text{Closest\_city}_n + \theta X_n + \lambda Rain_{nt} + \eta_{nt} \tag{5}$$

$$\text{Second Stage}: Y_{nt} = \alpha + \tau \hat{D}_{nt} + \xi X_n + \Lambda Rain_{nt} + \epsilon_{nt} \tag{6}$$

where *Closest_city* corresponds to the instrument. Table 15 in the Appendix summarizes the findings: despite being dissatisfying for two-way clustering, the IV is strongly relevant for the treatment specifications which are the paramount (*state-based conflict, one-sided violence, civilians' deaths*) when we just use `war zone` as cluster. The corresponding coefficients augment in absolute value as opposed to TWFE (Table 13), yet they are statistically insignificant.

Partialling-out approach The 2SLS results may denote that we do not manage to properly isolate causation and and the concern of omitted variables is left open. We further investigate the robustness of our analysis by selecting five controls to partial out from the variation in the treatment variable. This choice is taken upon the findings of Balance Table 1 and of LASSO[28]. The methodology slightly differs from the IV with Two-Stage Least Squares and takes the following form:

$$\text{First Stage}: D_{nt} = \gamma + \beta \text{Z}_{nt} + v_{nt} \tag{7}$$

$$\text{Second Stage}: Y_{nt} = \alpha + \tau \hat{v}_{nt} + \xi X_n + \Lambda Rain_{nt} + \epsilon_{nt} \tag{8}$$

where X_n captures the set of basic controls (geography, land, natural resources). In practice, we examine the relation between the outcome (share of arable land being cultivated or NDVI) and the variation in treatment orthogonal to Z_{nt}. We cluster at war zone level and run separate regressions for every specification of D_{nt} (like Equations 2 and 3). In this empirical strategy we adopt only the treatments which have been found significant in the precedent methods: (i) total conflicts; (ii) state-based conflicts; (iii) one-sided violence; (iv) civilians' deaths. The findings (Table 7) are aligned with IV estimates for the same type of clustering (Column (1) in Table 15). The magnitude is almost identical and the treatment effects are still stronger than using TWFE. Taken together, the values provide robust evidence of the war-related shock to Syrian agriculture.

[28]Specifically, we use `nearest city distance, distance to Egypt, distance to Homs, wheat suitability, ruggedness` (which we call Z_{nt})

Table 7: OLS with **Partialling-out**

	Share Land Cultivated	Mean NDVI
Residual Treatment 1	-0.0000622**	-0.0000828*
Total conflicts	(0.0000236)	(0.0000348)
Residual Treatment 2	-0.0000574*	-0.0000791*
State-based conflict	(0.0000240)	(0.0000353)
Residual Treatment 4	-0.00342**	-0.00182
One-sided violence	(0.00106)	(0.00144)
Residual Treatment 7	-0.0000297***	-0.0000329**
Civilians deaths	(0.00000817)	(0.0000118)
Outcome mean	0.11356	0.3658
Observations	643	643

Robust Clustered Standard errors at war zone level in parentheses. Basic Controls include: *longitude, latitude, area, wheat suitability, ruggedness, precipitation annual deviation.* Each row of the table corresponds to a specific treatment variable adopted, thus, each value refers to a separate regression (different treatment and outcome).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6 Conclusions

The civil war in Syria, originated from the Arab Spring movement, officially broke out in March 2011. The conflict has evolved since then, turning from high-intensity combats to a more prolonged struggle. The agricultural sector has faced severe drop-back, as a consequence of terrible losses in local human and physical capital. In a nutshell, the region faces the largest refugee crisis in modern history, with more than 12 millions displaced. Besides hundreds of thousands of deaths (500,000 - 618,000), the undernourishment rate peaked at more than 30% in 2023, bringing 7.6 million Syrians to experience food insecurity (Food and Agriculture Organization of the United Nations, 2023). Already these numbers provide a glimpse of the war effects on agriculture and food production, to which one should add destruction of infrastructure, reported scorched-earth tactics and political instability.

The literature has focused on the Syrian conflict and the corresponding agricultural damage by tracking over time the changes in land suitability and crops under cultivation. To do so, satellite imagery-based monitoring is required to circumvent the problem of missing data and to provide a valid quantification of the consequences. Nonetheless, most of these studies do not have solid econometric analyses, thus they do not isolate the link between civil war and agricultural performance. Our attempt is to bridge this gap and use satellite remote-sensing to feed a causal empirical strategy. To test the hypothesis of a substantial productivity shock, we employ two distinct techniques. We begin by conducting a patch-level Staggered Difference-in-Differences (SDID), for which we partition Syria into 2.1×2.1 km^2 areas. Within this framework, we define a binary absorbing treatment to indicate the presence of armed conflict within a given patch.

Our results reveal a dynamic negative impact of conflict on population density and agricultural productivity, with the most pronounced economic costs materializing approximately five years post-conflict onset. In the long run, however, affected regions exhibit partial recovery.

While our methodology does not capture the maximum spillover radius, the *patch-donuts* approach and the definition of thin and thick donuts provide two key insights: (i) anticipatory effects manifest through population relocation in adjacent patches, suggesting that conflict expectations influence migration patterns; (ii) regions that indirectly experience conflict exhibit slower long-run recovery than those directly exposed to combats. To further quantify the total impact of armed conflict (i.e., the sum of direct and spillover effects), we extend our analysis to the nahya level, implementing a Two-Way Fixed Effects (TWFE) estimator alongside instrumental variables (IV) and partialling-out approach. Although the treatment effects in the IV strategy are imprecise, we provide alternative methods to gain in reliability and robustness. Our findings are consistent with existing literature on the economic consequences of civil wars and they clearly suggest a large contraction of national agricultural output during periods of active armed conflict.

Future research directions are multiple. For instance, we suggest modelling the Syrian food production with local inputs that capture the elements (and their extent) which truly affect farmers' decisions. Furthermore, scholars might be interested in deriving valid identification strategies to study causation at meso level. In fact, our nahya-level IV is relevant but does not return statistically significant estimates. Lastly, the area in which most improvements can be done pertains to unravel the specific mechanisms which connect armed-conflict incidences with cultivation. Our major hypothesis, corroborated by patch-level results, lies in population displacement, also because we do not find sufficient evidence about the access-to-market channel. Nevertheless, we do not measure migration flows precisely. Moreover, other mechanisms deserve equally researchers' attention and effort: an example is the levels of chemicals in the soil. Isolating the prominent mediators from the entire bundle would add value to the explanation of the dynamics characterizing the Syrian civil war.

Appendix

6.1 Civil War and Production inputs

A civil conflict affects the agricultural sector, consequently local development, from a multi-faceted perspective. The literature provides ethnographic evidence and empirical findings to study the war-related turmoil and the consequent changes of the key variables in the food production function. A detailed and input-specific reasoning is provided below. In summary, we assess that for several intertwined reasons (destruction of resources and infrastructure, physical displacement, deaths, social and material exchanges, ...) fighting has potentially devastating repercussions on the primary sector by strongly affecting the determinants of supply and demand.

Physical Capital and Labour One of the first things associated to wars is material destruction. This aspect can take different forms and target various crucial agricultural inputs. Traditional combats with bombing and mines destroy infrastructure, livestock, and equipment; consequently, they hinder farming operations. While resources during warfare are typically converted for military purposes, this case is less relevant for the Syrian civil war. Nonetheless, the impact on humans' lives is unquantifiable. Migration, deaths, and conscription during war reduce the availability of healthy and dedicated farmers (Stanikzai, Ali, & Kamarulzaman, 2021). Moreover, since crop-management knowledge comes mostly from either outside or within the farming community (Lamers & Feil, 1995; Brhane, Lulseged, G., & Kirubel, 2016), war produces negative effects via degraded social networks.

Access to Resources War-induced displacement and disruption of trade routes severely limit market access (both nationally and internationally). Geopolitical instability compounds these issues: imports and emergency food assistance[29] will be likely compromised, due to weaker diplomatic relations[30]. Key inputs for increasing agricultural production in less developed countries (manure, pesticides and chemical fertilisers) decrease in availability (Koussoubé & Nauges, 2016; Hemming et al., 2018). Their supplies are scarce due to internal combats and the limited amount of these resources inflate prices.

A similar logic applies to access to water. While materially the distance of farms to the closest coast or natural source of water (river, lake...) cannot vary, freshwater systems (canals, aqueducts and wells) are particularly vulnerable because of their central position in conflicts (as a cause, objective, resource) and their connectedness. Additionally, these infrastructures cannot be easily restored to their original state, and conflict-related impairment is likely to be long-lived (Francis, 2011). The Ukrainian war provides a

[29] To understand the scale of the Syrian crisis, since 2012 United States of America have contributed more than USD $3.2 billion in emergency food assistance across the governorates of the country – data updated as of 2019.

[30] A very recent example is the decision of Russia to suspend supplies following the fall of Bashar al-Assad; vice versa, Ukrainian Agriculture Minister Vitaliy Koval has confirmed the intention to replace Russia in this role as food supplier. We can foresee how these sudden variations go at the expense of Syrian citizens (Source)

straightforward example of the consequences on water availability and quality, hindering consumption and farming (Shumilova, Tockner, & Sukhodolov, 2023).

Land Suitability Intuitively, intense wars degrade the soil. Attacks, mines and bombs devastate fields and increase terrain ruggedness, which has been proven very detrimental. In the case of the Ukrainian war, (Kussul et al., 2023) show that crop productivity has majorly fallen because of a reduction in arable land; in Syria, the series of articles 'Syrian Diaries' (Monde, 2024) provide similar insights. Although fewer hectares of cultivated areas may raise productivity in case of diminishing returns to scale (Saini, 1969; Berck & Helfand, 2014), this hypothesis is seldom sustained for Syria.

Weather conditions and geography are elements which are notably linked to the suitability of a given territory to host agricultural activities. The fact that Syria has been experiencing more and more extreme droughts and floods due to the climate change[31] is a phenomenon which cannot be attributed to conflict incidences. In this sense, war does not vary such exogenous components, however few words are worth spending on a possible reverse association. In Africa, rainfall variability has been demonstrated to have a significant effect on political conflicts, like civil wars and insurgencies (Cullen & Idean, 2012). (Maertens, 2021) quotes former US president Barack Obama (2015) : *"[...] more intense droughts will exacerbate shortages of water and food [...], severe drought helped to create the instability in Nigeria that was exploited by the terrorist group Boko Haram"*. Accordingly, (Maertens, 2021) finds a U-shaped relationship between rainfall and the risk of civil conflict and war in (Sub-Saharan) African countries. A relationship that comes from the "hump-shaped relationship between rainfall and agricultural output" in the first place. *In medio stat virtus*: too little rain hurts crops to the same extent as excessive rain does. Whether this reasoning, which can be extended to temperature and further weather status (Tackseung, 2017), holds with analogous precision for the Arabian Peninsula has not been investigated yet. We leave this possibility open and argue that the decennial persistence of the war in Syria may hide a general dissatisfaction of the population for the unstable living conditions partly exacerbated by the climate change.

6.2 Demand of Agricultural products

Since the literature of demand functions for agricultural products is poor (de Janvry & Sadoulet, 2020), we extend our framework modelling crops as storable commodities according to (Magdoff, 2008). The underlying assumption is of no right to adequate nutrients, although people have a biological need of eating. Henceforth, food behaves as a common market good. *"People without what economists call "effective demand" cannot buy sufficient nutritious food. Of course, lack of "effective demand" in this case means that the poor don't have enough money to buy the food they need"* (Magdoff, 2008). The crucial role of price elasticity of demand, which determines business and market decisions, performance and activities, is widely accepted in the literature (Predrag, Aleksandar, & Jelena, 2017). Prices are also extremely important for ensuring

[31] FAO (2021): "Syrian Arab Republic: Precipitation analysis, 1980–2021". Red Cross and Red Crescent Movement, Climate Centre (2024). "Syria: Climate fact sheet 2024".

social order (Bellemare, 2015): developing countries are considered less stable than developed ones also because of the volatility in the costs of agricultural products (Jacks et al., 2009). While price is traditionally interpreted as a fundamental driver of demand, food is quite price-inelastic because people buy it regardless of the cost (Waugh, 1964). A cross-state analysis within the United States on 25 individual crop and livestock output supplies and 6 input demands showed that the own-price input demand elasticities were generally low (Villezca-Becerra & Shumway, 1992). Similarly, (Seale, Regmi, & Bernstein, 2003) estimate expenditure responsiveness with price and income changes for each food subcategory across 114 countries: most nations worldwide (including Syria) report inelastic coefficients. In addition, when the literature considers the impact of non-price factors, too, the demand-price association becomes slightly positive for many agricultural products. The latter, however, are neither inferior goods (the Giffen's Paradox does not hold) nor luxury goods (the Veblen effect is unrelated). Whatever phenomenon underlies the reversal of the correlation, the demand in agricultural markets appears largely price insensitive.

Shifting the focus on non-price components of food demand, we examine other potential inputs and we simultaneously study their sensitivity to the war. Like price, income is a traditional demand trigger, yet appears to not affect much consumption habits of agricultural items (Shenggen, J., & L., 1995; D. Chen, Abler, Zhou, Yu, & Thompson, 2016). Notwithstanding the evidence which is much robust across the literature (Babu, Gajanan, & Hallam, 2017), considering wealth in this cultivation-shock study is needed because of the intense fluctuations to which Low Middle-Income Countries are exposed to. These nations react more to economic challenges, like fighting (Muhammad, Jr, Meade, & Regmi, 2011; Melo et al., 2015). Impediments to capital accumulation cause exploding poverty rates and reduce average income, thus purchasing power. Two channels which determine these results are *off-farm employment* and *credit access*: conflicts hinder the role of these mechanisms in reducing household financial constraints (Matshe & Young, 2004; Zereyesus, Embaye, Tsiboe, & Amanor-Boadu, 2017; de Janvry & Sadoulet, 2020).

Strictly linked to income is the market size. Because of missing precise information on domestic trade flows, we associate this element to population density in a given area (Antle, 1999). The trend for number of citizens had always been monotonically positive before the outbreak of the civil war in 2011. The latest years follow a U-shaped function, instead[32]: after declining sharply, the population has resumed its growth since mid-2016 (the historical minimum), which generates an increased demand pressure. At the same time, Syria is facing a significant contraction in sectoral exports due to border closures, affecting trade with key partners (Jordan, Lebanon, Turkey, Iraq)[33].

An additional element to consider is taste. The effect that crises prompt on individual preferences are multiple. Given the subsistence need, conflicts boost the demand of primary goods like food (Johannes et al., 2021; Narter, 2023). They may also "solve" common behavioural inconsistencies existing in developing regions (Banerjee & Duflo, 2011), where the consumption of primary goods (despite the adjective itself) is

[32]World Bank Data. "Syrian Arab Republic - Population, Total".

[33]United Nations Economic and Social Commission for Western Asia (ESCWA) & Centre for Syrian Studies (CSS), 2020: "Syria at war: eight years on"

not that primary. As concerns, the role of substitutes is subtle and needs decomposing. When we consider alimentation as unit of reference, it is difficult to imagine the existence of substitutes which can satisfy physiological needs. Though, poor-country citizens often engage in actions which may seem irrational but that are totally rational given the situation they are in (Banerjee & Duflo, 2011): it is common to observe families in retarded regions diverting resources from food to other products[34]. The reason stands in how subsistence and primary needs, which by definition denote the necessary level of nutrients for survival (Wolpe, 2023; Mohammed, 1986), are interpreted in the daily life. While wealth nations lay stress on physiological requirements (eating, drinking, sleeping), underdeveloped areas attribute a wider sense to the expression. When living in perennial harsh conditions, food may lose its priority over more entertaining items which alleviate the hardship of life much more than what wheat would do. In practical terms, by addressing the same survival need from a mental-challenge stance, they act as potential substitutes to agricultural products. Same reasoning holds for spirituality, which brings people to engage in behavioural responses compensating for physiological needs[35](Cavenar & Spaulding, 1977; Rafique, Anjum, & Raheem, 2019). Although it may be true that in ordinary situations the purchase of aliments is not of primary interest, this preference can be silenced by war-induced famine and poverty, inducing households to re-orient their expenses.

6.3 Instrument validity

Besides letting LASSO decide which instruments are appropriate for factoring out war's endogeneity, we impose the selection of *nearest city distance*. For being valid, this variable must satisfy both relevance and exclusion restrictions.

Relevance Despite contemporary literature has not found an increasing urbanization of armed conflicts (Elfversson & Höglund, 2021), a recent report by the European Asylum Support Office confirms that for Syria most of the damaging attacks have taken place in densely populated areas[36]. This information is valuable for hypothesizing that inhabiting closer to a city raises the likelihood of being exposed to any sort of war-related violence. As a matter of fact, this consideration is corroborated by Table 1, which outlines that urban areas were the first being involved into the conflict.

Exclusion restriction *Distance to closest city* must affect agriculture only through the probability of suffering war-related consequences. However, it may impact on how many hectares of land are cultivated in a certain territory especially via logistics. Cultivation requires suitable characteristics of the land, in terms of fertility, proximity to water sources, low ruggedness. These necessary conditions make agricultural practices,

[34]The typical anecdote is the entertainment and conspicuous consumption in poor households of developing countries at the post-capitalism era, as studied by Nobel-prize winners Banerjee and Duflo, who ascertain that "TV is more important than food" (Banerjee & Duflo, 2011).

[35] *"We shall certainly test you with fear and hunger, and loss of property, lives, and crops. But [Prophet], give good news to those who are steadfast"* (Surah Al-Baqarah, 2:155), and *"as for those who disbelieve and die as disbelievers, God rejects them, as do the angels and all people"* (Surah Al-Baqarah, 2:161). These verses are a typical example of Muhammad suggesting converters and non-converters that they should bear suffering to wash-off their sins.

[36]Source: European Asylum Support Office (EASO). Syria Security situation: Country of Origin Information Report. (2019).

particularly the location of a plot, quite unrelated to urban areas. However, the distance to important markets and communities may be important if farmers have easier access to equipment, physical capital (labour force, as well) and credit. Living close to a city can actually be beneficial to cut transportation costs (Kalvi et al., 2010; Fliehr, Zimmer, & Smith, 2019) and obtain resources for increasing crop yields, thus land value (Stewart, 1936): fertilisers or other tools for levelling the ground and tilling the soil are typical examples. In brief, the distance city-farm can correlate to agricultural production via access to the market. At the same time, these dynamics are not generally valid, especially in developing regions whose urban-rural connections are inefficient and discourage movement (infrastructures, costs, security, ...). If this impact really mattered and was persistent over time, the effects would always be detectable and, in our framework, especially before the war began in 2011.

Although this assumption is untestable by definition, we construct a placebo test to reinforce our hypothesis that distance does not affect the agricultural sector expect via the war. We study whether the instrument affects the outcomes of interest (NDVI and share of cultivated plots over arable land) during the pre-war periods up to 2011. Methodologically, we run a set of pooled OLS regressions using panel data covering the pre-conflict baseline scenario (2003-2010) clustered at three different levels (war zone, war zone-nahya and war zone-district). Since war zones do not exist before the outbreak of the conflict, we reproject these areas (identified post-2011) at sub-district level. We recreate the same clusters before their actual existence.

Econometrically, the strategy consists in:

$$Y_{nt} = \alpha + \beta Z_{nt} + \xi X_n + \Lambda Rain_{nt} + \epsilon_{nt}$$

Z corresponds to *distance to the closest city*, our main variable of interest as well as the instrument of the original model. We add X_n, i.e., a rich set of time-invariant controls for geography, location, natural endowments, land. We include as well time-varying deviations from annual precipitation. To not reject the IV exclusion restriction, the estimates must be either statistically insignificant or close to zero. This is what Table 8 reports. Conclusively, if throughout the ten years prior to the civil war distance to a major city did not affect agriculture, we find improbable that the association would become relevant unless because of the conflict. Besides, the hostilities cause great logistics issues, likely inhibiting the potential channel via which distance could supposedly alter cultivated land.

Table 8: Placebo 2000-2010 on land outcomes

Outcome	Share Land Cultivated (1)	Mean NDVI (2)
Distance to closest city with clustering at:		
War zone	0.000191	-0.000420
	(0.000356)	(0.000395)
War zone-Sub district	0.000191	-0.000420
	(0.000356)	(0.000395)
War zone-District	0.000191	-0.000420
	(0.000417)	(0.000443)
Outcome mean for 2000-2010	0.1099	0.3727
Observations	2168	2168

Robust Clustered Standard errors in parentheses. The controls included are: *longitude, latitude, area, wheat suitability, ruggedness, precipitation annual deviation.*

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.4 Variable description

Variable Name	**Description**
polygon_id	Index specifying nahya, from 0 to 272.
contour_id	A unique index that identifies the war zone contour, where the ID remains consistent across the entire period rather than serving as a repeated cross-sectional identifier. Since the geographical distribution of conflict coordinates varies annually, the contour ID dynamically represents the evolving conflict boundaries. At the Nahya level, if multiple intersections occur between a Nahya and the war zone, the contour ID is assigned based on the largest overlapping area with the conflict zone.
war zone	A dummy variable recording if nahya or patch is located in war zone.

productivity_mean	Nahya level productive patch averaged over the full number of valid patches. The data source is based on `https://www.nature.com/articles/s43016-021-00432-4`. Productive patches have been defined by a classification algorithm presenting whether the land is being cultivated. The data is constructed using Moderate Resolution Imaging Spectroradiometer (MODIS) and agricultural statistical data via supervised classification. Two key factors are essential to guarantee the representativeness and accuracy of the training process: (i) training samples should be chosen from multiple years, including a dry year (2007), a wet year (2002), and a year with moderate precipitation (2012), to ensure sample diversity; (ii) high-resolution Google Earth images are necessary to provide accurate visual interpretation of different land-cover types.
num_conf_typ'x'	Number of conflicts of type x in nahya and year t. 1 = state-based conflict, 2 = non-state conflict, 3 = one-sided violence.
side_a_mort	Mortality of the first party involved in the conflict.
side_b_mort	Mortality of the second party involved in the conflict.
civ_mort	Number of civilian deaths reported.
mean_ndvi	Average Normalized Difference Vegetation Index (NDVI) for vegetation health. Source: Copernicus Europe. NDVI values range from [-1,+1]: negative values (< 0) for water, snow, or clouds; 0 - 0.2 for barren areas like rock, sand, or soil with minimal vegetation; 0.2 - 0.5 for sparse vegetation, such as grasslands or shrublands; 0.5 - 1 for dense vegetation, such as forests or croplands. The patch averaging process filters out the negative patches (i.e., removing all water and snow patches).
sum_ndvi	Total NDVI for the region.
Controls	
total_pop_scan	Total population sourced at nahya level from Landscan. The data is measured as the number of people in one patch. The resolution level is 30 arc-seconds ≈1 km.
mean_ruggedness	Average ruggedness of the terrain in the region, sourced from `https://www.earthenv.org/topography`.
total_pop_sum	Total population at nahya level sourced from WorldPop. Estimated total number of people per grid-cell. The dataset is available to download in Geotiff format at a resolution of 3 arc (approximately 100 m at the equator). The projection is Geographic Coordinate System, WGS84.

mean_luminosity	Average nighttime light intensity (a proxy for economic activity) in the corresponding nahya. The data source is `https://eogdata.mines.edu/products/dmsp/` for years 2000 to 2012. The resolution is 30 arc-second (roughly 1 km at the Equator). For years 2013 to 2020, the source is `https://eogdata.mines.edu/nighttime_light/annual/v20/` with a resolution of 15 arc-second (roughly 500 m at the Equator).
total_lum_sum	Total sum of nighttime light intensity values. The same source as above except valid patches being summed in one nahya.
longitude	Longitude coordinate of the nahya centroid.
latitude	Latitude coordinate of the nahya centroid.
wheat_suitability_mean	Average suitability of the region for wheat cultivation. Crop suitability index values are computed for all land and current cropland, separately for rain-fed and irrigated land. Evaluation is based on inputs, management, and water supply systems. The index is calculated as: $SI = 100 \times \frac{90\times VS+70\times S+50\times MS+30\times mS+15\times VmS+0\times NS}{90}$ where VS, S, MS, mS, VmS, and NS represent the shares of area extension in different suitability classes within a 5 arc-minute grid cell.
wheat_suit_sum	Total suitability index for wheat cultivation in the region.
distance_to_city	Distance (in km) from the centroid of the nahya polygon to the centroid of cities in the list of Damascus, Aleppo, Homs, Latakia, Tartus, Deir ez-Zor, Raqqa, Al Hasakah, Daraa, Qamishli, Idlib, Hama.
distance_to_egypt	Distance (in km) from the centroid of the Nahya polygon to the nearest border with Egypt.
distance_to_iraq	Distance (in km) from the centroid of the nahya polygon to the nearest border with Iraq.
distance_to_turkey	Distance (in km) from the centroid of the nahya polygon to the nearest border with Turkey.
worldpop_density	Nahya level population density from the World population source (taking all patches into account).
landscan_density	Nahya level population density from Landscan source (taking all patches into account).
ann_dev	Annual sum of monthly precipitation deviation (in absolute terms) from the 2003-2009 averaged precipitation in the corresponding month.

6.5 Figures

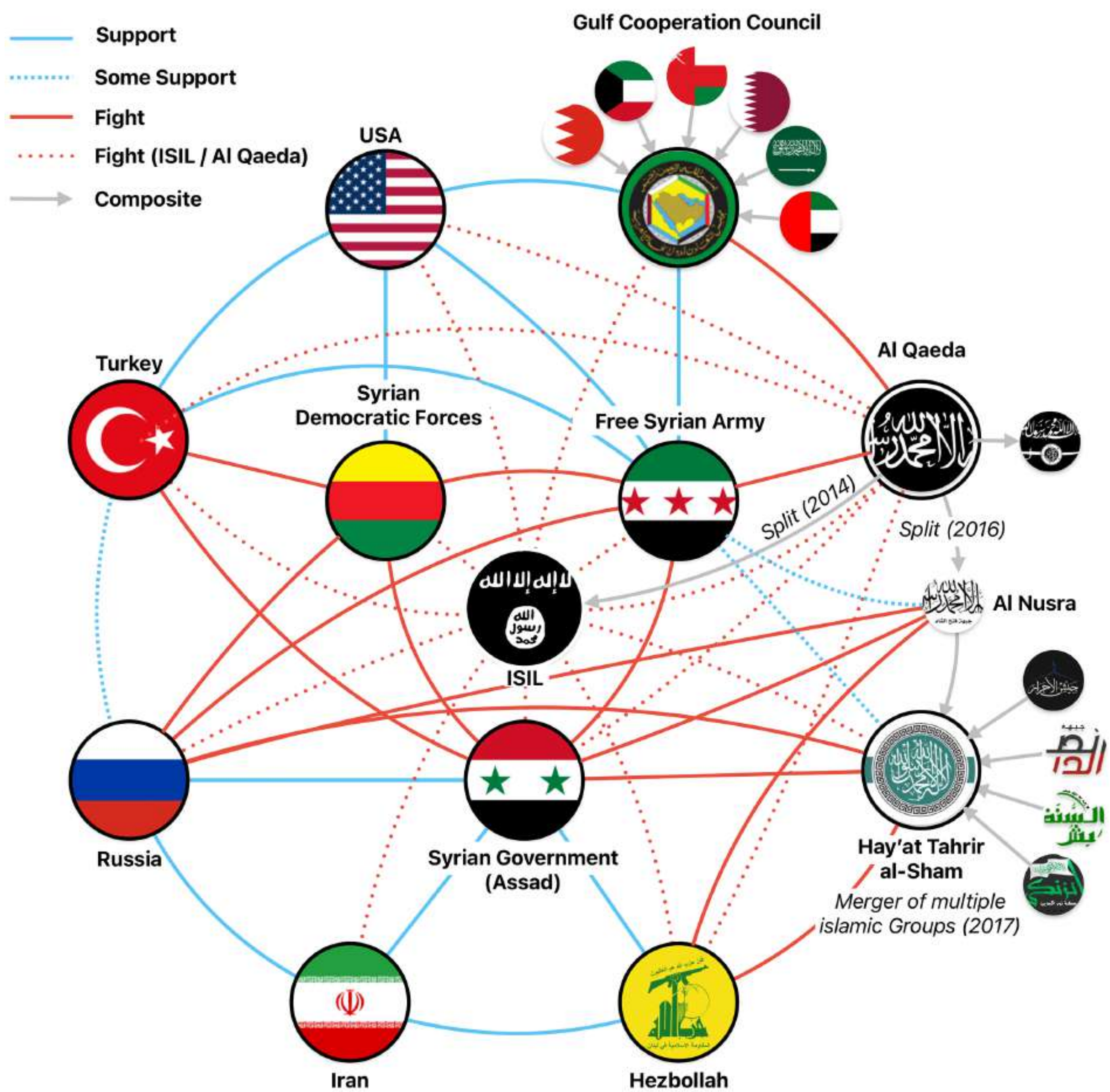
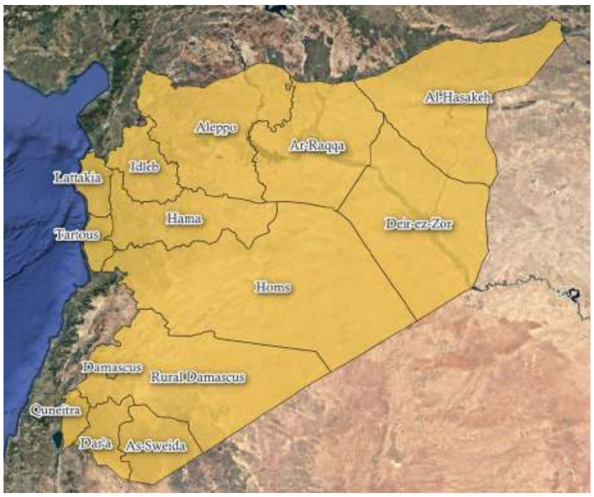
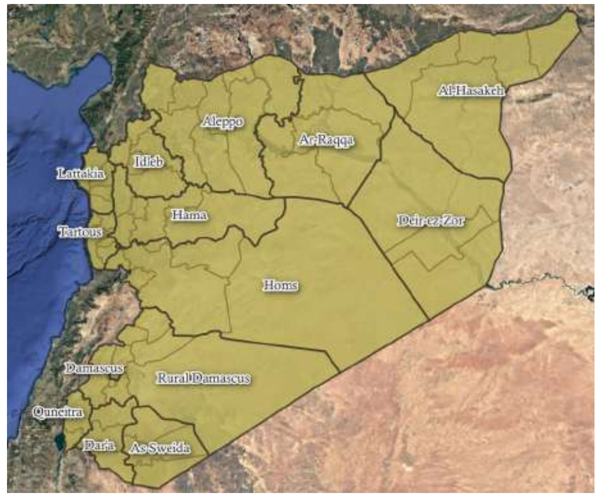


Figure 9: Major players in the Syrian Civil War (December 2024)

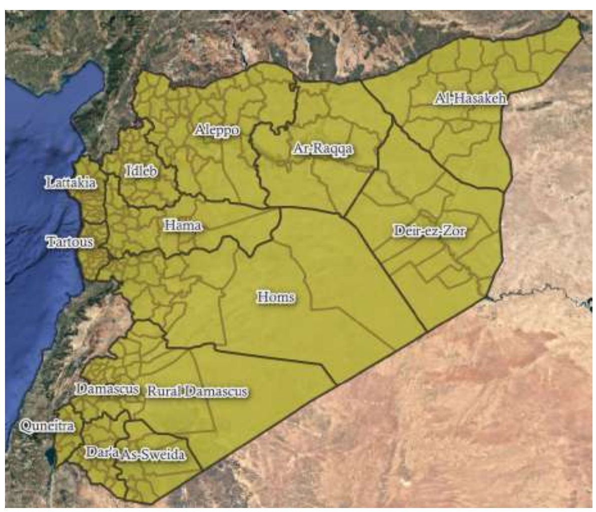
Figure 10: Syrian administrations



(a) 1^{st} level - Governorates/Provinces

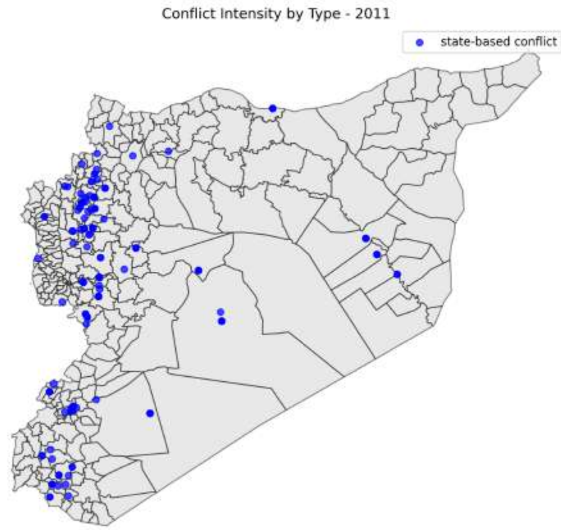


(b) 2^{st} level - Districts (thinner gray line)

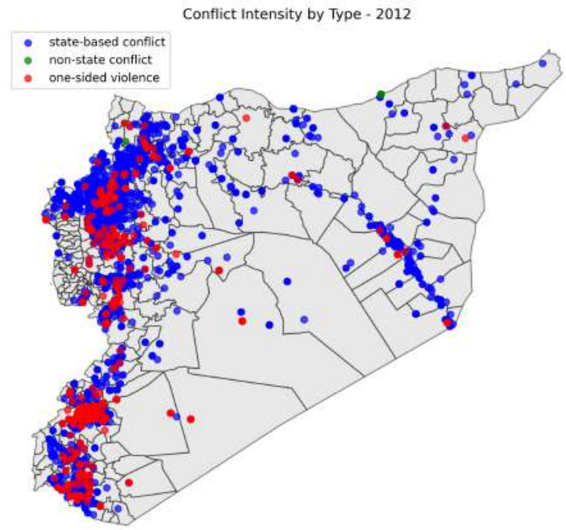


(c) 3^{rd} level - Nahyas (municipalities) (thin brown line)

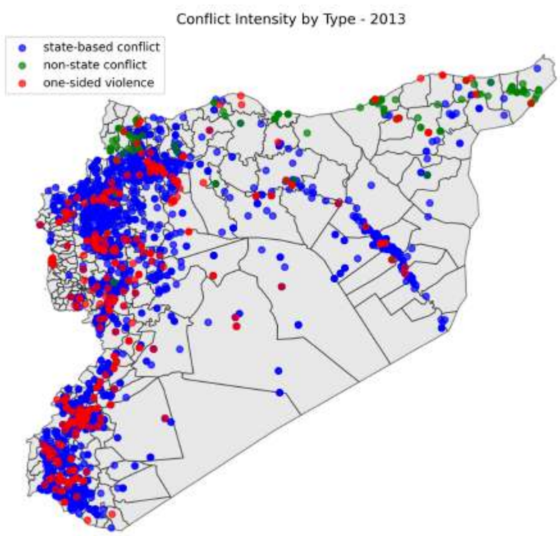
Figure 11: Conflict Intensity (2011-2016)



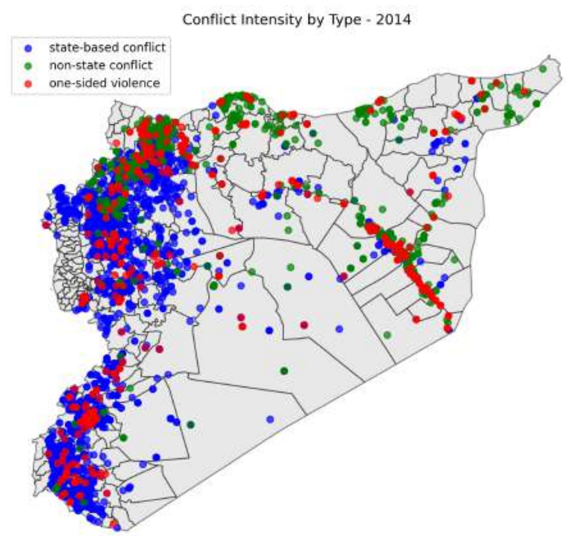
(a) Conflict Map 2011



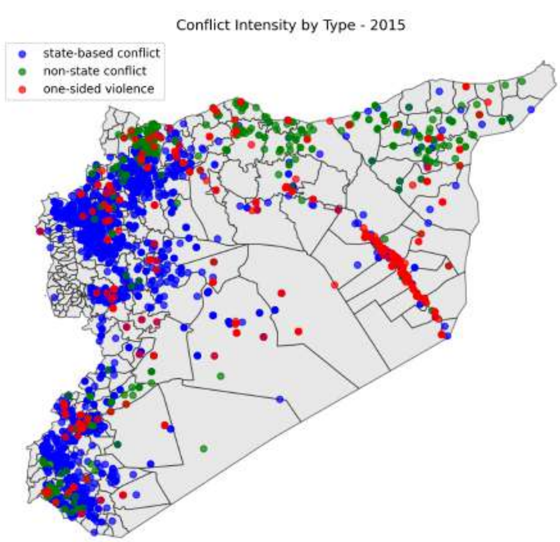
(b) Conflict Map 2012



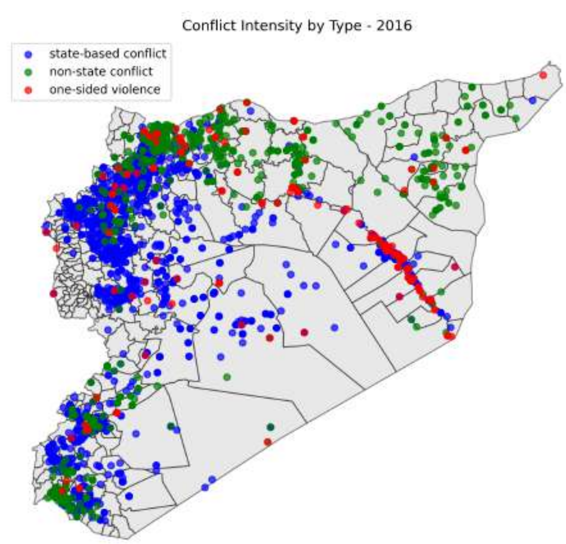
(c) Conflict Map 2013



(d) Conflict Map 2014

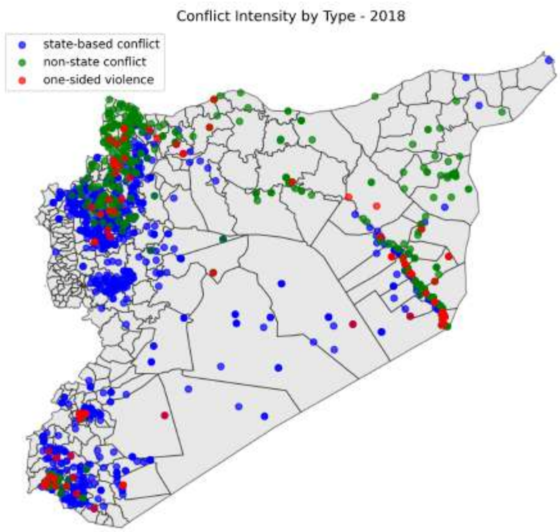


(e) Conflict Map 2015

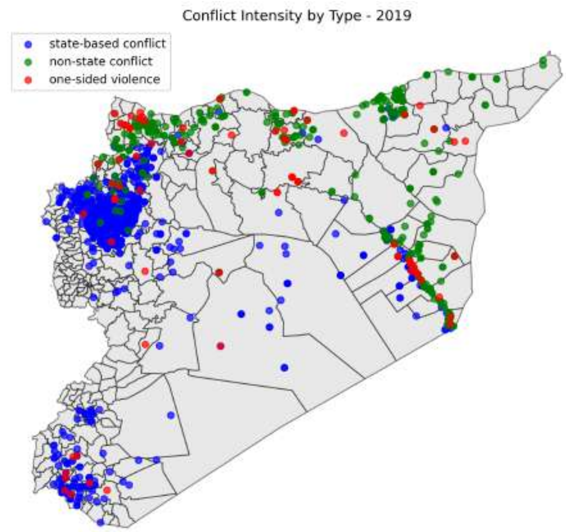


(f) Conflict Map 2016

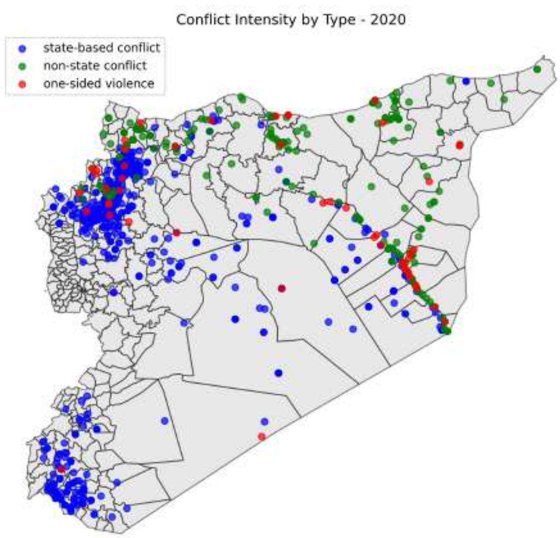
Figure 12: Conflict Intensity (2018-2023)



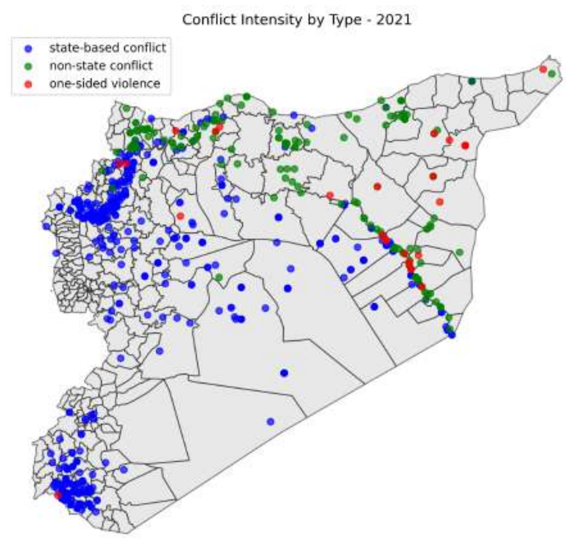
(a) Conflict Map 2018



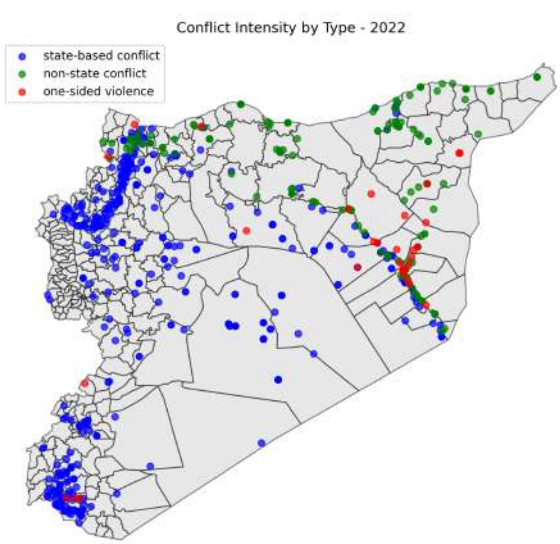
(b) Conflict Map 2019



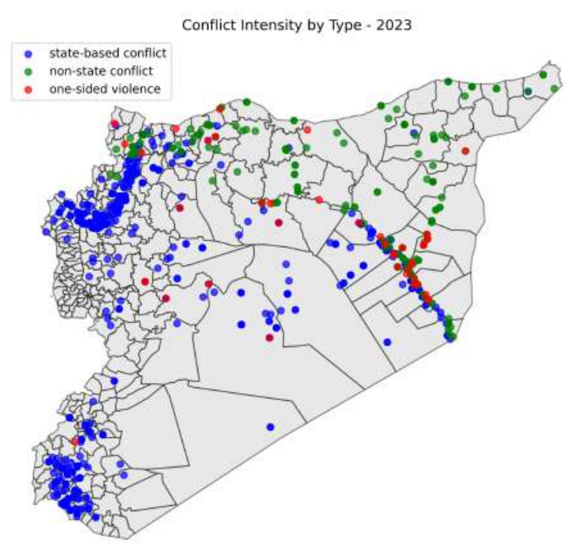
(c) Conflict Map 2020



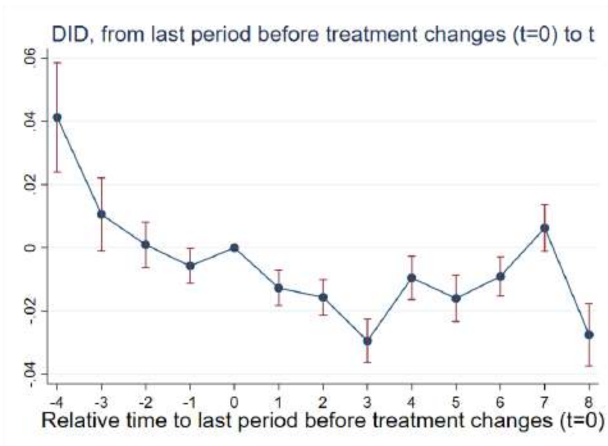
(d) Conflict Map 2021



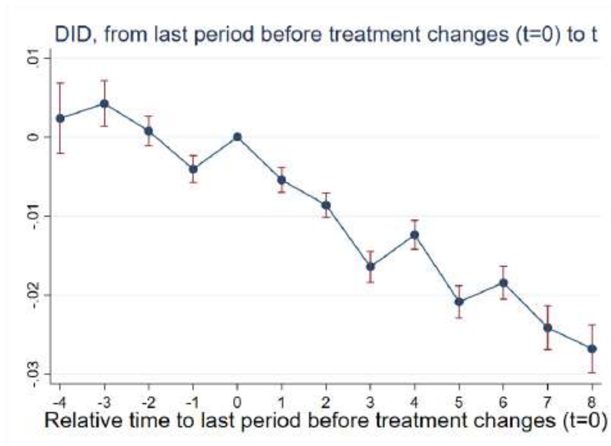
(e) Conflict Map 2022



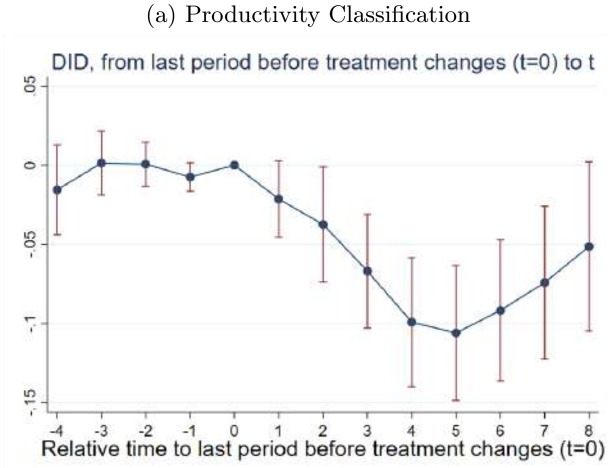
(f) Conflict Map 2023



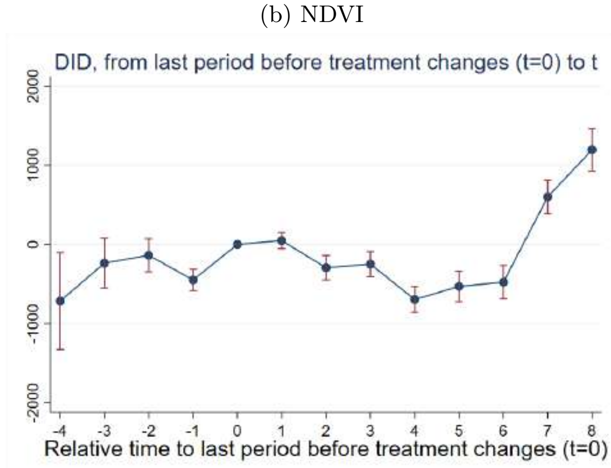
(a) Productivity Classification



(b) NDVI

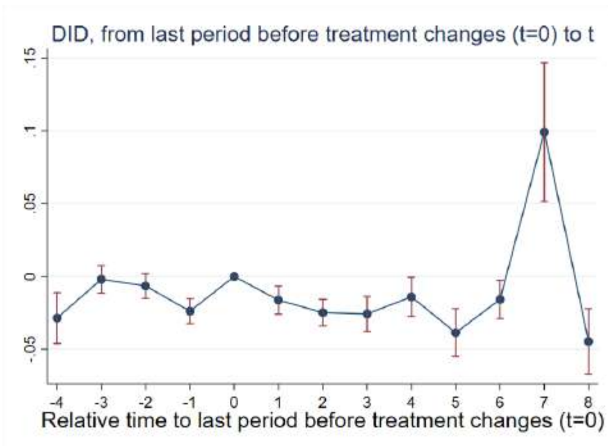


(c) Landscan Population

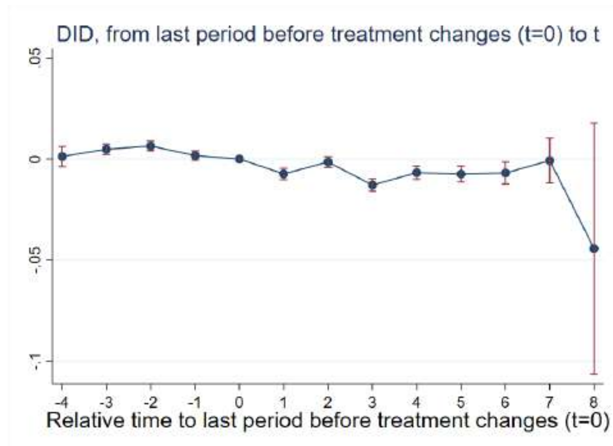


(d) Luminosity

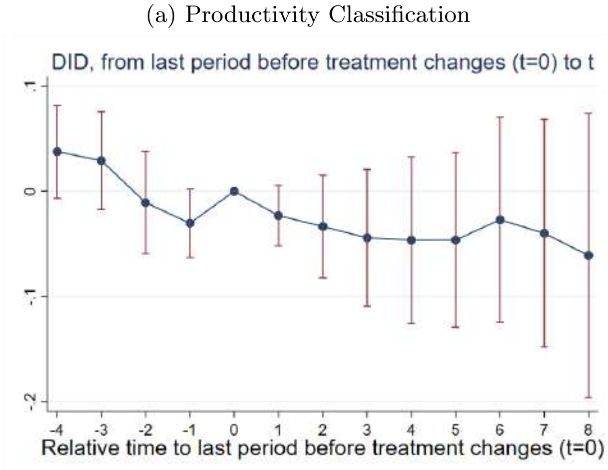
Figure 13: Staggered Difference-In-Differences over **full sample**. We provide the event studies with additional pre-trend test on our dependent variables: classification of productivity, NDVI, population density from Landscan, and luminosity. To have a uniform time-span over the plots, we take 8 post-war periods and 4 pre-periods. Period 0 is omitted for comparison. The brackets record the 95% confidence interval. The treatment is defined as a binary indicator for whether the type 1 of the conflict (state-based violence) happened in the patch.



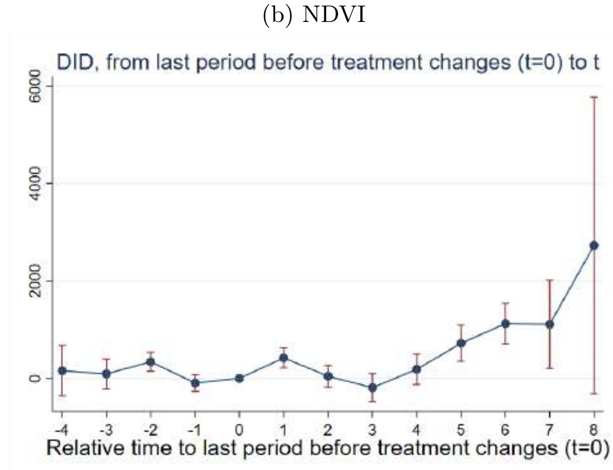
(a) Productivity Classification



(b) NDVI

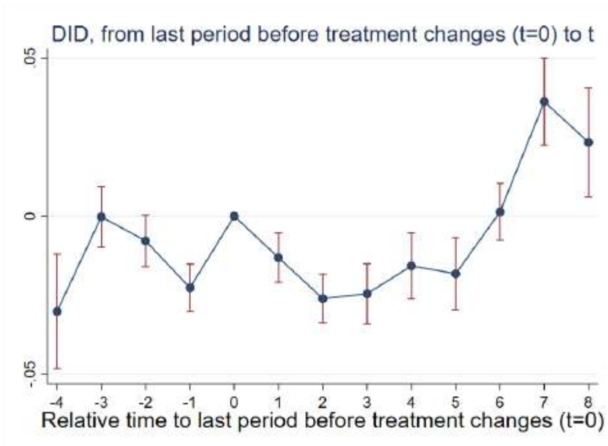


(c) Landscan Population

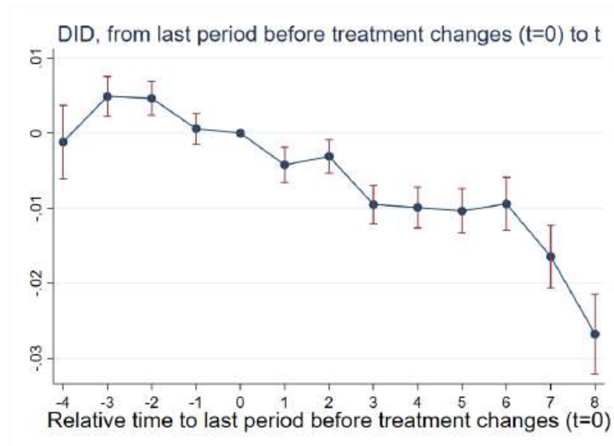


(d) Luminosity

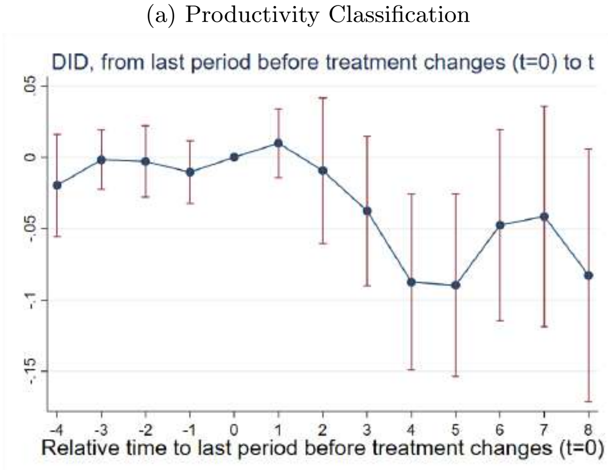
Figure 14: Staggered Difference-In-Differences over **full sample**. We provide the event studies with additional pre-trend test on our dependent variables: classification of productivity, NDVI, population density from Landscan, and luminosity. To have a uniform time-span over the plots, we take 8 post-war periods and 4 pre-periods. Period 0 is omitted for comparison. The brackets record the 95% confidence interval. The treatment is defined as a binary indicator for whether the type 2 of the conflict (non-state violence) happened in the patch.



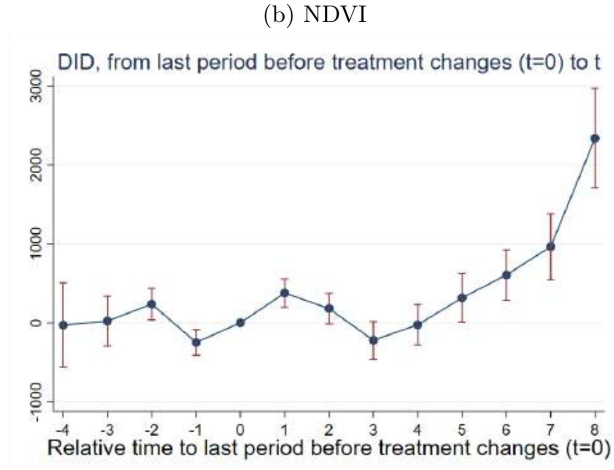
(a) Productivity Classification



(b) NDVI

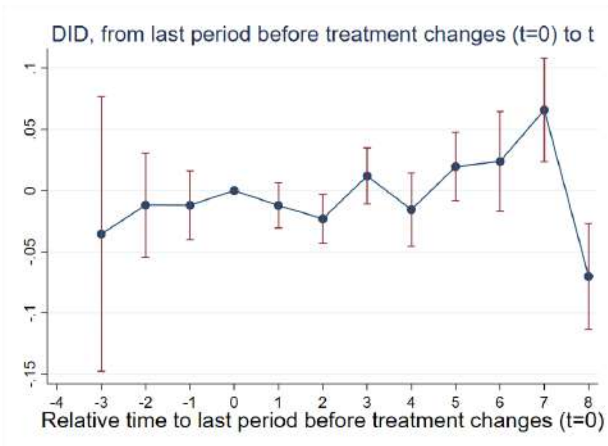


(c) Landscan Population

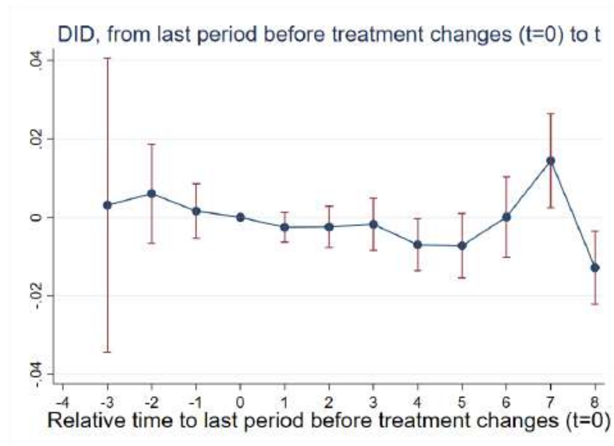


(d) Luminosity

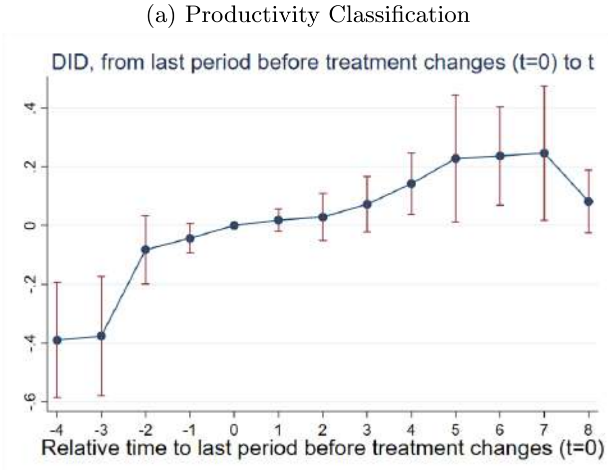
Figure 15: Staggered Difference-In-Differences over **full sample**. We provide the event studies with additional pre-trend test on our dependent variables: classification of productivity, NDVI, population density from Landscan, and luminosity. To have a uniform time-span over the plots, we take 8 post-war periods and 4 pre-periods. Period 0 is omitted for comparison. The brackets record the 95% confidence interval. The treatment is defined as a binary indicator for whether the type 3 of the conflict (one-sided violence) happened in the patch.



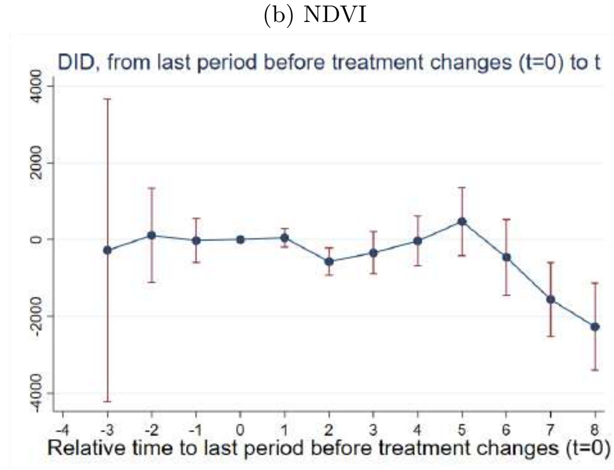
(a) Productivity Classification



(b) NDVI

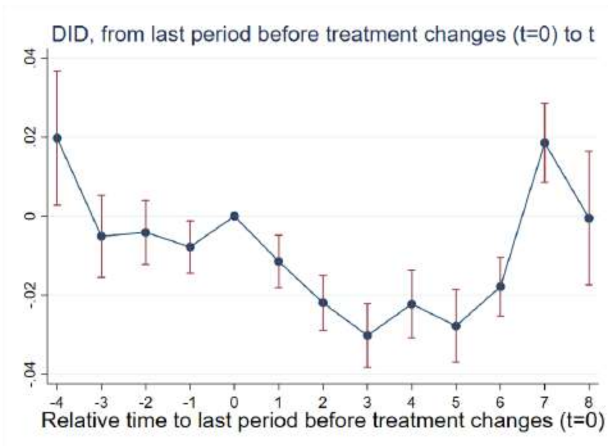


(c) Landscan Population

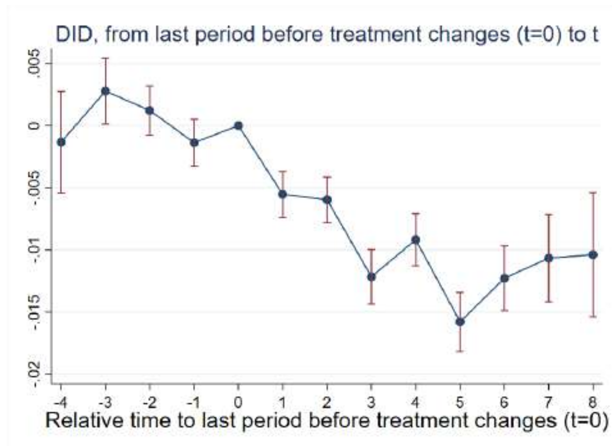


(d) Luminosity

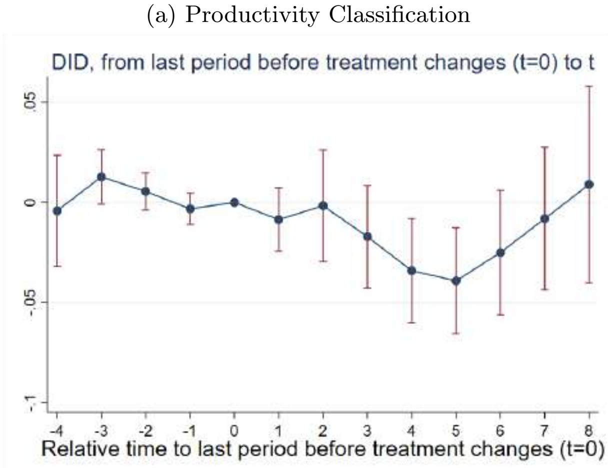
Figure 16: Staggered Difference-In-Differences over **war-zone sample**. We provide the event studies with additional pre-trend test on our dependent variables: classification of productivity, NDVI, population density from Landscan, and luminosity. To have a uniform time-span over the plots, we take 8 post-war periods and 4 pre-periods. Period 0 is omitted for comparison. The brackets record the 95% confidence interval. The treatment is defined as a binary indicator for whether the type 3 of the conflict (one-sided violence) happened in the patch.



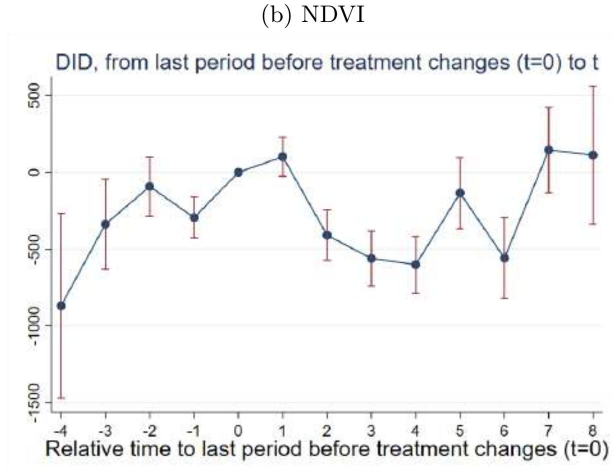
(a) Productivity Classification



(b) NDVI



(c) Landscan Population



(d) Luminosity

Figure 17: Staggered Difference-In-Differences over **war-zone free sample**. We provide the event studies with additional pre-trend test on our dependent variables: classification of productivity, NDVI, population density from Landscan, and luminosity. To have a uniform time-span over the plots, we take 8 post-war periods and 4 pre-periods. Period 0 is omitted for comparison. The brackets record the 95% confidence interval. The treatment is defined as a binary indicator for whether the type 3 of the conflict (one-sided violence) happened in the patch.

6.6 Tables

Table 10: Summary Statistics, patch level

Variable	Obs	Mean	Std. Dev.	Min	Max
Mean Nighttime Luminosity	660,688	6,075.663	6,097.130	0	25,040.4
Sum of Nighttime Luminosity	660,688	2.49e+07	2.50e+07	0	1.03e+08
Mean LandScan Population	1,691,292	0.076	0.622	0	44.594
Mean WorldPop Population	1,164,051	0.817	4.493	0.000037	198.917
Mean NDVI (Vegetation Index)	1,443,320	0.121	0.111	-0.08	0.936
Total Conflict Events	1,887,555	95.831	428.770	0	2,023
Annual Deviation	1,463,931	35.050	81.471	0	1,065.625
Mean Luminosity (8 Neighbors)	660,733	6,102.291	5,976.398	0	23,476.22
Mean LandScan Pop (8 Neighbors)	1,704,225	0.077	0.501	0	33.836
Mean WorldPop Pop (8 Neighbors)	1,197,844	0.835	4.154	0.000038	187.761
Mean NDVI (8 Neighbors)	1,453,826	0.121	0.098	-0.033	0.731
Mean Luminosity (24 Neighbors)	660,733	6,121.562	5,919.769	0	22,871.85
Mean LandScan Pop (24 Neighbors)	1,707,302	0.078	0.437	0	26.119
Mean WorldPop Pop (24 Neighbors)	1,220,981	0.853	3.965	0.000039	169.166
Mean NDVI (24 Neighbors)	1,454,531	0.121	0.096	-0.021	0.572
Mean Luminosity (48 Neighbors)	660,733	6,139.929	5,860.245	0	21,523.18
Mean LandScan Pop (48 Neighbors)	1,709,844	0.080	0.381	0	22.861
Mean WorldPop Pop (48 Neighbors)	1,244,901	0.874	3.768	0.000041	142.706
Mean NDVI (48 Neighbors)	1,454,559	0.121	0.094	-0.013	0.508
Mean Luminosity (16 Neighbors)	660,733	6,121.562	5,919.769	0	22,871.85
Mean LandScan Pop (16 Neighbors)	1,707,302	0.078	0.437	0	26.119
Mean WorldPop Pop (16 Neighbors)	1,220,981	0.853	3.965	0.000039	169.166
Mean NDVI (16 Neighbors)	1,454,531	0.121	0.096	-0.021	0.572
Mean Luminosity (25 Neighbors)	660,733	6,139.929	5,860.245	0	21,523.18
Mean LandScan Pop (25 Neighbors)	1,709,844	0.080	0.381	0	22.861
Mean WorldPop Pop (25 Neighbors)	1,244,901	0.874	3.768	0.000041	142.706
Mean NDVI (25 Neighbors)	1,454,559	0.121	0.094	-0.013	0.508

Note: NDVI represents the Normalized Difference Vegetation Index, a measure of vegetation density. Nighttime luminosity data is derived from satellite observations to gauge economic activity. Population density estimates come from WorldPop and LandScan datasets. Variables with (8 Neighbors, 16 Neighbors, 24 Neighbors, 25 Neighbors, 48 Neighbors) indicate aggregation across the corresponding number of surrounding grid patches.

Table 11: Summary Statistics, nahya level

Variable	Obs	Mean	Std. Dev.	Min	Max
Total Conflicts	4,624	16.43	66.46	0	1,804
State-Based Conflict Events	4,624	15.19	64.67	0	1,762
Non-State Conflict Events	4,624	0.995	7.442	0	386
One-Sided Violence Events	4,624	0.254	1.328	0	39
Fatalities (Side A)	4,624	30.78	383.0	0	16,403
Fatalities (Side B)	4,624	25.26	217.3	0	8,263
Civilian Fatalities	4,624	26.00	144.1	0	4,230
Rainfall Annual Deviation	4,624	16.03	7.797	0	62.31
Longitude	4,624	37.14	1.474	35.67	42.13
Latitude	4,624	34.97	1.230	32.38	37.09
Area	4,624	1.034e+09	2.506e+09	342,784	2.519e+10
Wheat Suitability	4,624	2,414	1,962	0	7,036
Ruggedness	4,607	1.06e-05	1.06e-05	7.16e-07	4.28e-05
Total Population	4,624	1.899e+07	1.774e+06	1.667e+07	2.231e+07
NDVI (Vegetation Index)	4,607	0.366	0.176	0.0768	0.780
Nighttime Luminosity	4,624	3.07e-05	2.41e-05	0	8.25e-05
Population Density (WorldPop)	4,624	0.000353	0.00128	0	0.0134
Population Density (LandScan)	4,624	0.310	3.369	0.000662	65.09
Share Cultivated Land over arable land	4,624	0.114	0.145	0	0.712
Mean Nighttime Luminosity (2010)	4,624	4.72e-05	4.37e-06	0	5.58e-05
Share Cultivated Land over arable land (2010)	4,624	0.126	0.155	0	0.678
Population Density (WorldPop, 2010)	4,624	0.000397	0.00142	0	0.0134
Population Density (LandScan, 2010)	4,624	0.354	3.841	0.000863	63.44

Note: Conflict data is sourced from the Uppsala Conflict Data Program (UCDP). NDVI represents the Normalized Difference Vegetation Index, a measure of vegetation density. Nighttime luminosity data is derived from satellite observations to assess economic activity. Population density estimates come from WorldPop and LandScan datasets.

Table 12: **OLS at nahya level**

	Share Land Cultivated		**Mean NDVI**	
	Basic Controls	Full Controls	Basic Controls	Full Controls
Treatment 1	-0.0000773**	-0.0000132	-0.0000964**	-0.0000677*
Total conflicts	(0.0000229)	(0.0000199)	(0.0000341)	(0.0000318)
Treatment 2	-0.0000749**	-0.00000497	-0.0000952**	-0.0000596
State-based conflict	(0.0000232)	(0.0000201)	(0.0000345)	(0.0000319)
Treatment 3	-0.000290	-0.000510*	-0.000304	-0.000679*
Non-state conflict	(0.000224)	(0.000213)	(0.000270)	(0.000304)
Treatment 4	-0.00394***	-0.00188*	-0.00231	-0.000587
One-sided violence	(0.00111)	(0.000753)	(0.00157)	(0.00115)
Treatment 5	-0.00000510*	-0.00000200	-0.00000855**	-0.00000557
Side A deaths	(0.00000245)	(0.00000234)	(0.00000293)	(0.00000306)
Treatment 6	-0.0000155*	-0.00000553	-0.0000186*	-0.0000114
Side B deaths	(0.00000595)	(0.00000373)	(0.00000764)	(0.00000613)
Treatment 7	-0.0000356***	-0.0000114	-0.0000368**	-0.0000232*
Civilians deaths	(0.00000883)	(0.00000753)	(0.0000126)	(0.0000115)
Outcome mean	0.11356	0.11356	0.3658	0.3658
Observations	643	643	643	643

Robust Clustered Standard errors at war zone level in parentheses. Basic Controls include: *longitude, latitude, area, wheat suitability, ruggedness*. Full controls add: *distance to Egypt, Iraq, Turkey and a set of Syria major cities, luminosity in 2010, cultivated land in 2010, population density in 2010, precipitation annual deviation.* Each row of the table corresponds to a specific treatment variable adopted, thus, each value refers to a separate regression (different treatment and outcome).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: **Unstandardised estimates in TWFE at nahya level**

Cluster	War zone		War zone-Sub district		War zone-District	
Outcome	(1) Share Land Cultivated	(2) Mean NDVI	(3) Share Land Cultivated	(4) Mean NDVI	(5) Share Land Cultivated	(6) Mean NDVI
Treatment 1	-0.0000252	-0.00000290	-0.0000252*	-0.00000290	-0.0000252**	-0.00000290
Total conflicts	(0.0000137)	(0.0000143)	(0.0000106)	(0.0000110)	(0.00000908)	(0.0000116)
Treatment 2	-0.0000203	-2.25e-08	-0.0000203*	-2.25e-08	-0.0000203*	-2.25e-08
State-based conflict	(0.0000138)	(0.0000149)	(0.00001000)	(0.0000111)	(0.00000862)	(0.0000124)
Treatment 3	-0.000227	-0.0000890	-0.000227	-0.0000890	-0.000227	-0.0000890
Non-state conflict	(0.000174)	(0.000149)	(0.000116)	(0.000105)	(0.000121)	(0.000110)
Treatment 4	-0.000972	-0.00142*	-0.000972	-0.00142*	-0.000972	-0.00142*
One-sided violence	(0.000751)	(0.000673)	(0.000589)	(0.000612)	(0.000571)	(0.000642)
Treatment 5	0.000000295	-0.00000222	0.000000295	-0.00000222	0.000000295	-0.00000222
Side A deaths	(0.00000183)	(0.00000190)	(0.00000178)	(0.00000114)	(0.00000192)	(0.00000115)
Treatment 6	0.00000191	0.00000653	0.00000191	0.00000653**	0.00000191	0.00000653***
Side B deaths	(0.00000334)	(0.00000351)	(0.00000351)	(0.00000194)	(0.00000354)	(0.00000174)
Treatment 7	-0.0000183**	-0.0000108	-0.0000183***	-0.0000108*	-0.0000183**	-0.0000108*
Civilians' deaths	(0.00000649)	(0.00000630)	(0.00000516)	(0.00000513)	(0.00000540)	(0.00000473)
Nahya-year FE	✓	✓	✓	✓	✓	✓
Outcome mean	0.11356	0.3658	0.11356	0.3658	0.11356	0.3658
Observations	600	600	600	600	600	600

Robust Clustered Standard errors in parentheses. Each row of the table corresponds to a specific treatment variable adopted, thus, each value refers to a separate regression (different treatment, outcome and clustering method).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: **Within-R Squared of TWFE at nahya level**

Cluster	War zone		War zone-Sub district		War zone-District	
Outcome	(1) Share Land Cultivated Within R-sq	(2) Mean NDVI Within R-sq	(3) Share Land Cultivated Within R-sq	(4) Mean NDVI Within R-sq	(5) Share Land Cultivated Within R-sq	(6) Mean NDVI Within R-sq
Treatment 1 Total conflicts	0.0055	0.0229	0.0055 *	0.0229	0.0055 **	0.0229
Treatment 2 State-based conflict	0.0042	0.0229	0.0042 *	0.0229	0.0042 *	0.0229
Treatment 3 Non-state conflict	0.0085	0.0238	0.0085	0.0238	0.0085	0.0238
Treatment 4 One-sided violence	0.0051	0.0293 *	0.0051	0.0293 *	0.0051	0.0293 *
Treatment 5 Side A deaths	0.0021	0.0237	0.0021	0.0237	0.0021	0.0237
Treatment 6 Side B deaths	0.0024	0.0261	0.0024	0.0261 **	0.0024	0.0261 ***
Treatment 7 Civilians' deaths	0.0146 **	0.0271	0.0146 ***	0.0271 *	0.0146 **	0.0271 *
Nahya-year FE	✓	✓	✓	✓	✓	✓
Outcome mean	0.11356	0.3658	0.11356	0.3658	0.11356	0.3658
Observations	600	600	600	600	600	600

This table reports the within R-squared for each combo outcome-treatment-cluster from the results in Table 13.
Each value refers to a separate regression.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$: the significance levels correspond to the point estimates in Table 13

Table 15: **IV estimation at nahya level**

Cluster	War zone		War zone-Sub district		War zone-District	
Outcome Outcome mean = 0.11356	(1) Share Land Cultivated	First-stage IV F statistic	(2) Share Land Cultivated	First-stage IV F statistic	(3) Share Land Cultivated	First-stage IV F statistic
Treatment 1 Total conflicts	-0.0000668 (0.000185)	15.93	-0.0000668 (0.000168)	5.41	-0.0000668 (0.000119)	5.85
Treatment 2 State-based conflict	-0.0000684 (0.000189)	15.97	-0.0000684 (0.000171)	5.35	-0.0000684 (0.000122)	5.60
Treatment 3 Non-state conflict	-0.0117 (0.112)	0.01	-0.0117 (0.110)	0.01	-0.0117 (0.0988)	0.01
Treatment 4 One-sided violence	-0.0000684 (0.0110)	12.33	-0.0000684 (0.00971)	8.39	-0.0000684 (0.00689)	9.43
Treatment 5 Side A deaths	0.0000126 (0.0000451)	4.04	0.0000126 (0.0000374)	0.98	0.0000126 (0.0000250)	1.19
Treatment 6 Side B deaths	0.0000539 (0.000226)	0.84	0.0000539 (0.000188)	0.32	0.0000539 (0.000125)	0.39
Treatment 7 Civilians' deaths	-0.0000281 (0.0000798)	11.91	-0.0000281 (0.0000715)	4.92	-0.0000281 (0.0000502)	5.05
Controls	✓	✓	✓	✓	✓	✓
Observations	643	643	643	643	643	643

Robust Clustered Standard errors in parentheses. In red we report the first-stage F statistics related to the relevance of the instrument (distance to the closest major city) which do not meet the rule-of-thumb cutoff at 10. In green the strongly relevant IVs. The controls included are: *longitude, latitude, area, wheat suitability, ruggedness, precipitation annual deviation.* Each row of the table corresponds to a specific treatment variable adopted, thus, each value refers to a separate regression (different treatment, outcome and clustering method).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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