Agricultural shocks and long-term conflict risk: Evidence from desert locust swarms

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This version: May 1, 2025

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Abstract

Can transitory agricultural shocks affect long-term violent conflict risk? This paper studies this question using data on conflict events and desert locust swarms—localized agricultural disasters—across 0.25° grid cells in Africa and the Arabian peninsula from 1997-2018. A staggered event study approach shows that having been exposed to a locust swarm increases the average annual probability of any violent conflict in a cell by 2.0 percentage points (71%) in subsequent years. Effects are driven by swarms arriving during the main growing season in cells with cropland, with no effects in non-agricultural areas. Previous studies find persistent adverse effects of locust exposure on measures of household well-being and agricultural profits. I show it also reduces agricultural activity and increases out-migration over the long-term, but does not affect measures of agricultural productivity at the cell level. I explore income-related mechanisms with a model of occupational choice. I find null effects on swarms on conflict in the year of exposure and a lag of 7 years before the largest effects, which are not consistent with predictions based on an opportunity cost mechanism alone. Impacts on conflict are driven by periods of local insecurity or famine, which explains the delay in the largest impacts of swarm exposure and are consistent with a grievance mechanism creating variation in the perceived returns to fighting. Patterns of long-term impacts on violent conflict and heterogeneity by local grievances are similar for exposure to severe droughts, indicating the mechanisms are not specific to locust swarms. These results add further motivation for policies mitigating the risk of agricultural shocks and promoting household resilience and long-term recovery.

JEL codes: D7; O13; Q10; Q54

Keywords: conflict; agriculture; desert locusts; natural disasters; Africa

I thank Daniel Agness, Maximilian Auffhammer, Kirill Borusyak, Abdoulaye Cissé, Alain de Janvry, Joel Ferguson, Ethan Kapstein, Ethan Ligon, Jeremy Magruder, Ted Miguel, Betty Sadoulet, Jed Silver, Sofia Villas-Boas, and seminar participants at UC Berkeley, Princeton University, Aix-Marseille School of Economics, CERDI, Nova SBE, New Mexico State University, CSAE 2025, NEUDC 2024, Fragile Lives 2024, PacDev 2023, MWIEDC 2023, the 2023 AAEA Annual Meeting, the 2023 WEAI Graduate Student Workshop, and ESOC 2022 for helpful comments. All errors are my own.

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1 Introduction

A large economic literature explores the impacts on conflict risk of transitory agricultural shocks which do not permanently affect potential land productivity. This is an important policy concern given the prominence of agricultural livelihoods in many of the areas most affected by civil conflict, the threat to agriculture posed by climate change, and the severe economic and human harms of civil conflict (see e.g., Blattman and Miguel, 2010; Fang et al., 2020). Studies of this relationship focus on short-term impacts, and those that analyze shocks to agricultural production are limited in their ability to identify causal mechanisms.[1] This paper analyzes the dynamic long-term impacts of a severe transitory shock to agricultural production—exposure to a desert locust swarm—on violent conflict, and tests for evidence of income-related mechanisms.

Desert locusts are the world's most dangerous and destructive migratory pest (Cressman et al., 2016; Lazar et al., 2016) and effectively constitute an agriculture-specific natural disaster. Climate change is creating conditions more conducive to swarm formation (Qiu, 2009), potentially undoing progress from increased international monitoring and control efforts in recent decades. The arrival of a locust swarm often leads to complete destruction of agricultural production and other vegetation (Symmons and Cressman, 2001; Thomson and Miers, 2002), without the effects on infrastructure or human physiology which may result from precipitation or temperature shocks. Swarm flight patterns create quasi-random variation in the areas exposed to agricultural destruction in a swarm's migratory path, and their migratory nature means that exposure to a swarm does not increase future risk from locusts.These characteristics make locust swarms a useful natural experiment for analyzing how transitory agricultural production shocks affect the long-term risk of conflict.

Using data on the location and timing of desert locust swarm observations from the Food and Agricultural Organization of the United Nations (FAO) and of conflict events from the Armed Conflict Location & Event Data Project (ACLED) and Uppsala Conflict Data Program (UCDP), I estimate a model of conflict at the annual level for 0.25° (around 28×28km) grid cells between 1997-2018 across Africa and the Arabian peninsula.[2] As severe

[1]Several studies find that shocks to agricultural prices increase conflict incidence (e.g., Dube and Vargas, 2013; Fjelde, 2015; McGuirk and Burke, 2020; Ubilava et al., 2022). Impacts on agricultural productivity are speculated to explain the widely-studied relationship between climate or weather shocks and conflict risk (see Burke et al. (2015), Carleton et al. (2016), Dell et al. (2014), Hsiang and Burke (2013), Koubi (2019), and Mach et al. (2019) for reviews), though weather may affect conflict through mechanisms other than agriculture and some studies find results that are not consistent with effects through agricultural productivity (e.g., Bollfrass and Shaver, 2015; Sarsons, 2015).

[2]I include all countries where at least 10 locust swarms are reported during the sample period. Torngren Wartin (2018) estimates short-term impacts of desert locusts on conflict in Africa using similar data. That paper focuses on potential measurement issues around short-term impacts which I discuss in Sections 4.2 and

agricultural shocks may have persistent effects on wealth and productivity which could affect conflict risk, I define exposure to a locust swarm as an absorbing treatment. I estimate average impacts of swarm exposure as well as dynamic impacts using event study designs from the recent literature on difference-in-differences with staggered treatment timing (Borusyak et al., 2024; De Chaisemartin and d'Haultfoeuille, 2024; Roth et al., 2023).

Locust swarms increase the annual probability of any violent conflict event occurring in a 0.25° grid cell by 2.0 percentage points (71%) on average in years after exposure to the swarm, compared to unaffected areas. I find no significant impacts of locust swarms on violent conflict in the year of exposure but increases in all following years up to 12 years after exposure. Impacts are entirely driven by cells with crop or pasture land, and by swarms arriving in crop cells during the main growing or harvest season in particular. I find limited evidence of conflict spillovers outside of exposed cells. The results are robust to a variety of alternative specifications.

I interpret the results and evaluate income-related mechanisms through the lens of a commonly-used model of individual occupation choice between production and conflict (Chassang and Padró i Miquel, 2009; Dal Bó and Dal Bó, 2011). In the model, transitory agricultural shocks affect the short-term risk of conflict by changing both the returns to engaging in agricultural production—the *opportunity cost* mechanism—and the returns to fighting over agricultural output—the *rapacity* mechanism. I extend the model to allow past agricultural production shocks to affect conflict risk through a wealth or *permanent income* mechanism. Adoption of insurance against negative agricultural shocks is very low in the study area, leading households to undertake costly consumption smoothing strategies and reducing household wealth (financial, physical, and human capital).[3] This wealth effect can decrease long-run productivity, leading to persistent reductions in the opportunity cost of fighting. Drawing on models of grievance and conflict (Buhaug et al., 2021; Collier and Hoeffler, 2004), I allow for time-varying factors to affect the returns to fighting and propose a *grievance* mechanism affecting when a prior shock is more likely to increase conflict risk.

The results do not align with predictions under an opportunity cost mechanism alone. Locust swarms have no significant effect on violent conflict in the year of exposure and a small effect the following year despite this being the period when the opportunity cost effect from reduced agricultural productivity should be strongest. This is true for measures of both

8. It does not consider long-term impacts of locust swarms or mechanisms that are the main contributions of this paper.

[3] See for example Alderman et al. (2006), de Janvry et al. (2006), Dercon (2004), Dercon and Hoddinott (2004), Dinkelman (2017), Fafchamps et al. (1998), Hallegatte et al. (2020), Hoddinott (2006), Hoddinott and Kinsey (2001), Maccini and Yang (2009), and Townsend (1995) on coping strategies LMIC agricultural households use to respond to uninsured shocks being largely uninsured and their impacts on household wealth/assets, including long-term consequences.

output conflict and conflict over territory or factors of production, indicating that the null immediate impact is not due to an offsetting effect under the rapacity mechanism.

Long-term conflict risk also does not increase uniformly, with the largest effects on violent conflict risk coming 7-12 years after swarm exposure. This lag aligns with the gap between the main locust exposure event in 2003-2005 and the onset of various conflicts in the sample countries caused by the Arab Spring, various civil conflicts, and the spread of terrorist organizations. In line with a grievance mechanism, I find that long-term impacts of past swarm exposure on violent conflict are concentrated in periods of greater insecurity or grievance caused by these broader factors. This heterogeneity can rationalize the null short-term impact on conflict. Fighting is inherently a group activity motivated by some particular goal, and individuals in areas exposed to locust swarms may have lower opportunity costs or greater underlying grievances and therefore be more likely to mobilize around proximate drivers of violent conflict. The results thus show that severe agricultural shocks need not cause the onset of new conflicts and highlight the importance of contextual factors in determining effects of shocks on conflict incidence.

I directly test for evidence of persistent effects of swarm exposure on measures of economic activity that could affect the opportunity cost of fighting, in line with a permanent income mechanism. I find no significant long-term effects on the Normalized Difference Vegetation Index (NDVI) or on measures of local crop yields using remote sensing (Cao et al. (2025)) or Demographic and Health Survey (DHS) data (IFPRI 2020). This indicates no permanent decrease in agricultural productivity, though analyses at the level of 0.25° cells may struggle to capture such effects when the median locust swarm would affect just 6% of cell area. I do observe significant long-term decreases in crop area cultivated and quantity harvested together with increases in out-migration, indicating transitions away from agricultural work. Together with evidence from other studies using survey data to show persistent adverse effects of locust swarms on agricultural production and measures of human capital, these results suggest that a long-term decrease in the opportunity cost of fighting is a plausible mechanism but more evidence from household-level analyses is needed to test it further.

Finally, to analyze whether the dynamic effects on conflict risk I estimate are specific to locust swarms I also test impacts of exposure to severe drought, measured using monthly Standardized Precipitation and Evapotranspiration Index (SPEI) data. I find large time-varying increases in conflict risk that are also driven by locations and periods with more insecurity, implying that the same mechanisms underly the effects of both types of agricultural shocks. The long-term increases in conflict risk indicate that analyses defining shock exposure as transitory and estimating short-term impacts using fixed effects (the main method in studies of climate or agricultural shocks and conflict) are misspecified for shocks with nonzero average long-term effects. I show that such specifications result in downward-biased estimates of the short-term impacts of both locust swarms and severe drought on violent conflict, affecting the policy implications.

This paper makes several contributions to the literature. First, I add to our understanding of the drivers of conflict (Bazzi and Blattman, 2014; Blattman and Miguel, 2010; Collier and Hoeffler, 1998; Dube and Vargas, 2013; Grossman, 1999; Hodler and Raschky, 2014; McGuirk and Burke, 2020; Miguel et al., 2004), and the roles of climate (Burke et al., 2024; Mach et al., 2020) and shocks to agricultural production (Crost et al., 2018; Harari and La Ferrara, 2018; McGuirk and Nunn, 2025; Von Uexkull et al., 2016) in particular. While a relationship between climate and conflict has been repeatedly demonstrated the mechanisms driving this impact are not fully understood . Weather shocks affect a variety of economic and social outcomes in addition to reducing agricultural labor productivity and agricultural output (Dell et al., 2012, 2014; Mellon, 2022), but much of the literature has emphasized an opportunity cost mechanism to explain increases in conflict risk.[4] The results of this paper indicate that the opportunity cost of fighting mechanism alone cannot explain dynamic impacts of locust swarms and severe drought on conflict risk over time. Similar to Buhaug et al. (2021)'s analysis of short-term effects of drought on conflict but considering longer-term dynamics, I highlight the importance of grievances and insecurity in determining when adverse effects of past shock exposure may lead to violent conflict.

Second, I contribute to a broader literature on the dynamic impacts of environmental shocks and natural disasters. Many papers have explored how environmental shocks can have persistent effects on poverty and well-being (Baseler and Hennig, 2023; Carter and Barrett, 2006; Carter et al., 2007; Lybbert et al., 2004), but these mechanisms have not been related to conflict risk. Studies of the impacts of agricultural shocks on conflict have focused on the short-term.[5] More generally, the evidence on long-term impacts of disasters such as hurricanes and droughts is limited, inconclusive, and focused on a small number of outcomes (see Botzen et al. (2019) and Klomp and Valckx (2014) for reviews). I study dynamic impacts of desert locusts swarms—an extreme shock to agricultural production akin to a natural disaster—on conflict risk and test whether patterns are consistent with a

[4]Little attention is given to the rapacity mechanism in the climate-conflict literature. Studies showing evidence of opportunity cost and rapacity mechanisms in agriculture have primarily explored impacts on conflict risk of changes in global prices of agricultural goods (e.g., Dube and Vargas, 2013; Fjelde, 2015; McGuirk and Burke, 2020) rather than shocks to local agricultural production. McGuirk and Nunn (2025) is an exception, analyzing impacts of drought on conflict between pastoralists and farmers.

[5]Crost et al. (2018) and Harari and La Ferrara (2018) estimate effects of weather shocks on conflict 1 and 4 years afterward. Iyigun et al. (2017) is an exception, considering long-run effects on conflict risk of a *positive and permanent* agricultural productivity shock from the introduction of the potato to the Eastern Hemisphere. To my knowledge, no study has explored long-term impacts on conflict risk of a transitory negative shock to agricultural production.

permanent income mechanism. I find significant increases in long-term conflict risk following locust and drought exposure and some support for a permanent income mechanism, though this and other channels could be explored more in further research. The dynamic long-term impacts on conflict risk imply that studies estimating transitory short-term impacts of severe economic shocks may be biased, even if the direct effects of those shocks are temporary.

Third, this paper adds a new dimension to studies on the economic impacts of agricultural pests (Oerke, 2006), including desert locusts (see e.g., Thomson and Miers, 2002), and builds on a small literature on the long-term impacts of such shocks (R. Baker et al., 2020; Banerjee et al., 2010). The range of many agricultural pests is expanding due to climate change and globalization, and though locust outbreaks have become less frequent in recent decades due to increased monitoring desert locusts are ideally situated to benefit from climate change (Qiu, 2009). A growing body of research finds that locust swarm exposure adversely affects education (Asare et al., 2023; De Vreyer et al., 2015), health (Conte et al., 2023; Gantois et al., 2024; Le and Nguyen, 2022; Linnros, 2017), and production (Marending and Tripodi, 2022) outcomes, but I am not aware of any study considering the impacts of a pest shock on conflict. The impacts of locust swarms on long-term economic activity and conflict risk should be considered in determining policy around desert locust prevention and control.

The remainder of the paper is organized as follows. Section 2 provides background on desert locusts and summarizes the literature on agricultural shocks and conflict. Section 3 presents a model of how productivity shocks affect occupational choice and the decision to fight over time through income-related mechanisms. Section 4 describes the data used in the analyses and Section 5 outlines the empirical approach. Section 6 presents the results for the average and dynamic impacts of locust swarm exposure on violent conflict. Section 7 tests potential mechanisms in light of the model and compares impacts of exposure to locust swarms and severe drought. Section 8 discusses implications of the results for econometric specifications in the literature on economic shocks. Section 9 concludes.

2 Background

2.1 Desert locusts

Desert locusts (*Schistocerca gregaria*) are a species of grasshopper always present in small numbers in desert 'recession' areas from Mauritania to India.[6] They usually pose little threat to livelihoods but favorable climate conditions in breeding areas—periods of repeated rainfall

[6]Additional detail on desert locusts is included in Appendix B. Any time I use 'locusts' in this paper I am referring exclusively to desert locusts.

and vegetation growth overlapping with the breeding cycle—can lead to exponential population growth. Unique among grasshopper species, after reaching a particular population density locusts undergo a process of 'gregarization' wherein they mature physically and begin to move as a cohesive unit (Symmons and Cressman, 2001), with adult winged locusts forming large mobile swarms. When swarms migrate away from breeding areas and affect multiple countries this is referred to as an outbreak or upsurge. Climate change is expected to increase the risk of locust swarm formation and upsurges, as desert locusts can easily withstand elevated temperatures and the increased frequency of heavy rainfall events can create conditions conducive to population growth (McCabe, 2021; Qiu, 2009; Youngblood et al., 2023).

Locust swarms vary in density and extent, but the average swarm includes around 50 locusts per m^2 and can cover tens of square kilometers, including billions of locusts (Symmons and Cressman, 2001). About half of swarms exceed 50km^2 in size (FAO and WMO 2016). The size of swarms is what makes them so destructive. A small swarm covering one square kilometer consumes as much food in one day as 35,000 people and the median swarm consumes 8 million kg of vegetation per day (FAO, 2023), without preference for different types of crops (Lecoq, 2003.

The arrival of a swarm can lead to the total destruction of local vegetation (Symmons and Cressman, 2001; Thomson and Miers, 2002). For example, during the 2003-2005 locust upsurge in North and West Africa, 100, 90, and 85% losses on cereals, legumes, and pastures respectively were recorded, affecting more than 8 million people and leading to 13 million hectares being treated with pesticides (Showler, 2019). Over 25 million people in 23 countries were affected during the most recent 2019-2021 upsurge and damages were estimated to reach $1.3 billion (Green, 2022), with control efforts—including treating over 2 million hectares with pesticides—estimated to have prevented over $1 billion in damages (Newsom et al., 2021).

Locusts live 2-6 months and swarms continue breeding and migrating until dying out from a combination of migration to unfavorable habitats, limited vegetation in breeding areas, and control operations (Symmons and Cressman, 2001). The migration patterns of desert locust swarms are key to this paper's identification strategy. Locusts swarms fly 9-10 hours per day, generally downwind, and easily move 100km or more in even with minimal wind (FAO and WMO 2016). Conditional on being in the migratory path during an upsurge, swarm flight patterns create quasi-random variation in exposure as some areas in the flight path are flown over and spared any damages.[7]

Knowledge of locust breeding patterns and swarm flight characteristics inform efforts

[7]Figure B4 illustrates the local and temporal variation in exposure to swarms for the area around Mali.

to predict locust swarm formation and movements, but forecasts remain highly imprecise (Latchininsky, 2013). Even given such information, farmers have no proven effective recourse when faced with the arrival of a locust swarm (Dobson, 2001; Hardeweg, 2001; Thomson and Miers, 2002). The only current viable method of swarm control is direct spraying with pesticides, which can take days to have effects as well as being slow and costly to organize and requiring robust locust control infrastructure (Cressman and Ferrand, 2021). Farmers in affected areas report viewing locust swarms as an unpredictable natural disaster that is the government's responsibility to address (Thomson and Miers, 2002). Extensive locust monitoring and control operations are conducted in countries at regular risk from locust swarms. These are insufficient to prevent all upsurges but can help limit their spread and damages.

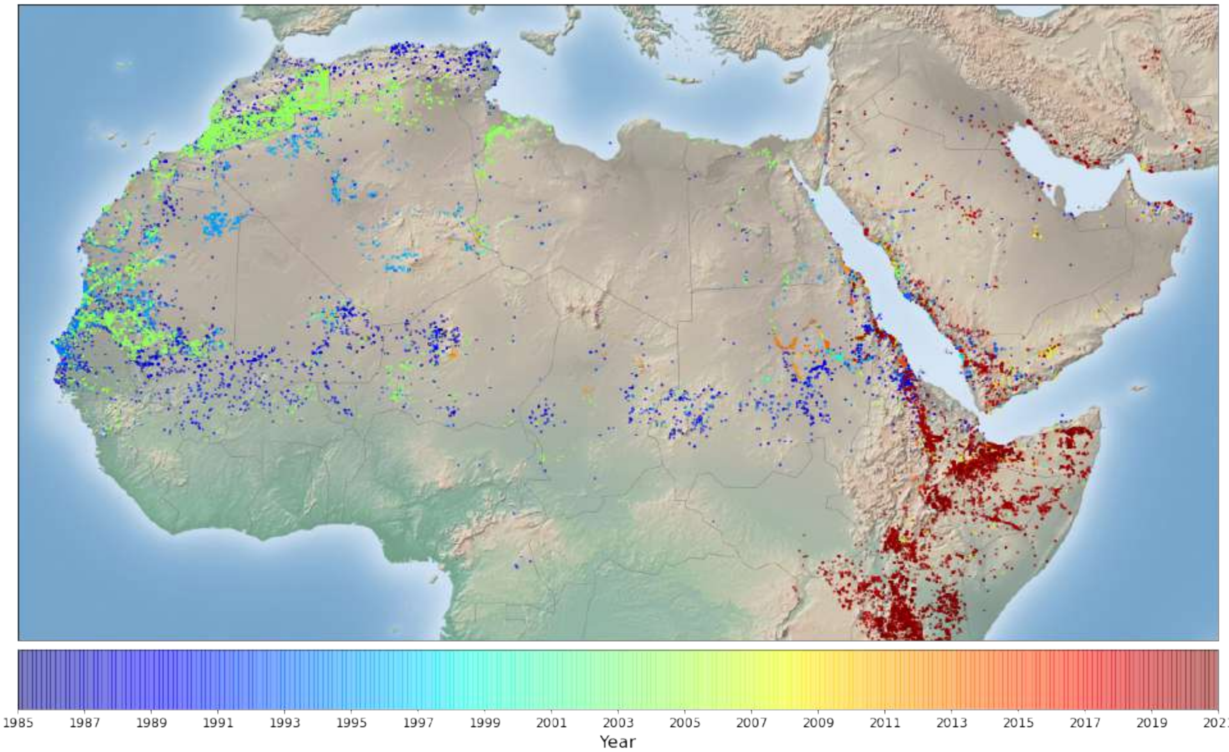
Households exposed to locust swarms use a variety of measures to cope with the adverse food security and livelihood effects. In addition to seeking help from social networks and food aid, households commonly report selling animals and other assets, consuming less food, sending household members away, taking loans and cutting expenses, and consuming seed stocks as coping strategies (Thomson and Miers, 2002). A swarm exposure shock therefore represents a shock to income and household wealth as well as a shock to agricultural productivity in the year of exposure.

Figure 1 displays the locations of desert locust swarm observations recorded in the FAO Locust Watch database from 1985 (the first year they were recorded) to 2021, for the area of interest for this study.[8] As illustrated by the figure, nearly all locust swarms are observed during periods of major upsurges. Which locations are exposed during an upsurge depends on which breeding areas fostered initial swarm formation and on wind patterns in the months following swarm formation. The countries affected by the 2003-2005 upsurge (in green in Figure 1), which originated from multiple small outbreaks in Summer 2003 in the Western Sahel, are not the same as those exposed to the 2019-2021 upsurge (in red), which originated in the southern Arabian Peninsula.

The characteristics of desert locust swarms make them a useful natural experiment for analyzing the long-term impacts of agricultural production shocks on the risk of conflict. First, the timing of upsurges and patterns of swarm flight create quasi-random temporal and local variation in swarm exposure. The arrival of a swarm also does not change future risk (Figure B3 shows this empirically), so the direct shock to agricultural production is transitory. Second, the arrival of a swarm is effectively a locally and temporally concentrated natural disaster where all crops and pastureland are at risk (Hardeweg, 2001), but other

[8] Desert locust swarms also affect other countries in the Middle East and South Asia, but not during the time period of this study.

Figure 1: FAO Locust Watch swarm observations by year



Note: Map created by author using locust swarm records in the FAO Locust Watch database.

aspects of the economy are importantly unaffected. Temperature and precipitation shocks may affect infrastructure or physiology as well as agricultural production. Locust swarms may have some psychological effects, but are well-suited for studying income-related mechanisms linking agricultural shocks and conflict. Third, the level of damage to agriculture from swarms and lack of tools for farmers to prevent damages imply severe reductions in agricultural production. Decreased wealth following such a catastrophic shock may be more likely to persist and affect labor productivity in following seasons, increasing the potential for long-term impacts on conflict through the opportunity cost channel.

2.2 Agricultural shocks and conflict

A growing literature explores the impacts of climate or weather on conflict (see Burke et al. (2015, 2024), Carleton et al. (2016), Dell et al. (2014), Hsiang and Burke (2013), Koubi (2019), and Mach et al. (2019) for reviews), primarily analyzing impacts of deviations of precipitation or temperature from local historical norms with some also looking at droughts. Most studies find that weather shocks increase short-term conflict risk, with the recent Burke et al. (2024) meta-analysis finding a mean increase in the risk of intergroup conflict of 2.5%

for a one standard deviation adverse change in climate and a median effect of 5%, with more consistent effects of temperature increases than of adverse precipitation realizations.These results have important implications for conflict risk as climate change increases the frequency and severity of weather shocks.

The majority of papers in the climate-conflict literature looking at low- and middle-income countries (LMICs) focus on income-related mechanisms, following early work in Miguel et al. (2004). Arguments typically follow the models in Chassang and Padró i Miquel (2009) and Dal Bó and Dal Bó (2011), discussing how weather affects agricultural labor productivity and therefore the opportunity cost of engaging in conflict for agricultural producers. Studies frequently use variation in effects by land cover or timing relative to the growing season to show support for this mechanism (e.g., Caruso et al., 2016; Crost et al., 2018; Gatti et al., 2021; Harari and La Ferrara, 2018; McGuirk and Nunn, 2025; Von Uexkull, 2014).

Although the evidence is generally consistent with an opportunity cost mechanism, reviews of the climate-conflict literature agree that the mechanisms remain unclear and deepening insight into them is highlighted as a priority for future climate-conflict research in Burke et al. (2024) and Mach et al. (2020). Weather affects the economy and society through multiple channels besides agricultural production (Dell et al., 2012, 2014; Mellon, 2022), and studies have pointed to physiological, psychological, and infrastructural effects of weather shocks as also helping to explain impacts on conflict (Baysan et al., 2019; Burke et al., 2024; Carleton et al., 2016; Chemin et al., 2013; Dell et al., 2014; Hsiang and Burke, 2013; Sarsons, 2015; Witsenburg and Adano, 2009). An advantage of analyzing the effects of locust swarm exposure is that physiological and infrastructural effects should be limited—though psychological effects may be important—allowing a cleaner identification of the importance of income-related mechanisms.

Income mechanisms have been discussed and tested in the literature on the drivers of conflict more generally including studies of agricultural shocks not affecting production. Several studies have shown that plausibly exogenous changes in prices of agricultural commodities affect the risk local conflict in areas producing the affected goods (Bazzi and Blattman, 2014; Dube and Vargas, 2013; Fjelde, 2015; McGuirk and Burke, 2020; Ubilava et al., 2022). A recent literature explores how the onset of harvest season in agricultural areas affects economic incentives to fight (Guardado and Pennings, 2025; Hastings and Ubilava, 2023). These studies illustrate different ways in which agricultural shocks affect both the opportunity cost of fighting related to agricultural labor productivity and the returns to rapacity, or predatory capture of agricultural output. In some cases the opportunity cost mechanism appears to dominate (Bazzi and Blattman, 2014; Dube and Vargas, 2013; Fjelde, 2015; Guardado and

Pennings, 2025) while in others the rapacity mechanism is decisive (Koren, 2018; Ubilava et al., 2022), sometimes within the same context (Hastings and Ubilava, 2023; McGuirk and Burke, 2020). Studies identifying results consistent with rapacity emphasize the role of armed groups such as militias or insurgents which coordinate such attacks, which indicates that broader insecurity or grievances may create heterogeneity in the impacts of shocks to agriculture on conflict risk.

The majority of studies on agricultural shocks and conflict focus on impacts within the same time period, with a few exceptions. Crost et al. (2018) and Harari and La Ferrara (2018) find that growing season weather shocks have inconsistent effects on conflict in the same year, but consistently increase conflict risk the following year. Harari and La Ferrara (2018) finds some persistence of impacts up to 4 years afterward. Crost et al. (2018) argue that lagged effects on conflict could be due to storage and savings offsetting effects in the same year. This appears inconsistent with effects driven by reduced opportunity costs as the largest impacts on agricultural labor productivity should be realized in the same season as the rainfall shock. To my knowledge, only Iyigun et al. (2017) consider how a permanent agricultural productivity shock impacts conflict in the long term. They find that introducing potatoes to Europe, the Near East, and North Africa led to a large and persistent reduction in the risk of conflict in subsequent centuries by comparing changes in areas with different suitability for potato cultivation. A paucity of evidence on long-term impacts is a limitation of the literature on natural disasters more generally (Botzen et al., 2019), and particularly in low-income countries (Baseler and Hennig, 2023).

3 Model

Agricultural shocks may affect conflict risk through a variety of channels. Most of the literature focuses on direct effects on agricultural production, but certain agricultural shocks can also directly affect infrastructure (e.g., floods) and human physiology (e.g., high temperatures). In addition, shocks may affect local institutions and human psychology by for example undermining trust in governments, increasing social or economic inequality or divisions, or influencing beliefs about future risk of shocks. These channels may be important in determining the effect of agricultural shocks on conflict risk (Burke et al., 2024), but for the purpose of this paper I focus on testing mechanisms operating through effects on agricultural production. This seems appropriate for the case of desert locust swarms which do not have direct effects on infrastructure or human physiology, though effects on institutions and human psychology may be important and a subject for future study.

The standard models discussed in the economics literature on agricultural production and conflict are models of occupational choice (as in French and Taber, 2011; Heckman and Honore, 1990; Roy, 1951) where actors allocate their labor between productive activities and fighting.[9] These models emphasize the role of opportunity costs in conflict risk (Collier and Hoeffler, 2004). In particular, Chassang and Padró i Miquel (2009) develop a bargaining model of conflict where groups allocate labor to crop production or fighting over land, and Dal Bó and Dal Bó (2011) model individuals choosing between a labor-intensive sector, a capital-intensive sector, and an 'appropriation' sector fighting over output. McGuirk and Burke (2020) develop this model to allow both factor and output conflict and incorporate consumers who may also engage in fighting. In Appendix D I present a simple model of occupational choice allowing for long-term effects of transitory shocks, but focus in this section on the intuition and testable hypotheses resulting from the model.

In the model, agricultural shocks affect the risk of conflict through two main, opposing, mechanisms. First, negative shocks such as low prices or drought reduce the returns to agricultural labor. This means the *opportunity cost* of fighting is lower: producers have less to lose by engaging in conflict. At the same time, lower agricultural prices or output reduce the returns to predatory attacks: bandits or looters have less to gain from fighting. Dube and Vargas (2013) refer to this as the *rapacity* mechanism. These mechanisms are not unique to agricultural shocks, as they are also discussed in earlier work on the economic drivers of conflict more generally (Collier and Hoeffler, 2004; Grossman, 1999).

In general, the effect of a negative agricultural shock on the decision to fight is ambiguous, particularly if there is a strong positive correlation between shocks over space as in most agricultural shocks. At the same time as agricultural producers' opportunity cost of fighting is reduced, the decrease in local agricultural production makes conflict over output (i.e., banditry) less attractive. For transitory agricultural shocks which do not have a permanent direct effect on local agricultural productivity, although the value of output available to capture in that period falls the value of factors of production—land in particular—is less affected.[10] In line with this, the literature generally finds that the opportunity cost mechanism dominates for shocks that temporarily reduce agricultural returns, increasing conflict risk. Another implication is that conflict may spill over from affected areas if affected populations seek to capture agricultural output to make up for their own shortfalls. For example, McGuirk and Nunn (2025) find that drought in pastoral areas leads to conflict spillovers in

[9] These models follow an early application by Becker (1968), who uses a similar setup to model interpersonal conflict such as theft.

[10] Transitory shocks may have some effect on the returns to factors if they affect individuals' ability to productively utilize factors or if they affect expectations about future productivity. Shocks that have direct permanent productivity effects, for example through soil erosion or other land degradation, would have larger effects on the returns to factors.

nearby agricultural areas.

Agricultural destruction due to desert locusts is both particularly severe and less spatially correlated than other agricultural shocks, due to swarm flight patterns. This implies both a sharp decrease in the opportunity cost of fighting for agricultural producers in affected areas and potentially more localized spillovers of this conflict. In the case of this paper, I analyze impacts of swarm exposure at the level of 28×28km grid cells, such that the median locust swarm would only affect around 6% of cell area. Conflict incited by locust destruction may be more likely to be realized within a grid cell rather than spilling into neighboring cells than might be the case for a highly spatially-correlated drought shock.

These considerations imply two testable predictions:

1. If the opportunity cost mechanism dominates, the local risk of violent conflict should increase in the year of shock exposure.
2. If the rapacity mechanism offsets the opportunity cost mechanism, this should attenuate short-term effects on measures of conflict over output but not for conflict over factors.

Prior research models transitory agricultural shocks as having only temporary effects on conflict, as there is no direct persistent effect on agricultural productivity. But a severe shock could affect long-term conflict risk through other channels, including indirect long-term effects on productivity. Maintaining a focus on income-related channels, I propose a wealth or *permanent income* mechanism whereby a transitory shock persistently reduces productivity through direct effects on productive assets. Most agricultural households in developing countries lack insurance and have constrained access to credit. Strategies to smooth consumption following an income shock, such as selling animals and other assets, taking loans, reducing food, health, and education spending, and sending members away reduce household physical and human capital (e.g., de Janvry et al., 2006; Dercon and Hoddinott, 2004; Dinkelman, 2017). The resulting reductions in wealth mean transitory shocks can have persistent impacts on productivity (Dercon, 2004; Donovan, 2021; Hallegatte et al., 2020; Hoddinott, 2006; Karim and Noy, 2016). In the context of an occupational choice model of conflict, this permanent income effect increases the long-term risk of conflict by reducing the long-term opportunity cost of fighting. As in the short-term, persistent decreases in production reduce the returns to predatory attacks, potentially offsetting the permanent income mechanism. Dynamic effects will depend on whether affected areas are able to recover over time, but in general the productivity shock and therefore the impacts under the opportunity cost mechanism should be largest in the period immediately following the shock.

Persistent effects through a permanent income mechanism should be more likely for more severe shocks. Several papers have documented persistent effects of locust swarms on outcomes which could influence productivity and therefore the opportunity cost of fighting. Studies using the DHS show that young children exposed to locust swarms are more likely to drop out of school (Asare et al., 2023) and achieve lower educational attainment (De Vreyer et al., 2015), and also have lower height-for-age (Conte et al., 2023; Gantois et al., 2024; Le and Nguyen, 2022; Linnros, 2017) when they are older. Such human capital effects of swarm exposure could decrease permanent labor productivity. More directly, Marending and Tripodi (2022) find that agricultural profits of households in parts of Ethiopia exposed to locust swarms in 2014 are 20-48% lower two harvest seasons after swarm arrival. This indicates a persistent decrease in agricultural productivity despite the fact the swarms have migrated and are no longer directly affecting productivity.

The model therefore suggests two more testable predictions for long-term impacts of a transitory agricultural shock on conflict risk:

3. If the permanent income mechanism reduces the long-term opportunity cost of fighting, we should observe persistent increases in conflict risk. Assuming some households can recover from the initial shock, increases in conflict risk should at least be non-increasing over time.

4. If the permanent income mechanism is important, we should observe long-term average reductions in measures of productivity following the initial shock.

Since violent conflict is not the norm in most locations and periods, it implies the returns are generally low. While there is evidence that agricultural shocks motivate the formation of fighting groups and cause the onset of new violent conflict immediately following the shock (Harari and La Ferrara, 2018; McGuirk and Burke, 2020), it is not clear when a negative productivity shock will lead an individual to switch from another activity to fighting. In practice, individuals are unlikely to engage in violent conflict alone, as such fighting generally involves organized armed groups which recruit members and pay them a wage or share of the returns from victory (Collier and Hoeffler, 2004; Cramer, 2002; Grossman, 1999).

Buhaug et al. (2021) note that opportunity cost models can explain motives for engaging in conflict but not when these motives actually translate into action, and proposes a model of civil conflict that predicts an income shock to increase violence primarily in a context of collective grievances. In line with this model, they find that drought shocks do not in general increase the risk of rebellion of affected ethnic groups, but do increase this risk among marginalized ethnic groups more dependent on agriculture. This implies that dynamic impacts of an agricultural shock on conflict risk should be greater in periods of grievance when groups are already mobilized around particular causes. Under this *grievance* mechanism, existing shared frustration or mobilization reduces the costs of fighting and increases the probability of capturing returns for individuals with reduced opportunity costs of fighting following a shock.

These considerations motivate a final testable prediction:

5. If grievance is an important mechanism, the dynamic impacts of a transitory shock on violent conflict should be concentrated in periods of heightened grievance, frustration, or popular mobilization. Long-term effects under this mechanism require persistent effects of the shock on measures of productivity or well-being.

4 Data

The Locust Watch database (FAO 2022) reports observations of desert locust swarms as well as smaller concentrations of locusts from 1985 to the present.[11] I consider only data on locust swarms, which pose the greatest threat to agriculture and whose flight patterns create local variation in exposure. The Locust Watch data include latitude, longitude, and date of swarm observations. Locust observations are recorded by national locust control and monitoring officers on the ground, but incorporate reports from agricultural extension agents, government officials, and other sources. Local farmer scouts are also often trained in locust monitoring and reporting (Thomson and Miers, 2002).

Data on conflict events come primarily from the Armed Conflict Location & Event Data Project (ACLED) database (Raleigh et al., 2010). The database records the location, date, actors, and nature of conflict events globally starting from 1997 by compiling and validating reports from traditional media at different levels, from institutions and organizations, from local partners in each country, and from verified new media sources. The analysis focuses on events categorized by ACLED as "violent conflict," which includes battles, explosions, and violence against civilians. I also test impacts on protest and riot events recorded by ACLED and on larger-scale violent conflicts from the Uppsala Conflict Data Program (UCDP; Sundberg and Melander, 2013) and distinguish between conflict that does and does not involve state actors, as these types of conflict will involve different mechanisms. The UCDP database goes back to 1989 and only records conflicts involving at least one "organized actor" and resulting in at least 25 battle-related deaths in a calendar year. The ACLED database has no organized actor or minimum death threshold requirements. McGuirk and Burke (2020) characterize UCDP events as more likely to represent conflict over territory and factors of production, and I follow them in constructing a measure of output conflict (i.e., banditry) using ACLED records of violence against civilians, rioting, and looting.

[11] I retrieved data from the Locust Watch database in 2022. As of Spring 2025, the data on desert locust presence appear to no longer be publicly available.

I collapse the data to a raster grid with annual observations for cells with a 0.25° resolution (15 arcminutes, approximately 28×28km). Analyzing impacts at this spatial level reduces potential measurement error about the specific areas affected by swarm and conflict events and allows me to leverage local variation in swarm presence created by their flight patterns. The median swarm covers around 50km^2, so nearly all swarms will be contained within 0.25° cells (∼784km^2), except those near cell boundaries. I test for robustness to analyzing data at the level of 0.5° and 1° cells, which will also capture potential spillovers from swarm exposure (McGuirk and Nunn, 2025). In each cell and year I measure whether any locust swarm and conflict event was recorded. I do not account for variation in the counts of swarm or conflict events as the individual events are not themselves of consistent magnitudes. To test for spatial spillovers, I also measure whether any swarms are observed within 100km outside of each cell-year.

I determine the country and highest sub-national administrative level in which each cell centroid lies using country boundaries from the Global Administrative Areas (2021) database v3.6. I use sub-national boundaries at the first administrative level to create a set of 285 regions, all of which include at least 32 individual grid cells except for small countries with fewer than 32 cells. These regions are either existing sub-national administrative units or combinations of adjacent units within the same country. I cluster standard errors at the level of these regions.

Given the role of weather in desert locust biology, its importance in determining agricultural production, and the well-documented relationship between weather shocks and conflict, all analyses control for local weather to isolate the impact of locust swarm exposure. I measure total annual precipitation (in mm) and maximum temperature (in °C) using high-resolution monthly data from WorldClim available through 2018.[12] I use monthly Standardized Precipitation and Evapotranspiration Index (SPEI) from the Global Drought Monitor (Begueria et al., 2014) to create a measure of severe drought exposure, which I define as at least 4 consecutive months in a year where the SPEI in a cell is below -1.5 (with values from -1 to 1 indicating normal conditions).

I also incorporate raster population data for every 5 years from CIESIN, 2018, linearly interpolating within cells between years where the population is estimated, and raster data on land cover in 2000 from CIESIN, giving the share of land cover in each cell that is cropland and pasture (Ramankutty et al., 2010). I combine the land cover data with cropland mapping of Africa from 2013-2014 (Xiong et al. (2017)) to identify cells with any cropland during the

[12]CRU-TS 4.03 (Harris et al., 2014) downscaled with WorldClim 2.1 (Fick and Hijmans, 2017). I test sensitivity to measuring rainfall using CHIRPS (Funk et al., 2015) and temperature using ERA5 (Hersbach et al., 2019) to account for satellite-based weather measurement error (Josephson et al., 2024).

study period. I include additional cell characteristics from the PRIO-GRID dataset (Tollefsen et al., 2012), assigning all 0.25° cells the values for the 0.5° PRIO-GRID cell in which they are located.

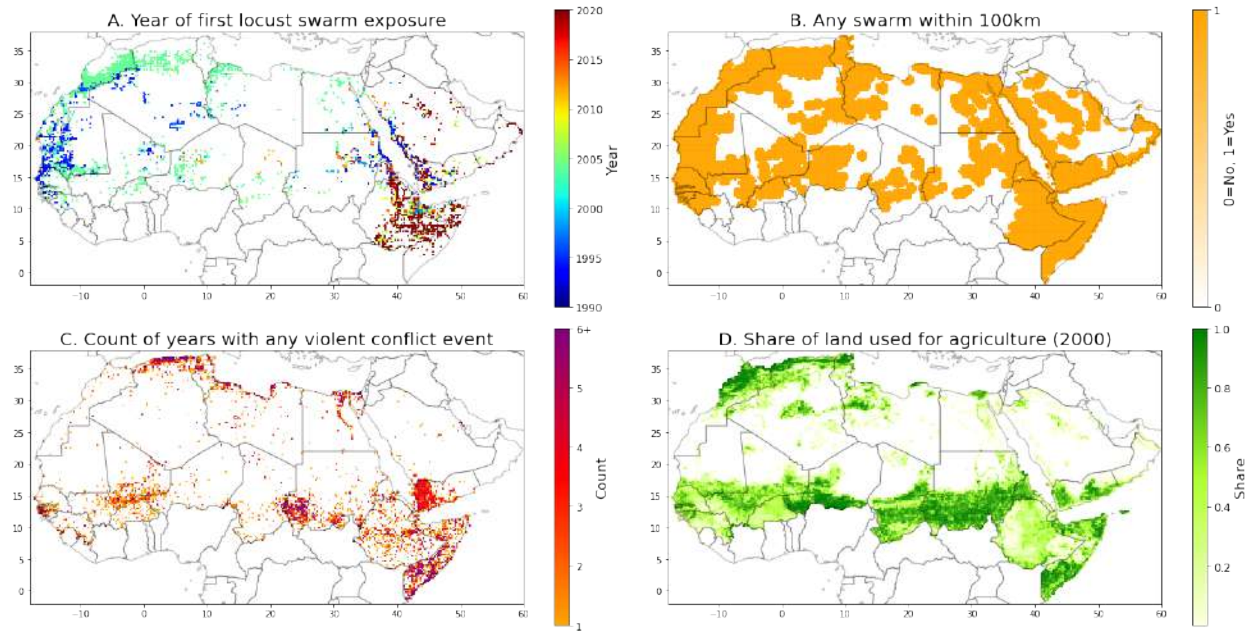
For the analysis of mechanisms, I incorporate data on agricultural production, economic activity, and net migration. Household-level estimates of agricultural production come from the DHS AReNA database (IFPRI 2020), which includes geolocated data at the level of household survey clusters for 40 surveys from 9 countries in the study sample conducted between 1992 and 2018. I also incorporate two satellite-based measures of agricultural productivity. I use 16-day 1km satellite imagery from MODIS (Didan, 2015) for the period 2000-2019 to calculate the Normalized Difference Vegetation Index (NDVI), taking the maximum of monthly means in each grid cell to construct an annual value. I use global annual yield data for four major crops—maize, rice, wheat, and soybean—at the 5 arcminute resolution for 1982-2015 from Cao et al. (2025), estimated via multiple machine learning models incorporating crop statistics, satellite data, weather data, and soil and agricultural characteristics. Yield is only estimated in cells growing a given crop. Most cells only include data for one of the four crops, but for cells with multiple crops in the dataset I define the 'main' crop as the crop with the highest yield. As a rough proxy of economic activity, I use measures of gridded gross cell product from the G-Econ dataset v4.0 (Nordhaus, 2006), available for the years 2000 and 2005 during the sample period and estimated based on population, production, income, and employment data at subnational levels. Finally, net migration at the 5 arcminute resolution for 2000-2019 come from Niva et al. (2023), who estimate net migration based on subnational annual data on population, births, and deaths.

4.1 Sample and summary statistics

Since ACLED records conflicts beginning in 1997 and the main weather data are available until 2018, the analysis sample includes observations from 1997 to 2018. I restrict the analysis to countries with at least 10 locust swarm observations in this period. These countries include all of North Africa, most of the Arabian Peninsula and West Africa, and the Horn of Africa. The resulting analysis sample covers 22 years across 25,435 cells, for a total of 557,018 observations with data on all main estimation variables. Figure 2 visualizes swarm exposure, violent conflict incidence, and agricultural land cover for the sample countries. Summary stats are included in Table A1.

Locust swarms are relatively rare events, with swarms reported in less than one percent of cell-years (Table A1 Panel A). But at least one locust swarm is recorded in the Locust Watch database for 9% of cells in the study period of 1997-2018 and 55% are within 100km

Figure 2: Swarm exposure, violent conflict incidence, and land cover in sample countries



Note: Land used for agriculture includes crop land and pasture land. Panel D shows most clearly which countries in West, Central, and East Africa are excluded from the study sample.

of any locust swarm report (Figure 2 Panel B), and these numbers increase to 12% and 62% when considering the period from 1985-2023 (Table A1 Panel B). To account for the possibility of persistent effects of swarm exposure, I identify for each cell the first year after 1989 in which a locust swarm is recorded (Figure 2 Panel A), and define a cell as exposed to a locust swarm in each following year and not exposed in all other years or if no locust swarm is ever observed.[13] Locations where locust swarms are observed in more than one year (9.8% of exposed cells) are not distinguished from those where they are observed only once. Cells first exposed to a swarm from 1990-1997 (in dark blue in Figure 2 Panel A) are considered treated during the entire sample period and therefore do not inform the analyses, while cells first exposed to a swarm after 2018 (in red) are considered not treated during the sample period. Just over seven percent of cells are first exposed to a swarm during the sample period, including 5.3% exposed during the 2003-2005 upsurge (in teal).

Violent conflict is also uncommon, with events reported in two percent of cell-years (Table A1 Panel A). Conflict is spatially correlated (Figure 2 Panel C), with 13% of cells experiencing at least one violent conflict event during the study period, in 3.4 different years on average (Table A1 Panel B). The large majority of conflict events are recorded after 2010. The risk of any violent conflict is fairly low from 1997-2010 before increasing significantly over the remainder of the sample period (Figure 4 Panel A). Part of this increase may related

[13] A major locust upsurge occurred from 1985-1989, so considering this in the treatment definition would have excluded a large share of the sample but the results are robust to defining treatment starting in 1985.

to changes in ACLED data collection methods, though I observe a similar increase in the UCDP data. More directly, the increase corresponds with the timing of the Arab Spring movements, the spread of Islamic militant groups, and multiple civil wars and separatist movements in the sample countries. I consider how this variation may affect the impacts of locust swarm exposure in testing the dynamic impacts of exposure on violent conflict under the grievance mechanism.

Over half the cells (57%) in the sample have agricultural land: 56% have pasture land while 31% have crop land. Across all cells, the mean share of land allocated to agriculture is 23% (Figure 2 Panel D, Table A1 Panel B), with 18% pasture land and 5% crop land. Given that locust swarms should affect outcomes through agricultural destruction, I test for heterogeneity in impacts by land cover.

4.2 Locust swarm monitoring

The Locust Watch database does not include all locations of swarm exposure events over time, due to monitoring capacity limitations. Randomly missing swarm events—classical measurement error—would attenuate estimated effects, but swarm monitoring is likely correlated with characteristics that might also be correlated with conflict risk, such as agricultural activity and population levels. For example, Gantois et al. (2024) find heterogeneity in locust reporting across country borders, indicating differences in country monitoring capacities. Unreported swarms are an important challenge for studies using household survey data that must define exposure at the level of specific community coordinates, and studies such as Gantois et al. (2024) and Marending and Tripodi (2022) take different approaches to deal with this concern. An advantage of defining swarm exposure as a dummy variable at the level of grid cells is that only one swarm needs to be reported in a particular area to define the cell as exposed. But differences in cell-level monitoring effort may still lead to biased estimates.

The main empirical specification accounts for this in two ways. First, I restrict the sample to only cells where a locust swarm was ever reported within 100km. This drops cells with no real risk of swarm exposure as well as cells far from any monitoring activity. Second, in all regressions I control for population and weather variables which are likely to be strongly correlated with both conflict risk and monitoring intensity, particularly as monitoring efforts are guided in part by the relationship between weather and locust breeding.

In addition, I conduct several types of robustness checks to test whether issues in locust monitoring may affect the estimated effects on conflict risk. First, I estimate the propensity for a cell to have been exposed to a swarm during the study period, which accounts for differences in both swarm risk and monitoring, and test the sensitivity of results to weighting observations using inverse propensity weights. Second, I aggregate the analysis to the level of larger cells, which reduces the risk that individual unreported swarms may affect the analysis as such swarms are more likely to be co-located with other swarms that are reported in larger cells. Third, I systematically exclude different regions from the sample to check whether results are driven by areas with particular conflict and locust monitoring conditions. Fourth, I conduct simulations randomly imputing 'missing' locust swarms across all cells near the locations of reported swarms, to see how different levels of potential swarm underreporting would affect the results.

A specific concern might be that locust reporting is correlated with violent conflict. This concern is the focus of Torngren Wartin (2018)'s analysis of the impact of locusts on conflict, which uses similar data but focuses on the short-term, modeling locusts as temporary shocks. Showler and Lecoq (2021)—which I refer to as 'SL2021' in analyses below—review how insecurity has affected national and international desert locust control operations from 1985-2020 across countries where locusts are active. They mention Chad, Mali, Somalia, Sudan, Western Sahara, and Yemen as countries with areas where insecurity has constrained locust control operations in certain periods since 1997. Insecurity in Yemen is considered a key factor for the 2019-2021 desert locust outbreak across much of the Horn of Africa and beyond.

Insecurity is likely less of a constraint for locust monitoring than for control operations. FAO locust monitoring guidelines discuss conducting aerial surveys and using reports from local scouts, agricultural extension agents, security forces, and other sources (Cressman, 2001), which would allow reporting even in insecure areas. The Locust Watch data includes observations of locust swarms even in countries and periods where Showler and Lecoq (2021) indicate control operations have not been possible. For example, the authors mention that control operations in Western Sahara have been largely infeasible due to Polisario activity over the whole sample period, but 166 swarms have been recorded there in 9 different years from 1996-2018. None of the monthly FAO locust swarm bulletins published during the 2003-2005 upsurge—the major locust event in the sample period—mention issues related to insecurity affecting locust monitoring efforts.

But conflict may still suppress monitoring. The share of cells within 50km of a locust swarm observation in a given year that have reports of both violent conflict and a locust swarm in the cell is 27% in the set of countries Showler and Lecoq (2021) indicate pose challenges for locust control, similar but below the 34% in all other countries. Gantois et al. (2024) find that contemporaneous conflict reduces the probability of any locust monitoring by 11.7%, though this combines reports of locust ecology and different locust life stages.

The study shows that effects of conflict on locust swarm reporting in particular are generally not statistically significant. This may reflect greater importance or resources for swarm monitoring, or better-established methods for collecting reports of swarms from disparate sources.

Missing swarm observations in high-conflict areas would bias my estimates downward by including in the control group areas exposed to locusts with likely higher future levels of conflict, as conflict risk is serially correlated. I test the sensitivity of the results to excluding the countries listed in SL2021 as potential locations of locust swarm under-reporting, and to systematically excluding different regions from the sample to check whether results are driven by areas with particular conflict and locust monitoring conditions. In addition, I conduct simulations randomly imputing 'missing' locust swarms particularly in cells experiencing conflict near the locations of reported swarms to test effects of potentially underreporting in these areas.

5 Empirical approach

I estimate the causal impacts of locust swarm exposure on conflict using a difference-in-differences approach allowing for long-term effects of this transitory agricultural shock. I estimate both static average impacts using two-way fixed effects (TWFE) models and dynamic impacts over time using event study approaches. The TWFE linear probability models take the form:

$$Conflict_{ict} = \alpha + \beta Exposed_{ict} + \delta X_{ict} + \gamma_{ct} + \mu_i + \epsilon_{ict} \quad (1)$$

where i indexes cells, c countries, and t years. $Conflict$ is a dummy variable for observing any conflict event and $Exposed$ is an absorbing dummy variable for having been exposed to a locust swarm. The primary specifications focus on impacts on violent conflict using the ACLED data. I consider effects on other outcomes in tests of the impact mechanisms. Analyzing conflict as a binary variable at an annual level reduces potential measurement error and is the main approach in the climate and conflict literature. γ_{ct} are country-by-year fixed effects, and μ_i are cell fixed effects. X_{ict} is a vector of time-varying controls at the cell level including annual total precipitation, maximum temperature, and population in the main specifications. Standard errors (SEs) are clustered at the sub-national region level (285 clusters) to allow for correlation in the errors within nearby areas over time.[14]

[14] This is likely more restrictive than necessary and will lead to a conservative interpretation of the results. Patterns of statistical significance are largely unchanged when using two-way clustered errors at the year and region level and using Conley (1999) Heteroskedasticity and Autocorrelation-Consistent (HAC) SEs allowing

I estimate dynamic impacts over the 12 years before and after locust swarm exposure using staggered treatment event study models, including the same fixed effects and clustering as in Equation 1.[15] These event study approaches deal with concerns with TWFE estimators when there is heterogeneity in treatment effects by time since treatment or across treatment cohorts, which can lead to 'forbidden' comparisons between late- and early-treated groups and negative weighting of effects for certain treatment groups or periods (Goodman-Bacon, 2021). The methods effectively estimate an average treatment effect on the treated in each time period separately for groups exposed in different years, and calculate event study estimates by taking weighted averages of these treatment effects. I primarily present results using the approach developed in Borusyak et al. (2024) but test the sensitivity of results to alternative esimators including Callaway and Sant'Anna (2021), Cengiz et al. (2019), and De Chaisemartin and d'Haultfoeuille (2024). The estimators mainly differ in how they estimate pre-trends; Borusyak et al. (2024) impute counterfactual untreated outcomes for all units and make comparisons against the average over all pre-treatment periods, leading to smoother pre-treatment dynamics (Roth et al., 2023).

To test for heterogeneity in the impacts of swarms, I estimate Equation 1 fully interacting the right-hand side variables with another variable of interest. I test robustness of the results to different controls and fixed effects, restrictions of the analysis sample, cell sizes, and clustering of SEs. Results of robustness tests are included in Appendix C.

The key identifying assumption of this design is that trends in conflict risk would be parallel over time in exposed and unexposed areas within the same country in the absence of locust swarm exposure, after controlling for effects of weather and population. While this assumption is not possible to test directly, I can explore its plausibility in two main ways: testing for baseline balance in cell characteristics and testing for parallel trends prior to exposure.

Cells exposed to a locust swarm during the sample period have different baseline characteristics than unexposed cells which are largely consistent with desert locusts rarely being observed in the interior of the Sahara desert (as shown in Figure 2). Exposed cells have larger populations, are closer to capital cities, have a greater share of pasture land and smaller share of barren land, and have lower maximum temperatures (Table A2). These differences remain significant but are smaller when restricting the sample to cells within 100km of any locust swarm from 1996-2021 (a joint test of differences in cell characteristics yields $F = 3.35$ and $p < 0.01$). I estimate the propensity of any locust swarm exposure during the study period

for spatial correlation over 100 and 500km and serial correlation over 0 or 10 time periods, following Hsiang (2010)'s approach.

[15]The main estimates do not include controls but results are robust to including the same controls as in the TWFE analyses. The results are similar when varying the number of pre-exposure periods included.

as a function of baseline cell characteristics including land cover, population, distances to the capital and to a national boundary, mean weather realizations, and country fixed effects. I use the results to construct inverse propensity weights as $\frac{1}{p}$ for cells that were exposed and $\frac{1}{1-p}$ for cells that were not, where p is the estimated probability of swarm exposure. I assign cells with estimated probabilities outside the range of common support a weight of 0. Differences in cell characteristics by treatment status are largely eliminated when weighting observations by these inverse propensity weights, and I test the sensitivity of the results to including these weights (Stuart et al., 2014).

To account for these baseline differences in cell characteristics, the main analyses restrict the sample to cells within 100km of any locust swarm and within the range of common support of the estimated probability of swarm exposure across exposed and unexposed cells. I test the sensitivity of the results to alternative restrictions.

Baseline differences by swarm exposure status are not a concern if they do not affect conflict risk or only affect levels of conflict, but it is plausible that some of the differences would affect conflict trends. However, the controls in the empirical specifications should absorb most of these differences. Cell fixed effects control for time invariant cell characteristics that might affect the risk of conflict such as distance to major cities or country boundaries, topography, and agricultural suitability.Country-by-year fixed effects flexibly control for factors varying over time at the country level that might affect conflict risk, such as food price shocks, weather patterns, the policy environment and national economic and social conditions. Importantly, they also control for trends in violent conflict incidence, which increases over the sample period. I also directly control for time-varying characteristics that differ between exposed and unexposed cells: population, precipitation, and temperature.

Further, I find similar probability of violent conflict by swarm exposure in the pre-exposure periods (Figure 3). The main event study estimate shows significantly *lower* risk of violent conflict in exposed cells in one pre-exposure period (9 years before exposure), but the other pre-exposure coefficients are fairly close to 0 and not statistically significant. A joint test of significance of all 12 pre-exposure coefficients yields $p = 0.342$, indicating no differential conflict risk pre-trends.[16] Though this does not preclude the possibility that trends would differ in the years after swarm exposure for reasons unrelated to agricultural

[16] Figure C5 shows results using alternative estimators. Pre-exposure standard errors are larger in the main Borusyak et al. (2024) method, likely because comparisons are made against averages over the full pre-treatment period and there are not 12 years of pre-exposure data for most treated cells. But patterns are similar with fewer pre-treatment periods (**??**). I find a similar pre-trends pattern using the Cengiz et al. (2019) event study estimator, with point estimates slightly more negative on average. No pre-exposure coefficients are significant using the De Chaisemartin and d'Haultfoeuille (2024) and Callaway and Sant'Anna (2021) methods, but point estimates for periods 8 to 12 years before exposure are more positive, potentially due to not being able to use country-by-year fixed effects in the Stata packages for these estimates.

destruction, it is an encouraging sign that the parallel trends assumption may be likely to hold.

Another identification assumption relevant to event study designs with staggered treatment timing is the no anticipation assumption: knowledge of future treatment timing does not affect current outcomes (Roth et al., 2023). Populations may expect a higher probability of swarm exposure in years of major upsurges but cannot perfectly anticipate timing of exposure. For example, the FAO Desert Locust Watch publishes monthly forecasts of areas predicted to be at risk of locust swarm exposure but the predictions include a great deal of uncertainty due to unpredictable minor variations in swarm flight patterns. Consequently, areas forecast to be at risk are generally quite large, the majority of which end up not being affected by locusts.[17]Anticipation may also have limited effects as there are no effective methods of defending vegetation against locust swarms, and farmers in at-risk areas typically describe locust prevention and control as out of their hands and the responsibility of governments (Thomson and Miers, 2002).

6 Results

6.1 Average impacts of swarm exposure on violent conflict

Table 1 presents the results from estimating average long-term impacts of swarm exposure on the annual risk of violent conflict. On average cells exposed to locust swarms are 2.0 percentage points (pp) more likely to experience any violent conflict in a given year in the period after swarm exposure than cells not exposed.[18] A 2.0pp increase on the probability of any violent conflict in a year represents an 71% increase over the mean for cells not exposed to locusts.

The average long-term impact of swarm exposure is large compared to the same-year effect of a standard deviation (SD) increase in precipitation relative to cell averages during the sample period, but similar to the effect of a SD increase in maximum temperature. A 1 SD increase in annual precipitation increases the probability of violent conflict in the same year by 0.4pp (14%) compared to 1.9pp (68%) for a 1 SD increase in the maximum

[17]I find that monthly forecasts of at-risk areas during the major upsurge in 2004 covered on average 40.6% of 0.25° cells in sample countries, but nearly one-quarter of swarms in this period were recorded outside of these areas.

[18]The average impact of locust exposure remains statistically significant at the 99% confidence level under other forms of standard error clustering, including two-way clustering at the region and year level and using Conley (1999) SEs allowing for spatial correlation within 100 and 500km and serial correlation over 0 or 10 years (Figure C1). Clustering at the sub-national region level consistently leads to SEs at least as large as Conley SEs allowing for spatial correlation within 500km and serial correlation over 10 years, implying the main SEs I report are conservative and may understate statistical significance of certain estimates.

annual temperature. The effect of temperature is in the upper end of the distribution of estimates of the impacts of climate on intergroup conflict in Burke et al. (2024)'s meta-analysis, potentially because of the use of maximum temperature and the time period studied. Cell population is also positively associated with conflict risk, with an increase of 10,000 people associated with a 0.9pp (32%) increase in the probability of any violent conflict event in a year.

Table 1: Average impacts of exposure to locust swarms on violent conflict risk by land cover

Outcome: Any violent conflict event	(1) All land	(2) Land = Any crop or pasture land	(3) Land = Any crop land
Exposed to any locust swarm	0.020***	0.004	0.005
	(0.005)	(0.006)	(0.005)
Total annual precipitation (SDs)	0.004**	0.002*	0.002*
	(0.002)	(0.001)	(0.001)
Max annual temperature (SDs)	0.019***	0.018***	0.018***
	(0.006)	(0.006)	(0.006)
Population (10,000s)	0.009***	0.026**	0.007
	(0.002)	(0.011)	(0.006)
Exposed to any locust swarm × Land= 1		0.018**	0.022**
		(0.008)	(0.008)
Total annual precipitation (SDs) × Land= 1		0.003	0.003*
		(0.002)	(0.002)
Max annual temperature (SDs) × Land= 1		0.002	0.003
		(0.004)	(0.005)
Population (10,000s) × Land= 1		-0.017	0.001
		(0.011)	(0.006)
Observations	327646	327646	327646
Outcome mean post-2004, no exposure	0.028	0.028	0.028
Country-Year FE	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Note: The table presents results from three separate regressions in each panel: one with no land cover interactions and the other two interacting all right-hand side variables with cell land cover dummies. The 'Land=1' rows show the coefficients for the interaction of right-hand side variables with cell land cover dummies indicated in the column heading. The outcome mean for control cells is shown for post-2004 for comparison with exposure impacts in the period after the majority of swarm exposure occurred. Observations are grid cells approximately 28×28km by year. SEs are clustered at the sub-national region level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

I test for differences in the impacts on violent conflict of swarm exposure and weather by whether a cell has any agricultural (crop or pasture) land or any crop land in particular. Effects of precipitation are marginally significantly larger in cells with any crop land but remain significant in non-agricultural cells. Effects of temperature do not vary by land cover. These results echo previous work questioning whether agricultural mechanisms explain the relationship between climate and conflict (Bollfrass and Shaver, 2015; Sarsons, 2015). The association between population and conflict risk does not vary significantly with land cover. The estimated effect in non-agricultural cells is very large but there is little identifying variation driving this estimate.

In contrast, I find clear heterogeneity in the effects of locust swarm exposure by land cover. Swarm exposure in non-agricultural cells (43% of the sample) has no significant effect while in agricultural cells annual violent conflict risk increases by 2.2pp. Locust swarms increase annual violent conflict risk by 2.7pp in crop cells (31% of the sample) compared to no significant effect in non-crop cells (35% of which have pasture land). These differences are consistent with locust swarms affecting conflict risk through agricultural destruction.

To further test that locust swarms represent shocks that affect the economy and society solely through their impacts on agricultural production, I consider heterogeneity in impacts by both land cover and by timing of swarm exposure relative to local crop calendars. I categorize swarms as arriving during particular stages of the crop production cycle by matching the month in which a swarm is observed to crop calendar information from the PRIO dataset, filling in missing data with country-level crop calendars from The United States Department of Agriculture (USDA) (2022).[19] The off season—between harvesting and planting—lasts between 3 and 6 months in most of the sample countries, with an average of slightly over 4 months. I distinguish between swarms arriving during the off season and planting season (first two months of the crop calendar) when they are unlikely to significantly damage crop production, from swarms arriving in the growing and harvesting season when potential damages should be greatest. Figure A1 presents the timing of locust swarms by region across the sample period. Swarms in cells with crop land are fairly evenly distributed across stages of the crop calendar.

As with the main analysis, I use the first year a cell was exposed to a locust swarm during a particular season to construct an absorbing treatment variable. I then estimate Equation 1 with the two seasonal swarm exposure treatments and fully interact all variables with a dummy for having any crop land in a cell. Table 2 shows that effects on violent conflict risk are driven by exposure to locusts swarms during the growing or harvest season in crop cells. Exposure to off-season or planting season swarms in crop cells has no significant effect, and the impacts are significantly different ($p = 0.087$). What we might consider 'placebo' swarms in non-crop cells during the off or planting seasons have an estimated effect close to 0, in line with expectations. The effect of growing or harvest season swarms in non-crop cells is close to being marginally significant ($p = 0.113$), suggesting effects through destruction of pasture or other vegetation. The finding relates to studies showing that the impact of weather shocks on conflict risk varies depending on whether the timing of the shock is such that it is likely to decrease agricultural productivity (Caruso et al., 2016; Crost et al., 2018; Harari and La Ferrara, 2018).

[19] In countries with different agricultural cycles by crop, I identify the crop activity associated with the most commonly grown crops each month.

Table 2: Impacts of swarm exposure by land cover and swarm timing

Outcome: Any violent conflict event	(1)
Off/planting season	0.001
Non-crop cell	(0.006)
Off/planting season	0.008
Crop cell	(0.007)
Growing/harvest season	0.011
Non-crop cell	(0.007)
Growing/harvest season	0.027***
Crop cell	(0.008)
Observations	327646
Outcome mean post-2004, no exposure	0.028
p, off/plant season non-crop=crop effect	0.368
p, grow/harvest season non-crop=crop effect	0.131
p, non-crop off/plant=grow/harvest effect	0.311
p, crop off/plant=grow/harvest effect	0.087
Country-Year FE	Yes
Cell FE	Yes
Controls	Yes

Note: The table presents results from a single regression interacting two seasonal swarm exposure treatment variables with a dummy for crop land cover with the same fixed effects and controls as in Equation 1. The coefficients and standard errors are calculated using Stata's *xlincom* command based on the sums of the coefficients for the non-crop seasonal effects and the crop interaction terms. Observations are grid cells approximately 28×28km by year. SEs are clustered at the sub-national region level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.2 Robustness

The heterogeneity in effects of swarm exposure by timing and land cover is reassuring as it indicates that the estimated impacts are not driven by potential bias in where locust swarms are reported. I further test the potential for missing swarm observations to affect the estimates by simulating how the results change as I increase the share of cell-years where locust swarms are randomly imputed within 100km of a locust swarm report. A particular concern is that swarms may be particularly unreported in insecure areas (Gantois et al., 2024; Showler and Lecoq, 2021; Torngren Wartin, 2018). This type of measurement error should bias my estimates downward as conflict is serially correlated, and I confirm that estimated effects of swarm exposure increase if I impute 'missing' swarms in areas experiencing violent conflict near existing swarm observations (Figure C2 Panel A).

Estimated effects of swarm exposure on violent conflict risk fall if I randomly impute hypothetical missing swarms across all cell-years with nearby swarms reported. This could indicate that swarms are more likely to be reported in locations with higher long-term conflict risk, but is also consistent with attenuation from random error in the treatment definition. Although I cannot distinguish these explanations, the results are useful in bounding the potential effect of locust swarm exposure. Even if I randomly assign 50% of cell-years near a swarm report to be exposed to locusts, the estimated effect of swarm exposure remains economically and statistically significant, with a mean 0.5pp increase in violent conflict risk that is significant at the 95% level in 83% of simulations (Figure C2 Panels B and C). These results strongly imply that the estimated effects of locust swarm exposure are not driven by selection in where swarms are reported.

I test the sensitivity of the results to various alternative specifications and estimate similar impacts of locust swarm exposure on violent conflict risk (Appendix C). Estimated impacts are largely unchanged when varying the set of control variables included, though are larger with no controls and slightly smaller when including year rather than country-by-year fixed effects (Figure C3 Panel A). The standard error is smaller but the coefficient is almost identical when using sub-national region by year fixed effects to identify effects off of more local variation in swarm exposure. The magnitudes of the effect of swarm exposure on violent conflict risk are slightly smaller but remain strongly statistically significant when weighting observations by the inverse of the propensity to have been exposed to a swarm (Figure C3 Panel B), indicating that restricting the sample to areas within 100km of a swarm observation and cells within the range of common support for this propensity is largely sufficient for identifying a set of control cells to serve as a counterfactual.

Results are similar when including all cells in the sample and when dropping cells in particular geographic regions. This addresses concerns that the long-term impacts on violent conflict may be spurious and due to swarm exposure during the sample period being correlated with factors driving later conflict emergence. For example, dropping North Africa ensures that results are not driven by the Arab Spring and dropping Arabia ensures results are not driven by the civil war in Yemen. The estimated magnitudes are slightly smaller when dropping countries where Showler and Lecoq (2021) report insecurity prevented some locust control operations during the sample period, and when dropping cells that experienced violent conflict during the 2003-2005 locust upsurge which might have prevented swarm reporting (Figure C4 Panel A). The similar results in these samples imply conflict-driven underreporting of locust swarm exposure during the study period is unlikely to be a meaningful factor in the analysis. Dropping individual years when locust swarm exposure events occurred does not affect the estimates, though the estimate is much noisier when dropping the main 2004 exposure event (Figure C4 Panel B).

Absolute effects are larger when collapsing the data to the level of 0.5 or 1° cells, but effects relative to the probability of any violent conflict in unexposed cells are similar (Figure C3 Panel B). Using larger grid cells addresses several potential measurement issues. First, it minimizes the possibility that the area exposed to a locust swarm recorded in a cell exceeds the boundaries of the cell. Second, it reduces concerns about nearby areas that might have been affected by unreported swarms since the entire cell is considered exposed if any swarm is reported within it. Third, it limits the potential for conflict spillovers outside the cell. Downsides to analyzing impacts in a more coarse grid are dilution of treatment intensity (as the share of the cell affected by swarms weakly decreases with cell size) and the loss of local variation in swarm exposure which is important to the identification approach.

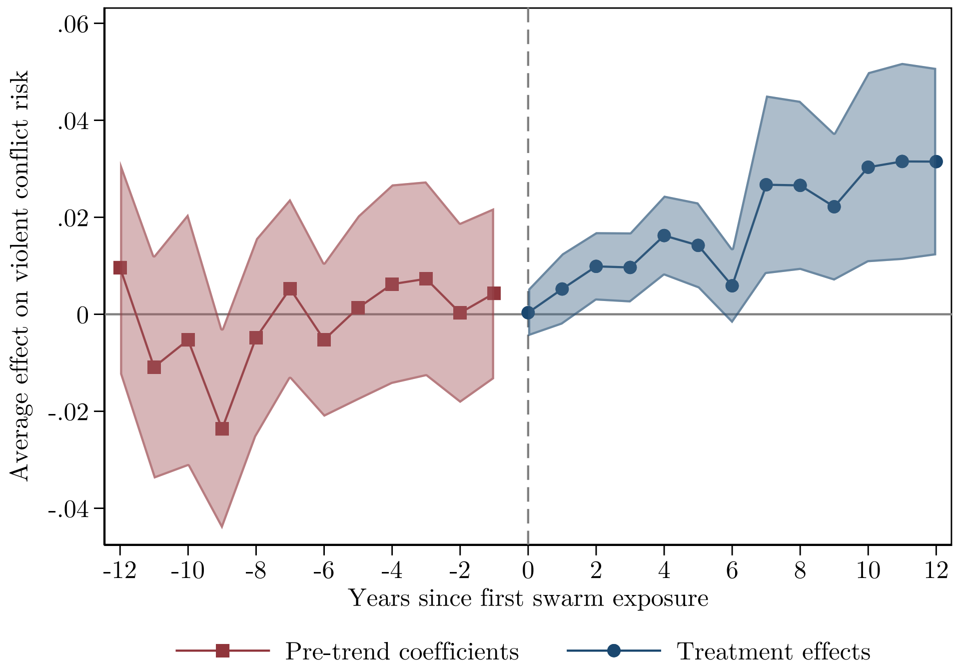
Larger estimated magnitudes when using larger grid cells despite dilution of treatment intensity indicate potential spillovers of violent conflict outside exposed cells, and test for this directly I define a spillover exposure treatment as being within 100km of a swarm outside of the cell. I find a fairly precise null average effect of this spillover treatment when controlling for direct swarm exposure, though spillovers from the 2003-2005 upsurge are marginally significant and indicate a 0.7pp average long-term increase in conflict risk for cells within 100km of a swarm during that upsurge (Table C1). Focusing on impacts within 0.25° cells may therefore understate the full effect of swarm exposure on violent conflict risk around affected areas, but the results indicate that most effects are contained within cells. Limited spillovers could reflect variation in the actual shock to agricultural production within treated cells which may foster conditions for more local conflict, in contrast with shocks such as drought which are more widespread and may cause conflict spillovers by inducing certain populations to move (McGuirk and Nunn (2025)).

6.3 Dynamic impacts of swarm exposure on violent conflict

I now estimate pre-exposure differences and dynamic impacts of locust swarms on violent conflict over time. Figure 3 presents event study estimates using the staggered treatment timing difference-in-differences approach developed in Borusyak et al. (2024). I can reject that the pre-exposure effect is different from zero at a 95% confidence level for one of 12 periods—on average violent conflict is 2.4 percentage points less likely in areas exposed to locust swarms compared to unexposed areas 9 years before exposure. No other pre-exposure coefficient is larger than 0.011 in magnitude, and 7 are positive while 5 are negative. The average pre-exposure difference is -0.001, and I fail to reject that pre-exposure differences are jointly equal to 0 ($p = 0.342$). If anything, the one significant pre-exposure difference being negative suggests exposed cells may have lower baseline risk of violent conflict.

Despite the large average long-term effects of swarm exposure shown in Table 1, the point estimate for the effect on violent conflict risk in the year locusts arrive is a fairly precise 0. This contrasts with much of the literature on climate and conflict which focuses on short-term effects and generally finds significant concurrent increases in conflict risk, though Crost

Figure 3: Impacts of exposure to locust swarms on violent conflict risk over time



Note: The dependent variable is a dummy for any violent conflict event in a cell-year. Estimated impacts in each time period are weighted averages across effects for swarm exposure in particular years, calculated using the Borusyak et al. (2024) approach. Time period 0 is the year of first swarm exposure. A joint test that the pre-exposure coefficients equal 0 gives $p = 0.342$. Shaded areas represent 95% confidence intervals using SEs clustered at the sub-national region level. All regressions include country-by-year and cell fixed effects. Observations are grid cells approximately 28×28km by year.

et al. (2018) and Harari and La Ferrara (2018) also find that growing season weather shocks have null or inconsistent effects on conflict in the same year and Bazzi and Blattman (2014) find that commodity price shocks primarily affect conflict incidence and not conflict onset

All other estimated treatment effects are positive, and all but the effects in periods 1 and 6 after the year of swarm exposure are statistically significant at a 99% confidence level. The average effect across all post-exposure periods is a 1.9 percentage point increase in the annual risk of any violent conflict event. This average is very close to the TWFE estimate in Table 1—a 2.0pp increase—indicating limited bias in the TWFE estimates from staggered timing of swarm exposure, potentially because close to three-quarters of exposure occurred in the same period in 2003-2005.

The estimated effects are not stable over time. After null effects in the year of exposure, I also find generally increasing effects over time with the exception of a smaller marginally significant increase in year 6 post-exposure. The average effect in years 1-6 post-exposure is a 1.0 percentage point increase in conflict risk compared to 2.8 over years 7-12, with highly significant effects over this later period even as the standard errors increase with more time since exposure.

The pattern of results is similar using alternative event study estimators including Callaway and Sant'Anna (2021), Cengiz et al. (2019), and De Chaisemartin and d'Haultfoeuille (2024), varying the fixed effects and controls, and reducing or increasing the number of pre-exposure effects estimated (section 10). Importantly, although estimated treatment effects are smaller in magnitude and lose significance for years 1-6 post-exposure when I include inverse propensity weights based on the estimated probability of being exposed to a swarm during the study period, effects in years 7-12 post-exposure remain large and statistically significant (Figure C6 Panel B).

I observe similar patterns in impacts of exposure over time when collapsing the data to 0.5° or 1° cells, with smaller and marginally significant effects in the first 6 years post exposure and larger and highly significant effects in years 7-12 (Figure C7). There are some positive pre-trends at the 1° level, and estimated effects in larger cells are larger in absolute magnitude but these results should be interpreted with caution as much of the quasi-random local variation in swarm exposure underpinning the identification strategy is lost at this level of aggregation.

The results are similar when including the full sample of cells and when dropping various geographic regions (Figure C8). Effects of swarm exposure are slightly smaller in magnitude and less precise when dropping countries where Showler and Lecoq (2021) indicate insecurity has limited locust control operations. If missing swarms were strongly correlated with violent conflict we might have expected larger effects when dropping these countries by reducing the share of cells incorrectly classified as not exposed to any swarm; instead the smaller effects reflect lower average levels of violent conflict in the rest of the sample countries.

7 Mechanisms

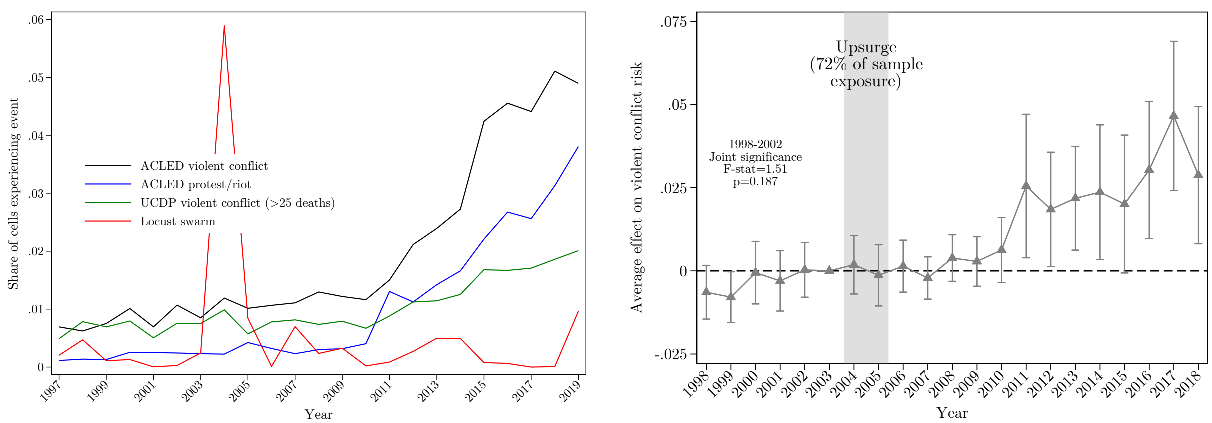
7.1 Explaining the timing of conflict effects

The pattern of dynamic long-term impacts of locust swarm exposure on violent conflict are not intuitive. Why are the largest impacts delayed, particularly given the null effect in the year of exposure and minimal effect the following year? The opportunity cost mechanism alone, acting through immediate effects of swarm exposure on agricultural productivity or through persistent effects on permanent income, would suggest that impacts of swarm exposure on conflict risk should be largest in the short-term and either fall over time as affected areas recover or be fairly stable if households reach a new productivity equilibrium—predictions 1 and 3 from Section 3. Instead, these predictions are rejected by the results, indicating another mechanism creating heterogeneity in impacts.

An important observation is that the gap between swarm exposure and the largest impacts on violent conflict risks corresponds to the gap between the timing of the main swarm exposure event in the sample period—the 2003-2005 upsurge—and the years when the general risk of conflict increased across the sample countries due to the Arab Spring, the spread of Islamic terrorist groups, and multiple civil wars, as shown in Figure 4 Panel A. Panel B shows that exposure to this upsurge did not significantly increase the risk of violent conflict until 2011, the year of several uprisings related to the Arab Spring, but that effects remain large and statistically significant in subsequent years. I find similar patterns when looking at effects of the upsurge in different countries with different events precipitating the spread of violent conflict (Figure C9).

Figure 4: Changes in conflict environment and impacts of exposure to 2003-2005 locust upsurge on violent conflict risk

A) Swarm and conflict trends   B) Event study 2003-2005 upsurge



Note: Panel A shows the share of sample cells experiencing any locust swarm or conflict event by year. Panel B shows results for an event study of exposure to the 2003-2005 desert locust upsurge, with 2003 as the reference period, following Equation 1. The dependent variable is a dummy for any violent conflict event, and treatment is defined as any locust swarm observation from 2003-2005. The bars represent 95% confidence intervals using SEs clustered at the sub-national region level. A joint test that the pre-exposure coefficients equal 0 gives $p = 0.187$. Observations are grid cells approximately 28×28km by year.

As the 2003-2005 locust upsurge accounts for 72% of swarm exposure in the sample period, its effects drive the main event study including all swarm exposure events. Figures 3 and 4 show clearly that exposure does not generally cause the immediate onset of new violent conflicts. Instead, exposed areas appear to be more vulnerable or susceptible to changes in the general conflict environment, implying mechanisms related to the returns to engaging in conflict and not just the opportunity cost of fighting.

Prediction 5 of the model provides a potential explanation: variation is impacts of swarm exposure is due to variation in local grievances. Null short term effects may reflect relatively peaceful conditions at the time of the main locust exposure events, limiting the feasibility of fighting and the potential net returns. Significant increases 2-6 years after exposure in the main event study compared to null effects over this period for the 2003-2005 upsurge are consistent with later swarm exposure events occurring closer to or during the period of generally greater grievances and insecurity. The largest impacts of swarm exposure are realized in periods of multiple grievances, manifested in popular uprisings, civil wars, and Islamic militancy.

To formally test prediction 5 that effects of swarm exposure will vary by intensity of local grievances, I test for heterogeneity in average long-term impacts by a variety of variables representing situations of likely heightened grievances. At the cell-year level, I measure whether there are any concurrent violent conflict events in surrounding cells and whether there are drought conditions. At the country-year level, I measure whether there are famine conditions and whether the country has experienced violent conflict related to the Arab Spring, to civil conflict, to separatist movements, or to Islamic terror groups, with each of these latter indicators defined as absorbing variables.

Table 3 shows that average long-term impacts of locust swarm exposure on violent conflict are smaller and in some cases not statistically significant in locations and areas not characterized by some form of grievance, as proxied by conflict, insecurity, drought, or famine. Consistent with prediction 5, effects of swarm exposure are significantly larger in all situations except for drought, and the magnitudes of these differences are all quite large. The largest difference is for areas with concurrent violent conflict in the surrounding 1 degree cell. In these situations, past swarm exposure increases the probability of any violent conflict within the cell by 6.2pp, meaning areas exposed to locusts are more susceptible to the spread of violent conflicts.

Table 3: Heterogeneity in impacts of exposure to locust swarms on violent conflict risk by indicators of grievances

Outcome: Any violent conflict event	(1) Any violent conflict in surrounding 1 deg cell	(2) Any violent conflict in surrounding sub-region	(3) Post-onset of Arab Spring in country	(4) Post-onset of civil conflict in country	(5) Post-onset of separatist movement in country	(6) Post-onset of Islamic terror groups in country	(7) Any active famine in country	(8) Any active drought in cell
Exposed to any locust swarm	0.007***	0.006**	0.009***	0.002	0.006*	0.006	0.017***	0.011***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.006)	(0.005)	(0.004)
Grievance proxy	0.119**	0.091***						0.003
	(0.050)	(0.035)						(0.004)
Exposed to any locust swarm × Grievance proxy	0.062***	0.028***	0.036***	0.032***	0.040***	0.024*	0.028**	-0.000
	(0.014)	(0.007)	(0.011)	(0.012)	(0.015)	(0.013)	(0.014)	(0.006)
Observations	327646	327646	327646	327646	327646	327646	327646	267644
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table presents results from separate regressions where I interact Equation 1 with a dummy variable for an indicator of more intense local grievances. The grievance proxy indicators in columns 1-2 and 8 are time-varying cell-level variables. The indicators in columns 3-6 are absorbing variables defined at the country level based on the timing that Arab Spring uprisings, civil conflicts, separatist movements, or Islamic terror attacks began in the country. Countries not exposed to such conflicts are coded as 0 for all years. Column 7 is also defined at the country level but varies by year rather than being absorbing after an initial famine exposure in the sample period. Effects of the grievance proxy indicators are absorbed by the country-year fixed effects in columns 3-7. The sample size is smaller in column 8 because the drought data only cover 1996-2014. Observations are grid cells approximately 28×28km by year. SEs are clustered at the sub-national region level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The heterogeneity in locust swarm impacts by indicators of local insecurity could potentially be due to mechanisms other than grievances. First, insecurity may further decrease local labor productivity, decreasing the opportunity cost of fighting. If effects of the initial swarm exposure are not sufficient to motivate affected individuals to choose to fight, an additional negative shock could provide the necessary push. In this case I would also expect impacts of swarm exposure to be larger in periods with other negative agricultural shocks. But while effects are indeed larger in years when countries are experiencing a famine as shown in the table, there is no significant difference in effects by whether a cell is experiencing a drought.

Second, areas exposed to locust swarms may be less able to defend themselves from attacks and therefore be targeted by armed groups when these become active. The same mechanisms that would make exposed areas more vulnerable—persistent reductions in wealth—would also make them less attractive targets, however, so it is unclear how the expected returns to predation in these areas would change.

The other possibility relates to the returns to engaging in violent conflict, and how grievances may both reduce the costs of and increase expected benefits from fighting. Individuals in areas with lower opportunity costs of fighting following a severe prior agricultural shock may generally not find switching to fighting optimal as violent conflict is generally a costly and collective activity. Formation of armed groups and recruitment of fighters will be easier in areas of greater grievances reducing the social, emotional, and monetary costs of fighting. While swarm exposure may itself create lasting grievances, the local variation in exposure may prevent this from leading to general mobilization except in situations of broader grievances prompted by other factors or events.

Looking instead at a positive agricultural shock, Hastings and Ubilava (2023) show that the onset of rice harvest in Southeast Asia—a temporary increase in the returns to fighting over agricultural output—only increases violence against civilians in areas with fighting groups active during the growing season. Though this result emphasizes the rapacity mechanism rather than the opportunity cost mechanism, it similarly shows that the costs of engaging in conflict are a critical factor in determining impacts of an agricultural shock.

The heterogeneity in swarm impacts also relate to Buhaug et al. (2021)'s finding that drought only causes the onset of civil conflict among ethnic groups experiencing recent political marginalization, an indicator of likely heightened grievances. The authors argue that the economic shock acts like a trigger to transform preexisting grievances into violent conflict. I do not find evidence of such a trigger effect in this study, as the effect of swarm exposure on violent conflict in the same year is null and the effect the following year is small and marginally significant. Instead, the results indicate that past exposure to an agricultural shock can affect how future grievances—caused by a variety of social, political, and economic factors—affect conflict incidence.

Exposure to locust swarms may increase vulnerability to future grievances through channels other than the permanent income mechanism presented in Section 3. Desert locust swarms are localized natural disasters with concentrated effects on agricultural production in only part of each 0.25° cell, increasing within-cell inequality which may create discontent and cause conflict (Gurr, 2015). Local inequality , and several empirical studies show evidence of that greater inequality—particularly horizontal inequality between groups—is associated with increased conflict (Bartusevičius, 2014; Østby, 2008, 2013), though causal identification appears largely limited to panel analyses. Future work could test this mechanism empirically by estimating measures of inequality over time in areas surrounding locust swarm reports, and by comparing impacts of swarm exposure on violent conflict in cells with different levels of ethnic diversity.

Swarm exposure could also have psychological effects on affected populations, as documented in other studies of the climate-conflict relationship (see Burke et al. (2024) for a review). In this context, effects on religiosity may be important. The dominant religion in the sample countries is Islam, where locusts are mentioned as both a punishment from Allah and as a sign of Judgment Day. Sinding Bentzen (2019) finds that earthquake exposure persistently increases religiosity using survey data from 96 countries, with results consistent with a religious coping mechanism. If locust swarms increase religiosity in exposed areas this may affect the perceived returns to fighting by increasing social, emotional, and supernatural costs, suppressing immediate violent conflict. Increased religiosity could also help explain higher conflict incidence in exposed areas following the onset of various civil conflicts and Islamic terror movements in the sample countries. This mechanism could be tested empirically by analyzing differences in impacts of swarm exposure on conflict by a measure of religious identity across cells, and by considering how swarm exposure affects measures of religiosity.

7.2 Exploring the opportunity cost mechanism

The dynamic impacts of locust swarm exposure on violent conflict are not consistent with the predictions coming from an opportunity cost mechanism alone (predictions 1 and 3 of Section 3). But one interpretation of the heterogeneity by indicators of insecurity or economic shocks is that a persistent reduction in opportunity costs of fighting following a severe agricultural shock is only sufficient to induce affected individuals to switch to fighting in periods of heightened grievances when engaging in fighting is more accessible. In this section I further test for evidence of a role of changes in opportunity costs in explaining the long-term effects of locust swarms.

7.2.1 Effects on agricultural and economic activity

Effects of swarm exposure on the opportunity cost of fighting through the immediate productivity shock or through a permanent income mechanism should be observable on measures of productivity in affected areas (prediction 4). Severe negative effects of locust swarms on agricultural output are well-documented (Green, 2022; Newsom et al., 2021; Showler, 2019; Symmons and Cressman, 2001; Thomson and Miers, 2002). While immediate decrease in agricultural productivity and thus in the opportunity cost of fighting in affected areas seems incontrovertible, there is less evidence on the longer-term effects of desert locusts on productivity.

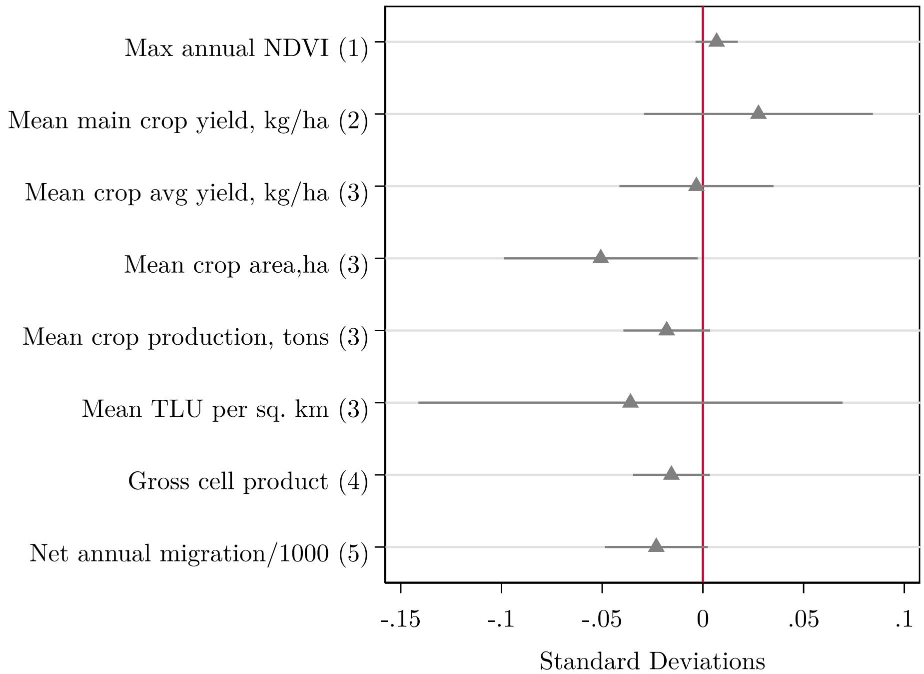
I present results of tests of average long-term effects of swarm exposure on various measures related to economic activity in Figure 5. I first test for effects on measures of agricultural productivity, considering the annual maximum of the cell-level Normalized Difference Vegetation Index (NDVI), the maximum annual yield across major crops (Cao et al., 2025), and mean crop yield in DHS survey locations (IFPRI 2020).

NDVI is a commonly-used satellite-based measure of vegetation greenness which in crop land can be considered a rough proxy for agricultural production. On average, locust swarm exposure has no significant effect on NDVI in subsequent years and the point estimate is very small. While I find significant decreases in NDVI in the years in which locust swarms are reported and the following year (Figure A2), these effects do not persist.[20] I also find no average long-term effects of swarm exposure on measures of crop yield estimated via machine learning combining administrative statistics and remotely sensed data (Cao et al. (2025)) or in the periods and locations where DHS surveys were conducted (IFPRI 2020).

These null effects are consistent with locust swarms—a migratory pest—being a transitory shock that does not affect agricultural productivity fundamentals. They also indicate that to the extent swarm exposure affects later labor productivity this is not reflected in measures of NDVI or crop yields at the cell level. Another possible reason for the non-significant average effects of locust exposure is that these intent to treat estimators include too small a share of treated areas. The median locust swarm covers around 50 km^2, or 6% of the area of a 0.25 degree cell. Most DHS clusters in cells exposed to locust swarms will likely not have experienced any agricultural destruction, so the intent to treat effects I estimate will

[20] An event study analysis of impacts on maximum NDVI in crop cells (Figure A2) shows generally higher NDVI in exposed cells in the years prior to swarm exposure, indicating baseline differences in productivity. These differences are generally reversed in the post-exposure period, as 9 of 12 point estimates for treatment effects are negative though only 3 are statistically significant. Unexpectedly, I also find significant *increases* in maximum NDVI in two post-exposure periods.

Figure 5: Average impacts of exposure to locust swarms on measures of agricultural production and economic activity



Note: The figure shows coefficients and 95% confidence intervals from separate regressions of swarm exposure on different outcomes, following Equation 1. All outcomes are normalized so units are standard deviations. (1) NDVI is calculated from MODIS satellite imagery (Didan, 2015) as the maximum of monthly average NDVI values in each cell for 2000-2018. (2) Crop-specific yield data are from Cao et al. (2025)) for 1997-2015, where the 'main' crop in cells with multiple crops is defined as the highest-yield crop in the cell. (3) DHS cluster data are from the DHS AReNA database for 1997-2018 (IFPRI 2020) and represent average values within DHS clusters at the time surveys were conducted. 'TLU' indicates Tropical Livestock Units. (4) Gross cell product is from Nordhaus (2006) as included in the PRIO-GRID database, with data only available for 2000 and 2005. (5) Annual net cell migration for 2000-2018 is from Niva et al. (2023). Observations are grid cells approximately 28×28km by year. SEs are clustered at the sub-national region level. Results from the regressions for non-normalized outcomes are reported in Table A3.

be biased toward 0. Taking average NDVI or crop yield values over the entire cell will also attenuate any impacts in areas actually affected.

Despite these null effects on measures of agricultural productivity, I do find significant effects on measures of agricultural production and economic activity. Using outcomes from the DHS AReNA database, I find that locust swarm exposure significantly decreases total crop area planted and production in survey clusters in the years following exposure, by 111 ha (4.0%) and 640 metric tons (3.6%), respectively (Table A3). These decreases balance out and result in a null effect on crop yields, but indicate a transition away from agricultural production in exposed areas. I do not find any impact of locust swarms on density of livestock ownership (measured in Tropical Livestock Units), indicating limited average long-term effects on this important aspect of household wealth at the grid cell level.

I find a nearly marginally significant ($p = 0.109$) decrease in gross cell product following swarm exposure. This outcome from Nordhaus (2006) is based on estimates of total income at the cell level combining data on population and output in agricultural and non-agricultural activities. These estimates are only available for 2000 and 2005 in the sample period, so the results represent the immediate impact of exposure to the 2003-2005 locust upsurge. Total income in a cell falls by 4.3 million USD in 1990 PPP terms (6.1%) in cells exposed to locust swarms. While this outcome measure is only an estimate of cell-level income and should be interpreted with caution, the result indicates large immediate economic impacts in line with research on the agricultural damages from locust swarms. A reduction in income of this magnitude, particularly if concentrated in the subset of the cell actually affected by locusts, could conceivably reduce household wealth and permanent income.

Finally, I consider effects on migration. Leaving to search of work is a common response to locust crop destruction (Thomson and Miers, 2002) and over 8 million people were displaced across East Africa as a result of the 2019-2021 locust outbreak (The World Bank, 2020). I find that locust swarm exposure decreases net annual migration by 5 people per 1,000 population ($p = 0.076$) using data from Niva et al. (2023), meaning significantly more people are migrating out of these areas each year on average. This effect indicates that past swarm exposure drives persistent out-migration from affected areas, which could be consistent with lower labor productivity.[21]

These analyses are limited by the grid cell-level approach I employ in this paper. While this approach is appropriate for an analysis of impacts of economic shocks on violent conflict, because conflict is mostly likely to be realized in the area surrounding affected populations rather than in their particular location, it is less appropriate for an analysis of economic impacts. More targeted intent to treat analyses focusing on economic impacts of locust swarms only in the close vicinity of the swarm reports would be more likely to detect effects, though raise difficulties in determining how to define exposed areas.

Indeed, a growing body of evidence using such approaches finds persistent effects of swarm exposure on outcomes that could imply reduced productivity. Most directly, Marending and Tripodi (2022) find that agricultural profits of households in parts of Ethiopia exposed to locust swarms in 2014 are 20-48% lower two harvest seasons after swarm arrival, driven by a large drop in farm revenues. This indicates that impacts on agricultural productivity are not limited to the year of swarm exposure. Indirectly, several studies show that young children exposed to locust swarms achieve lower educational attainment (Asare et al. (2023) and De Vreyer et al. (2015)) and have lower height-for-age (Conte et al., 2023; Gantois et al., 2024; Le and Nguyen, 2022; Linnros, 2017) when they are older. Such human capital effects

[21] Out-migration could cause conflict spillovers in migrant destinations due to increased competition over local output and resources (see e.g., McGuirk and Nunn (2025), and Burke et al. (2024) for a review of this mechanism), but I find limited evidence of spillovers from swarm exposure (Table C1).

of swarm exposure could decrease permanent labor productivity.

Taken together, the results on the effects of swarms exposure on economic outcomes at the grid cell level in Figure 5 are mixed with regards to a possible permanent income mechanism. NDVI and crop yields do not decrease significantly, indicating agricultural productivity is not reduced in years following a locust swarm on average. Livestock ownership is also not significantly lower, which does not align with a permanent income mechanism based on an initial income shock depleting household assets.

On the other hand, significant decreases in crop production and increases in out-migration suggest some households leave agriculture in favor of migrating, in line with reductions in agricultural productivity prompting a shift in occupation. If migration is an attractive alternative to agricultural production for households in areas exposed to locust swarms it may be the case that engaging in violent conflict would also be attractive in some circumstances, particularly in periods of heightened grievance. Studies linking swarm exposure to household surveys also present strong evidence of persistent adverse effects which could both foster grievances and decrease productivity. Additional work using approaches similar to those presented in Gantois et al. (2024) and Marending and Tripodi (2022) are needed to further test predictions of the permanent income and opportunity cost mechanisms but conducting such analyses is beyond the scope of this paper.

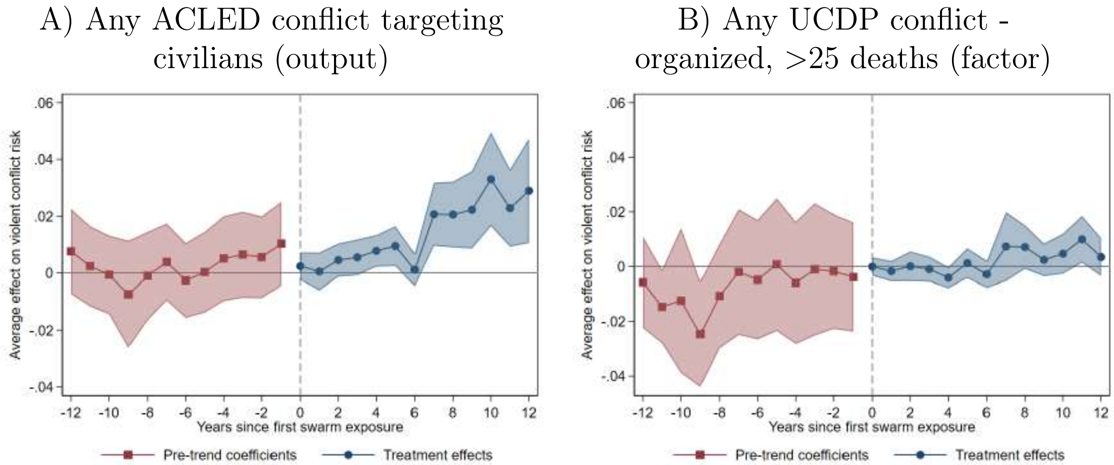
7.2.2 Opportunity cost vs. rapacity

Having tested for evidence of a persistence decrease in opportunity costs of fighting following swarm exposure, I now consider why the immediate reduction in opportunity costs caused by the agricultural destruction does not cause the immediate onset of violent conflict (prediction 1 of Section 3). One possibility for the null effects of locust swarms on violent conflict in the year of exposure is that the rapacity mechanism is offsetting the opportunity cost mechanism in the short term. Studies of shocks to agricultural prices have shown instances where the rapacity mechanism outweighs the opportunity cost mechanism: McGuirk and Burke (2020) and Ubilava et al. (2022) both document increases in violent conflict in cells producing agricultural goods following increases in the global price of these goods.

If this is the case, we would expect smaller short-term effects for conflict over output—reduced by the agricultural production shock and therefore decreasing returns to predatory attacks—than over factors of production, whose returns are not directly affected by the transitory shock (prediction 2). I follow McGuirk and Burke (2020) in using reports of violence against civilians, riots, and looting from ACLED as representing conflict over output and violent conflict events reported in the UCDP database as more likely to represent conflict over factors of production.

[Figure 6](#) presents event studies for the effects of swarm exposure on these measures of output and factor conflict. I find null effects on swarms on conflict risk in the year of exposure and the following year for both conflict types, with point estimates close to 0. Contrary to prediction 2, if anything the point estimates are slightly larger (though statistically indistinguishable) for output compared to factor conflict. Decreased returns to predatory attacks therefore do not appear to explain the null short-term effects of swarm exposure on violent conflict.

Figure 6: Impacts of swarm exposure on conflict risk over time, by conflict type



Note: The dependent variables are dummies for any conflict event being observed in a cell in a year, with the conflict type specified in the panel title. Each panel replicates Figure 3 for a different conflict outcome. See the figure note for Figure 3 for more detail. Shading represents 95% confidence intervals using SEs clustered at the sub-national region level.

More generally, effects on UCDP conflict are generally not statistically significant including in the period 7-12 years after exposure. In contrast, effects on conflict targeting civilians from ACLED are much greater in this period follow that same patterns as effects on any ACLED violent conflict in Figure 3.[22] Larger long-term effects on a measure of output conflict than one of factor conflict implies much of increase in violent conflict following swarm exposure stems from banditry, looting, terrorism, and other attacks on civilians rather than civil conflict over control of territory. This could be consistent with joining or forming an armed group as a livelihood decision with the capture of output to pay wages for group members prioritized over potentially more risky conflict over territory with government forces.

[22] I find significant average long-term increases in conflict risk across multiple types of conflict following exposure to a locust swarm (Table A4). Using ACLED data, estimated effects are similar for violent conflict that does and does not involve any state actor, but are relatively larger for conflict targeting civilians and for protests and riots. Impacts of swarm exposure are smaller in both absolute and relative terms using UCDP reports of violent conflict, which require at least one organized actor and >25 deaths in year. I find no significant effects on fatalities using either ACLED or UCDP data.

Locust swarm exposure should not increase the returns to such rapacity, so increases in output conflict must be driven by other factors. Persistent decreases in the opportunity cost of fighting interacting with periods of heightened grievances is one potential explanation. The lack of any widespread insecurity and major grievances—though acknowledging that many specific local grievances will have existed—in the period of the main 2003-2005 locust upsurge can help explain why the agricultural destruction in affected areas did not cause violent conflict to break out at that time.

7.3 Comparing locust swarms and severe drought

Locust swarms are a unique and catastrophic agricultural shock, but the model described in Section 3 is general and predicts similar patterns of impacts on the risk of violent conflict for other severe shocks to agricultural production. In this section I compare the impacts of locust swarm exposure to the impacts of exposure to a severe drought.

Following Harari and La Ferrara (2018) and others I use the Standardized Precipitation and Evapotranspiration Index (SPEI) which combines both precipitation and the ability of the soil to retain water. The units of the SPEI are standard deviations from the historical average within a grid cell, where deviations within 1 are typically considered near normal conditions. In particular, I use measures from the PRIO-GRID database of the share of months within a year that are part of the longest streak with one-month SPEI values below -1.5, with those SPEI values taken from the SPEI Global Drought Monitor (Begueria et al., 2014). I define a cell as experiencing a 'severe' drought shock in a particular year if there are at least 4 consecutive months where the SPEI is below -1.5. This value is chosen to reduce the probability of multiple such drought exposures during the study period. A streak of at least 4 drought months is observed in 3.6% of all cell-years, compared to 7.7% for streaks of at least 3 months and 22.3% for streaks of at least 2 months.[23]

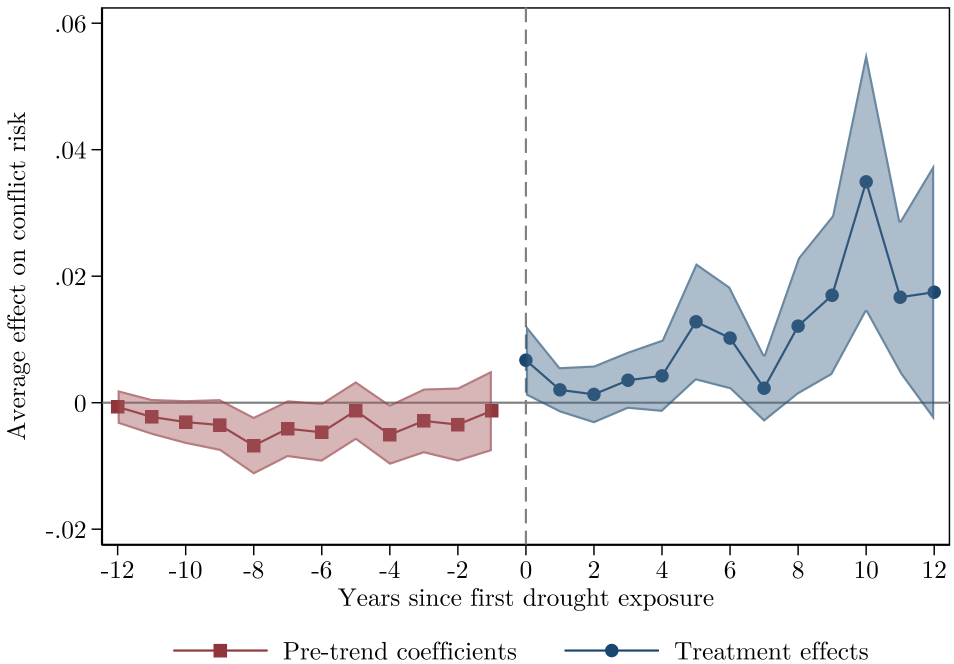
As with locust swarm exposure I identify the first year in which a cell experiences a severe drought and consider cells to be 'affected' in all subsequent years. Across all sample cells, 48.6% experience at least one severe drought from 1996-2014. Nearly half (48.8%) of all exposure occurs in 2010 when around one-third of the study area was affected by drought, with no other year accounting for more than 8% of exposure.

Figure 7 shows the results from an event study of drought exposure. Pre-exposure coefficients are uniformly negative and small in magnitude but are statistically significant at a 90% confidence level in 6 of 12 pre-exposure periods. This indicates a slightly lower baseline risk of violent conflict in areas ever exposed to drought compared to those not yet or never

[23]Patterns of treatment effects are similar but standard errors are much larger if I use a threshold of 5 or 6 months.

exposed. But there is no evidence of changes in this difference over time before the first severe drought exposure in the sample period. Conflict risk increases by a statistically significant 0.7 percentage points in the year of exposure ($p = 0.018$). Treatment effect estimates are positive and statistically significant for years 5-6 and 8-12 post-exposure, with the largest effects in the latter period though these estimates are noisier because the main exposure event was in 2010. The average effect over the 12 years post-exposure is a 1.1pp increase in the annual risk of violent conflict.

Figure 7: Impacts of exposure to severe drought on violent conflict risk over time



The dependent variable is a dummy for any violent conflict event in a cell-year. Estimated impacts in each time period are weighted averages across effects for drought exposure in particular years, calculated using the Borusyak et al. (2024) approach. Time period 0 is the year of first exposure to severe drought in the sample period, defined as ≥4 consecutive months in the year with SPEI<-1.5. Shaded areas represent 95% confidence intervals using SEs clustered at the sub-national region level. All regressions include country-by-year and cell fixed effects. Observations are grid cells approximately 28×28km by year.

A significant increase in the probability of any violent conflict in the year of exposure to a severe drought, in contrast to null immediate effects of exposure to a desert locust swarm, suggests droughts cause the onset of some conflict. Null effects in the several next years indicate that any conflict onset is short-lived, while significant and large conflict increases after a lag of 4 years mirror the delayed effects of desert locust swarm exposure. The main drought exposure event was in 2010, around the time that insecurity and violent conflict in the study area began to increase (Figure 4 Panel A), and lags in the largest impacts are consistent with the timing of the largest increases in violent conflict. This pattern indicates potential heterogeneity by local insecurity and grievances.

I test for this heterogeneity by estimating average long-term impacts of swarm and drought exposure by activity of armed groups in the surrounding cells in a given year, a factor shown in Table 3 to particularly increase the risk of violent conflict in exposed cells. Table 4 shows that the TWFE estimate of the average impact of severe drought is a significant 0.6pp increase in the annual risk of violent conflict. This estimate is smaller than the average of the event study treatment period effects, likely because the large impacts in years 8-12 post-exposure are driven by a small share of cells exposed earlier in the study period. As with locust swarms, impacts of severe drought are concentrated in cells with any agricultural land.

I also find similar heterogeneity by local grievances and insecurity as proxied by years where there is any violent conflict in surrounding cells. The heterogeneity in impact of past shock exposure is particularly large for locust swarms—a 5.8pp increase compared to 2.8pp for drought—likely because the sample for the analysis of swarm exposure includes more high-conflict years from 2015-2018 that are not included in the drought analysis sample.

Table 4: Average impacts of exposure to agricultural shocks on violent conflict risk

Outcome: Any violent conflict event	(1) Swarm	(2) Swarm	(3) Swarm	(4) Drought	(5) Drought	(6) Drought
Exposed to shock	0.020***	0.004	0.007***	0.006**	-0.003*	0.001
	(0.005)	(0.006)	(0.002)	(0.002)	(0.002)	(0.001)
Exposed to shock × Any cropland or pasture in cell		0.018**			0.014***	
		(0.008)			(0.003)	
Any violent conflict elsewhere in 1 degree cell			0.023***			0.008***
			(0.004)			(0.003)
Exposed to shock × Any violent conflict elsewhere in 1 degree cell			0.058***			0.028***
			(0.012)			(0.007)
Observations	327646	327646	327646	454113	453831	454113

Note: The table presents results from three separate TWFE regressions for the average impacts of exposure to locust swarms and severe drought on a dummy for any violent conflict event observed. Locust swarm and drought exposure are absorbing treatments for all years starting from the first year in which the shock is recorded in the cell. The column labels indicate which agricultural shock is analyzed. Columns 1 and 4 include no interactions, columns 2 and 5 interact all right-hand side variables with a dummy for any agricultural (pasture or crop) land, and columns 3 and 6 do the same with a dummy for any violent conflict in the 15 other cells in the broader 1 degree cell in which the cell is located. Observations are grid cells approximately 28×28km by year for 1997-2018 for swarms and 1997-2014 for drought. The sample for impacts of swarm exposure is restricted to cells within 100km of a swarm observation. SEs clustered at the sub-national region level are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The similar patterns for impacts of exposure to severe drought and locust swarms on the risk of violent conflict indicate that they may be driven by similar mechanisms. The heterogeneity by local insecurity in particular highlight the importance of these shocks in creating conditions that increase vulnerability to future conflict prompted by more proximate grievances.[24]

[24] I find similar heterogeneity for the impacts of severe drought by local insecurity when using a 5 month threshold to define severe droughts, but the difference is not statistically significant when using a 6 month threshold (Table C2). In both cases, average impacts of drought exposure are null but significantly larger in agricultural cells.

The results also increase our confidence that the large long-term impacts of swarm exposure on violent conflict are not solely driven by bias in where locust swarms are reported. Identifying severe drought from remotely-sensed data does not depend on any reporting and where such droughts are realized over time and space is plausibly random, given that the drought index is cell-specific.

8 Implications for estimating effects of economic shocks

These results have implications for research on the impacts of economic shocks. The economic literature on weather or agricultural shocks and conflict has overwhelmingly focused on the short-term and assumes effects of shocks are transitory—lasting only for the period in which the shock occurs—or otherwise persisting for very few periods.[25] A common empirical approach is a distributed lag two-way fixed effects model which takes the form:

$$Conflict_{ict} = \alpha + \beta_1 Shock_{ic,t} + \beta_2 Shock_{ic,t-1} + \delta X_{ict} + \gamma_{ct} + \mu_i + \epsilon_{ict} \tag{2}$$

This follows the persistent effects model in Equation 1 with the exception that instead of the *Shock* variable representing an absorbing treatment status over subsequent years, in this transitory effects model the outcome is unaffected in the years following a shock except as captured by the one year lag. This lag allows for limited delays or persistence in impacts of the shock (Burke et al., 2015).

With cell fixed effects the short-term impacts in the transitory effects model are estimated relative to conflict risk in other years in the same cell where a shock is not observed, including years after exposure to a shock. For shocks that cause persistent increases in conflict, this implies that the transitory effects estimate will be biased downward as a result of comparing conflict risk in the year a shock is observed against later years with no shock but higher conflict risk *caused* by the initial shock.

Table 5 shows that this is the case for locust swarms and severe drought, comparing estimates from regression models assuming transitory (one year) effects or medium-term (five year) effects to the event study estimates which model the shock as a permanent treatment and accurately capture dynamic treatment effects. For locust swarms, the transitory effects model estimates a highly significant 1.5pp *decrease* in the probability of any violent conflict in the year of exposure relative to unaffected cells. The bias is not reduced by including

[25] See for example Fjelde (2015), Harari and La Ferrara (2018), McGuirk and Burke (2020), McGuirk and Nunn (2025), and Ubilava et al. (2022). These studies also use grid cell panel data to analyze the impact of various shocks on conflict in Africa. They vary in their samples, choice of controls, and size of grid cells but all use a similar econometric specification.

5 years of lags in the model, which allows for persistence of effects only for the number of periods included as lags. The year zero estimate in this model is 2.0pp lower than the event study estimates, while the estimates for the next five periods are consistently around 1.5-1.8pp lower. I can reject that the transitory and five-year estimates are the same as the event study estimates with high confidence, consistent with downward bias of these models when treatment effects are not only persistent but increasing over a long period.

Table 5: Impacts of agricultural shocks on the conflict risk, treating shocks as temporary vs. persistent

	(1)	(2) Locust swarm	(3)	(4)	(5) Severe drought	(6)
	Transitory effects	5 year effects	Event study effects	Transitory effects	5 year effects	Event study effects
Any shock during year	-0.015***	-0.020***	0.000	0.004	0.001	0.007**
	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)	(0.003)
Any shock, 1 year lag		-0.012**	0.005		0.000	0.002
		(0.006)	(0.004)		(0.002)	(0.002)
Any shock, 2 year lag		-0.007	0.010***		-0.001	0.001
		(0.006)	(0.004)		(0.002)	(0.002)
Any shock, 3 year lag		-0.008	0.010***		-0.002	0.004
		(0.006)	(0.004)		(0.002)	(0.002)
Any shock, 4 year lag		0.001	0.016***		-0.002	0.004
		(0.007)	(0.004)		(0.003)	(0.003)
Any shock, 5 year lag		-0.003	0.014***		-0.004	0.013***
		(0.007)	(0.005)		(0.004)	(0.005)
Average long-term effect (TWFE)			0.020***			0.006**
			(0.005)			(0.002)
p-value, year 0 equality with event study	<0.001	<0.001		0.479	0.157	
p-value, year 5 equality with event study		0.048			0.008	
Observations	327646	253181	327646	454113	327746	454113
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is a dummy for any violent conflict event observed in a cell-year. In columns (1) and (4) the shock is assumed to only have an effect in the year it is observed. Columns (2) and (5) allow for persistent or delayed effects of the shock for up to 5 years after it is observed. Columns (3) and (6) present a subset of the results from event study models estimating dynamic effects of the shock over time. At the bottom of these columns I present the TWFE estimates of average long-term effects of the shock from Table 4. Under this are p-values for tests of equality between coefficients under the short-term, medium-term, and event study models. Controls in all regressions include total cell population and current year measures of total precipitation and maximum annual temperature. The specification with 5 treatment lags also includes 5 lags of precipitation and temperature. Observations are grid cells approximately 28×28km by year for 1997-2018 for swarms and 1997-2014 for drought. The sample for impacts of swarm exposure is restricted to cells within 100km of a swarm observation. SEs clustered at the sub-national region level are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The transitory effects estimate for locust swarms—a 1.5pp decrease in violent conflict the year locusts are observed—is very close to Torngren Wartin (2018)'s estimate of a 1.3pp decrease using a similar method.[26] He interprets the result as suggesting endogenous under-

[26]Torngren Wartin (2018) employs the same general distributed lag specification with cell and country-by-

reporting of locust swarm presence correlated with violent conflict. The much larger event study estimate for the impact of swarms on conflict in the same year suggests the large negative estimate in the transitory effects regression can instead be attributed to downward bias from ignoring long-term impacts of swarm exposure on conflict risk.

In the case of severe drought, the transitory effects estimate for the year of exposure is a non-significant 0.4pp increase in violent conflict risk (similar to the estimate in Table 3), compared to a statistically significant 0.7pp increase in the event study estimate. While I cannot reject that these estimates are the same (p=0.479), the two approaches would yield different conclusions with different policy implications. As with the analysis with locust swarms, including five lagged shock variables aggravates the bias in the estimated year zero effect, though I still cannot reject equality with the event study estimate (p=0.157). The bias in the short-term effects estimates is generally lower when considering drought relative to locust shocks. This can be explained by the lower average long-term effect: a 0.6pp increase in conflict risk for severe drought compare to 2.0pp for locust swarms.

These results provide evidence of a potential misspecification of studies analyzing short-term impacts of transitory economic shocks. Studies of such shocks using specifications similar to Equation 2 and ignoring possible long-term effects will generate downward-biased short-term impact estimates to the extent the shocks increase long-term conflict risk. This concern is a special case of contamination in estimated effects of treatment leads and lags in settings with dynamic and heterogeneous treatment effects (Sun and Abraham, 2021), which can lead to errors in both magnitude and sign (Roth et al., 2023) as shown here for the impacts of locusts swarms on violent conflict risk. A large literature has studied this limitation of TWFE estimators and proposes a variety of event study estimators to address its limitations (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; Cengiz et al., 2019; De Chaisemartin and d'Haultfoeuille, 2024; Goodman-Bacon, 2021; Sun and Abraham, 2021).

Building on this literature and to provide intuition for the results in Table 5, I conduct simulations estimating different regression models under several scenarios of dynamic treatment effects (Figure A3, Table A5). I show that sign errors for TWFE estimators assuming transitory treatment effects are more likely when the true effect in the treatment period is small relative to effects in later periods. The magnitude of the bias in the transitory effects estimator depends on the average of treatment effects in subsequent periods rather than on particular dynamics of those effects. Including lagged terms attenuates this bias un-

year fixed effects as in columns 1 and 2 of Table 5 but with some different weather controls and varying lags of locust presence. His analysis is at the level of 0.5° and 0.1° cells and considers locust swarms and bands together while I focus on more destructive swarms alone. He also includes some African countries with very few locust swarm observations over time which I exclude, while excluding Arabian countries with extensive locust activity which I include.

der constant and decreasing long-term effects, but aggravates it under increasing long-term effects.

Attention to these estimation issues in difference-in-differences settings has been rapidly increasing (see A. Baker et al. (2025) for a recent guide for practitioners). Certain difference-in-differences methods can also be applied in settings with repeated treatments, an important consideration for shocks such as droughts or locust swarms which may recur in the same location over time. I abstract away from that in this study—where such recurrence is rare in the sample period—by considering only the first exposure during the study period and defining absorbing treatment variables. Future work could explore dynamic effects of agricultural shocks on conflict while accounting for potential repeated treatments.

9 Conclusion

Violent conflict and environmental shocks can have devastating consequences for economic and human development which are the subject of significant study even beyond the economics literature. This paper shows that exposure to a severe agricultural production shock—both desert locust swarms and drought—significantly increases long-term conflict risk.

The results emphasize the limitations of models focusing exclusively on the role of changing opportunity costs of fighting following a productivity shock. Exposure to locust swarms does not cause the immediate onset of violent conflict, as predicted under an opportunity cost mechanism. An analysis of the timing of the main locust swarm exposure event in the sample suggests this may be due to limited popular unrest in the study area during this period. I find that long-term impacts of both locust swarms and drought are concentrated in periods of heightened grievances or insecurity due to other proximate causes, when the feasibility of fighting and expected returns are likely to be higher and costs are lower. This is not a novel insight but has not been emphasized in the economics literature on climate and conflict, and has important implications for considering what areas are most likely to become engaged in future conflicts triggered by various proximate causes.

I propose a permanent income effect from initial agricultural destruction and coping strategies reducing later productivity and opportunity costs of fighting as a potential income-related mechanism for long-run effects on conflict risk. Swarm exposure does not persistently affect measures of agricultural productivity at the level of the 0.25° grid cells I analyze, but it reduces engagement in agriculture and promotes out-migration. These results add to other work showing long-term production and human capital effects of locust swarms and many studies showing long-term economic impacts of natural disasters. Further research on long-term impacts of transitory economic shocks on household measures of productivity, labor supply, food security, and wealth would help further explore the potential role of a permanent income mechanism.

The findings suggest additional future avenues of research in the literature on climate and conflict. I show that the methods typically used in this literature, which treat shocks as only affecting conflict risk in the short-term, can result in biased estimates of short-term effects when the shocks have long-term impacts. New event study analyses could test the extent and patterns of long-term impacts of other climate or economic shocks on conflict risk. Although not a focus of this paper, the lack of variation in the impacts of precipitation and temperature deviations on violent conflict risk by land cover cast further doubt on whether effects on agricultural production are the primary mechanism. The association between climate and conflict has been demonstrated in a wide variety of settings but the mechanisms remain unclear (Burke et al., 2024; Mach et al., 2020). A better understanding of the different mechanisms is essential to determining the appropriate policy responses. Analyses of long-term impacts of agricultural shocks on measures of local inequality and on psychological factors could be particularly helpful in understanding both income- and non-income-related mechanisms.

The economic and human costs of increased conflict risk following severe agricultural shocks highlights the importance of policy efforts to respond to such shocks. Burke et al. (2024) find robust evidence across studies that higher living standards reduce sensitivity of conflict risk to climate shocks. Additional research could explore whether policies that can promote resilience to agricultural shocks, such as cash transfers (Crost et al., 2016; de Janvry et al., 2006; Garg et al., 2020), livelihood graduation programs (Hirvonen et al., 2023), improved infrastructure (Gatti et al., 2021), and work programs (Fetzer, 2020) also reduce conflict risk.

The results also have implications for estimates of the economic and social costs of desert locust outbreaks. Past research on desert locusts has argued that limited impacts of outbreaks on aggregate national measures of agricultural production may mean expensive locust monitoring and control operations have limited net economic benefits (Joffe, 2001; Krall and Herok, 1997), though others have argued that local damages are extensive and motivate continued proactive locust control efforts (Showler, 2019; Zhang et al., 2019). A consideration of the broader long-term economic and social impacts of agricultural destruction by locusts into consideration could motivate greater investment in proactive locust monitoring and control, as well as increased cross-country communication and collaboration in response to threats of locust swarms.

Beyond contributing to our understanding of the relationship between agricultural production shocks and conflict risk, the findings are also relevant for considering multilateral policy around climate change mitigation and adaptation. Climate change is increasing the frequency and severity of agricultural shocks, including by creating conditions suitable for desert locust swarm formation. These shocks impose additional costs on society through their impacts on conflict risk which should be considered when weighing the costs and benefits of potential actions to reduce and respond to risks from agricultural shocks.

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10 Appendices

Appendix A: Additional Figures and Tables

Table A1: Summary statistics

Panel A: Yearly variables

	Mean	SD	Min	50^{th}	75^{th}	Max	N
Any violent conflict event - ACLED	0.02	0.14	0.0	0.0	0.0	1.0	557018
Any protest or riot event - ACLED	0.01	0.09	0.0	0.0	0.0	1.0	557018
Any violent conflict event - UCDP	0.01	0.10	0.0	0.0	0.0	1.0	557018
Any swarms in cell	0.00	0.07	0.0	0.0	0.0	1.0	557018
Any swarms within 100km outside cell	0.05	0.21	0.0	0.0	0.0	1.0	557018
Any swarms within 100-250km of cell	0.11	0.32	0.0	0.0	0.0	1.0	557018
Population (10,000s)	1.63	8.92	0.0	0.1	0.9	749.8	557018
Total annual rainfall (100 mm)	2.40	3.79	0.0	0.8	2.8	43.4	557018
Max annual temperature (deg C)	37.55	5.11	11.5	38.2	41.3	49.1	557018

Panel B: Fixed variables

	Mean	SD	Min	50^{th}	75^{th}	Max	N
Any ACLED violent conflict event in cell from 1997-2018	0.13	0.33	0.0	0.0	0.0	1.0	25435
Any protest/riot event in cell from 1997-2018	0.07	0.25	0.0	0.0	0.0	1.0	25435
Any UCDP violent conflict event in cell from 1997-2018	0.07	0.26	0.0	0.0	0.0	1.0	25435
Any locust swarm in cell from 1985-2023	0.12	0.33	0.0	0.0	0.0	1.0	25435
Any locust swarm in cell from 1997-2018	0.09	0.29	0.0	0.0	0.0	1.0	25435
Any locust swarm within 100km from 1985-2023	0.62	0.48	0.0	1.0	1.0	1.0	25435
Any locust swarm within 100km from 1997-2018	0.55	0.50	0.0	1.0	1.0	1.0	25435
First exposed to locust swarm between 1997-2018	0.07	0.26	0.0	0.0	0.0	1.0	25435
First exposed to locust swarm in 2003-2005 upsurge	0.05	0.22	0.0	0.0	0.0	1.0	25435
Any cropland or pasture in cell	0.57	0.50	0.0	1.0	1.0	1.0	25435
Share of cell allocated to crops or pasture	0.23	0.32	0.0	0.0	0.4	1.0	25435
Any pasture in cell	0.56	0.50	0.0	1.0	1.0	1.0	25435
Share of cell allocated to pasture	0.18	0.27	0.0	0.0	0.3	1.0	25435
Any cropland in cell	0.31	0.46	0.0	0.0	1.0	1.0	25435
Share of cell allocated to crops	0.05	0.13	0.0	0.0	0.0	1.0	25435

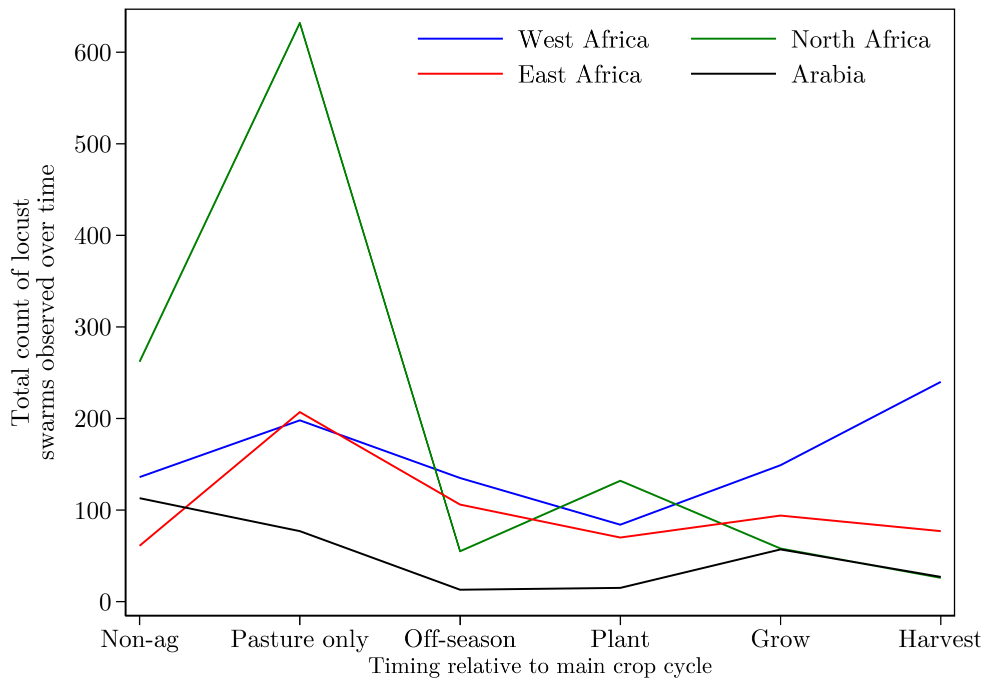
Note: Observations are grid cells approximately 28×28km by year. Values for land cover are for the year 2000.

Table A2: Balance in cell characteristics by exposure to any locust swarm

	All cells		W/in 100km of any swarm		All cells, exposure IPW	
	Control Mean (SD)	Treat Diff. (SE)	Control Mean (SD)	Treat Diff. (SE)	Control Mean (SD)	Treat Diff. (SE)
Population in 2000 (10,000s)	1.22	1.32***	1.56	0.98***	1.23	-0.00
	[6.94]	(0.37)	[8.35]	(0.33)	[6.97]	(0.43)
Mean of cell nightlights	0.05	0.01**	0.05	0.00	0.05	-0.00
1996-2012 (0-1)	[0.04]	(0.00)	[0.04]	(0.00)	[0.04]	(0.00)
Distance to national capital	707.75	-182.42***	611.63	-86.30**	707.37	91.46
(km)	[406.53]	(45.59)	[372.80]	(34.71)	[406.67]	(74.08)
Percent of cell covered by	4.66	0.85	5.50	0.01	4.70	0.03
crop land in 2000	[13.06]	(0.77)	[14.05]	(0.68)	[13.12]	(1.50)
Percent of cell covered by	17.58	10.86***	21.17	7.27***	17.73	-5.23*
pasture land in 2000	[26.75]	(2.38)	[27.96]	(2.20)	[26.83]	(3.01)
Percent of cell covered by	68.89	-9.93***	62.50	-3.55	68.61	6.59
barren area in 2009	[42.65]	(3.64)	[43.23]	(3.11)	[42.75]	(6.49)
Percent of cell covered by	0.08	0.10	0.09	0.09	0.08	-0.02
urban area in 2009	[0.75]	(0.07)	[0.85]	(0.07)	[0.75]	(0.03)
Mean annual rainfall 1997-2018	2.40	0.16	2.57	-0.01	2.42	-0.44
(100 mm)	[3.81]	(0.24)	[3.72]	(0.17)	[3.82]	(0.39)
Mean annual max temperature	37.66	-1.65***	36.92	-0.91**	37.64	0.45
1997-2018 (deg C)	[5.11]	(0.45)	[5.06]	(0.38)	[5.12]	(0.73)
Mean of cell annual share of	0.09	-0.00	0.09	-0.00	0.09	-0.01*
months with drought 1998-2014	[0.03]	(0.00)	[0.04]	(0.00)	[0.03]	(0.00)
		$F = 7.06$		$F = 3.35$		$F = 1.56$
Joint significance		$p < 0.01$		$p < 0.01$		$p = 0.03$

Note: The table shows results from separate bivariate regressions of baseline or mean cell characteristics on a dummy for being exposed to a locust swarm during the study period. The rows indicate which dependent variable is used. The first set of columns includes all cells while the second restricts the sample to cells within 100km of any locust swarm observation from 1996-2021. The third set of columns includes all cells but weights observations by the inverse of the estimated propensity to have been exposed to a locust swarm during the study period. I include results of joint tests that there is no relationship between any of the characteristics and swam exposure. Observations are grid cells approximately 28×28km by year. SEs clustered at the sub-national region level are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A1: Variation in swarm timing and location during study period



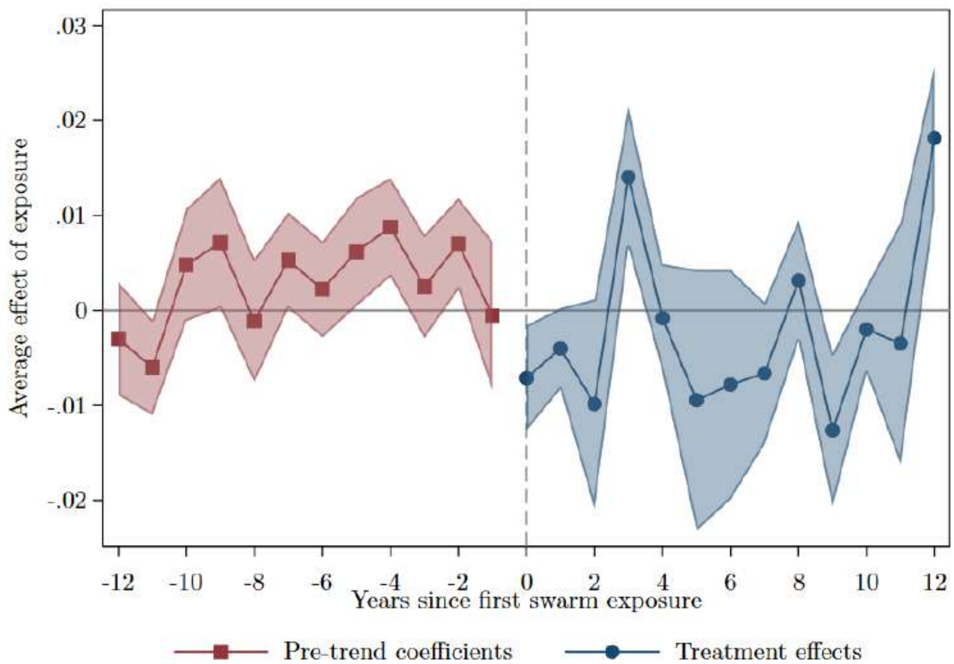
Note: The figure identifies the timing of swarm observations from 1997-2018 based on information on local crop calendars for major crops. This timing is used to define timing of swarm exposure used in Table 2.

Table A3: Average impacts of locust swarm exposure on measures of productivity

	N	Control Mean (SD)	Exposed to any locust swarm (SE)
Max annual NDVI	281371	0.235	0.001
		(0.200)	(0.001)
Mean cell estimated maize yield	29358	2072.215	-17.196
(kg/ha)		(1169.802)	(53.198)
Mean cell estimated rice yield	19872	3356.025	62.489*
(kg/ha)		(1270.746)	(33.578)
Mean cell estimated soybean yield	1697	1289.199	-17.256
(kg/ha)		(399.568)	(34.738)
Mean cell estimated wheat yield	4116	2034.063	116.586
(kg/ha)		(1052.607)	(119.430)
Mean cell estimated main crop yield	51670	2553.910	37.325
(kg/ha)		(1370.338)	(38.993)
Cluster average crop yield	3318	4059.864	-20.477
(kg/ha)		(6797.019)	(122.808)
Cluster total crop production area	3401	2801.772	-111.276**
(ha)		(2080.289)	(53.030)
Cluster total crop production	3401	17405.661	-640.352*
(metric tons)		(40885.904)	(385.024)
Cluster tropical livestock units	3401	47.678	-2.262
per sq. km		(70.180)	(3.323)
Gross cell product,	25998	70.219	-4.283
1990 USD PPP millions		(276.918)	(2.662)
Mean estimated net migration	272080	-0.566	-5.049*
(per 1000 population)		(218.342)	(2.829)

Note: This table presents results from the outcomes shown in Figure 5 along with crop-specific yield outcomes, but without normalizing the outcome variables. See the figure notes for descriptions of each variable. Differences in sample sizes are due to differences in data availability across outcomes. Crop-specific yield estimates are only available in cells where that crop is produced. All regressions include country-by-year and location fixed effects and controls for population and current and lagged precipitation and temperatature. SEs are clustered at the sub-national region level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A2: Impacts of exposure to locust swarms on max annual NDVI over time, crop cells



Note: NDVI is calculated from MODIS satellite data, and I take the maximum of annual 16-day NDVI observations in each cell-year. The event study is restricted to crop cells, where NDVI is a potential proxy for agricultural production. Observations are grid cells approximately 28×28km by year.

Table A4: Average impacts of locust swarm exposure on different conflict types

	N	Never exposed Mean (SD)	Swarm exposure treatment (SE)
Any violent conflict event - ACLED	327646	0.021	0.020***
(Battles, explosions, or violence against civilians)		(0.143)	(0.005)
Any violent state conflict - ACLED	327646	0.013	0.014***
(At least one state actor)		(0.113)	(0.003)
Any violent non-state conflict - ACLED	327646	0.014	0.014***
(No state actor)		(0.118)	(0.004)
Any violent one-sided conflict - ACLED	327646	0.012	0.014***
(Any civilian engagement)		(0.108)	(0.004)
Any conflict targeting civilians - ACLED	327646	0.013	0.017***
(Violence against civilians, riots, or looting)		(0.115)	(0.004)
Any protest or riot event - ACLED	327646	0.009	0.022***
(Protests or riots)		(0.094)	(0.004)
Any violent conflict event - UCDP	327646	0.010	0.007**
(At least one organized actor and >25 deaths in year)		(0.102)	(0.003)
Any violent state conflict - UCDP	327646	0.008	0.005*
(At least one state actor)		(0.086)	(0.003)
Any violent non-state conflict - UCDP	327646	0.002	0.002*
(No state actor)		(0.043)	(0.001)
Any violent one-sided conflict - UCDP	327646	0.002	0.002
(Any civilian engagement)		(0.050)	(0.001)
Total fatalities - ACLED	327646	0.735	0.882
		(65.031)	(0.611)
Total fatalities - UCDP	327646	0.594	0.645
		(107.449)	(0.587)

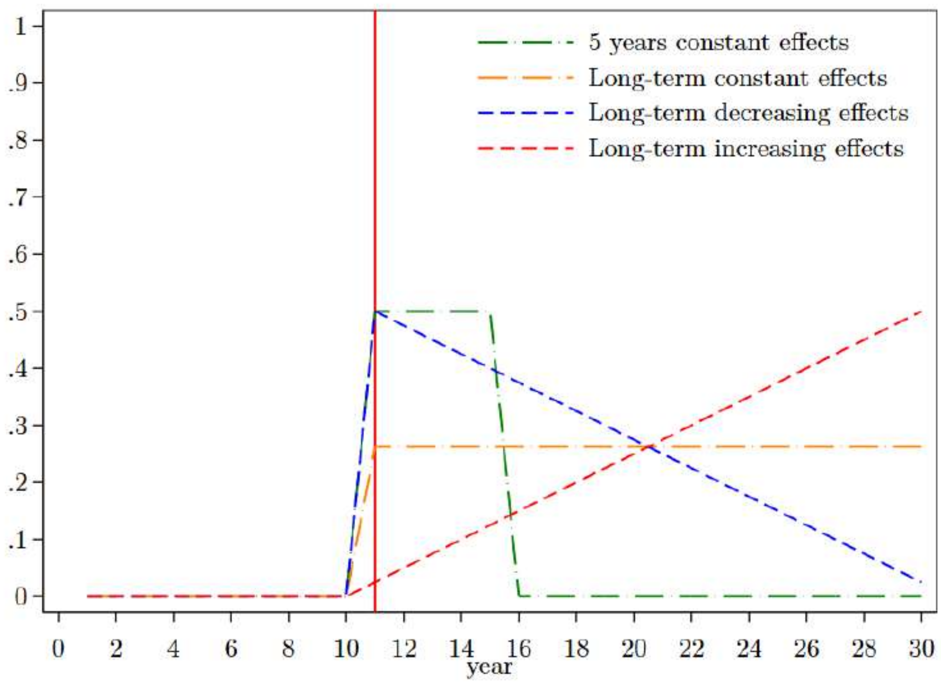
Note: Each row replicates Table 1 column 1 for a different conflict outcome. The dependent variables are dummies for any conflict event being observed in a cell in a year, with the conflict type specified in each row. See the figure note for Table 1 for more detail.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Simulation: bias in estimates of short-term effects of shocks under different dynamic treatment effects

	(1) Immediate effect only	(2) Constant 5 year effects	(3) Constant long-term effects	(4) Decreasing long-term effects	(5) Increasing long-term effects
A. True effects:					
tau0	0.500***	0.500***	0.262***	0.500***	0.025***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tau1	0.000	0.500***	0.262***	0.475***	0.050***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tau2	0.000	0.500***	0.262***	0.450***	0.075***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tau3	0.000	0.500***	0.262***	0.425***	0.100***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tau4	0.000	0.500***	0.262***	0.400***	0.125***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B. Estimated transitory effects:					
Treatment during current year	0.500***	0.431***	0.091***	0.336***	-0.155***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Difference from actual treatment effect	0.000	0.069	0.171	0.164	0.180
C. Estimated lagged effects:					
Treatment during current year	0.500***	0.500***	0.105***	0.380***	-0.170***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Treatment 1 year lag	0.000	0.500***	0.105***	0.355***	-0.145***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Treatment 2 year lag	0.000	0.500***	0.105***	0.330***	-0.120***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Treatment 3 year lag	0.000	0.500***	0.105***	0.305***	-0.095***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Treatment 4 year lag	0.000	0.500***	0.105***	0.280***	-0.070***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Differences from actual treatment effect	0.000	0.000	0.157	0.120	0.195
Observations	300000	300000	300000	300000	300000

Note: I simulate 10,000 observations across 30 periods, and assign 20% to be treated in period 11. I define the outcome as taking a value of 0 for all units before period 11, and then vary the value based on different possible dynamic treatment effects. In column (1) treatment increases the outcome by 0.5 in the initial treatment period only. In column (2) treatment increases the outcome by 0.5 in each of the first 5 treatment periods. In column (3) treatment increases the outcome by 0.5 in all subsequent periods. In column (4) treatment increases the outcome by 0.5 in the first treatment period, but the effect *decreases* linearly over all subsequent periods. In column (5) treatment increases the outcome by 0.025 in the first treatment period, but the effect *increases* linearly over all subsequent periods. The evolution of the outcome over time is shown in Figure A3. Patterns are similar with reversed signs if I simulate negative treatment effects. I estimate three treatment effect models for each scenario which make different assumptions about dynamic treatment effects. Panel A shows the results of event study estimates of the true effects for the first 5 treatment periods. Panel B shows the results of TWFE estimates that assume a transitory treatment that only affects the outcome in the initial treatment period. Panel C is similar to Panel B but includes four lagged treatment indicators, assuming treatment effects only persist for five periods. All regressions include period and unit fixed effects. SEs clustered at the unit level are in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A3: Simulation: evolution of outcome under different dynamic treatment effects



Note: This figure shows the evolution of the simulation outcome as described in the notes to Table A5.

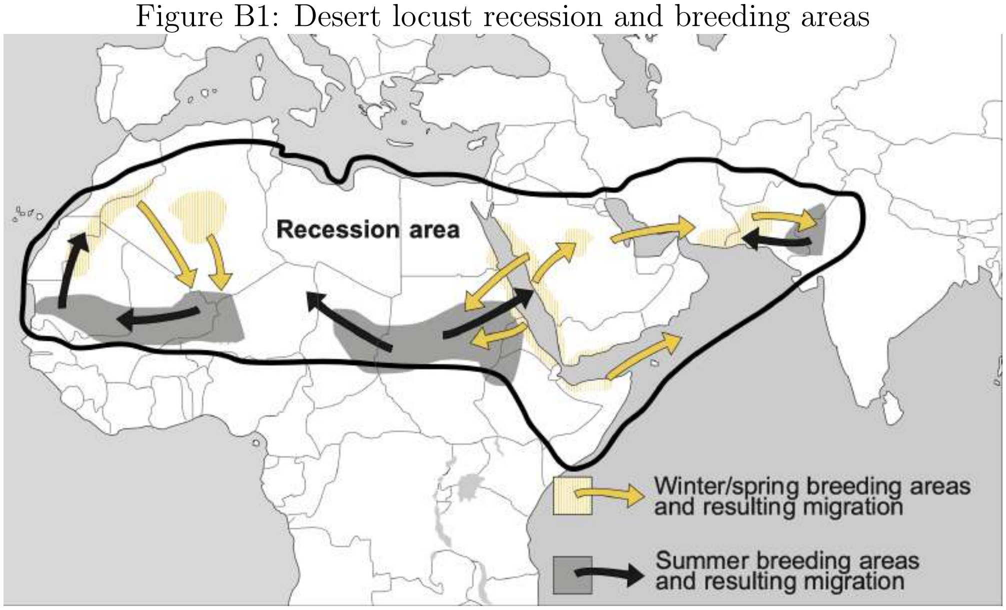
Appendix B: Desert locusts background

The desert locust is considered the world's most dangerous and destructive migratory pest (Cressman et al., 2016; Lazar et al., 2016). Locusts consume any available vegetation, and swarms frequently lead to the total destruction of local agricultural output (Showler, 2019). Damages from locust shocks can be extreme, with a small swarm covering one square kilometer can consume as much food in one day as 35,000 people. During the last locust upsurge in 2003-2005 in North and West Africa, 100, 90, and 85% losses on cereals, legumes, and pastures respectively were recorded, affecting more than 8 million people (Brader et al., 2006; Renier et al., 2015). Damages to crops alone were estimated at $2.5 billion USD and $450 million USD was required to bring an end to the upsurge (ASU, 2020).

In the most recent upsurge from 2019-2021 in East Africa and the Arabian Peninsula, over 40 million people in 10 countries faced severe food insecurity due to crop destruction. Locust control operations undertaken by the United Nations Food and Agriculture Organization (FAO) and its partners, primarily via ground and aerial spraying of pesticides, and global food aid efforts helped reduce the damages (FAO, 2022b). The FAO estimates that 3.5 million people were affected by locust destruction, but that control efforts saved agricultural production worth $1.7 billion USD.

Small numbers of locusts are always present in desert 'recession' areas from Mauritania to India (Figure B1). The population can grow exponentially under favorable climate conditions: periods of repeated rainfall and vegetation growth overlapping with the breeding cycle. The 2019-2021 upsurge persisted in large part because of repeated heavy precipitation out of season due to cyclones, prompting explosive reproduction (Cressman and Ferrand, 2021). The 2003-2005 upsurge was initiated by good rainfall over the summer of 2003 across four separate breeding areas. This was followed by two days of unusually heavy rains in October 2003 from Senegal to Morocco, after which environmental conditions were favorable for reproduction over the following 6 months (FAO and WMO 2016).

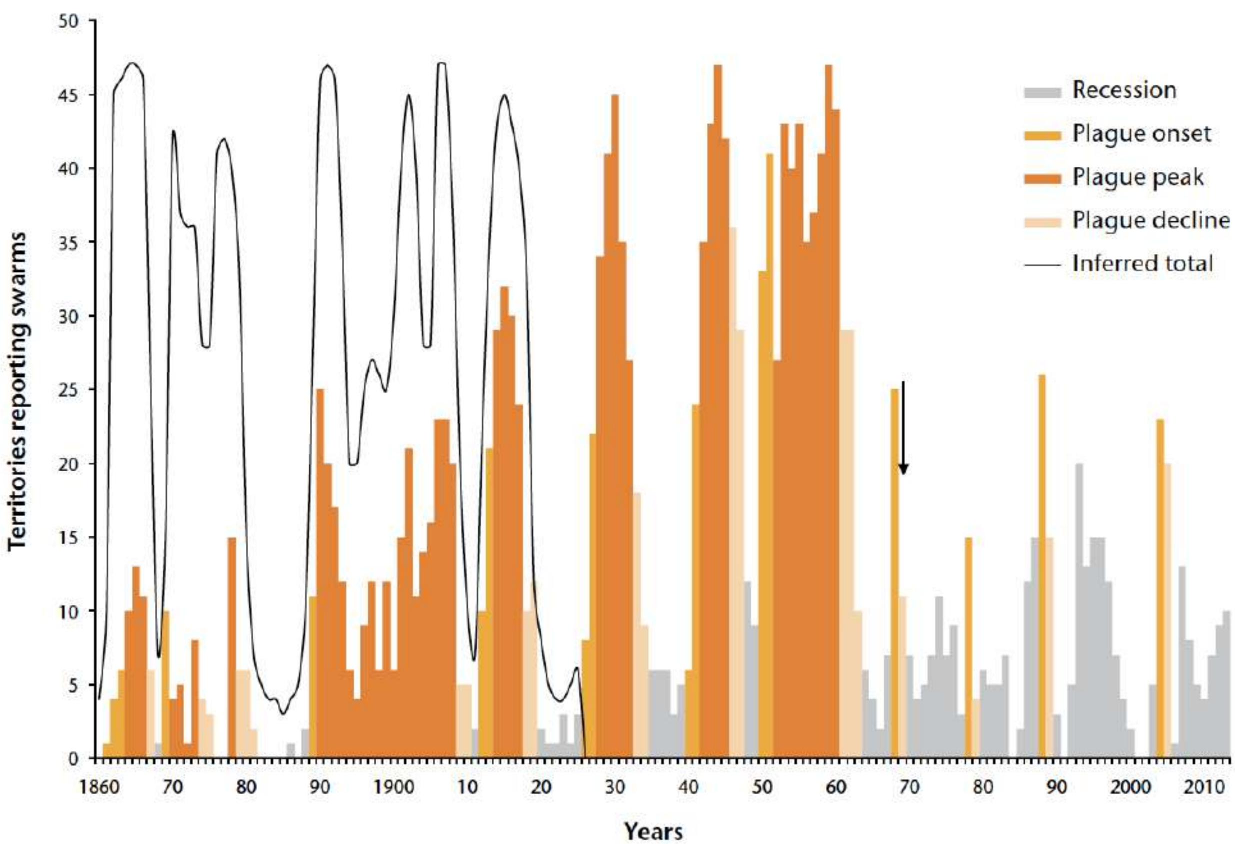
Figure B1: Desert locust recession and breeding areas



Source: Symmons and Cressman (2001).

Unique among grasshopper species, after reaching a particular population density desert locusts undergo a process of ‘gregarization’ wherein they mature physically and form large bands or swarms which move as a cohesive unit (Symmons and Cressman, 2001). Locust bands may extend over several kilometers and alternate between roosting and marching, typically downwind (FAO and WMO 2016). Locust swarms form when bands of locusts remain highly concentrated when they reach the adult stage and become able to fly. This formation of swarms can lead to ‘outbreaks,’ where locusts spread out from their largely desert initial breeding areas. Locusts in swarms have increased appetites and accelerated reproductive cycles, and are thus particularly threatening to agriculture. The FAO distinguishes different levels of locust swarm activity (Symmons and Cressman, 2001). I use the terms ‘outbreak’ and ‘upsurge’ interchangeably to refer to any locust swarm activity. By the FAO definition ‘outbreaks’ refer to localized increases in locust numbers while ‘upsurges’ refer to broader and more sustained locust activities. A third level, ‘plagues,’ is characterized by larger and more widespead locust infestations. Few locust swarms are observed outside of major outbreaks, as conditions favoring swarm formation tend to produce large swarms which reproduce and spread rapidly and are very difficult to control.

Figure B2: Desert locust observations by year

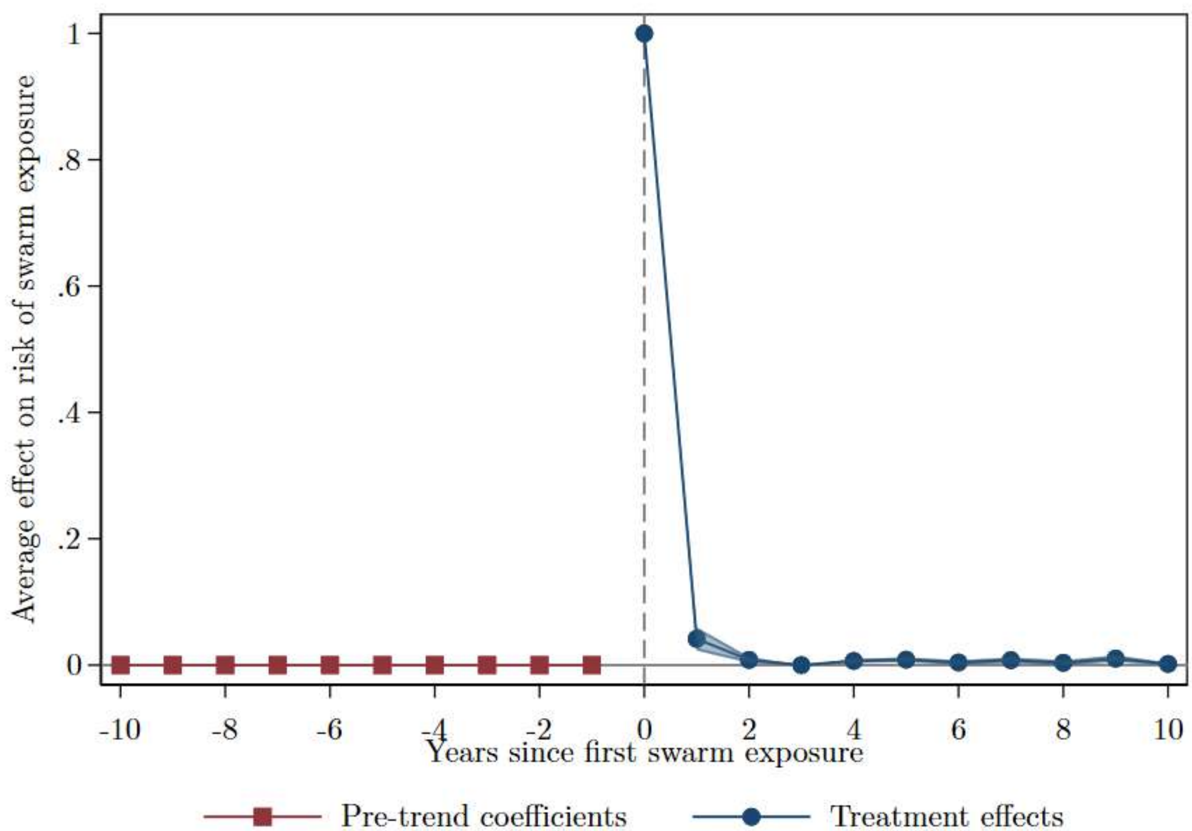


Source: Cressman and Stefanski (2016), Figure 6.

The frequency of large-scale outbreaks has fallen since around the 1980s (Figure B2), in large part due to increases in coordinated preventive operations (Cressman and Stefanski, 2016). Given their tolerance for extreme heat and responsiveness to periods of heavy precipitation, however, climate change might create conditions conducive to more frequent desert locust outbreaks.

As illustrated by Figure 1, locust swarms are not observed with any regularity over time or space. Desert locusts are migratory, moving on after consuming all available vegetation, and outside of outbreak periods are ultimately restricted to desert 'recession' areas. Unlike many other insect species, therefore, the arrival of a desert locust swarm does not signal a permanent change in local agricultural pest risk. Instead, the arrival of a swarm can be considered a locally and temporally concentrated natural disaster where all crops and pastureland are at risk (Hardeweg, 2001). Figure B3 illustrates how exposure to a locust swarm does not significantly affect the risk of exposure over the following years, consistent with exposure being a function of quasi-random variations in wind patterns and flight duration during swarm outbreaks.

Figure B3: Impact of swarm exposure on future exposure risk



Note: By construction, none of the exposed areas had any locust swarm recorded in the years preceding their first exposure since 1990.

Locust swarms vary in their density and extent (Symmons and Cressman, 2001). The average swarm includes around 50 locusts per m^2 with a range from 20-150, and can cover under 1 square kilometers to several hundred (Symmons and Cressman, 2001). About half of swarms exceed 50km^2 in size (FAO and WMO 2016), meaning swarms typically include over a billion individuals. Swarms fly downwind from a few hours after sunrise to an hour or so before sunset when they land and feed. Swarms do not always fly with prevailing winds and may wait for warmer winds. Small deviations in the positions of individual locusts in the swarm can also lead to changes in swarm flight trajectory, making their movements difficult to predict. Seasonal changes in these winds tend to bring locusts to seasonal breeding areas at times when rain and the presence of vegetation is most likely, allowing them to continue breeding (FAO and WMO 2016).

These movement characteristics inform efforts to predict locust swarm movements, but these remain highly imprecise. The desert locust bulletins produced monthly by the FAO include forecasts of areas at risk of desert locust activity, but the areas described are quite large, often encompassing several countries in periods with increased swarms. While breeding regions and the broad areas at risk over different time periods can generally be predicted with some accuracy (Latchininsky, 2013; Samil et al., 2020; Zhang et al., 2019), predicting specific local variation in swarm presence remains a challenge due to the multiple factors influencing specific flight patterns (FAO and WMO 2016).

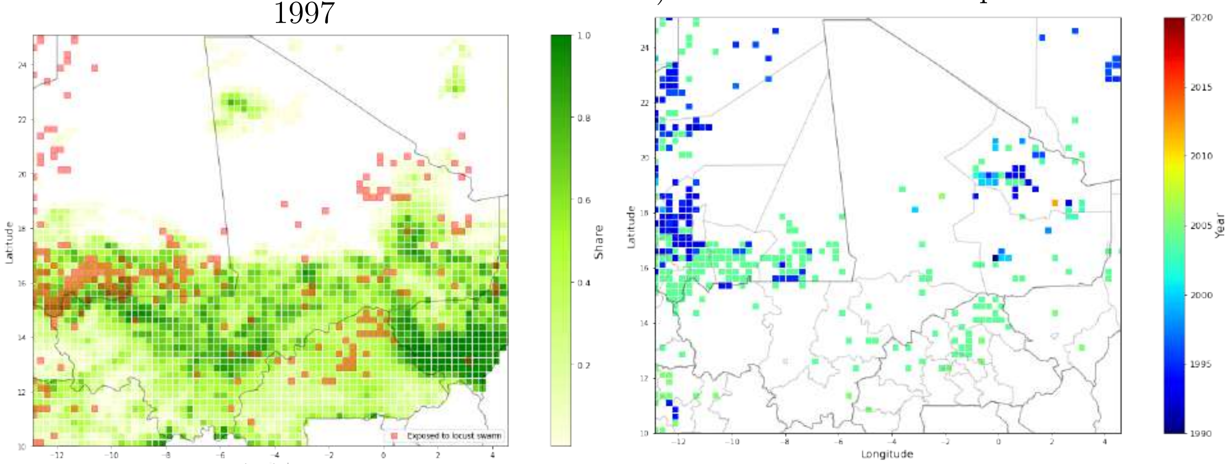
Patterns in swarm movements lead to local variation in locust swarm exposure. After taking off, swarms fly for 9-10 hours rather than landing as soon as they encounter new vegetation. A swarm can easily move 100km or more in a day even with minimal wind (Symmons and Cressman, 2001). Consequently, the flight path of a locust swarm will include both affected and unaffected areas, with the affected areas determined by largely by patterns of wind direction and speed over time from the initial swarm formation in breeding areas.

Figure B4 illustrates the variation in areas affected by locust swarms over space around Mali. Swarm reports are densely clustered in the breeding areas in southern Mauritania where locust swarms reproduced in summer 2004. Outside of this area there is considerable variation in where swarms were reported, with distances between reported swarms over time consistent with typical flight distances.

Figure B4: Reports of locust swarms around Mali

A) Areas exposed to locust swarms since 1997

B) Year of first swarm exposure since 1990



Note: The figure illustrates the grid cells exposed to locusts swarms for the area around the country of Mali. Locust swarm reports are from the FAO Locust Watch database. Panel A overlays these reports on a map of the share of agricultural land area in each cell, while Panel B illustrates the timing of first exposure to locust swarms.

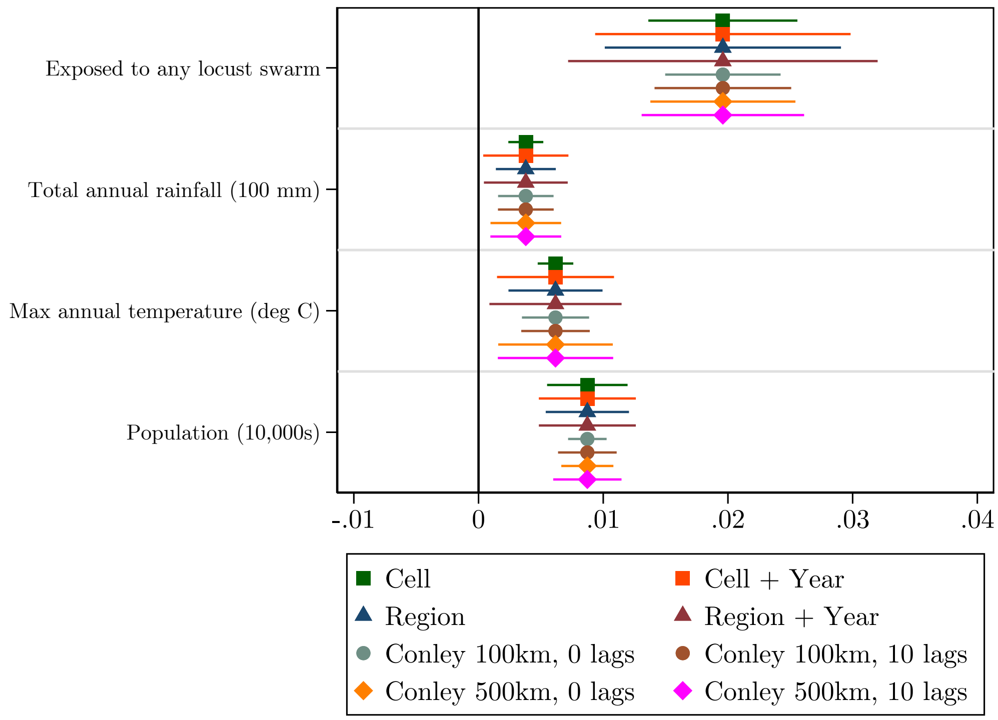
An important result of the local variation in locust swarm damages during outbreaks is that macro level impacts may be muted, since outbreaks occur in periods of positive rainfall shocks which tend to increase agricultural production in unaffected areas. Several studies find that impacts of locust outbreaks on national agricultural output and on prices are minimal, despite devastating losses in affected areas (Joffe, 2001; Krall and Herok, 1997; Showler, 2019; Thomson and Miers, 2002; Zhang et al., 2019). Chatterjee (2022) finds that wheat yields are 12% lower on average in Indian districts typically affected by desert locusts in years of locust outbreaks, in contrast to very large decreases in the specific areas exposed to locust swarms in those years.

Farmers have no proven effective recourse when faced with the arrival of a locust swarm, though activities such as setting fires, placing nets on crops, and making noise are commonly attempted. While these may slow damage they have little effect on locust population or total damages (Dobson, 2001; Hardeweg, 2001; Thomson and Miers, 2002). Locust outbreaks end due to a combination of migration to unfavorable habitats, failure of seasonal rains in breeding areas, and control operations (Symmons and Cressman, 2001). The only current viable method of swarm control is direct air or ground spraying with pesticides (Cressman and Ferrand, 2021). These control operations do not prevent immediate agricultural destruction as they take some time to kill the targeted locusts, but will limit their spread. The 2003-2005 locust upsurge ended due to lack of rain and colder temperatures which slowed down the breeding cycle, combined with intensive ground and aerial spraying operations which treated over 130,000km^2 at a cost of over US$400 million (FAO and WMO 2016).

Desert locust control is most effective before locust populations surge, and the FAO manages an international network of early monitoring, warning, and prevention systems in support of this goal (Zhang et al., 2019). While improvements in desert locust management have been largely effective in reducing the frequency of outbreaks (as seen in Figure B2), many challenges remain. Desert locust breeding areas are widespread and often in remote or insecure areas. Small breeding groups are easy to miss by monitors, and swarms can migrate quickly. In addition, control operations are slow and costly, resources for monitoring and control are limited outside of upsurges, and the cross-country nature of the thread creates coordination issues. Insecurity may also limit locust control activities (Showler and Lecoq, 2021).

Appendix C: Robustness

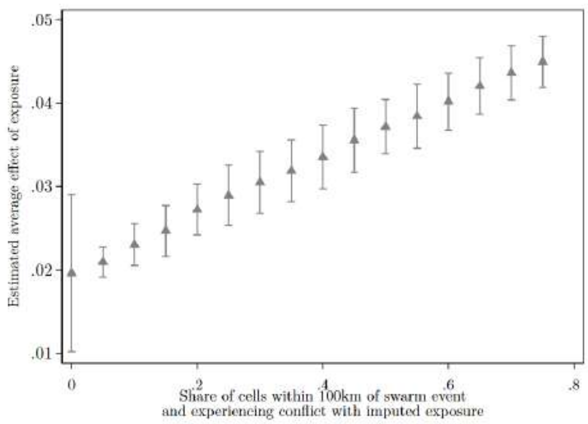
Figure C1: Estimated coefficients from Equation 1 with different SEs



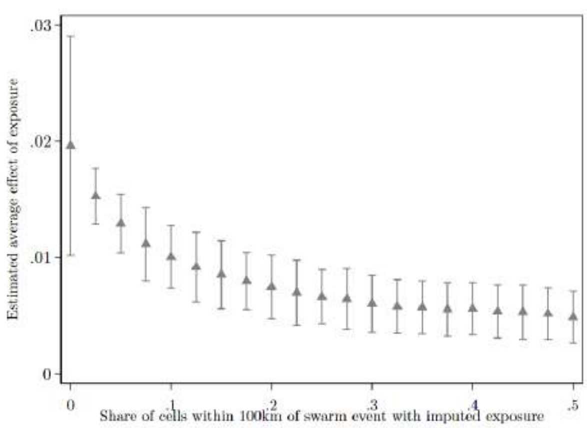
Note: The outcome variable is a dummy for any violent conflict observed. The figure shows 95% confidence intervals for estimates from Table 1 column (1) applying different clustering for the SEs. Observations are grid cells approximately 28×28km by year. Regressions also include country-by-year and cell FE.

Figure C2: Simulations of missing swarm observations

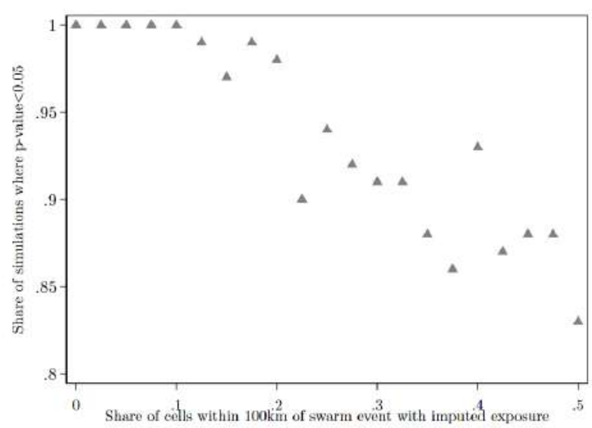
A) Betas, simulated swarms
in areas experiencing conflict
near swarm report



B) Betas, simulated swarms
in any area near swarm report

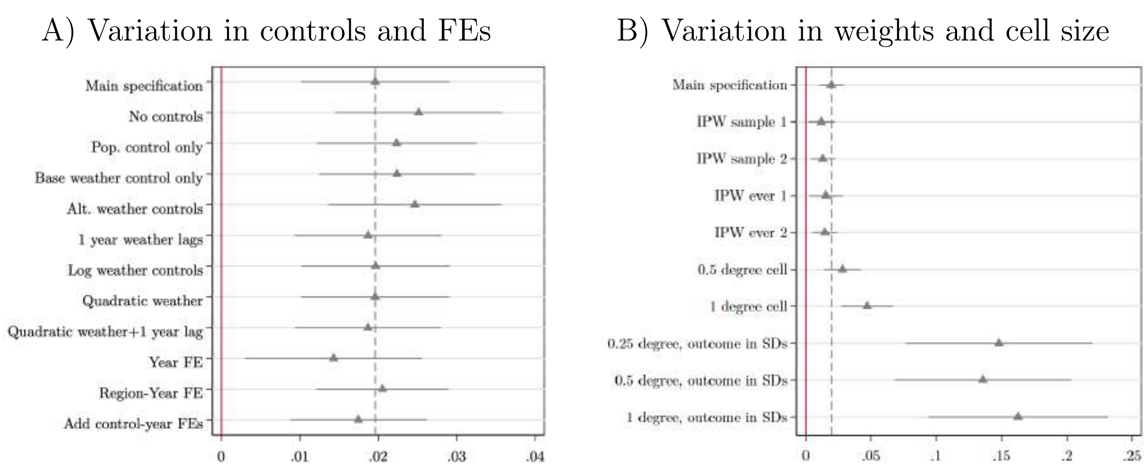


C) p-values, simulated swarms
in any area near swarm report



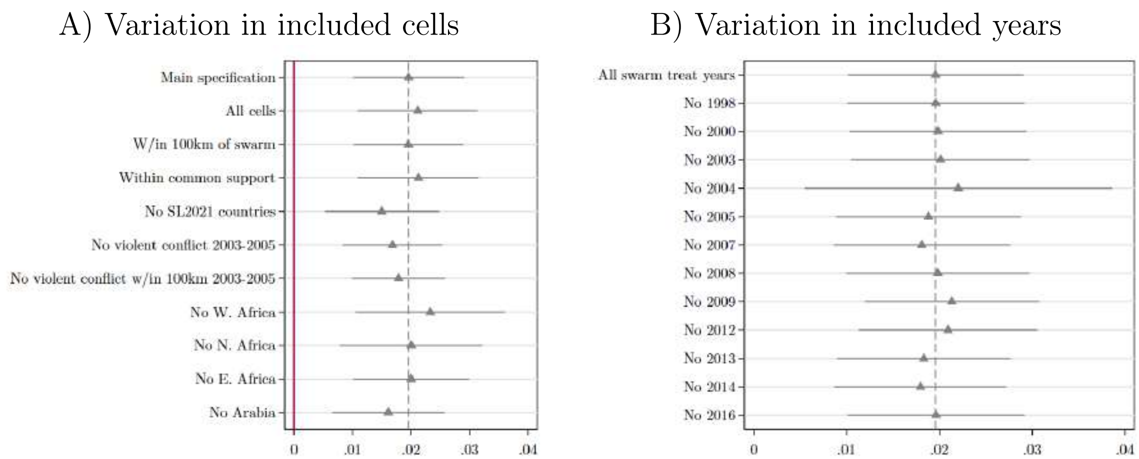
Note: The figures show the results from estimating Equation 1 in simulations imputing the presence of increasing shares of unreported locust swarms in cell-years with a locust swarm reported within 100km. For each share, I run 100 simulations randomizing which cell-years are imputed an unreported swarm, recalculating the swarm exposure treatment variable, and estimating the average impact of swarm exposure on violent conflict risk. In Panel A, I only impute swarms in cell-years both experiencing violent conflict and within 100km of a reported locust swarm, to simulate effects of missing swarm reports in insecure areas. In Panel B, I impute swarms across all cell-years within 100km of a reported locust swarm. Panels A and B report the average estimated effect across all simulations by share of imputed swarms, along with a 95% confidence interval for these estimates. Panel C reports the share of simulations where the p-value for the coefficient on swarm exposure is less than 0.05, by share of imputed swarms.

Figure C3: Sensitivity of average impacts of locust swarm exposure on violent conflict risk to alternative specifications



Note: Each estimate and 95% confidence interval is from a separate regression replicating Table 1 column 1 with a given modification. The dashed gray line indicates the main estimate from Table 1 column 1.
Panel A shows results varying controls and fixed effects. 'Alt.' weather controls replace the rainfall and temperature measures from WorldClim with measures from CHIRPS and ERA5, respectively.
Panel B shows results from applying weights to the regressions and increasing cell size from the base 0.25 degree cells. 'IPW' indicates inverse propensity weights based on the estimated probability of having been exposed to a locust swarm. I calculate propensity scores using a logit regression with a dummy for being exposed to a locust swarm on baseline cell characteristics and mean weather and country fixed effects. I calculate inverse propensity weights as $\frac{1}{p}$ for cells that were exposed and $\frac{1}{1-p}$ for cells that were not, where p is the estimated probability of swarm exposure. I assign cells with estimated probabilities outside the range of common support a weight of 0. 'Sample' weights are based on the probability of being exposed during the sample period, and 'ever' weights are based on the probability of being exposed at any point from 1985-2021. For both sets of weights, IPW 1 are the raw estimated weights and IPW 2 replaces weights above the 99th percentile with the 99th percentile weight.
For estimates in larger cells, I collapse the data by taking the maximum for swarm exposure and violent conflict dummies and means for rainfall, temperature, and population controls. I show effects on both a dummy for any violent conflict and on the standard deviation in the probability of any violent conflict, as the later approach maintains comparability in effect sizes as the baseline risk of any conflict in a cell-year increase with cell size.

Figure C4: Sensitivity of average impacts of locust swarm exposure on violent conflict risk to alternative samples



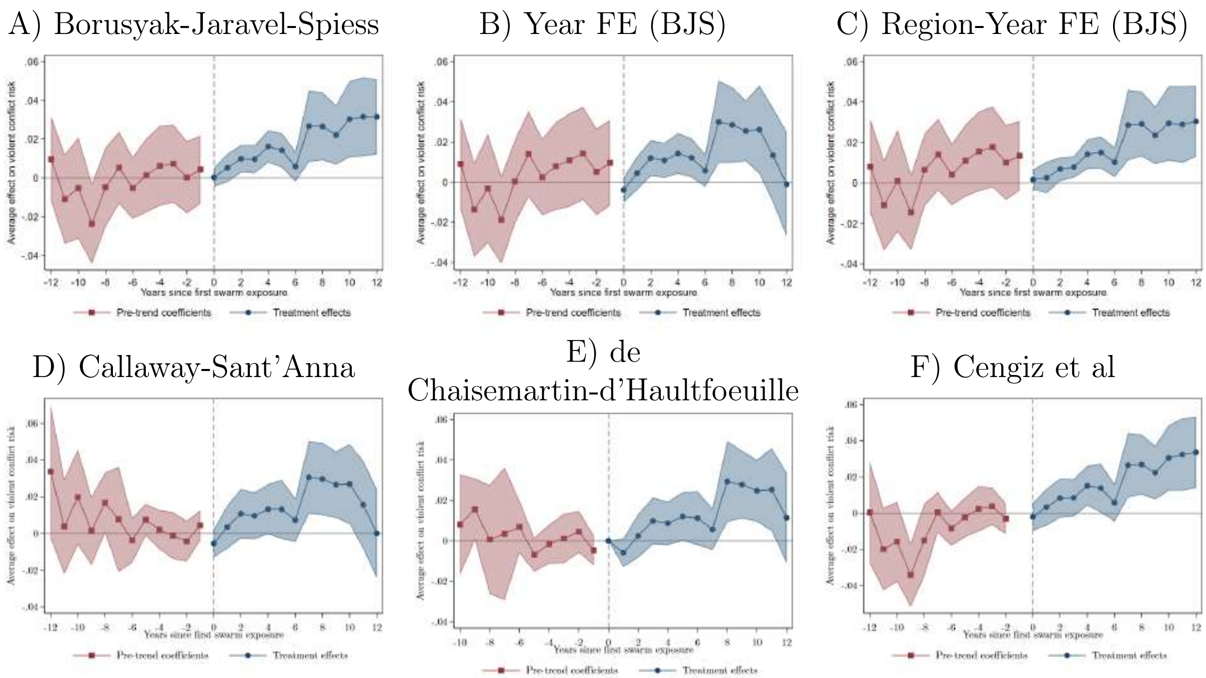
Note: Each estimate and 95% confidence interval is from a separate regression replicating Table 1 column 1 with a given modification. The dashed gray line indicates the main estimate from Table 1 column 1.
Panel A shows results varying the set of included cells. I first vary whether cells more than 100km from any swarm report and outside the range of common support of estimated swarm exposure probability are excluded. I then drop countries where Showler and Lecoq (2021) report insecurity prevented some locust control operations during the sample period and cells that experienced violent conflict during the 2003-2005 locust upsurge which might have prevented locust reporting. Finally I drop countries in particular geographic regions.
Panel B shows results from dropping individual years when locust swarm exposure events occurred.

Table C1: Average impacts of direct and spillover exposure to locust swarms on violent conflict risk

Outcome: Any violent conflict event	(1) All swarms	(2) 2003-2005 upsurge swarms
Exposed to swarm	0.020***	
	(0.005)	
Exposed to swarm w/in 100km outside cell	-0.002	
	(0.003)	
Exposed to swarm		0.018***
		(0.005)
Exposed to swarm w/in 100km outside cell		0.007*
		(0.004)
Observations	327646	327646
Outcome mean post-2004, no exposure	0.028	0.028
Country-Year FE	Yes	Yes
Cell FE	Yes	Yes
Controls	Yes	Yes

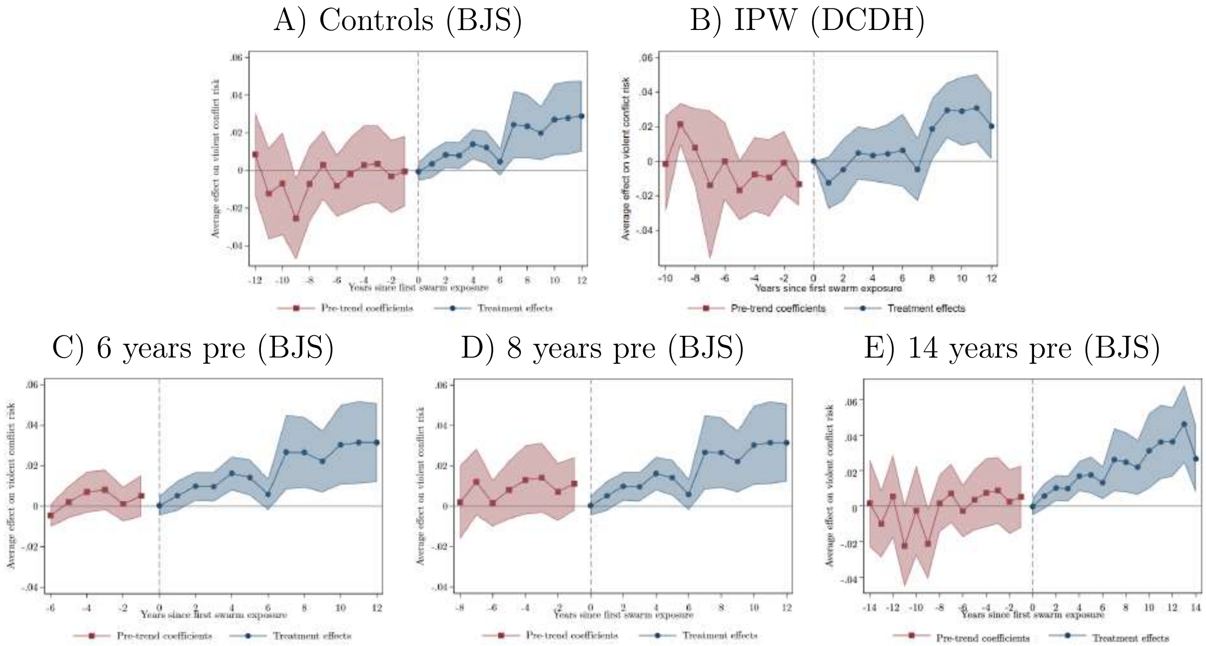
Note: The table presents results from estimating Equation 1 but including a spillover swarm exposure variable based on the first year a cell is within 100km of a swarm outside the cell. Column 1 considers all swarm exposure events while column 2 focuses on the 2003-2005 upsurge.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure C5: Alternative locust swarm exposure event study estimators



Each panel replicates Figure 3 but changes some aspect of the specification as indicated in the panel title. See the figure note for Figure 3 for additional detail on the estimation. 'BJS' refers to the Borusyak et al. (2024) method. The main specification uses BJS with country-by-year fixed effects and no controls. I first compare results varying level of year fixed effects included. I then present results using different event study methods: Callaway and Sant'Anna (2021), Cengiz et al. (2019), and De Chaisemartin and d'Haultfoeuille (2024). The De Chaisemartin and d'Haultfoeuille (2024) Stata package only estimates a maximum of 10 pre-treatment effects, and treats the year before treatment as year 0. The Callaway and Sant'Anna (2021) and De Chaisemartin and d'Haultfoeuille (2024) estimates only include year fixed effects as the Stata packages do not allow for more flexible time fixed effects. Patterns of treatment effects using Borusyak et al. (2024) with only year fixed effects are similar to these alternative estimators.

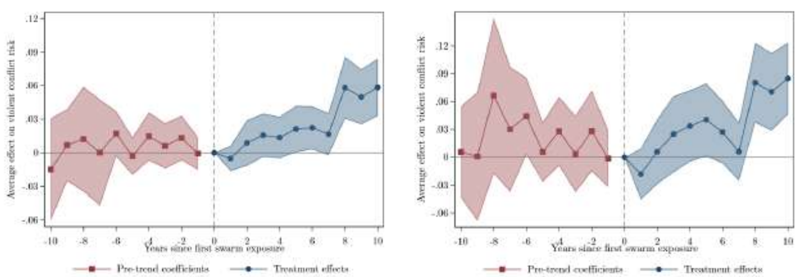
Figure C6: Sensitivity of locust swarm exposure event study results to different specifications



Each panel replicates Figure 3 but changes some aspect of the specification as indicated in the panel title. 'BJS' refers to the Borusyak et al. (2024) method. The main specification uses BJS with country-by-year fixed effects and no controls and 12 years of pre-exposure estimates. 'DCDH' refers to the De Chaisemartin and d'Haultfoeuille (2024) method, for which the Stata package natively allows the inclusion of weights whereas the BJS package does not. 'IPW' refers to inverse propensity weights, constructed based on the estimated probability of being exposed to a locust swarm during the study period. See the figure note for Figure 3 for more detail.

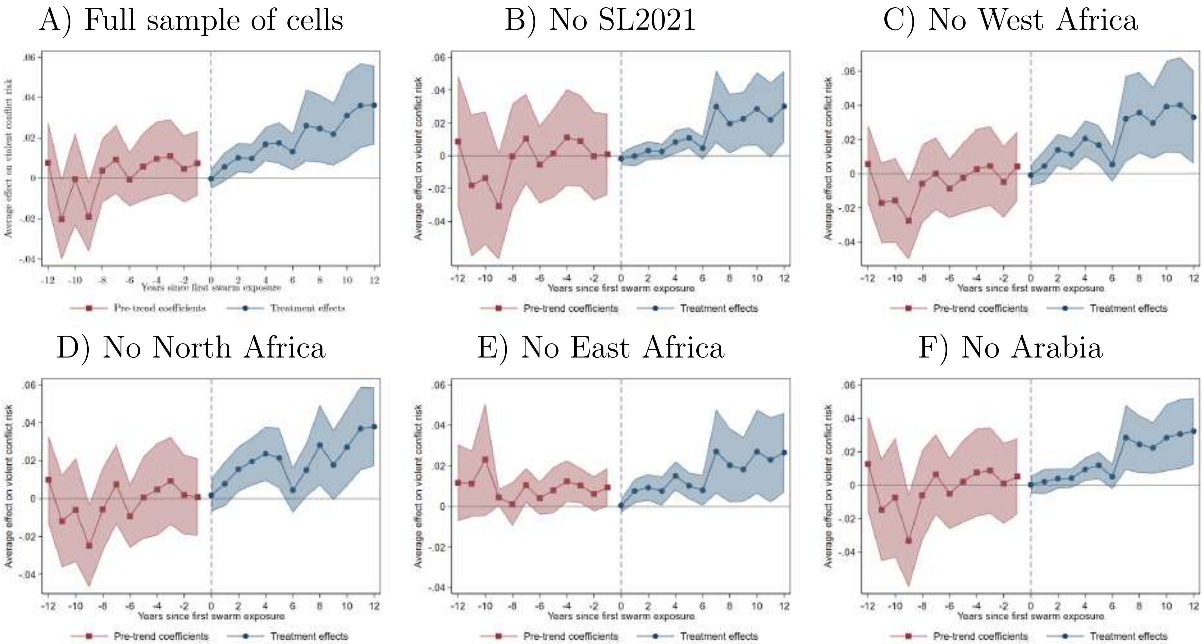
Figure C7: Dynamic impacts of swarm exposure on violent conflict risk at different scales

A) 0.5 degree cells B) 1 degree cells



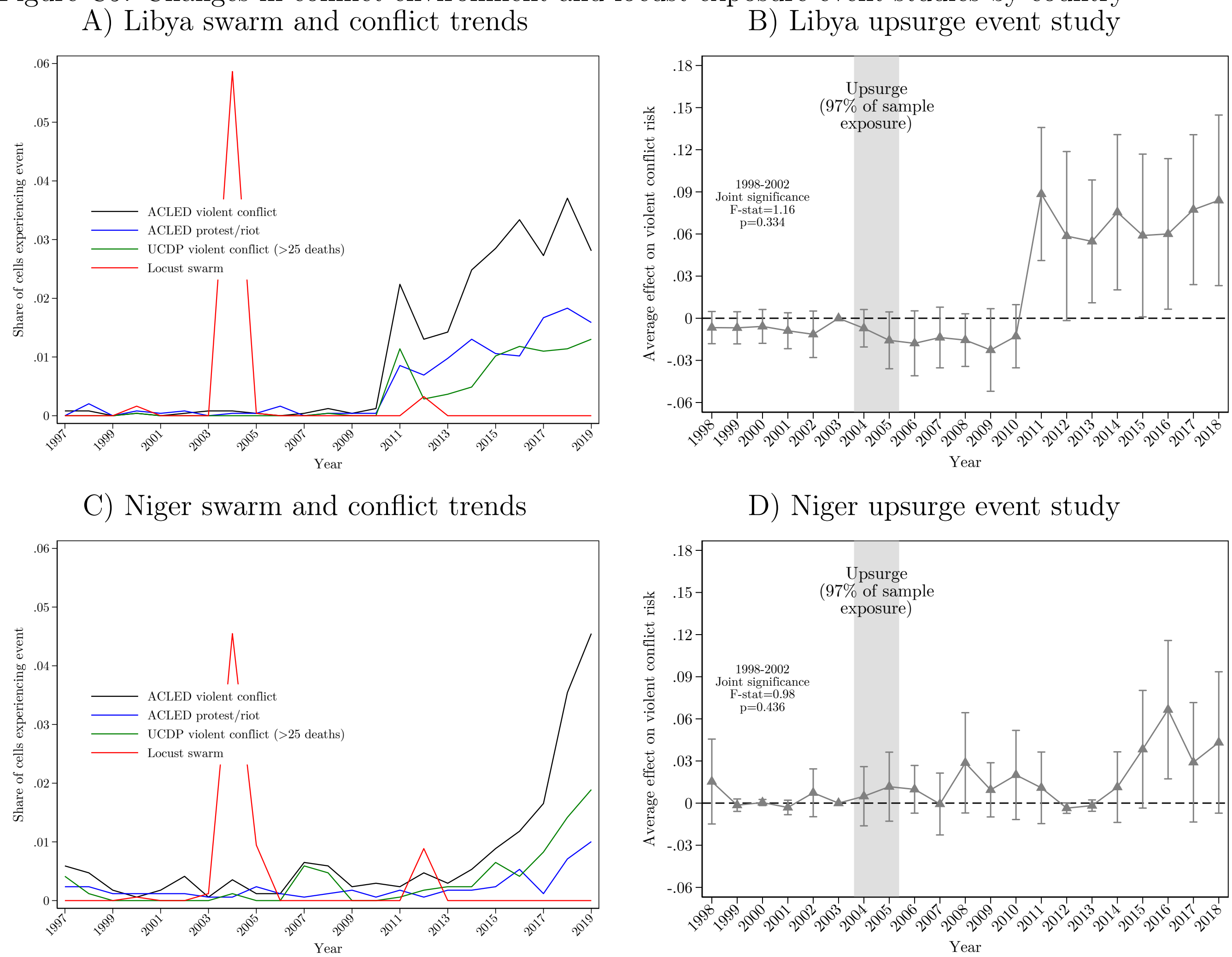
Each panel replicates Figure C5 Panel C estimating dynamic impacts of locust swarm exposure of the risk of any violent conflict event using the De Chaisemartin and d'Haultfoeuille (2024) method at different spatial scales. The main analysis uses 0.25° cells. When collapsing to larger cells I take the maximum of the swarm exposure and violent conflict variables and the mean of control variables across smaller cells within the aggregate cell. See the figure note for Figure 3 for more detail.

Figure C8: Sensitivity of locust swarm exposure event study results to different subsamples



Each panel replicates Figure 3 but changes the analysis sample as indicated in the panel title. The main analysis in Figure 3 excludes cells more than 100km from any locust swarm observation and outside the range of common support for the estimated probability of being exposed to a locust swarm in the study period across exposed and unexposed areas. 'SL2021' countries in panel B refers to the countries listed in Showler and Lecoq (2021) as areas where insecurity has limited desert locust control operations during the sample period. Panels C-F show results dropping specific geographic regions. See the figure note for Figure 3 for more detail.

Figure C9: Changes in conflict environment and locust exposure event studies by country



Note: The figure replicates Figure 4 for Libya and Niger alone, which were selected because of the strong concentration of locust exposure during the 2003-2005 upsurge.

Table C2: Robustness of severe drought estimates to changing number of consecutive drought months

Outcome: Any violent conflict event	(1) 5 months	(2) 5 months	(3) 5 months	(4) 6 months	(5) 6 months	(6) 6 months
Exposed to shock	0.002 (0.002)	-0.004** (0.002)	-0.001 (0.001)	-0.000 (0.002)	-0.004** (0.002)	-0.002 (0.001)
Exposed to shock × Any cropland or pasture in cell		0.009** (0.004)			0.007* (0.004)	
Any violent conflict elsewhere in 1 degree cell			0.013*** (0.003)			0.015*** (0.003)
Exposed to shock × Any violent conflict elsewhere in 1 degree cell			0.021*** (0.007)			0.005 (0.006)
Observations	453831	453831	453831	453831	453831	453831

Note: The table reproduces Table 4 changing the definition of what constitutes a 'severe' drought. The main definition uses at least 4 consecutive months of drought, and the alternative definitions presented here use thresholds of 5 and 6 months.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix D: Model

I present a streamlined model of occupational choice including a decision about whether to engage in violent conflict, as in Chassang and Padró i Miquel (2009), Dal Bó and Dal Bó (2011), and McGuirk and Burke (2020). I extend prior models by allowing for the possibility of dynamic long-term effects, and use the model to build intuition and generate hypotheses about the effects of agricultural shocks on conflict. These testable hypotheses are presented in section 3 of the paper.

In the model, individuals in each time period allocate one unit of labor L to either agricultural production, non-agricultural work, or violent conflict to maximize total net income I. Returns to all activities are affected by individual and location characteristics X such as land quality, level of education, fighting ability. An important time-varying location characteristic motivated by Buhaug et al. (2021) is the existence or importance of local collective political or social grievances. These grievances can be caused by a variety of factors and I do not focus on their origins but treat them as exogenous to the individual's decision in a given period.

Net returns to agricultural production $F^A(L^A, S, W, X)$ are affected by agricultural shocks S, with $\frac{\partial F^A}{\partial S} < 0$ and $\frac{\partial^2 F^A}{\partial S^2} < 0$. A larger S therefore reduces agricultural labor productivity—the *opportunity cost mechanism*. Agricultural production also depends on wealth W with $\frac{\partial F^A}{\partial W} > 0$, where wealth broadly includes human, physical, and financial capital. Wealth in period t is weakly increasing in income I from activities in period $t-1$. As agricultural shocks decrease income, this creates a relationship between past agricultural shocks S_{t-s} and agricultural production in period t, where $s \in [1, \tau]$ for some τ. We can write $F_t^A = F^A(L_t^A, S_t, W_t(\{S_{t-s}\}_{s=1}^{\tau}), X_t))$, with $\frac{\partial F_t^A}{\partial S_{t-s}} < 0$ causing a wealth or *permanent income mechanism*.

Net returns to non-agricultural work $F^N(L^N, X, W)$ are based on the most productive activity available outside of own agricultural production. The highest returns available depends on individual and location characteristics X and wealth W. As a simplifying assumption, I suppress the direct dependence of non-agricultural returns on S. Returns to non-agricultural work thus set a lower bound on how far the opportunity cost of fighting may fall following a negative agricultural shock. With $\frac{\partial F^N}{\partial W} > 0$, F^N will be weakly smaller for individuals primarily engaged in agriculture that experienced a past agricultural shock due to the permanent income mechanism.

Individual i can also decide to engage in violent conflict attacking a set of potential targets J near i that are feasible to attack within the time period. These targets may be individuals, enterprises, or organizations of different types including government-affiliated groups. These targets may be within the same broadly-defined location as i or in neighboring locations, and may experience the same or different agricultural shocks. The aim of the violent conflict may include both capture of outputs (rapacity) or attempts to capture and control factors of production, such as land or territory.

The potential net returns $F^C(L_i^C, X_i, \{I_j, W_j, X_j\}_{j \in J})$ depend on the incomes (production output), wealth (factors of production), and characteristics of the individuals in J. Agricultural shocks S_j for individuals $j \in J$ engaged in agriculture affect i's returns to fighting by decreasing the income available to capture: $\frac{\partial F_t^C}{\partial S_{j,t}} < 0$. This is the *rapacity mechanism*. Past agricultural shocks to individuals $j \in J$ will reduce both the output and the factors that i can capture through the permanent income mechanism, meaning $\frac{\partial F_t^C}{\partial S_{j,t-s}} < 0$.

The probability of success and costs of fighting depend on characteristics $X_{i,t}$ and $X_{j,t}$—some targets will be farther away or be better defended. An important variable in $X_{i,t}$ is whether there are high levels of local grievances. In such settings mobilization of collective fighting groups is likely to be less costly and perceived as offering greater potential returns. Costs of fighting are incurred with certainty and include economic, social, and emotional costs as well as risk of injury or death. These costs make fighting sub-optimal for most individuals in most time periods. In practice, individuals are unlikely to engage in violent conflict alone, as such fighting generally involves organized armed groups which recruit members and pay them a wage or share of the returns from victory (Collier and Hoeffler, 2004; Grossman, 1999). The presence of mobilization of active fighting groups that the individual could join reduces the costs of fighting for the individual and increase the probability of successfully capturing returns — this is the *grievance mechanism*.

The individual's problem in period t can be presented as choosing their labor allocation $L_{i,t}$ to maximize income $I_{i,t}$ given some current and past shock realizations S_i, S_j. For simplicity and intuition I ignore uncertainty in returns and suppose that decisions are made (or equivalently, updated) after the agricultural shocks in the period are realized.

$$\begin{aligned}
\max_{L_{i,t}^A, L_{i,t}^N, L_{i,t}^C} I_{i,t} =& F^A(L_{i,t}^A, S_{i,t}, W_{i,t}(\{S_{i,t-s}\}_{s=1}^{\tau}), X_{i,t}) + F^N(L_{i,t}^N, W_{i,t}(\{S_{i,t-s}\}_{s=1}^{\tau}), X_{i,t}) \\
&+ F^C(L_{i,t}^C, X_{i,t}, \{I_{j,t}, W_{j,t}(\{S_{j,t-s}\}_{s=1}^{\tau}), X_{j,t}\}_{j \in J}) \\
\text{subject to } & L_{i,t}^O \in \{0,1\}, \quad F^O(0,.) = 0, \quad \text{and } \sum_O L_{i,t}^O = 1 \text{ for } O \in \{A, N, C\} \\
& \frac{\partial F^A}{\partial S_{i,t}} < 0; \quad \frac{\partial F^A}{\partial S_{i,t-s}} < 0; \quad \frac{\partial F^C}{\partial S_{j,t}} < 0; \quad \frac{\partial F^C}{\partial S_{j,t-s}} < 0
\end{aligned}$$

This yields

$$\begin{aligned}
L_{i,t}^C = 1 \text{ iff } & F^C(1, X_{i,t}, \{I_{j,t}, W_{j,t}(\{S_{j,t-s}\}_{s=1}^{\tau}), X_{j,t}\}_{j \in J}) \\
& \geq \max(F^A(1, S_{i,t}, W_{i,t}(\{S_{i,t-s}\}_{s=1}^{\tau}), X_{i,t}), F^N(1, W_{i,t}(\{S_{i,t-s}\}_{s=1}^{\tau}), X_{i,t}))
\end{aligned}$$

In words: actor i chooses to engage in violent conflict if the net returns from fighting exceed their opportunity cost—the highest net returns they could receive from choosing another occupation.

Conflict occurs in the locations of the targets being attacked. The effect of an agricultural shock on the decision to fight in the same time period is ambiguous, particularly if there is a strong positive correlation between shocks over space, as in most agricultural shocks. When the shocks are correlated, larger $S_{i,t}$ will decrease i's returns to agricultural production in the same period but also be associated with a decrease in output available to capture from nearby targets. This makes conflict over output (i.e., banditry) less attractive, but has minimal effect on the returns to conflict over territory or factors of production assuming the shock is transitory.[27] These offsetting effects—a lower opportunity cost of fighting but lower

[27] I focus on transitory agricultural shocks which do not have a permanent direct effect on local agricultural

returns to fighting over output nearby—will be less important for shocks that vary more over space.

In this paper I analyze conflict within grid cells which contain many individual and targets. In the main analysis I define shock exposure at the level of 28×28km grid cells, such that the median locust swarm would only affect around 6% of cell area creating meaningful variation in exposure within the cell. This implies that potential targets for rapacity not exposed to a swarm will remain in proximity to exposed individuals. Although conflict could also spill over outside of these grid cells, this is not a situation where conflict *must* necessarily spill over, because not everyone in a cell defined as exposed actually experiences the agricultural productivity shock. I test the sensitivity of the results to using larger grid cells to capture spillovers of conflict outside the areas affected by agricultural shocks.

Under these conditions, I hypothesize that the opportunity cost mechanism should dominate, increasing the local risk of violent conflict in the year of shock exposure. To the extent that the rapacity mechanism offsets the opportunity cost mechanism, this should attenuate short-term effects on measures of conflict over output but not for conflict over factors.

The long-term effects of past agricultural shocks $S_{i,t-s}$ on the decision to engage in conflict in period t also involve offsetting mechanisms. Because of impacts on wealth as a result of consumption smoothing, the returns to both agricultural production and to fighting will be lower than before the shock in affected areas relative to unaffected areas, though higher than in the period of the shock. As with short-term impacts of an agricultural shock on violent conflict, long-term impacts should be smaller for conflict over output than over factors of production assuming their expected returns are not much affected by the transitory agricultural shock.

The permanent income effect is likely to be particularly strong following desert locust swarm exposure due to the severity of the income shock. Long-term effects on productivity and wealth should be directly observable if this is the mechanism through which a past shock affects current conflict. Assuming some households can recover from the initial shock, increases in conflict risk should at least be non-increasing over time.

Finally, the importance of local conditions in determining the costs and returns of fighting mean that we should expect heterogeneity in the effects of an agricultural shock on conflict risk. A reduction in the opportunity cost of fighting is more likely to increase the risk of violent conflict when the costs of forming or joining armed groups are lower or the returns to such engagement are higher. Following Buhaug et al. (2021), I hypothesize that this will be the case in periods of heightened local grievances, noting that the agricultural shock itself may contribute to grievances but that many other factors unrelated to the shock will as well. I therefore hypothesize that the dynamic impacts of a transitory agricultural shock on violent conflict should be concentrated in periods of heightened grievance, frustration, or popular mobilization. Long-term effects under this mechanism require persistent effects of the shock on measures of productivity or well-being.

productivity. Transitory shocks may have some effect on the returns to fighting over factors if they affect individuals' ability to productively utilize factors or if they affect expectations about future productivity. Shocks that have direct permanent productivity effects, for example through soil erosion or other land degradation, would have larger effects on the returns to capturing factors of production.