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Economic Fallout of Social Conflict: Evidence from Social Media and Satellite Images*

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Abstract

In this paper, we leverage a quasi-experimental design and innovative sources of information to examine the impact of rising social conflict and political instability in Haiti. By exploiting geographical heterogeneity and leveraging data from Facebook and satellite imagery, we show the impact of different types of violence on proxies of economic activity in the context of countries with limited data availability. In the short term, we find that one additional violent event reduces economic activity by approximately 3.1% within the ten-day window following its occurrence. In the medium term, one additional political or civil event in an arrondissement is associated with a decline of approximately 1.5% and 2.5%, respectively, in economic activity over the subsequent five-month period. Importantly, the Facebook data also allows for a disaggregation of the effects by sector, with the sectors most impacted by rising insecurity being home services and professional services. The long-term estimates indicate that an additional violent event is associated with a 1% decline in economic activity, as proxied by nighttime light intensity, one year following the event. These results show a sharp initial decline in economic activity, followed by smaller but lasting contractions, indicating limited recovery after violent events.

Keywords: Haiti, social conflict, economic performance, social media, activity quantile, nighttime lights.
JEL Codes: C80, O54, Q34, E32, R11.

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1 Introduction

Economic activity and social conflict are deeply interconnected, both exerting powerful influences that shape the trajectory of societal development. In the interplay of both elements, social conflict is often perceived as a threat to economic stability. There is a large body of literature documenting the strong association between social conflict and poor economic outcomes. While some studies directly focus on the negative impact of social conflict on the growth rate of output (Alesina and Rodrik, 1992; Rodrik, 1999; Collier, 1999; Abadie and Gardeazabal, 2003; Fang et al., 2020; Le et al., 2022), others look at the relationship between social conflict and a wide set of economic outcomes, such as economic inequality (Esteban and Ray, 2011; Genicot and Ray, 2017), investment and human capital accumulation (Benhabib and Rustichini, 1996; León, 2012; Ray and Esteban, 2017), consumption, trade and financial markets (Barro and Ursua, 2008; Amodio and Di Maio, 2018; Guiso et al., 2009; Novta and Pugacheva, 2021).

The literature highlights several key channels through which social conflict disrupts productive processes. Social conflict discourages human capital accumulation by limiting access to education and training opportunities (Bodea and Elbadawi, 2008; León, 2012; Cook, 2014; Ray and Esteban, 2017; Brück et al., 2019). It also increases firms' operating costs, acting as a barrier to innovation and entrepreneurship (Amodio and Di Maio, 2018; Prete et al., 2023; Couttenier et al., 2024). Similar patterns are found in Latin America, where violence has been shown to discourage investment, reduce productivity, and lead to business closures (Perez-Vincent et al., 2024). Spikes in social conflict reduce competitiveness and deters both national and foreign investment (Benhabib and Rustichini, 1996; Knight et al., 1996; Rodrik, 1999; Novta and Pugacheva, 2021). Labour demand often declines due to rising operational costs and firms ceasing operations, while labour supply may shrink as certain jobs or locations become too dangerous to sustain employment (Fernández et al., 2014; Ksoll et al., 2022; Maio and Sciabolazza, 2023). Social conflict can also incentivise brain drain, as skilled individuals seek safety and better opportunities elsewhere (Docquier and Rapoport, 2012). Finally, public resources are often diverted to managing social instability, crowding out investments that would otherwise go toward improving human capital or enhancing the productive capacity of the economy (Gupta et al., 2004; d'Agostino et al., 2016).[1]

The multidimensional disruption caused by social conflict creates a complex environment

[1]The literature on the relationship between crime and economic growth have identified similar channels by which economic performance is affected. However, crime also have specific impacts. For instance, individuals may reduce their participation in the labour market and turn to illegal activities if the marginal benefit of engaging in such activities exceeds the marginal cost (Becker, 1968; Anderson, 1999). Also, high crime rates are strongly linked to weak enforcement of property rights, which discourages innovation initiatives (Goulas and Zervoyianni, 2015).

where economic progress becomes difficult to sustain, effectively increasing the risk of becoming a conflict trap.[2] This is especially true for countries with high levels of institutional fragility, where social conflict exacerbates pre-existing vulnerabilities in terms of governance and public institutions (Besley and Persson, 2011). In such contexts, the state's ability to effectively manage resources, implement policies, and provide basic services is severely weakened, exacerbating the negative impact on economic growth. Therefore, understanding the specific dynamics between social conflict and economic activity is even more urgent in fragile states, where the risk of self-reinforcing cycles is heightened and targeted initiatives are essential to break this vicious circle.

While some studies have conducted research on the relationship between social conflict and economic performance in fragile states (Fang et al., 2020; Diwakar, 2015; Akresh et al., 2012; Rizvi, 2022; Nkurunziza, 2019; Ouedraogo, 2024), a recurring challenge has been data availability. In fact, not only these countries have limited statistical collection and production capacity, but the outbreak of conflict can further disrupt data collection efforts. Therefore, researchers have increasingly turned to non-traditional data sources, which are less reliant on local statistical capacities and less affected by conflict-related disruptions. Since the influential paper of Henderson et al. (2012) and seminal contributions made by Doll et al. (2006), Sutton et al. (2007) and Ghosh et al. (2009), the use of innovative sources of information, in particular satellite imagery, has become an invaluable tool that enables the analysis of the effects of social conflict on productive activities where data availability is scant (Haslam and Tanimoune, 2016; Racek et al., 2024; Levin et al., 2018; Joseph, 2022; Guo et al., 2023; Tähtinen, 2024). Yet, most studies exploring this relationship focus on national or highly aggregated subnational levels, often overlooking the heterogeneous impacts of social conflicts on more granular settings, and having more difficulties claiming causality.

In this paper, we aim to offer a more comprehensive analysis of the heterogeneous and granular impacts of social conflict on economic activity in fragile states. We focus on Haiti, a paradigmatic case of a country deeply affected by violence and social unrest. By leveraging satellite imagery, social media data and exploiting geographical heterogeneity, we investigate how social conflict causally influences economic outcomes across both regions and industries. This innovative approach enables us to uncover spatial and sectoral variations in economic performance, offering a nuanced perspective on how the effects of social conflict differently shape the development trajectory of regions and industry-specific performance.

[2]A conflict trap can be defined as a self-reinforcing cycle where low levels of development and economic setbacks increase the likelihood of social conflicts, and, conversely, social conflict hinders development and economic recovery. In this trap, repeated cycles of conflict and economic damage make it progressively harder for a country to escape, as each phase of social unrest further erodes economic stability and raises the risk of future conflicts (Collier et al., 2003).

Social conflict has been long rooted in the history of Haiti since its foundation as an independent country (Girard, 2005). Over the past few decades, Haiti has faced a series of crises, including natural disasters, frequent changes in leadership, corruption and a weak institutional framework, all of which have contributed to a deepening sense of instability and deterioration of public order. Particularly, since 2018 Haiti has endured a new cycle of political instability and social conflict, marked by a series of violent events that have significantly undermined governance and exacerbated pre-existing social and economic challenges. The situation of violence reached a critical point with the assassination of President Moïse in July 2021 (Congressional Research Service, 2023). Notably, this period has seen an increase and consolidation of criminal groups, in particular gang related violence. Power struggles between political actors increased political instability, an environment in which gangs increased their control over the capital. The surge in gang violence in Port-au-Prince has compelled numerous residents to flee their homes and seek safety in other areas. Importantly, gang control is no longer confined to the capital, it has expanded (although with less intensity) into other regions (Bertelsmann Stiftung, 2024).

While the Covid-19 pandemic played a role in the decline of production in 2020, insecurity appears to be the single most important factor influencing the poor economic performance in the last 7 years. Despite the aggregate evidence on the negative association between social conflict and Haiti's economic performance (as suggested by recent escalating levels of violence and a sustained decline in production), a deeper analysis is needed to understand the causal and heterogenous impact of the former on the later. Indeed, it is important to estimate the effect of insecurity on the economy in Haiti to show how violence and instability are blocking investment, closing businesses, and weakening economic growth. By measuring the economic impact, leaders can prioritize actions that not only improve safety but also create the conditions needed for jobs, education, and development.[3]

To shed light on this issue, we leverage a quasi-experimental design and innovative sources of information. The central hub of power in Haiti is Port-au-Prince, where escalating social turmoil has been mirrored by increasing gang violence as various groups compete for control of the capital. Consequently, violence has surged in Port-au-Prince to a much greater extent than in other regions of the country. We exploit this geographical heterogeneity to compare the economic disruptions experienced in Port-au-Prince due to the spike in violence with those in other regions where gang presence is more reduced. We leverage Facebook data and satellite imagery from the National Aeronautics and Space Administration (NASA) to

[3]An example of these mitigating efforts is the Rapid Crisis Impact Assessment for Haiti (RCIA) launched by the Government of Haiti in May 2024. The objectives of the RCIA were to evaluate the 2021-2024 crisis impact in key regions and sectors, develop a recovery framework and investment plan for FY2025-2026, and enhance coordination between the government and partners, supported by international institutions.

show the impact of different types of violence on economic activity in the context of countries with limited data availability. Specifically, we use Facebook's Business Activity Trends (BAT) – aggregate and by industries– and NASA's Black Marble night-time lights (NTL), both available at daily and monthly intervals, as proxies for economic activity.[4] [5] The BAT data are disaggregated to the administrative level 2 (*arrondissements* in Haiti, or districts), whereas the NTL data can be aggregated at the *arrondissement* and *commune* levels, the last one corresponding to administrative level 3. We complement this information with annual sub-national (*communes*) figures on crop and textile production.[6] This way, through a two-way fixed-effects model and using daily, monthly and yearly data for Haiti from the Armed Conflict Location & Event Data (ACLED)[7] (Raleigh et al., 2010), we can explore how increases in total violent events, political (violent) events , civil (violent) events , and related fatalities can affect economic activity in the short-, medium- and long-term.

Our results indicate that 1 more violent event in a district, is associated with a short-run decrease of economic activity (measured by Facebook's daily BAT) of 3.1 percent in the following week-time window. In the medium term, an extra political event decreases the production activity between 1.5 (Facebook's BAT) and 6.2 (NTL) percent in the following five months. In the longer term, we observe a decrease of economic activity of approximately 1 percent in the following year-time window. These results point to a sharp initial decline in economic activity, followed by persistent though smaller contractions over longer horizons, suggesting limited recovery dynamics after violent events. Thus, in the medium-long term the persistency of social conflict might leave long-lasting scars on production.[8] Importantly, the Facebook data also allows for a disaggregation of the effects by sector, with the most impacted sectors by rising insecurity being homer services and professional services. The public good sector instead exhibited greater resilience and did not experience significant changes in economic activity driven by increase in political or civil events.

Our paper is partially related to Yousuf and Muller (2022). These authors look at the effect of political violence on economic activity in Bangladesh by using ACLED's database and NASA's Black Marble night-time lights. Their results indicate that there is an immediate impact

[4]The BAT data covers the period from March 2020 to November 2022, while our NTL data spans the same time frame and extends further, covering January 2018 to December 2023.

[5]As we explain in Section 3.2, we decided not to use daily NTL data due to their strong autoregressive component, which largely stems from NASA's gap-filling procedure. This method fills missing values based on the most recent high-quality observation, introducing persistence that may distort temporal dynamics. This significantly limits attempts to establish a unidirectional causal link between violence and disruptions in economic activity, as the temporal sequence of events may be artificially reversed.

[6]This is proprietary data produced by GeoAdaptive (2024), and is based on sectoral production statistics, firms' spatial location, and satellite data.

[7]Which can be aggregated at the *arrondissement* and *commune* level.

[8]Indeed, Masri et al. (2024) highlight that social conflict can lead to persistent negative economic impacts.

of political violent protests on luminosity of -0.9 percent on daily night lights. The nationwide monthly impact is approximately 1.7 percent, which becomes evident within a 1-month time frame. While we also use ACLED's database and NASA's Black Marble imagery, there are important differences. First, our objective is to establish a unidirectional causal link between violence and disruptions in economic activity, whereas Yousuf and Muller (2022) does not elaborate on a design that could allow for strict causal inference. Second, we look at the case of Haiti, where the nature and reach of social unrest is more violent and more widespread than the case of Bangladesh. Third, we make a more detailed analysis of the different expressions of social conflict (civil and political events and related fatalities) and their differentiated impact on economic activity. Notably, by using Facebook's BAT we are able to analyse the impacts of social conflict on industries.

Our paper contributes to several strands of the literature. First, we add to the papers that have used nighttime lights for the specific case of Haiti. For instance, Mitnik et al. (2018) use communal-section and pixel level annual nighttime lights to approximate the impact of transport infrastructure investments on economic activity in Haiti, whereas Joseph (2022) uses annual nighttime lights to assess the differentiated subnational impact on economic activity of the 2010 earthquake. Owing to the need of using long annual time series, both papers combine harmonised nighttime light data coming from satellites with different resolution levels and saturation issues in brightly lit areas. Due to our time span, we rely exclusively on high-quality nighttime light data (NASA's Black Marble) coming from the Visible and Infrared Imaging Radiometer Suite (VIIRS), which Gibson et al. (2021) demonstrate provides a more accurate approximation of economic activity at finer spatial resolutions.

Second, our paper contributes to the growing literature on the causal impact of social conflict on economic activity in fragile countries. By leveraging novel data sources and exploiting regional heterogeneity in both the intensity of violence and its differential impact on economic activity, our paper allows a transparent discussion of causal attribution. Third, the use of daily, monthly and annual data on social conflict and variables highly correlated with economic activity allows us to evaluate the short-, medium- and long-term negative impacts of social conflict on productive activities. Fourth, our paper also highlights the usefulness of social media data to measure economic performance. While satellite data has been widely used to measure the economic impact of social turmoil, to the best of our knowledge, our paper is the first to leverage the use of Facebook's BAT for this purpose.[9] This points out the

[9]Despite its relative recent release, there are studies that have taken advantage of Facebook's business information. Eyre et al. (2020b), which constitutes the seed of the BAT, use Facebook data to asses the recovery of small businesses after natural hazard events in Nepal, Puerto Rico and Mexico. Whereas, Díaz and Henríquez (2024) use the BAT data to examine how the economic activity of small businesses influenced mental health outcomes across five Latin American countries during the initial phase of the Covid-19 pandemic.

usefulness of social media data to measure economic performance. Fifth, Facebook's BAT data enable us to examine the impacts of social conflict on various industries across different regions. This level of detail sheds light on the differential effects of social unrest, providing valuable information for policymakers and stakeholders aiming to support sectoral resilience in conflict-prone regions. This type of analysis is almost non-existent in studies focusing on fragile countries, even when satellite data is used.

The paper proceeds as follows. In Section 2 we describe the ACLED database and the different types of events it measures. Next, in Section 3 we describe in detail our two sources for approximating economic activity: Facebook's Business Activity Trends from Meta datasets and NASA's Black Marble night-time lights. Section 4 presents our empirical strategy and in Section 5 the results. Section 6 contains robustness checks applied to our baseline results and extensions of our analysis, while the last section concludes.

2 Measuring Social Conflict and Political Instability in Haiti: ACLED Database

To quantify the various manifestations of social conflict in Haiti, we leverage the geographic and temporal granularity of the Armed Conflict Location & Event Data Project (ACLED) database. ACLED is a detailed data repository tracking political violence, demonstrations, and conflict events globally. By drawing from a variety of sources, including local and international news outlets, reports from non-governmental organizations, and international bodies, ACLED offers almost real-time insights into various spheres of social and political violence and associated events, detailing their nature, participating actors, geographical location, dates, and other relevant attributes. Its emphasis on granular, location-specific data allows users to explore trends and patterns in violence and political activity at subnational levels. To get a detailed perspective on the surge in social conflict that has been impacting Haiti since mid-2018, we take advantage of this last feature and obtain daily, monthly and annual subnational data (at the level of *arrondissement* and *commune*[10]) on total violent events, political (violent) events, civil (violent) events and related fatalities (see Table 1 for definitions). We follow the classification used by the United Nations Office for the Coordination of Humanitarian Affairs to distinguish between political and civil events, as well as the associated fatalities.

[10]Haiti is divided into 10 departments, each of which is further subdivided into several *arrondissements*, giving a total of 42 *arrondissements*. An *arrondissement* typically comprises multiple *communes* (totaling 146 communes), which in turn are divided into communal sections.

Table 1: ACLED's Definitions of Violent Events and Related Fatalities

Category	Description
Total Events	A distinct incident reported to have occurred at a specific time and location, involving either the use of force by one or more actors, a demonstration, or a strategic political development. There are six types of events: battles, protests, riots, explosions/ remote violence, violence against civilians, strategic developments.
Political Events	Political events are single altercations where force is used by one or more groups toward a political end. These include ACLED's battles, violence against civilians, and explosions/remote violence event types, as well as the mob violence sub-event type of the riots event type.
Civil Events	Civil events involve civilians as the main actor or target of an altercation. According to ACLED's codebook, civilians, being unarmed by definition, lack the capacity to participate in acts of political violence. These incidents are asymmetrical, with the perpetrator being the sole party employing force. Civilian targeting events include violence against civilians and explosions/remote violence where civilians were directly targeted.
Total Fatalities	Fatalities occurring as a consequence of any of the six events captured by total violent events.
Political Fatalities	Fatalities occurring as a consequence of a political event.
Civil Fatalities	Fatalities occurring as a consequence of a civil event. Counts of "civilian fatalities" exclude civilians unintentionally killed during combat between armed groups or as a by-product of actions targeting those groups remotely, such as airstrikes on militant positions.

Notes: Strategic developments are defined as events that provide contextual insights into actions and developments involving groups that, while not classified as political violence or demonstrations, may influence future unrest or shape broader political trajectories within or between countries. Note that total events is not simply the sum of political and civil events, because some events fall into both categories and thus overlap. *Source:* Armed Conflict Location & Event Data (ACLED) Codebook.

Table 2 shows different moments of the monthly distribution of these six violence categories in Haiti.The distributions exhibit a right-skew, indicating the presence of relatively low counts in some *arrondissements* in comparison with few *arrondissements* where violent incidents are more widespread. An interesting finding is that, on average, political events tend to be more deadly than total and civil events. Specifically, during the period 2018-2023, political events resulted in an average of 1.68 fatalities per event, compared to 1.21 fatalities per civil event and 0.94 fatalities per total number of events.[11] Figure 1 illustrates that over the observed period, all six categories of violence progressively increased following the assassination of President Moïse in July 2021. This escalation notably led to a peak in political violence

[11]This pattern also appears when considering the share of events with at least one fatality: 58% of political events report at least one fatality, compared with 46% of civil events.

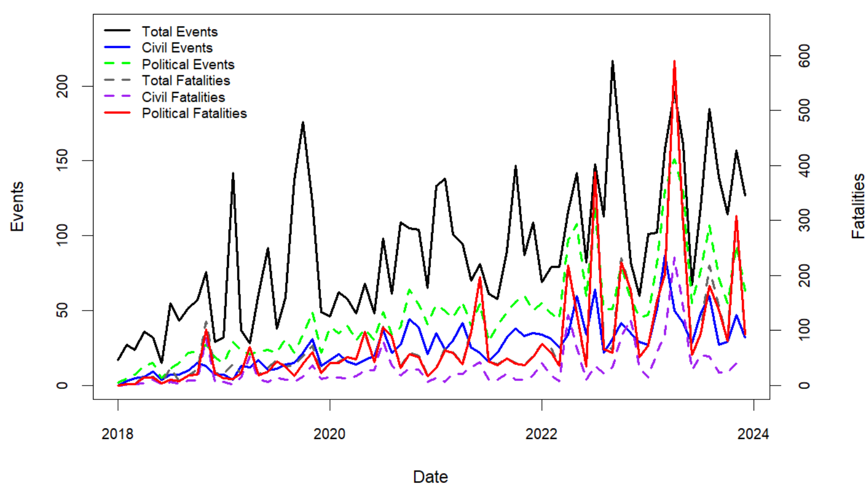
around March 2023, marked by 110 political events that resulted in 590 fatalities.

Table 2: Summary Statistics of Monthly Events and Fatalities in Haiti

Variable	Obs	Mean	Std. Dev.	Min	Max
Total Events	3,024	2.13	9.14	0	127
Political Events	3,024	1.14	5.69	0	101
Civil Events	3,024	0.62	3.23	0	66
Total Fatalities	3,024	2.00	14.22	0	386
Political Fatalities	3,024	1.92	14.10	0	386
Civil Fatalities	3,024	0.75	5.46	0	112

Notes: This table presents basic descriptive statistics for total events, political events, civil events and related fatalities for the period January 2018 -– December 2023 at the level of *arrondissement*. ACLED data were downloaded on 14 November 2024. *Source:* Raleigh et al. (2010), authors' own calculations.

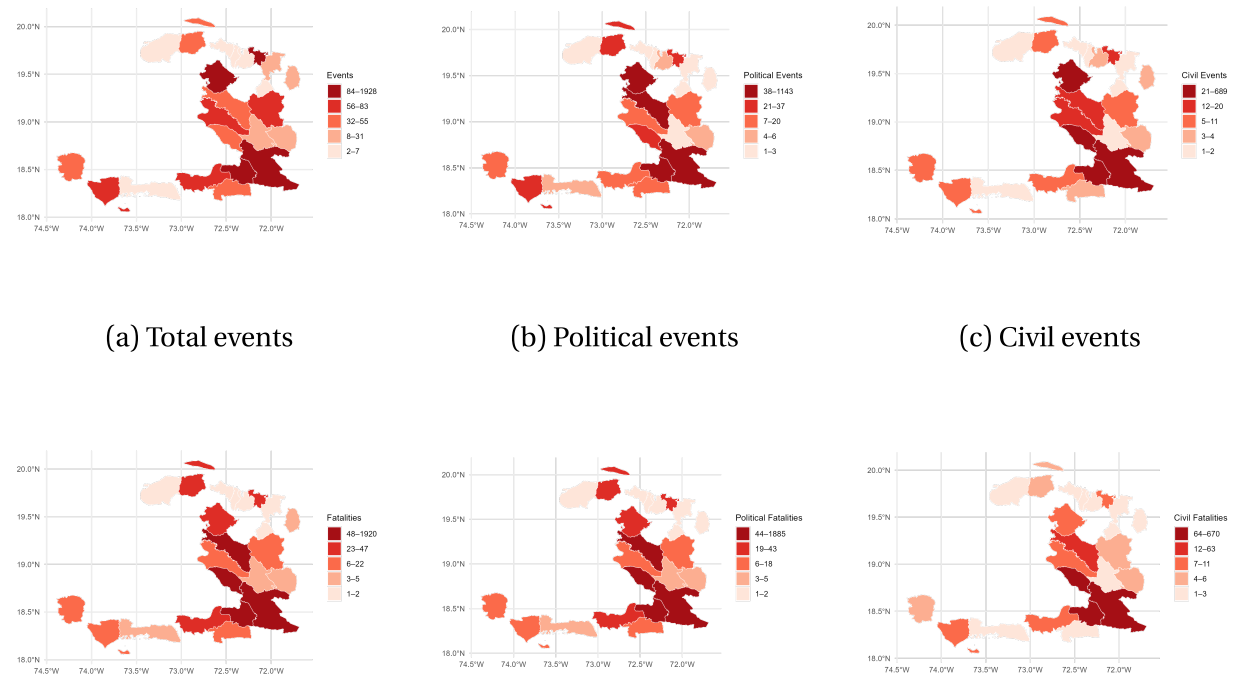
Figure 1: Time Series Evolution of Monthly Events and Fatalities in Haiti



Notes: This figure presents the time series evolution of total events, political events, civil events and related fatalities for the period January 2018 –- December 2023. ACLED data were downloaded on 14 November 2024. *Source:* Raleigh et al. (2010), authors' own calculations.

As suggested by Table 2, this surge in violence is unevenly distributed across *arrondissements* (see Figure 2). The six ACLED's categories of social conflict show a higher incidence in two *arrondissements*: Port-au-Prince and Croix-des-Bouquets (both located in the department of Ouest). Particularly, Port-au-Prince, the central hub of power in Haiti, has experienced a sharp escalation in gang violence over the last five years, reflecting the increasing social turmoil. As various groups vie for control of the capital, violence has intensified there far more significantly than in other parts of the country. Our identification strategy aims to take advantage of this geographical heterogeneity to identify the causal impact of social conflict on economic activity.

Figure 2: Heat Map of the Spatial Distribution of Monthly Events and Fatalities in Haiti



(a) Total events (b) Political events (c) Civil events

(d) Total fatalities (e) Political fatalities (f) Civil fatalities

Notes: This figure presents heat maps with the spatial distribution (arrondissement) of total events, political events, civil events and related fatalities for the period January 2018 –- December 2023. The label ranges represent quintiles of the corresponding variable, calculated excluding zero values. Areas with a value of zero are left blank. ACLED data were downloaded on 14 November 2024. *Source:* Raleigh et al. (2010), authors' own calculations.

3 Innovative Data to Measure Business Activity and Economic Performance

To analyse the short-, medium-, and long-term economic impacts of social conflict, we require to integrate ACLED's detailed spatial and temporal conflict data with subnational figures on economic activity.[12] This, however, poses significant challenges. First, Haiti's highest frequency indicator of economic activity –*Indicateur Conjoncturel d'Activité Economique* (ICAE)– is only available on a quarterly basis, thus, limiting short- and medium- term analyses. Moreover, given the data-collection challenges, the *Institut Haïtien de Statistique et d'Informatique* (IHSI) does not produce an indicator measuring economic activity at the subnational level. These constraints would prevent us from leveraging the spatial heterogeneity in violence and economic activity to identify the causal impacts of the former on the latter. While the lack of high frequency subnational data is often a limitation in fragile countries such as Haiti, with the advent of groundbreaking sources of information this is no longer a binding constraint. Indeed, since the influential paper of Henderson et al. (2012) and seminal contributions made by Doll et al. (2006), Sutton et al. (2007) and Ghosh et al. (2009), the use of innovative sources of information, in particular satellite imagery, has become an invaluable tool that enables the quantitative analysis of economic issues where data availability is scant.

In this paper, we take advantage of these new sources of information and use data highly correlated with economic activity to approximate the economic performance at the subnational level. For the short and medium term analyses, we leverage data from META-Facebook and satellite imagery from the National Aeronautics and Space Administration (NASA). Specifically, we use Facebook's BAT –aggregate and by industries– and NASA's Black Marble nighttime lights, both available at daily and monthly intervals and disaggregated to the administrative level 2 and level 3 (*arrondissements* –districts– and *communes*), as proxies for economic activity. For the long term analysis, we obtain *commune*-level annual values of the Black Marble NTL and complement this information with *commune*-level yearly indicators on real agricultural and textile production. The latter two indicators are proprietary data sourced from GeoAdaptive (2024). In the following paragraphs we describe each dataset in more detail.[13]

3.1 Facebook's Business Activity Trends (BAT)

Facebook's BAT is a dataset based on business social-media activity that intends to measure business activity after the occurrence of exogenous shocks, such as natural disasters or pandemics. This database was developed within Data for Good at Meta and is based on the work of Eyre et al. (2020a), which aims to nowcast business recovery following emergencies by utilising online posting activity as a key indicator. The authors' main assumption is that a sufficiently strong external shock can influence the aggregate posting behaviour of Facebook business pages, which, in turn, can serve as a proxy for business performance during disruptive events.

[12] The short-term impacts are measured using the daily data, the medium-term impacts are defined by the monthly data, and the long-term impacts are measured using the yearly data.

[13] Additional satellite-based data used in extensions and robustness checks are described in Appendix A.

Eyre et al. (2020a) compare their methodology with other measurements of economic activity based on business surveys, mobile phone information and time series of satellite imagery, concluding that their methodology renders reasonable similar estimates of the recovery period after the occurrence of natural disasters.

Lam et al. (2022) generally adopt this methodology to produce Facebook's BAT. The aggregate BAT is produced at the subnational level (level 2 of the Global Administrative Areas-GADM) and by industries (called business verticals[14]). The main metric of the BAT is what the authors call "activity quantile". This metric is the result of comparing the business daily post count with the daily posting frequency during the baseline period, where the baseline period is 90 days before any specific date. When its value is around 0.5, it signals a normal level of activity or, as the authors call it, the "pre-crisis-like behaviour". Thus, economic disruptions cause the activity quantile to deviate from the central value of 0.5: values below 0.5 indicate economic distress, while values above 0.5 signify economic expansion. Notice that Lam et al. (2022) adopt a fixed-cohort approach, where the sample of Facebook pages is chosen at a specific date (for instance, the shock date) and remains the same in the post-crisis period. Therefore, regional full recovery effectively means that the full sample of business pages return to their "normal" posting activity.[15]

In this paper, we leverage daily and monthly BAT data produced by Facebook in the context of the Covid-19 pandemic, which covers the period from March 2020 to November 2022. However, in our empirical analysis (Section 5) we restrict our sample to the period from July 2020 to November 2022 to avoid conflating the effects of social distancing measures implemented by public and private entities with the adverse impacts of violent events.[16] The quality filters applied by Facebook mean that we have good-quality data for 22 *arrondissements* out of 42, including the country's capital.[17] The descriptive statistics of the activity quantile by business vertical are shown in Table 3. Apart from the category "All" –which includes all industries–, the business verticals with more weight on our sample are "Public Good", "Professional Services" and "Business & Utility Services". On the other hand, "Grocery & Convenience

[14]The authors call business verticals to their grouping of businesses into different industries based on the page admin self-reported business type. Appendix B provides more details on this dataset, the list of business verticals and their corresponding description.

[15]Importantly, as pointed by the authors, the real-time nature of the activity quantile makes the adoption of a dynamic-cohort approach unfeasible. In a dynamic approach, the sample of business pages varies representing firms exiting and entering the markets. However, Lam et al. (2022) argue that in the short run it is not possible to determine whether a business that has stopped posting does so because it has exited the market or it is just a pause as a consequence of the disruption of an external shock.

[16]We select July 2020 as the starting point of our sample because the Oxford Stringency Index (OSI)—which measures the intensity of social distancing policies during the pandemic—shows a sharp decline in that month, indicating the relaxation of such measures.

[17]The list of these 22 *arrondissements* is provided in Appendix B. Notably, they accumulate 80.4% of Haiti's population in 2020.

Stores", "Lifestyle Services" and "Manufacturing" only report 33 observations each. The discrepancy in the number of observations arises from the exclusion of data points associated with fewer than 10 business pages, in accordance with privacy protection protocols.[18] Interestingly, over the period the average activity quantile of "Public Good" is slightly above 0.50, indicating that the spike in social conflict in Haiti has not disrupted the normal activity of this sector. This is not the case for "Travel", "Retail" and "Home Services", which are among the sectors (with a reasonable number of observations) that, on average, have deviated (downwards) more from the normal posting behaviour over the period.

Table 3: Summary Statistics of Activity Quantile by Business Vertical

Business Vertical	Observations	Mean	Std. Dev.	Min	Max
All	726	.43	.15	.011	.85
Business & Utility Services	231	.46	.11	.12	.81
Grocery & Convenience Stores	33	.36	.11	.13	.63
Home Services	198	.41	.13	.11	.75
Lifestyle Services	33	.35	.17	.06	.64
Local Events	66	.30	.12	.10	.58
Manufacturing	33	.49	.12	.30	.80
Professional Services	264	.40	.13	.10	.76
Public Good	297	.53	.15	.20	.91
Restaurants	132	.46	.15	.08	.86
Retail	165	.40	.18	.08	.95
Travel	165	.36	.13	.07	.67

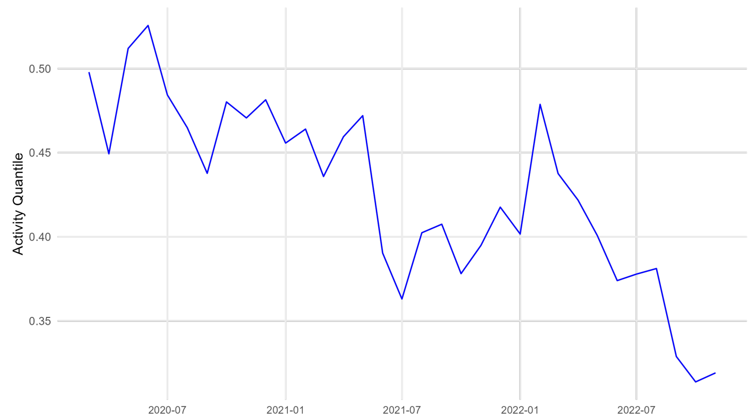
Notes: This table presents the activity quantile by business vertical for the period March 2020 – November 2022. The table includes 22 *arrondissements* for which BAT data is available. *Source:* Facebook's BAT, authors' own calculations.

The time series analysis (Figure 3) shows that the aggregate activity quantile has progressively deviated downwards from the value of 0.5, coinciding with the deteriorating social and political environment (see Figure 1), reaching its lowest value in the last quarter of 2022. Figure 4 reveals that the fallout is not limited to the political and economic capital, rather it has disrupted the economic activity in other *arrondissements*, as shown by the progressively lighter blue shading over time. To check how representative the BAT data is, we compare Facebook's network coverage with population counts across arrondissements and find a strong match, far from significant subnational biases (see Appendix B for visual depiction). While Facebook's BAT provide valuable insights into online business activity and industry-specific dynamics, they capture only few dimensions of economic performance (marketing and sales). To complement this, we incorporate NASA's Black Marble night-time lights data, which offer a broader, geospatial perspective on economic activity by measuring light emissions as a proxy

[18]Due to the small number of observations, we exclude these business verticals from our industry level analysis.

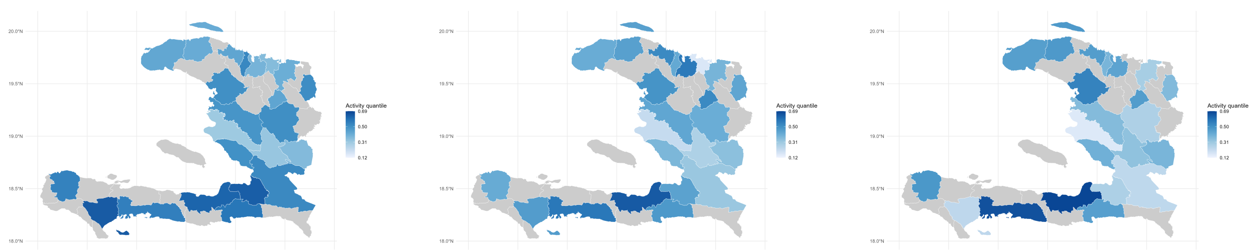
for infrastructure use and energy consumption. This combination allows us to analyse economic trends from both digital and physical lenses, enhancing the robustness of our findings.

Figure 3: Time Series Evolution of Activity Quantile (Business Vertical "All") by month-year



Notes: This figure presents the time series evolution of the average activity quantile (business vertical "All") for the period March 2020 – November 2022. The figure includes only *arrondissements* for which data is available. *Source:* Facebook's BAT, authors' own calculations.

Figure 4: Heat Map of the Spatial Distribution of the Activity Quantile (Business Vertical "All") by *Arrondissement*



(a) 2020 (b) 2021 (c) 2022

Notes: This figure presents heat maps with the geographical distribution (*arrondissement*) of the annual average activity quantile (business vertical "All") for the period March 2020 –- November 2022. *arrondissements* with unavailable data are left blank. *Source:* Facebook's BAT, authors' own calculations.

3.2 NASA's Black Marble night-time lights

Since the influential paper of Henderson et al. (2012) and seminal contributions made by Doll et al. (2006), Sutton et al. (2007) and Ghosh et al. (2009), NTL have become a well-established proxy for subnational economic activity, particularly in contexts where conventional subnational economic figures are not available. The economic rationale of using NTL as a proxy of economic activity is that they are strongly correlated with infrastructure, urbanization, and energy consumption. Importantly, electricity, which is one of the main producers of artificial lighting, is an economic "normal good", where its consumption increases as the available income rises. Geographically speaking, this means that as regions develop and residential and commercial infrastructure spreads, we would expect an increase in the production of artificial light and radiance. Thus, NTL can signal varying regional levels of economic development. In scenarios where data collection and production is not feasible and information and communication technologies have not penetrated, NTL provides a proxy for economic activity with wide coverage over time and across geographies.

In this paper we make use of NASA's Black Marble nighttime lights (BM-NTL). These radiance data are based on the Visible Infrared Imaging Radiometer Suite (VIIRS) of the Suomi National Polar-orbiting Partnership (SNPP) satellite.[19] NASA pre-process and provides radiance information that is cloud-free, atmospheric, terrain, vegetation, snow, lunar, and stray light-corrected DNB radiances.[20] This product, which was released in 2018, adds to the two well-known sources of NTL: 1) the DMSP-OLS nighttime lights, which is a low resolution (1km x 1km) radiance data that covers the period 1992-2013; 2) the high resolution (500m x 500m) radiance data based on the VIIRS which is provided by the Colorado School of Mines (CSM) (available from 2012 onwards in their monthly and annual versions). Importantly, NASA's Black Marble offers several advantages in comparison with these two sources. First, it offers a higher resolution than the DMSP-OLS NTL and avoids the well-known problem of top-coding (capping the maximum values of radiance or brightness that can be recorded). In addition, VIIRS NTL includes a built-in calibration to guarantee the comparability of data across both time and space. Second, it deals better with distortions related to snowfall and seasonal vegetation than the CSM's radiance data, offering a higher radiometer calibration (Iddawela, 2023). Furthermore, NASA's BM-NTL data is constructed based on specialised algorithms to remove stray light, cloud cover, and ephemeral lighting (e.g., wildfires, gas flares).

The NASA's BM-NTL comes in three main products (VNP46 products): VNP46A2, daily

[19]The Suomi NPP crosses the equator at approximately 13:30 PM (ascending node) and 1:30 AM (descending node). While capturing radiance at 1:30 AM might reduce the chance of identifying changes in economic activity in less populated/urbanised areas, it has the advantage of minimizing the risk of capturing non-human generated radiance and human activity tend to stabilise which facilitates across-time comparisons (Cao et al., 2022)

[20]Each of these issues can potentially decrease the quality of the NTL. Clouds, for instance, can make it difficult to detect the human-generated radiance on the Earth's surface. The atmosphere can capture and absorb light no-generated by human activity. The terrain conditions and the sharp angles this can generate might affect the amount of radiance detected by satellites. Dense vegetation, as clouds, can obstruct the emission of light generated by human activity. Snow, by reflecting moonlight, can make some areas to appear brighter than others, leading to an over-estimation of radiance. Something similar happens with moonlight, depending on the moon's phases. Finally, sunlight can reflect on the Earth's surface and this can be captured by satellites, contaminating the artificial light generated by human activity.

moonlight and atmosphere corrected NTL; VNP46A3, monthly composites generated from daily atmospherically- and lunar-BRDF-corrected NTL radiance; and VNP46A4, yearly composites generated from daily atmospherically- and lunar-BRDF-corrected NTL radiance (see Appendix A for more details).[21]

Despite the availability of the VNP46A2 daily NTL product, we opted to exclude it from this study. The most basic version of this product (DNB BRDF-Corrected NTL) contains a substantial number of zeros and missing values at the *arrondissement*-day and *commune*-day level, rendering the series unsuitable for our purposes.[22] To address this limitation, NASA provides an alternative product: the gap-filled daily series of DNB BRDF-corrected nighttime lights, which imputes missing observations to ensure temporal continuity in the data. NASA's gap filling procedure for this product uses the latest high-quality retrieval available in the previous days (Román, 2021).[23] While this allows researchers to have workable daily NTL time series, it exponentially increases the auto-regressive nature of the time series. More important for our purposes, it poses the risk of artificially reversing the temporal sequence of events needed to identify possible causal impacts of violence on economic activity.

The VNP46A3 product is based on the daily NTL data from VNP46A2. Specifically, all daily observations classified as clear-sky, high-quality data are first selected for inclusion in the construction of the monthly composite (this effectively means to remove observations affected by aurora, incorrect snow flag and cloud contamination). As a second step, boxplots metrics and inter-quantile ranges are used to identify and remove outliers. The monthly figures are calculated by obtaining the mean values of the observations left after applying the two previous steps. Finally, the monthly radiances with values smaller than 0.5 $W/m^2/sr$ are reclassified as zero (Wang et al., 2022). In the case of the VNP46A3 product, the gap filling procedure is based on historical data and not on the latest (day-specific) high-quality retrieval (Román, 2021). This procedure is arguably more neutral with respect to the timing of violence events, however, it still poses the risk of obscuring the temporal sequence of events. In this line, Wang et al. (2022) advice against the use of the VNP46A3/A4 composites marked with "gap-filled" quality flags for purposes of quantitative analysis or change detection.

For the monthly series (VNP46A3), we use the all-angle composite snow free (without gap-

[21]The radiance units of measure of these products is Watts per Square Meter per Steradian ($W/m^2/sr$), which measures the portion of a sphere covered by the light being observed.

[22]For instance, in the case of Haiti between 2018 and 2023 around 30% of the total number of observations in the pairs arrondissement-day are zero or missing values.

[23]Importantly, the gap-filling procedure is applied at the cell level before aggregation to the *commune* and *arrondissement* level. This means it not only affects *communes* and *arrondissements* with entirely missing and/or zero-valued cells on a given day, but also those with some missing and/or zero-valued cells in the non-gap-filled version. Therefore, when gap-filling is applied at the cell level and values are subsequently aggregated to the *commune* and *arrondissement* level, the resulting totals differ from those in the non-gap-filled version.

filled values), filtering out poor quality composites (where the number of observations used for the composite is less than or equal to three). We chose to use the all-angle composite band (combination of near-nadir and off-nadir angles), to make a reasonable balance between pixel resolution and full coverage of all possible sources of human-made radiance. While near-nadir (satellite's nadir point – limited area close to the area below the satellite) observations provide a higher resolution and reduce atmospheric interference, off-nadir observations provide an angle that is more suited to detect non-isotropic sources of radiance (radiance sources that radiate energy not uniformly across all angles), at the cost of having less resolution. We then aggregate the radiance values at the level of *commune* and *arrondissement* using the administrative boundaries of the Global Administrative Areas (GADM). After these manipulations, we obtain complete high quality, non-missing/non-zero and non-gap filled series for 45 *communes* and 23 *arrondissements*.[24] [25] Importantly, we conduct our baseline analysis (Section 5) and robustness checks (Section 6) at the *commune*-level, thereby expanding the cross-sectional dimension to 45 units (instead of 23 *arrondissement*), which provides sufficient variation for reasonable panel estimation. However, in our online appendix we include the results at the *arrondissement*-level.

Table 4 shows that the average monthly radiance fluctuates around 40.97 $W/m^2/sr$, with the maximum radiance registered in Port-au-Price. While the Covid pandemic negatively impacted the radiance levels during the first part of 2020, Figure 5 reveals a clear pattern over the whole period: as the recent episode of social conflict intensified, economic activity—proxied by NTL—declined. Notably, the downturn in productive activities after mid-2018 is consistently captured by both Facebook's BAT data and NASA's Black Marble NTL.

[24]We applied an additional cleaning step to the nighttime lights data for November 2023, as the radiance values for that month far exceed the pre-crisis levels observed in early 2018, without any plausible economic justification for such a surge. Indeed, the series shows a sharp spike between October and November 2023, which is fully reversed by December. This makes the radiance level of November 2023 an outlier not detected by NASA's algorithms. This surge is driven by a sharp drop in the number of zero-valued cells in November 2023 relative to the long-run trend, leading to abnormally high summed values at the arrondissement level . To address this issue, we retrieved pixel-level radiance data for Haiti for October and November 2023, and assumed that any pixel with a zero value in October would also have a zero value in November (this in addition to the zero-valued cells of November), this makes the number of zero values to return to its long-run trend. We then aggregate the data at the arrondissement level and compute the radiance growth rate between October and November, which we use to derive corrected values for November 2023.

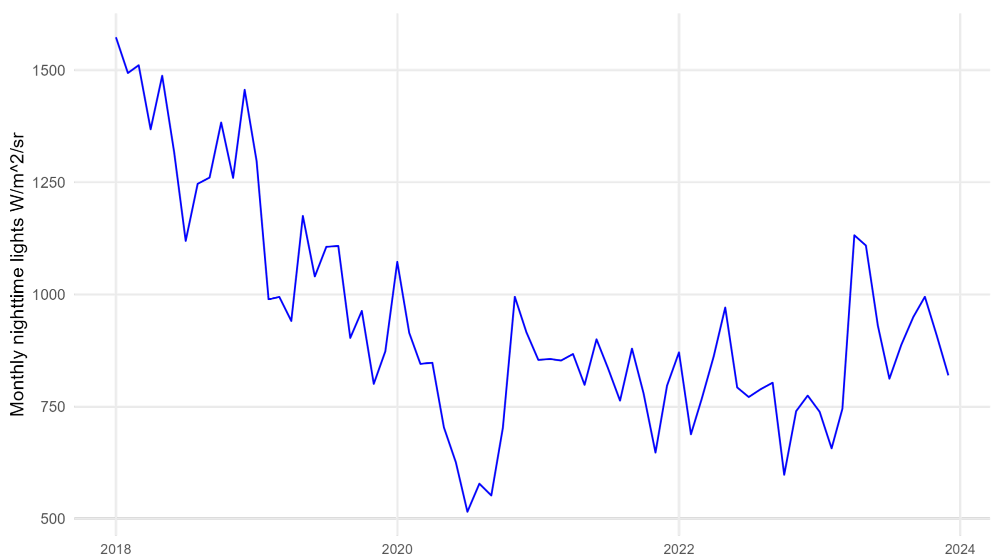
[25]The list of these 45 *communes* and 23 *arrondissements* is provided in Appendix A. They represent approximately 75% of Haiti's population in 2020.

Table 4: Summary Statistics of NASA's Black Marble Nighttime Lights

Variable	Obs	Mean	Std. Dev.	Min	Max
NTL radiance	1,656	40.97	114.31	0.1	941.14

Notes: This table presents basic descriptive statistics of the monthly nighttime lights (VNP46A3) for the period January 2018 – December 2023. The radiance units of measure of this product is $W/m^2/sr$. The table includes 23 *arrondissements* for which good quality data is available. *Source:* NASA's Black Marble night-time lights, authors' own calculations.

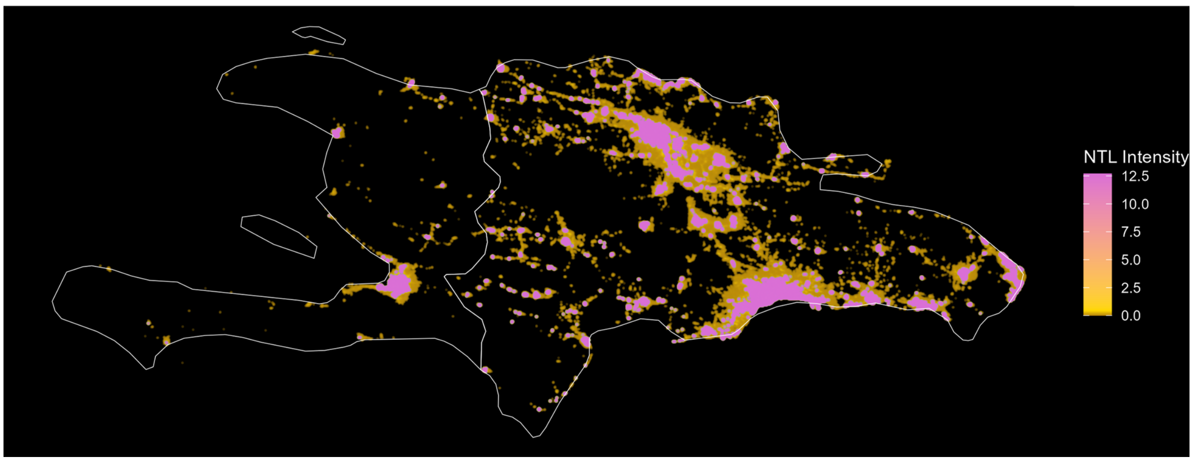
Figure 5: Time Series Evolution of NASA's Black Marble Nighttime Lights



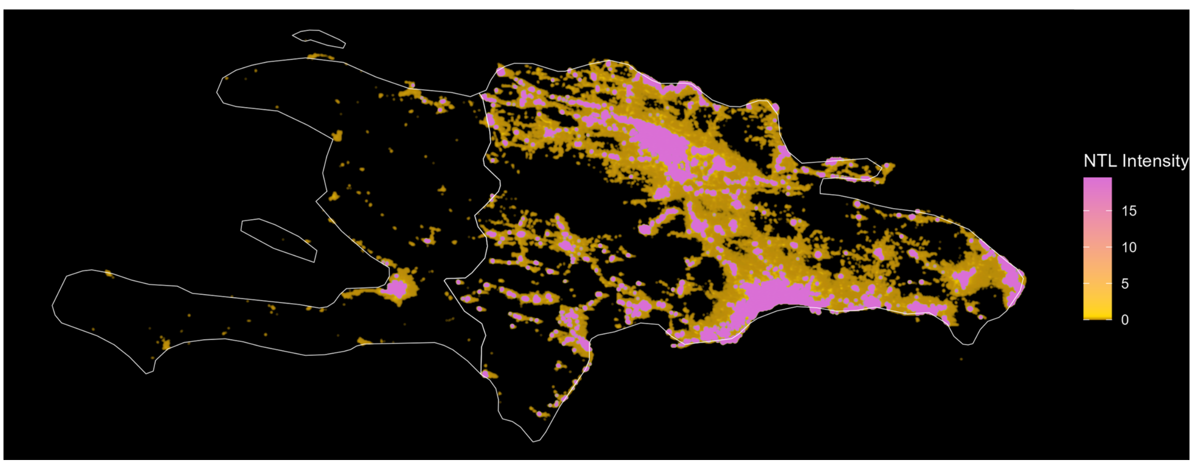
Notes: This figure presents the time series evolution of the monthly nighttime lights (VNP46A3) for the period January-2018 - December-2023. The figure includes 23 *arrondissements* for which good quality data is available. The radiance units of measure of this product is $W/m^2/sr$. *Source:* NASA's Black Marble night-time lights, authors' own calculations.

Figure 6 depicts the spatial distribution of the human-made radiance in the Isle of Hispaniola between 2018 and 2023. Notably, the radiance levels tell a story of two diverging development paths, where Dominican Republic is taking the highway in comparison to Haiti. In Haiti, the human-made radiance is concentrated around the *arrondissements* of Port-au-Prince, Croix-des-Bouquets, Arcahaie and Cap-Haïtien in the north. The temporal evolution of the radiance spatial distribution confirms that, while social unrest has affected most *arrondissements*, the impact varies significantly. For instance, there is a clear reduction in the extensive (number of lit pixels) and intensive (radiance intensity represented by the purple dots) margins of the NTL brightness around the capital after five years of social conflict. However, Cap-Haïtien (most brightly lit area in the north) has experimented an increase in the number of of lit pixels between 2018 – 2023, possibly indicating a pattern of internal displacement due to the raising levels of gang violence registered in the capital and neighboring arrondissement. Figure 6 confirms a reduction in the light intensity between 2018 and 2023 for Haiti, in contrast, the Dominican Republic has seen a substantial increase in both the extensive and intensive margins of nighttime light radiance, reflecting a widening development gap within Hispaniola between 2018 and 2023.

Figure 6: Map with the Spatial Distribution of NASA's Black Marble Nighttime Lights – Island of Hispaniola



(a) 2018



(b) 2023

Notes: This figure presents the pixel-spatial distribution of the annual nighttime lights (VNP46A4) in 2018 and 2023 in the Island of Hispaniola, comprised by Haiti (left) and Dominican Republic (right). The purple dots represent radiance values that are above the average radiance in 2018. Notice that the radiance values have not been aggregated at the level of arrondissement. The radiance units of measure of this product is $W/m^2/sr$. *Source:* NASA's Black Marble night-time lights, authors' own calculations.

3.3 Crop and Textile Production

We complement our daily and monthly BAT and BM-NTL data by using annual subnational figures on crop and textile production for the period 2018-2022 (both with non-missing values for all 42 *arrondissements* and 140 *communes* that make up Haiti). These are proprietary data produced by GeoAdaptive (2024), and are based on sectoral production statistics, firms' spatial location, and satellite data. Notice that crop and textile production play a strategic role in the Haitian economy. For instance, according to the IHSI, in 2024 agriculture and textile accounted for approximately 23% of the GDP. Furthermore, the World Bank estimates that in the 2018 around 50% of the households performed a productive activity linked to agriculture, while 27% relied on agriculture as their primary source of income. Importantly, during the period 2016-2019 apparel exports represented around 95% of total goods exports (World Bank, 2022). These figures suggest that sectoral production data on crop and textiles can offer valuable insights into the economic performance of Haiti in the last five years, thus, allowing us to provide a more comprehensive representation of the long-term impacts of violence on productive activities.

Specifically, the subnational crop production is estimated by first identifying Haiti's key crops, including bananas, legumes, maize, yams, potatoes, and rice. The annual production values for each crop comes from the agricultural production statistics maintained by FAOStat. To spatially distribute these values at the level of arrondissement, GeoAdaptive (2024) uses the FAO's Global Agro-Ecological Zones (GAEZ) dataset (grid level raster data available for the years 2000 and 2010) and remote sensed land cover data from the GLC_FCS30D dataset (with the aim to reflect land cover dynamics).[26] Basically, this approach builds upon and extends the methodology proposed by Grogan et al. (2022). The final outcome is a rasterized layer of crop production aggregated at the level of *commune* and *arrondissement*, expressed in current USD (thousands). To obtain real values, we deflate the nominal production using the Consumer Price Index (base year 2010) from the World Development Indicators (WDI).

To obtain subnational estimates on textile production, GeoAdaptive (2024) uses export data. There are two main reasons to follow this approach: 1) There are not reliable sources of information that provide a good quality time series of textile production, 2) More than 90% of the textile production is exported to the US, therefore, US textile imports from Haiti are good quality source to inform Haiti's textile (apparel) production trends. National textile production is then allocated to *communes* and *arrondissements* based on the geographic distribution of textile firms and their corresponding shares of total textile employment recorded in 2015. A limitation of this approach is that it assumes that the spatial distribution of textile

[26] The GLC_FCS30D is a high-resolution global dataset that tracks land-cover changes at a 30m scale from 1985 to 2022.

firms in the period 2015-2022 mirrors the 2015 distribution. The values of textile production are expressed in USD (thousands) at constant prices of 2010. As with the BM-NTL data, the analyses presented in Sections 5 and 6 are conducted using data aggregated at the *commune* level. Table 5 presents the summary statistics for both types of production. The average textile production during this period is roughly three times greater than crop production, indicating the higher value added content of the former. Figure 7 shows that real textile production has been steadily decreasing since 2018, likely because textile activity is highly concentrated in urban areas—where violence has risen disproportionately. In contrast, crop production appears more resilient, possibly because the main agricultural areas are located far from the primary hot spots of violence.[27]

Figure 8 confirms the link of spatial location, violence and economic disruption. While all *arrondissements* record some level of crop production, with Hinche and those *arrondissements* north of Port-au-Prince exhibiting the highest production levels, only three *arrondissements* concentrate the textile production: Port-au-Prince, Ouanaminthe and le Trou-du-Nord, where the country's capital approximately accounts for one out of every two dollars produced during the period.[28]

Table 5: Summary Statistics of Crop and Textile Production

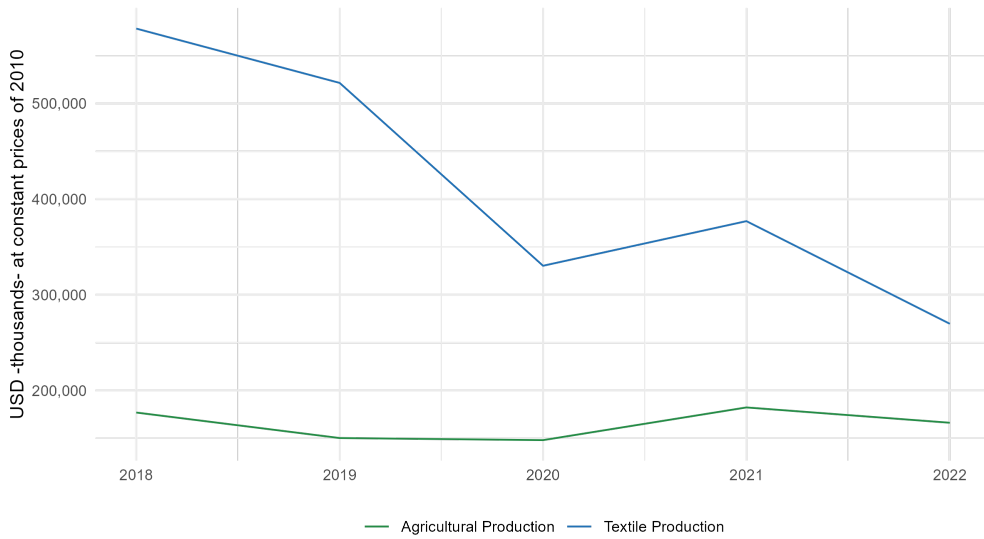
Real Production (USD -thousands- at constant prices of 2010)					
Variable	Obs	Mean	Std. Dev.	Min	Max
Crop Production	210	3,922.93	2,613.11	0	14,469.88
Textile Production	210	9,890.44	42,384.20	0	323,636.50

Notes: This table presents basic descriptive statistics of the total annual crop and textile production for the period 2018 – 2022, measured at the *arrondissement* level . Values are in USD -thousands- at constant prices of 2010. *Source:* GeoAdaptive (2024).

[27] Appendix C which compares the spatial and temporal distribution of the Normalized Difference Vegetation Index (NDVI)-—an indicator of crop growth and health—-confirms that crop production areas are largely located away from conflict hot spots. This geographic separation has likely protected them from experiencing sharper declines in output.

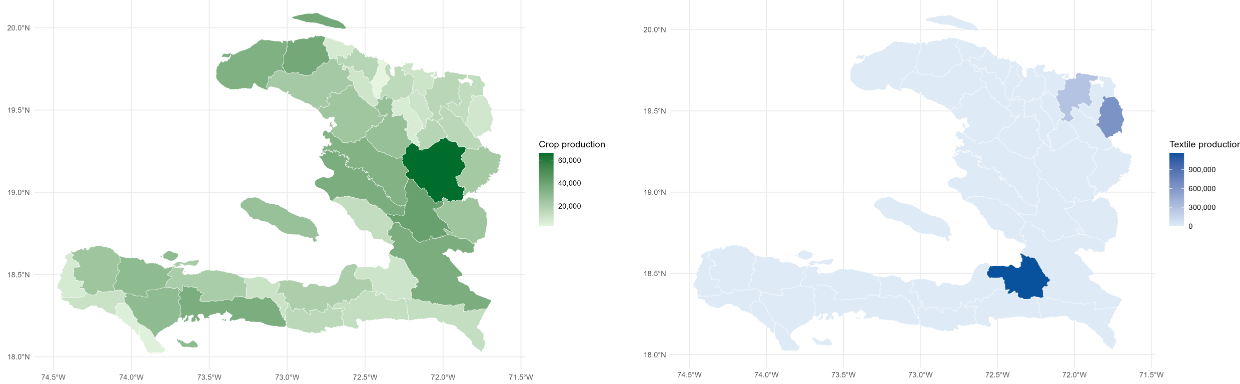
[28] Appendix A contains the description of other satellite data we use in extensions and additional robustness checks.

Figure 7: Time Series Evolution of Crop and Textile Production



Notes: This figure presents the time series evolution of the total annual crop and textile production for the period 2018 – 2022. Values are in USD -thousands- at constant prices of 2010. *Source:* GeoAdaptive (2024).

Figure 8: Heat Map of Spatial Distribution of Crop and Textile Production



(a) Crop Production

(b) Textile Production

Notes: This figure presents heat maps with the spatial distribution (arrondissement) of the total crop and textile production for the period 2018 – 2022. Values are in USD thousands at constant 2010 prices. *Source:* GeoAdaptive (2024).

4 Empirical Strategy

Our empirical strategy employs a quasi-experimental design to assess the causal impact of rising political and social violence on economic activity. The central hub of power in Haiti is Port-au-Prince, where escalating political turmoil has been mirrored by increasing gang violence as various groups vie for control of the capital. Consequently, violence has surged in Port-au-Prince to a much greater extent than in other regions. We take advantage of this geographical heterogeneity to compare the economic disruptions experienced in Port-au-Prince due to the spike in violence with those in other regions where gang presence is more reduced.

Most of the key variables in our dataset can be disaggregated at any of the following levels: *arrondissement*/*commune*-year, *arrondissement*/*commune*-year-month and *arrondissement*-year-month-day. Moreover, when focusing only on Facebook's BAT data, we can add business verticals (industries) as an additional level of analysis, thus we are able to examine the causal impacts of social conflict on economic activity for any *arrondissement*-business vertical pair. Given that Facebook's BAT data is available only for the period 2020 to 2022, we use it to capture short- and medium-term impacts. In contrast, Black Marble nighttime lights data is employed to assess medium- and long-term impacts, while annual crop and textile production figures are used solely to examine long-term effects. In our baseline specification, we estimate two-way fixed effects models to measure the short- (Equation 1), medium- (Equation 2), and long-term (Equation 3) impacts of social conflict as follows:

$$y_{ist} = \alpha_0 + \sum_{k=1}^{10} \alpha_k v_{it-k} + \sum_{k=1}^{10} \gamma_k \eta_{it-k} + \mu_{is} + \lambda_t + \epsilon_{ist} \tag{1}$$

$$y_{ist} = \alpha_0 + \sum_{k=1}^{5} \alpha_k v_{it-k} + \sum_{k=1}^{5} \gamma_k \eta_{it-k} + \mu_{is} + \lambda_t + \epsilon_{ist} \tag{2}$$

$$y_{it} = \alpha_0 + \alpha_1 v_{it-1} + \gamma_1 \eta_{it-1} + \mu_i + \lambda_t + \epsilon_{it} \tag{3}$$

Where y_{ist} is economic activity as measured either by nighttime lights, Facebook's BAT, crop production or textile production in *arrondissement* or *commune* i and time t (and business vertical s when Facebook data is used). In the short-term, t represents the triplet year–month–day. In the medium-term, t represents the pair year–month. In the long-term, t represents years. v_{it} is the number of events or fatalities in *arrondissement* or *commune* i at time t. The term $\eta_{i,t}$ shows up when we perform our heterogeneity analysis by event type, as it represents all the other events or fatalities in an *arrondissement* or *commune* i at time t not registered under the type of event of fatality being analyzed (ν_{it}).[29] When we analyze total events and total fatalities, $\eta_{i,t}$ is not included in the regressions. To avoid contemporaneous endogeneity issues and capture dynamic effects, events and fatalities only show up as lags. To determine the optimal lag structure in the short- and medium-terms, we use the Akaike Information Criteria (AIC), resulting in 10 and five lags, respectively (see Appendix C for the model selection based on the AIC). For the long-term analysis we only include one lag, given the length of our annual time series. In the short-term, the daily cumulative impact is given by $\alpha_1 + \alpha_2 + ... + \alpha_{10}$ (measuring the impact of a rise in events or fatalities at day t on economic activity over the following 10 days), whereas the monthly cumulative impact is expressed by $\alpha_1 + \alpha_2 + ... + \alpha_5$ (measuring the impact of a rise in events or fatalities at month t on economic activity over the following 5 months). μ_{is} are administrative area fixed effects (and administrative area-business vertical s when Facebook data is used) and λ_t are time fixed effects, both included to reduce the risk of omitted variable bias and to consider *arrondissement*-specific differences and aggregate changes over time. Standard errors ϵ_{ist} are clustered at the *arrondissement* or *commune* level (and arrondissement level-business vertical s when Facebook's BAT data is used).

We depart from our baseline specification to implement several extensions and robustness checks. To ensure that any observed changes in the outcome variables are not driven by pre-existing trends before events and fatalities, the robustness analysis includes a test for potential anticipation effects. Specifically, in our short-term specification we use 10 lead terms of ν_{it}, whereas in the medium-term analysis we incorporate up to five lead terms, and one lead in the long-term regressions. If the outcome variables exhibit a downward trend prior to the spike of violence, it would indicate that events and fatalities follow economic performance rather than drive it. We also explore alternative clusterisation for the standard errors. Acknowledging the influence of population density on the varying levels of recorded events and fatalities across *arrondissements* and *communes*, we introduce a specification that considers population weights. Specifically, we incorporate analytic weights, where the weights are determined by the proportion of the total population represented by each *arrondissement*. We also control for time-varying variables and dummy variables reflecting natural disasters to further reduce the risk of omitted variables bias. For the analysis using Facebook's BAT data, we run the baseline regression using only the business vertical "All", this robustness check allows us to assess whether our results are driven by sector-specific business verticals. Finally, given the relatively small number of *arrondissements*, we also compute wild cluster bootstrap

[29]We follow this approach to prevent that our estimates are affected by omitted variable bias.

tests to assess both individual and joint significance of estimated coefficients.[30]

5 Results

This section presents the baseline results for the short-, medium-, and long-term time frames, based on equations 1, 2, and 3, respectively. For the short- and medium-term impacts (sections 5.1 and 5.2), we present results based on BAT's activity quantiles, BM-NTL, and a heterogeneity analysis by violence type and BAT's business verticals. For the long-term (Section 5.3), the analysis focuses on shifts in crop and textile production and annual BM-NTL.

5.1 Short-term impacts

The analysis begins by assessing the short-term impact of violence on economic activity, using Facebook Business Activity Trends (BAT's activity quantiles, including all business verticals available in each *arrondissement*[31]) as a proxy, followed by an exploration of heterogeneity across types of violence and business verticals. Table 6 shows that violent events and fatalities significantly reduce economic activity, though the effects do not manifest immediately. Instead, the decline begins around three days after a violent incident. As can be seen, one additional violence event in a given *arrondissement* leads to a 0.3% decrease in activity quantile three days later. Similarly, one fatality results in a 0.1% reduction in the same time frame. The negative impact of events is more pronounced than that of fatalities. Starting from the third day after an incident, the negative effect of events intensifies, peaking six days after the event with a 0.6% reduction in activity. In contrast, the peak effect for fatalities remains more modest at 0.1%. Cumulatively, events cause a 3.1% drop in economic activity over a 10-days window, while fatalities are associated with only a 1% decline.

[30]We do not conduct a treatment heterogeneity analysis. The main reason is that our empirical setting does not follow the classical staggered-adoption difference-in-differences framework, since all violent events and fatalities are measured as a continuous, highly time-varying intensity that can increase, decrease, or return to zero in any commune/arrondissement and day/month/year. All spatial units are at risk of being affected by violence and, in the majority of our regressions, Port-au-Prince (the capital and *arrondissement* more affected by violence) has non-zero value for violent events since the beginning of the series. Thus, units do not transition from an untreated to a permanently treated state, and the heterogeneity concerns emphasized in the recent TWFE literature are less of an issue in our setting. Instead, we estimate a TWFE model with violence counts entered as a continuous regressor and interpret the coefficient as the average marginal effect of one additional violent event on economic activity, under the assumption that this marginal effect is homogeneous across units and over time.

[31]The average correlation coefficient between the business vertical "All" and the other verticals across all *arrondissements* equals 0.44. As a robustness check, we include the baseline regressions using only business vertical "All" in Appendix D.

Table 6: Short-term Effects of Violence on Activity Quantile (logs)

	Total events	*Total fatalities*
$v_{i,t-1}$	-0.001	-0.000
	(0.002)	(0.001)
$v_{i,t-2}$	-0.002	-0.000
	(0.002)	(0.000)
$v_{i,t-3}$	-0.003*	-0.001**
	(0.001)	(0.000)
$v_{i,t-4}$	-0.003**	-0.001**
	(0.001)	(0.000)
$v_{i,t-5}$	-0.004***	-0.001***
	(0.001)	(0.000)
$v_{i,t-6}$	-0.006***	-0.001***
	(0.001)	(0.000)
$v_{i,t-7}$	-0.005***	-0.001
	(0.002)	(0.000)
$v_{i,t-8}$	-0.004**	-0.001*
	(0.002)	(0.000)
$v_{i,t-9}$	-0.003*	-0.001*
	(0.002)	(0.000)
$v_{i,t-10}$	-0.001	-0.000
	(0.002)	(0.001)
$\sum_{k=1}^{10} v_{i,t-k}$	-0.031***	-0.007*
Wald test: p value	0.005	0.050
Observations	61,912	61,912
R-squared	0.457	0.457
Average Y	-0.977	-0.977
Av. X	0.418	0.381

Notes: This table reports coefficients from estimating equation (1), not including $\eta_{i,t}$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 10$ days. The row labelled $\sum_{k=1}^{10} v_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" is from a joint significance test of those ten lags. All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*–sector level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

5.1.1 Heterogeneity analysis by event type

Breaking down the effects by the type of violence, Table 7 shows that civil events are associated with a short-run increase in economic activity. This positive effect may reflect the nature of such events, which are often brief, localized, and can stimulate temporary surges in commercial and media-related activity. Moreover, since these events typically do not pose an immediate threat to production or infrastructure, businesses may continue operating normally or even experience short-lived increases in activity. In contrast, civil fatalities and political instability can quickly permeate the economic environment, affecting regular business operations, such as social media engagement. Specifically, political events lead to significant reductions in economic activity starting six days after their occurrence, with a 0.5% decline at that point. Political fatalities and civil fatalities show a statistically significant impact beginning three days post-incident. This reduction remains significant in subsequent days, indicating a sustained negative impact. When we distinguish by type of event, we find that in line with our previous results, protests and violence against civilians display negligible cumulative short-term effects on activity quantile (Table 8). For protests, no significant effects are found at any point in the following 10-day window.

By contrast, battles and riots show persistent and significant negative economic effects. Battles cause an immediate decline in business activity (approximately -1.3% the next day), which remains significant for several days. Riots begin to show a negative effect around day four, with the impact peaking at an estimated -1.6% on day eight. Strategic developments –events that offer context for actions and developments involving groups that, although not defined as political violence or protests, could impact future unrest or influence broader political dynamics– are the most economically damaging. Strategic developments often result in profound and sustained disruptions, especially when they alter access to or control of productive infrastructure. Their impact is immediate, persistent and severe, with a cumulative 10-day reduction of -15.1% in activity quantile. These findings highlight how the type and nature of violence influence the degree of economic disruption, with events involving collective chaos (battles and riots) or strategic intent (strategic developments) causing the most severe impacts on business activity.

Table 7: Short-term effects of violence on Activity Quantile (logs) by violence type

	Violence Type			
	Political Events	Civil Events	Political Fatalities	Civil Fatalities
$v_{i,t-1}$	-0.002	0.009*	-0.000	-0.001
	(0.004)	(0.005)	(0.001)	(0.001)
$v_{i,t-2}$	-0.001	0.008*	-0.000	-0.001
	(0.003)	(0.004)	(0.000)	(0.001)
$v_{i,t-3}$	-0.003	0.004	-0.001**	-0.002**
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t-4}$	-0.002	0.007*	-0.001**	-0.001
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t-5}$	-0.003	0.004	-0.001***	-0.002**
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-6}$	-0.005**	0.002	-0.001***	-0.001
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-7}$	-0.003	0.002	-0.001	0.000
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-8}$	-0.001	0.004	-0.001	0.000
	(0.003)	(0.003)	(0.000)	(0.001)
$v_{i,t-9}$	0.001	0.005	-0.001	0.000
	(0.003)	(0.003)	(0.000)	(0.001)
$v_{i,t-10}$	0.003	0.009**	-0.000	0.000
	(0.003)	(0.003)	(0.001)	(0.001)
$\sum_{k=1}^{10} v_{i,t-k}$	-0.017	0.053	-0.007**	-0.008
Wald test: p value	0.449	0.105	0.049	0.355
Observations	61,912	61,912	61,912	61,912
R-squared	0.457	0.458	0.460	0.457
Average Y	-0.977	-0.977	-0.977	-0.977
Av. X	0.238	0.140	0.373	0.127

Notes: This table presents the coefficient estimates of equation (1), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1,\dots,10$ days. The row $\sum_{k=1}^{10} v_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those ten lags. All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

Table 8: Event Type effect on Activity Quantile (in logs)

	Event Type				
	Battles	*Protests*	*Riots*	*Strategic Developments*	*Violence Against Civilians*
$v_{i,t-1}$	-0.013**	-0.005	0.008*	-0.020***	0.009*
	(0.005)	(0.007)	(0.004)	(0.007)	(0.005)
$v_{i,t-2}$	-0.008**	-0.002	0.001	-0.020***	0.008*
	(0.004)	(0.007)	(0.004)	(0.008)	(0.004)
$v_{i,t-3}$	-0.007**	0.004	-0.003	-0.017**	0.004
	(0.003)	(0.006)	(0.004)	(0.008)	(0.004)
$v_{i,t-4}$	-0.007**	0.004	-0.010***	-0.016*	0.007*
	(0.003)	(0.007)	(0.003)	(0.009)	(0.004)
$v_{i,t-5}$	-0.005	0.005	-0.012***	-0.016*	0.004
	(0.003)	(0.006)	(0.003)	(0.008)	(0.003)
$v_{i,t-6}$	-0.007**	0.005	-0.014***	-0.014*	0.002
	(0.003)	(0.006)	(0.003)	(0.008)	(0.003)
$v_{i,t-7}$	-0.005	0.006	-0.015***	-0.009	0.002
	(0.004)	(0.005)	(0.003)	(0.007)	(0.003)
$v_{i,t-8}$	-0.003	0.004	-0.016***	-0.012*	0.004
	(0.005)	(0.005)	(0.004)	(0.007)	(0.003)
$v_{i,t-9}$	-0.003	0.001	-0.012***	-0.016**	0.005
	(0.005)	(0.005)	(0.004)	(0.007)	(0.003)
$v_{i,t-10}$	-0.001	-0.004	-0.009**	-0.012*	0.009**
	(0.006)	(0.005)	(0.004)	(0.006)	(0.003)
$\sum_{k=1}^{10} v_{i,t-k}$	-0.059***	0.019	-0.081	-0.151***	0.053
Wald test: p value	0.000	0.379	0.117	0.000	0.553
Observations	61,912	61,912	61,912	61,912	61,912
R-squared	0.457	0.457	0.458	0.457	0.458
Average Y	-0.977	-0.977	-0.977	-0.977	-0.977
Av. X	0.0917	0.0648	0.0889	0.0326	0.140

Notes: This table presents coefficient estimates from equation (1), separately by event type at the most disaggregated level (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s, and day t (period July 2020 – November 2022). Column (1) shows the effect of lagged battles $v_{i,t-k}$; column (2), protests; column (3), riots; column (4), strategic developments; and column (5), violence against civilians, for $k = 1, \ldots, 10$ days. The row $\sum_{k=1}^{10} v_{i,s,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those ten lags. All regressions include sector– *arrondissement* and year–month fixed effects. Standard errors, clustered at the arrondissement level, are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

5.1.2 Heterogeneity analysis by sector

Tables 9 and 10 provide an analysis of the short-term effects of violence on activity quantile across various industries (business verticals). Table 9 presents the effects of total events, while

Table 10 displays the effects of total fatalities, with results shown over a ten-day period. We established a cutoff at 6,000 observations per business vertical to ensure that our analysis is based on robust and significant data pools. By excluding less represented sectors, this threshold enabled us to focus on the most economically represented industries (that collectively account for approximately 61% of the total observations in the dataset): “Public Good”, “Professional Services”, “Business & Utility Services”, and “Home Services”.

Some sectors are more vulnerable than others. The “Business & Utility Services” vertical shows minimal sensitivity to events, but a delayed reaction to fatalities. “Home Services” shows strong sensitivity to both events and fatalities, with reductions of up to -1.0%. Fatalities, in particular, cause a more immediate and persistent disruption, possibly due to the nature of services (driven by demand from individual events at home) and the perceived danger of operating in places where fatalities have recently occurred. In the “Professional Services” vertical, events cause relatively limited disruptions. The fact that these services are less reliant on on-the-ground mobility[32] protects them more from violent events compared to “Home Services”. Finally, “Public Good” services appear the most resilient, showing only weak and delayed effects in response to violence. Overall, the activity quantile metric captures reduced business engagement through Facebook posts, reflecting declines in business activity following violent events and fatalities.

[32]Due to the nature of professional activities, these type of services are normally provided by professionals with fixed locations, such as offices. Also, in case of disruption, these services are more prone to be performed remotely (see, for example, Dingel and Neiman (2020)).

Table 9: Heterogeneity with all events on Activity Quantile (in logs) by sector

	(1) Business & Utility Services	(2) Home Services	(3) Professional Services	(4) Public Good
$\nu_{i,t-1}$	0.002**	-0.001	-0.003	0.004
	(0.001)	(0.004)	(0.005)	(0.005)
$\nu_{i,t-2}$	-0.000	0.001	-0.001	0.003
	(0.002)	(0.003)	(0.005)	(0.005)
$\nu_{i,t-3}$	0.000	0.001	-0.003	0.001
	(0.002)	(0.002)	(0.005)	(0.005)
$\nu_{i,t-4}$	0.002	0.002	-0.003	0.000
	(0.001)	(0.002)	(0.007)	(0.005)
$\nu_{i,t-5}$	-0.001	-0.001	-0.006	-0.001
	(0.001)	(0.002)	(0.006)	(0.005)
$\nu_{i,t-6}$	-0.003	-0.006***	-0.008	-0.003
	(0.002)	(0.001)	(0.007)	(0.005)
$\nu_{i,t-7}$	-0.003	-0.007***	-0.009	-0.005
	(0.002)	(0.002)	(0.005)	(0.005)
$\nu_{i,t-8}$	-0.001	-0.009**	-0.007	-0.005
	(0.002)	(0.003)	(0.005)	(0.004)
$\nu_{i,t-9}$	-0.002	-0.008*	-0.007	-0.007
	(0.002)	(0.003)	(0.005)	(0.004)
$\nu_{i,t-10}$	0.002	-0.004	-0.006	-0.005
	(0.002)	(0.004)	(0.005)	(0.005)
$\sum_{k=1}^{10} \nu_{i,t-k}$	-0.002	-0.031	-0.053	-0.017
Wald test: p value	0.831	0.146	0.349	0.719
WB joint test: p value	0.563	0.750	0.773	0.980
Observations	6,104	5,232	6,976	7,848
R-squared	0.281	0.348	0.426	0.375
Average Y	-0.853	-1.016	-1.023	-0.706
Av. X	0.393	0.446	0.355	0.322

Notes: This table presents coefficient estimates from equation (1), not including $\eta_{i,t}$, by business vertical. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s, and day t (period July 2020 – November 2022). All columns reports the effects of lagged total events $\nu_{i,t-k}$, for $k = 1, \ldots, 10$ days. Columns (1)–(4) correspond to Business & Utility Services (regression includes 7 arrondissement), Home Services (regression includes 6 arrondissement), Professional Services (regression includes 8 arrondissement), and Public Good (regression includes 9 arrondissement), respectively. The row $\sum_{k=1}^{10} \nu_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those ten lags. "WB joint test: p-value" reports the Wild cluster bootstrap p-value from the joint significance test of those ten lags. All regressions include *arrondissement* and year–month fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 10: Heterogeneity with all fatalities on Activity Quantile (in logs) by sector

	(1) Business & Utility Services	(2) Home Services	(3) Professional Services	(4) Public Good
$\nu_{i,t-1}$	0.000	-0.003**	0.000	0.001
	(0.000)	(0.001)	(0.001)	(0.001)
$\nu_{i,t-2}$	0.000	-0.002***	0.000	0.001
	(0.000)	(0.001)	(0.001)	(0.001)
$\nu_{i,t-3}$	-0.000	-0.003***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\nu_{i,t-4}$	-0.000	-0.003***	-0.000	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)
$\nu_{i,t-5}$	-0.000	-0.003***	-0.001**	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)
$\nu_{i,t-6}$	-0.000	-0.002***	-0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)
$\nu_{i,t-7}$	0.000	-0.003***	-0.000	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)
$\nu_{i,t-8}$	-0.001**	-0.003***	-0.000	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
$\nu_{i,t-9}$	-0.002***	-0.003**	-0.000	-0.002***
	(0.000)	(0.001)	(0.000)	(0.001)
$\nu_{i,t-10}$	-0.001***	-0.002	0.000	-0.002*
	(0.000)	(0.001)	(0.000)	(0.001)
$\sum_{k=1}^{10} \nu_{i,t-k}$	-0.004	-0.026***	-0.003	-0.009
Wald test: p value	0.280	0.003	0.551	0.185
WB joint test: p value	0.313	0.719	0.430	0.086
Observations	6,104	5,232	6,976	7,848
R-squared	0.281	0.353	0.424	0.376
Average Y	-0.853	-1.016	-1.023	-0.706
Av. X	0.363	0.408	0.311	0.285

Notes: This table presents coefficient estimates from equation (1), not including $\eta_{i,t}$, by business vertical. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s, and day t (period July 2020 – November 2022). All columns reports the effects of lagged total fatalities $\nu_{i,t-k}$, for $k = 1, \ldots, 10$ days. Columns (1)–(4) correspond to Business & Utility Services (regression includes 7 arrondissement), Home Services (regression includes 6 arrondissement), Professional Services (regression includes 8 arrondissement), and Public Good (regression includes 9 arrondissement), respectively. The row $\sum_{k=1}^{10} \nu_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those ten lags. "WB joint test: p-value" reports the Wild cluster bootstrap p-value from the joint significance test of those ten lags. All regressions include *arrondissement* and year–month fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

5.2 Medium-term impacts

The next step in our analysis is to disentangle the medium-term effects of social conflict on economic activity. A key novelty of this section is the inclusion of NASA's Black Marble Nighttime Lights (NTL) data as an additional proxy of economic activity. NTL are strongly correlated with infrastructure, urbanization, and energy consumption, providing an alternative lens through which we can assess the economic disruption caused by violence in Haiti.

As in Section 5.1, we start by analyzing the relationship between violence and BAT's activity quantile. Table 11 shows that total events have a significant and negative impact over a five-month horizon.

Table 11: Medium-term effects of violence on Activity Quantile (logs)

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t-1}$	-0.003**	-0.000**
	(0.001)	(0.000)
$v_{i,t-2}$	0.001	-0.001*
	(0.001)	(0.000)
$v_{i,t-3}$	-0.002***	-0.002***
	(0.001)	(0.000)
$v_{i,t-4}$	-0.005***	-0.001**
	(0.001)	(0.001)
$v_{i,t-5}$	-0.005***	-0.001***
	(0.001)	(0.000)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.015***	-0.005***
Wald test: p value	0.003	0.001
Observations	1,704	1,704
R-squared	0.648	0.657
Average Y	-0.977	-0.977
Av. X	12.94	12.38

Notes: This table reports coefficients from estimating equation (2), not including $\eta_{i,t}$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*–sector level, are in parentheses. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

Specifically, one additional violent event in an *arrondissement* decreases Facebook posting behavior by 0.3% after one month. While the effect dips in the second month, it returns and remains significantly negative in the third through fifth months. The cumulative five-months effect of an event on business' social media engagement is approximately -1.5%. Fatalities also have negative effects that emerge in the first month, but these are smaller in magnitude than those of total events. Notably, the negative medium-term impact of total events on activity quantile is smaller than the short-term effect (see Table 6). A plausible explanation to this is that social conflict initially causes mobility restrictions and business closures, which ease over time as producers and consumers adapt to the new conditions.

NTL data reveal a stronger and quicker response to violence than social media engagement (Table 12). One additional violent event in an *arrondissement* reduces NTL by almost 1.5% in the month following its occurrence, with effects tepering off in subsequent months. Fatalities exhibit a more persistent effect, with only the fourth lag being not statistically significant in the five-months window.

Table 12: Medium-term effects of violence on Nighttime Lights (logs)

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t-1}$	-0.015***	-0.007***
	(0.003)	(0.001)
$v_{i,t-2}$	-0.010***	-0.005***
	(0.003)	(0.001)
$v_{i,t-3}$	-0.011***	-0.004***
	(0.002)	(0.001)
$v_{i,t-4}$	-0.002	-0.002
	(0.004)	(0.002)
$v_{i,t-5}$	-0.007	-0.006**
	(0.005)	(0.003)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.045***	-0.025***
Wald test: p value	0.002	0.002
Observations	3,015	3,015
R-squared	0.869	0.869
Average Y	3.982	3.982
Av. X	1.725	1.395

Notes: This table reports coefficients from estimating equation (2), not including $\eta_{i,t}$. The dependent variable is the log of nighttime lights $Y_{i,t}$ in *commune* i and month t (period January 2018 – December 2023). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. All specifications include *commune* and year–month fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

This difference may reflect how NTL captures immediate business closures, electricity supply disruptions and reduced business hours that respond faster to violence than social media behavior (Facebook posting activities might also be prone to delays inherent in human data processing and social media activity reporting). The cumulative effects are more pronounced when examining NTL, with each additional event linked to a 4.5% decline in economic activity and each additional fatality associated with a 2.5% decrease.

5.2.1 Heterogeneity analysis by event type

When distinguishing by type of violence, civil events –while not impactful in the short term– exhibit substantial medium-term effects (see Table 13). This suggests that although isolated incidents may be manageable, sustained civil unrest increases uncertainty and operational difficulties, leading to more substantial economic disruption. Political events and civil events reduce economic activity starting three months after their occurrence. Moreover, for 10 additional deaths related to political events, economic activity as measured by activity quantile decreases by 6%.

Table 13: Medium-term effects of violence on Activity Quantile (logs)

	(1) Political Events	(2) Civil Events	(3) Political Fatalities	(4) Civil Fatalities
$v_{i,t-1}$	0.003**	0.003	-0.001***	-0.000
	(0.001)	(0.003)	(0.000)	(0.001)
$v_{i,t-2}$	-0.000	-0.002	-0.001*	0.001
	(0.001)	(0.002)	(0.000)	(0.001)
$v_{i,t-3}$	-0.007***	-0.009***	-0.002***	0.001
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-4}$	-0.009***	-0.012**	-0.001*	0.004*
	(0.002)	(0.005)	(0.000)	(0.002)
$v_{i,t-5}$	-0.001	-0.004	-0.002***	0.000
	(0.003)	(0.004)	(0.000)	(0.001)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.015***	-0.025*	-0.0062***	0.005
Wald test: p value	0.009	0.089	0.000	0.145
Observations	1,704	1,704	1,704	1,704
R-squared	0.666	0.656	0.666	0.663
Average Y	-0.977	-0.977	-0.977	-0.977
Av. X	7.529	4.323	12.13	3.987

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Disaggregating by violence type (see Table 14), all forms of violence (except for civil events) negatively affect NTL in the month immediately following an event, with political events showing particularly strong and persistent effects. The cumulative five-month NTL impact of political events is approximately –6.2%, making them the most economically damaging in the medium term.

Table 14: Medium-term effects of violence on Nighttime Lights (logs)

	(1) Political Events	(2) Civil Events	(3) Political Fatalities	(4) Civil Fatalities
$v_{i,t-1}$	-0.019***	-0.016	-0.007***	-0.008***
	(0.004)	(0.011)	(0.001)	(0.002)
$v_{i,t-2}$	-0.013***	-0.017	-0.005***	-0.008**
	(0.004)	(0.012)	(0.001)	(0.004)
$v_{i,t-3}$	-0.012***	-0.011*	-0.004***	-0.006**
	(0.003)	(0.006)	(0.001)	(0.003)
$v_{i,t-4}$	-0.006	-0.002	-0.003	-0.005
	(0.004)	(0.011)	(0.002)	(0.003)
$v_{i,t-5}$	-0.012**	-0.012	-0.007**	-0.011**
	(0.006)	(0.008)	(0.003)	(0.005)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.062***	-0.058	-0.025***	-0.040**
Wald test: p value	0.000	0.163	0.001	0.017
Observations	3,015	3,015	3,015	3,015
R-squared	0.869	0.869	0.869	0.869
Average Y	3.982	3.982	3.982	3.982
Av. X	0.891	0.496	1.325	0.553

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *commune* i, and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *commune* and year–month fixed effects. Standard errors are clustered at the *commune* level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

We also examine the effects of specific event types. Table 15 shows that protests and riots have an immediate negative impact the month after the incident, but these effects are short-lived. Note the change in the sign of the impact for protests, with the effect turning positive in the fourth and fifth lags. While this is a counter-intuitive result, it might be signaling the fact that businesses adapt to operate during protest after experiencing a decrease in their activity. For instance, after a negative reaction, businesses might be taking advantage of the temporary agglomeration of people, as these gatherings might provide business opportunities to formal and informal vendors as well as transport operators. Something similar could explain the sign changes for riots, which display a non-linear pattern: early negative effects followed by a temporary rebound, but ultimately a non-significant cumulative decline.

Table 15: Event Type effect on Activity Quantile (in logs)

	(1) *Battles*	(2) *Protests*	(3) *Riots*	(4) *Strategic Developments*	(5) *Violence Against Civilians*
$v_{i,t-1}$	0.000	-0.016***	-0.009***	-0.015**	0.003
	(0.002)	(0.005)	(0.002)	(0.006)	(0.003)
$v_{i,t-2}$	0.003	-0.005	0.001	0.000	-0.002
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
$v_{i,t-3}$	-0.007***	0.000	0.005**	0.006	-0.009***
	(0.003)	(0.005)	(0.002)	(0.005)	(0.003)
$v_{i,t-4}$	-0.008**	0.013**	0.000	-0.014***	-0.012**
	(0.003)	(0.006)	(0.002)	(0.004)	(0.005)
$v_{i,t-5}$	-0.015***	0.021***	-0.002	-0.008	-0.004
	(0.003)	(0.006)	(0.002)	(0.005)	(0.004)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.028***	0.015	-0.005	-0.031**	-0.024*
Wald test: p value	0.007	0.257	0.317	0.016	0.089
Observations	1,704	1,704	1,704	1,704	1,704
R-squared	0.659	0.665	0.656	0.651	0.656
Average Y	-0.977	-0.977	-0.977	-0.977	-0.977
Av. X	3.012	1.830	2.711	1.064	4.323

Notes: This table presents coefficient estimates from equation (2), separately by event type at the most disaggregated level (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s, and month t (period July 2020 – November 2022). Column (1) shows the effect of lagged battles $v_{i,t-k}$; column (2), protests; column (3), riots; column (4), strategic developments; and column (5), violence against civilians, for $k = 1, \ldots, 5$ months. The row $\sum_{k=1}^{10} v_{i,s,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *arrondissement*-sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*-sector level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Strategic developments also have immediate negative effects on economic activity, which deepen during the second and third months before reemerging in the fourth month. Over the five-month time window, strategic developments display a large overall negative impact on economic activity. Finally, the adverse effects of battles and violence against civilians emerge with a lag of approximately three months following the occurrence of such events, both resulting in cumulative negative impacts of between 2.54% and 2.80%.

Table 16: Event Type Effect on Nighttime Lights (in logs)

	(1) *Battles*	(2) *Protests*	(3) *Riots*	(4) *Strategic Developments*	(5) *Violence Against Civilians*
$v_{i,t-1}$	-0.025**	0.006	0.000	-0.042***	-0.016
	(0.010)	(0.013)	(0.007)	(0.015)	(0.011)
$v_{i,t-2}$	-0.011	0.013	0.003	-0.031***	-0.017
	(0.008)	(0.014)	(0.009)	(0.010)	(0.012)
$v_{i,t-3}$	-0.018**	0.004	0.004	-0.050***	-0.011*
	(0.007)	(0.013)	(0.007)	(0.015)	(0.006)
$v_{i,t-4}$	-0.014**	0.014	0.011	-0.009	-0.002
	(0.006)	(0.011)	(0.008)	(0.024)	(0.011)
$v_{i,t-5}$	-0.021***	-0.010	0.015***	-0.008	-0.012
	(0.007)	(0.012)	(0.005)	(0.023)	(0.008)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.089***	0.028	0.033	-0.141**	-0.058
Wald test: p value	0.000	0.532	0.248	0.016	0.163
Observations	3,015	3,015	3,015	3,015	3,015
R-squared	0.869	0.869	0.870	0.870	0.869
Average Y	3.982	3.982	3.982	3.982	3.982
Av. X	0.323	0.337	0.411	0.158	0.496

Notes: This table presents coefficient estimates from equation (2), separately by event type at the most disaggregated level (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *commune* i and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged battles $v_{i,t-k}$; column (2), protests; column (3), riots; column (4), strategic developments; and column (5), violence against civilians, for $k = 1, \ldots, 5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *commune* and year–month fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

In contrast, the NTL response to battles and strategic developments is both immediate and sustained (Table 16). These events cause reductions in radiance starting the month after occurrence, suggesting immediate shutdowns in electricity use and physical activity. Moreover, the cumulative negative impact after five months of occurrence revolves around 9% to 14%. Protests and riots, however, show no significant negative effect on NTL, highlighting the difference between social engagement metrics and physical infrastructure disruptions. This difference may stem from the fact that the activity quantile reflects posting behavior driven by the identification of market opportunities, which can emerge or disappear in response to riots and protests.

5.2.2 Heterogeneity analysis by sector

Sectoral analysis reveals important differences in medium-term vulnerability (Table 17). "Business & Utility Services" and "Professional Services" register clear cumulative negative effects five months following the occurrence of violent events.

Table 17: Heterogeneity with all events on Activity Quantile (in logs) by sector

	(1) Business & Utility Services	(2) Home Services	(3) Professional Services	(4) Public Good
$\nu_{i,t-1}$	-0.000	-0.005	-0.008***	0.001
	(0.004)	(0.004)	(0.001)	(0.004)
$\nu_{i,t-2}$	0.001	-0.002	-0.001	0.001
	(0.002)	(0.001)	(0.002)	(0.002)
$\nu_{i,t-3}$	-0.007***	-0.001	-0.002	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)
$\nu_{i,t-4}$	-0.007**	-0.006	-0.008***	-0.003
	(0.002)	(0.003)	(0.002)	(0.003)
$\nu_{i,t-5}$	-0.006	-0.009	-0.006**	0.000
	(0.004)	(0.004)	(0.002)	(0.004)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.020*	-0.023	-0.024**	-0.002
WB joint test: p value	0.063	0.219	0.031	0.602
Observations	168	144	192	216
R-squared	0.566	0.545	0.707	0.625
Average Y	-0.866	-1.010	-1.004	-0.683
Av. X	12.22	13.90	11.04	10.03

Notes: This table presents coefficient estimates from equation (2), not including $\eta_{i,t}$, by business vertical. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s, and month t (period July 2020 – November 2022). All columns reports the effects of lagged total events $\nu_{i,t-k}$, for $k = 1, \ldots, 5$ months. Columns (1)–(4) correspond to Business & Utility Services (regression includes 7 arrondissement), Home Services (regression includes 6 arrondissement), Professional Services (regression includes 8 arrondissement), and Public Good (regression includes 9 arrondissement), respectively. The row $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "WB joint test: p-value" reports the Wild cluster bootstrap p-value from the joint significance test of those five lags. All regressions include *arrondissement* and year–month fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

"Public Good" services remain largely unaffected—likely due to their essential nature of public services, which are tried to be kept running even during periods of instability with the aim of maintaining some level of institutional continuity.

Table 18: Heterogeneity with All Fatalities on Activity Quantile (in logs) by sector

	(1) Business & Utility Services	(2) Home Services	(3) Professional Services	(4) Public Good
$v_{i,t-1}$	-0.001***	-0.001	-0.001***	0.001
	(0.000)	(0.000)	(0.000)	(0.001)
$v_{i,t-2}$	-0.001***	-0.002***	-0.001*	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$v_{i,t-3}$	-0.003***	-0.003***	-0.001**	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
$v_{i,t-4}$	-0.001***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.001)	(0.000)	(0.000)
$v_{i,t-5}$	-0.001*	-0.000	-0.002**	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.006	-0.008	-0.007**	-0.004
WB joint test: p value	0.203	0.281	0.0391	0.203
Observations	168	144	192	216
R-squared	0.539	0.588	0.706	0.650
Average Y	-0.866	-1.010	-1.004	-0.683
Av. X	12.02	13.23	10.08	9.463

Notes: This table presents coefficient estimates from equation (2), not including $\eta_{i,t}$, by business vertical. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s, and month t (period July 2020 – November 2022). All columns reports the effects of lagged total fatalities $v_{i,t-k}$, for $k = 1, \ldots, 5$ months. Columns (1)–(4) correspond to Business & Utility Services (regression includes 7 arrondissement), Home Services (regression includes 6 arrondissement), Professional Services (regression includes 8 arrondissement), and Public Good (regression includes 9 arrondissement), respectively. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "WB joint test: p-value" reports the Wild cluster bootstrap p-value from the joint significance test of those five lags. All regressions include *arrondissement* and year–month fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Fatalities follow a similar pattern. "Professional Services" register a persistent negative impact on activity quantile following fatalities, which amounts to a cumulative reduction of approximately 1.0% in the next five months after occurrence. For "Home Services" and "Public Good" the medium-term impacts on specific lags are more notorious than in the short term. However, for both sectors the cumulative impact of fatalities in activity quantile is not statistically significant (WB joint test), reinforcing the point, in the case of "Public Good", of the need of maintaining some level of institutional continuity.

Overall, our medium-term analysis confirms that events are the most disruptive expressions of social unrest, in line with what we observed in the short-term. While civil events may not appear highly disruptive in the short term, their recurrence over several months can gradually erode the business environment, resulting in notable medium-term impacts. Importantly, the use of NTL offers complementary insight, highlighting how violence quickly affects a different facet of business activity. Indeed, NTL reacts quicker to violence-related disruptions than activity quantile, likely due to the nature of radiance emissions, which reflect business closures, electricity supply disruptions, and reduced operating hours.

5.3 Long-term impacts

The next step is to examine the long-term impacts of different types of violence on economic activity. We rely on NASA's Nightime Lights (NTL) from 2018 to 2023, complemented by *commune* level real crop and textile production figures covering the period 2018–2022.[33] The first set of results is presented in Table 19. Panel A and B present the results taking real crop and textile production in levels, as the two variables alone have an important number of zeros in the pair *commune*-year. To facilitate the interpretation, the series are then standardized by expressing them in terms of standard deviations. Table 19 shows that total events do not have a long-term impact on crop production. However, fatalities do have a significant and negative impact: for every additional fatality in an *commune*, crop production decreases by 0.001 standard deviations. In terms of agriculture activities, fatalities might be perceived as an explicit signal of public order breakdown, leading to population displacements in the affected areas. This, in turn, can lead to labor shortages and the abandonment of agricultural land. In contrast, events –possibly perceived as less immediately threatening–do not carry the same weight in signaling a breakdown of local order.

In the case of real textile production, both total events and fatalities do not have a significant impact. Panel C of Table 19 also includes the logarithm of total real production (sum of total crop and textile production in USD). In both cases there is a reduction, where both events and fatalities negatively impact real production in the long-term. Finally, panel D shows that NTL are more sensible to events than fatalities, where one additional event in an *commune* decreases NTL radiance in 1% the next year. Note that the long-run impact on NTL is smaller than the cumulative effect observed over the five-month period after an event in our medium-term analysis.

[33] We do not include Facebook's BAT in this analysis, as we have only three years in the time series.

Table 19: Long-term Effects of Violence on Economic Activity

	Violence type	
	Total events	*Total fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)		
Events last year	-0.001	-0.001*
	(0.001)	(0.001)
Observations	484	484
R-squared	0.993	0.993
Average Y	-0.0234	-0.0234
Av. X	6.320	5.140
Panel B: Real Textile Production (effect sizes in standard deviations)		
Events last year	-0.015	-0.004
	(0.010)	(0.004)
Observations	484	484
R-squared	0.952	0.944
Average Y	-0.0164	-0.0164
Av. X	6.320	5.140
Panel C: Total Real Production (in logs)		
Events last year	-0.005***	-0.002***
	(0.002)	(0.001)
Observations	484	484
R-squared	0.997	0.997
Average Y	7.162	7.162
Av. X	6.320	5.140
Panel D: Nighttime Lights (in logs)		
Events last year	-0.010***	-0.007**
	(0.002)	(0.003)
Observations	210	210
R-squared	0.933	0.934
Average Y	4.022	4.022
Av. X	15.46	12.25

Notes: This table reports coefficients from estimating equation (3), not including $\eta_{i,t}$. The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *commune* i and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. All specifications include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

5.3.1 Heterogeneity analysis by event type

Now we turn our attention to our analysis by event type. Panel A shows that crop production is mostly affected by civil and political fatalities. Panel B shows that real textile production at the *commune*-level is not being affected by increasing levels of violence. This might suggests that the effects of violent events are localized disruptions that this sector can absorb relatively quickly. However, when we add both types of production we observe that political events and political fatalities occurred the previous year have a significant and negative impact on total real production in the current year. This impact ranges from 0.2% to 0.5% decrease in total real production per one unit increase in political fatalities and political events, respectively. In line with the medium-term results, this panel confirms that political related violence tend to have the highest disruption capacity on economic activity. Finally, Panel D contains the long term impact of events and fatalities on NTL. Interestingly, the results align quite well with the long-term impacts of political events and related fatalities identified in total real production.

In Table 21 we also present the heterogeneity analysis by type of event. For crop production we do not identify significant impacts a year after the occurrence of these different types of violent events. For textile production, strategic development event decreases production by 0.044 standard deviations. While strategic development also have a significant negative impact on total real production, riots also affect real production in the year immediately after. Interestingly, when violent events are analyzed separately by type, the estimates reveal no statistically significant effects on NTL one year after their occurrence. This pattern suggests that disaggregated event categories may primarily capture localized or transitory disturbances whose economic repercussions dissipate relatively quickly. By contrast, when events are aggregated, the combined or interacting effects of different forms of violence (whether occurring concurrently or in succession) may give rise to broader and more persistent disruptions in economic activity, which become statistically discernible only at higher levels of aggregation.

Table 20: Long-term effects of violence on economic activity

	Violence type			
	Political Events	*Civil Events*	*Political Fatalities*	*Civil Fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)				
Events last year	-0.002	-0.004	-0.001*	-0.002***
	(0.002)	(0.003)	(0.001)	(0.001)
Observations	484	484	484	484
R-squared	0.993	0.993	0.993	0.993
Average Y	-0.0234	-0.0234	-0.0234	-0.0234
Av. X	3.112	1.729	4.907	2.041
Panel B: Real Textile Production (effect sizes in standard deviations)				
Events last year	-0.009	-0.007	-0.004	-0.008
	(0.009)	(0.012)	(0.005)	(0.010)
Observations	484	484	484	484
R-squared	0.953	0.953	0.946	0.944
Average Y	-0.016	-0.016	-0.016	-0.016
Av. X	3.112	1.729	4.907	2.041
Panel C: Total Real Production (in logs)				
Events last year	-0.005**	-0.005	-0.002***	-0.001
	(0.002)	(0.004)	(0.001)	(0.002)
Observations	484	484	484	484
R-squared	0.997	0.997	0.997	0.997
Average Y	7.162	7.162	7.162	7.162
Av. X	3.112	1.729	4.907	2.041
Panel D: Nighttime Lights (in logs)				
Events last year	-0.011***	-0.016*	-0.007**	-0.007
	(0.004)	(0.009)	(0.003)	(0.007)
Observations	210	210	210	210
R-squared	0.933	0.933	0.934	0.934
Average Y	4.022	4.022	4.022	4.022
Av. X	7.843	4.352	11.57	5.290

Notes: This table presents the coefficient estimates of equation (3), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *commune* i, and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. All regressions include *commune* and year fixed effects. Standard errors are clustered at the *commune* level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table 21: Heterogeneity of long-term effects by event type

	Event type				
	Battles	*Protests*	*Riots*	*Strategic Developments*	*Violence against civilians*
Panel A: Agriculture Production Real (effect sizes in standard deviations)					
Events last year	-0.001	0.001	0.001	-0.005	-0.004
	(0.004)	(0.005)	(0.002)	(0.004)	(0.003)
Observations	484	484	484	484	484
R-squared	0.993	0.993	0.993	0.993	0.993
Average Y	-0.0234	-0.0234	-0.0234	-0.0234	-0.0234
Av. X	1.188	1.430	1.607	0.366	1.729
Panel B: Textile Production Real (effect sizes in standard deviations)					
Events last year	0.008	-0.008	-0.031	-0.044*	-0.007
	(0.014)	(0.013)	(0.019)	(0.023)	(0.012)
Observations	484	484	484	484	484
R-squared	0.954	0.953	0.954	0.953	0.953
Average Y	-0.016	-0.016	-0.016	-0.016	-0.016
Av. X	1.188	1.430	1.607	0.366	1.729
Panel C: Total real production (in logs)					
Events last year	-0.005	0.000	-0.004*	-0.025***	-0.005
	(0.005)	(0.003)	(0.002)	(0.004)	(0.004)
Observations	484	484	484	484	484
R-squared	0.997	0.997	0.997	0.997	0.997
Average Y	7.162	7.162	7.162	7.162	7.162
Av. X	1.188	1.430	1.607	0.366	1.729
Panel D: Nighttime Lights (in logs)					
Events last year	-0.016	-0.018	0.003	0.003	-0.016*
	(0.011)	(0.013)	(0.006)	(0.033)	(0.009)
Observations	210	210	210	210	210
R-squared	0.933	0.933	0.934	0.933	0.933
Average Y	4.022	4.022	4.022	4.022	4.022
Av. X	2.748	3.233	3.781	1.343	4.352

Notes: This table presents coefficient estimates from equation (3), separately by event type at the most disaggregated level (coefficients γ_k are not presented in this table). The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *commune* i and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Column (1) shows the effect of one year lag of battles $v_{i,t-k}$; column (2), protests; column (3), riots; column (4), strategic developments; and column (5), violence against civilians. All regressions include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

6 Robustness Checks

This section presents a series of robustness checks and extensions designed to assess the reliability and consistency of our main results. We begin with short-term analyses that focus exclusively on Facebook's Business Activity Trends (BAT) quantiles to capture immediate effects. The medium-term analysis expands on this by incorporating both BAT and nighttime lights (NTL) data. Finally, the long-term robustness checks focus on NTL and observed trends in real crop and textile production, providing additional validation to effects on physical economic output indicators.

6.1 Short-term

To ensure that observed changes in the outcome variables are not driven by pre-existing trends prior to events and fatalities, the robustness analysis includes a test for potential anticipation effects. Table D.1 presents results from an exercise where we add 10 leads to our daily baseline specification. For total events, none of the lead terms are statistically significant, confirming the absence of anticipation effects. This is further confirmed by the anticipation effect coefficient reported at the bottom of Table D.1, which is not statistically different from zero, indicating that the forward coefficients are jointly not statistically different from zero. In the case of total fatalities, four lead terms appear individually statistically significant. Although significant, these early leads are positive in direction, opposite to the subsequent negative effects. Moreover, the sum of anticipation effects indicates that, collectively, there is no statistically significant evidence of anticipation effects in the 10 days leading up to a violent incident involving a fatality.

To control for time-varying confounders and environmental shocks that may bias our estimates, we augment our baseline specification with a series of covariates. These additional controls are intended to capture factors that vary within geographical units over time and could confound the relationship between conflict and economic outcomes. Specifically, we include Land Surface Temperature, Precipitation, Reach of Health Services, Reach of Education Services, and two dummy variables indicating the occurrence of recent natural disasters in Haiti. Table D.2 shows that none of these additional covariates affects our baseline results, confirming their robustness.

To account for potential spatial correlation in the error term, we re-estimate our model clustering standard errors at the department level. This approach will help us avoid potential biases arising from within-cluster dependence at finer levels. The results of this exercise are presented in Table D.3. In general terms, these results go in the same direction as our baseline conclusions. However, the different clustering makes the first seven lags of both total events and total fatalities become statistically significant at the 1% level, compared to the 5% level in our original specification.

To account for the role of population density on the variation in recorded events and fatalities across *arrondissements*, we introduce a specification that incorporates population-based weights. Specifically, each *arrondissement* is weighted by analytic weights, where the weights correspond to the population of each *arrondissement* in 2020. The results of this exercise are presented in Table D.4. The findings remain consistent with our baseline results, indicating that the inclusion of population density does not alter the main conclusions and thus supports their robustness. In our baseline specification, we include all business verticals available for a given *arrondissement*. To assess the robustness of our findings, Table D.5 reports results obtained when restricting the analysis to the aggregate business vertical "All." The results show that our baseline conclusions remain unchanged. Finally, given the number of *arrondissements* (23) included in our baseline, one might worry that standard errors can be downward biased leading to over-rejection of the null hypothesis. To account for this, in Table D.6 we re-estimate our baseline specification using wild cluster bootstrap procedures to test for both individual and joint significance. The results confirm that our main findings are robust, as the significance levels of the coefficients remain largely unchanged.

We also replicate the six robustness checks described above for the cases where we focus specifically on political and civil events, as well as the associated fatalities. First, when we add the ten leads to the baseline specifications (see Table D.7), we observe that the lead terms are not jointly statistically significant for political events, political fatalities and civil fatalities, as shown by the sum of anticipation coefficients and its corresponding significance level. In contrast, for civil events, there is evidence of anticipations effects, as indicated by individual leads and jointly significance level. The anticipation effects are positive, indicating that civil events tend to increase where economic activity is at least temporarily improving, but after civil events occur, there are no significant changes in economic activity, as in our baseline. When we add control variables (Table D.8), we observe that they do not significantly alter our baseline results. Note that when we change the clustering to a higher spatial aggregation–departments–, the majority of the coefficients turn to be statistically significant, all showing negative and persistent impacts on economic activity, as measured by the activity quantile. Applying population weights does not significantly alter our baseline results (see Table D.10). In addition, using only the business vertical "All" (Table D.11) and using wild cluster bootstrap significance tests (Table D.12) does not change our conclusions.

6.2 Medium-term

The robustness checks for the medium term mirror those applied to the short-term, with the main difference being the inclusion of NTL in the medium-term analysis. We start by implementing our sensitivity analysis to activity quantile. First, we introduce forward terms into our baseline regressions to test for anticipatory effects. Results are reported in Table D.13. In the case of total events and total fatalities, one lead is significant (at 10% and 1%, respectively); however, the cumulative effect of all anticipation terms is not statistically significant. Therefore, we can rule out reverse causality between total events or fatalities and economic activity. The second robustness check involves adding control variables to our baseline specification, as shown in Table D.14. The results indicate that our baseline findings remain robust to the inclusion of additional covariates. Among these, only the estimated coefficients for land surface temperature, the lag of the 2021 earthquake indicator and floods are statistically significant.

In the third set of robustness checks (presented in Table D.15), we cluster the standard errors at the department level instead of the *arrondissement* level. As in the short run, the change in the clustering leaves our main conclusions unchanged: both events and fatalities continue to negatively affect Facebook posting behavior, reflecting their impacts on economic activity. We apply analytic weights to our baseline regression to account for the differences in population, as presented in Table D.16. The results remain robust under this modification. In Table D.17 we restrict the sample of our baseline regressions to observations corresponding to business vertical "All." The results are consistent with our baseline estimates, confirming the robustness of our findings. Finally, running wild cluster bootstrap test for individual and joint significance (Table D.18) does not change our conclusions. We also perform the same type of robustness checks for civil and political events and related fatalities, with results presented in Tables D.19 to D.24. These robustness checks further confirm that the conclusions drawn from our baseline remain generally unchanged.

We also conduct medium-term robustness checks on our results using NTL. Table D.25 tests for anticipatory effects in our baseline results. While the first and fourth forward terms for total events are statistically significant, the cumulative impact of all the leads taken together is not, allowing us to rule out anticipatory effects in this case. However, for total fatalities, both the individual forward terms and the cumulative five-month anticipation term are statistically significant. This means that we cannot rule out reverse causality between fatalities and economic activity as measured by NTL.The second robustness check with NTL adds control variables to the baseline specification. Table D.26 shows that our conclusions for total events hold. Clustering standard errors at the *arrondissement* level instead of *commune* (Table D.27) improves the significance level for all lags, making each individual lag statistically significant. If anything, this sensitivity test reinforces our conclusions. Adding population as analytic weight does not quantitatively alter our results (Table D.28).

We also perform our sensitivity tests for political and civil events and related fatalities. Table D.29 confirms that there are no anticipation effects when it comes to civil events, although we confirm their existence for political events, political fatalities and civil fatalities. The presence of anticipation effects for fatalities and political events, but not for civil events, may reflect that fatalities are a clearer signal of serious instability, prompting preemptive responses, whereas the impact of events is harder to predict in advance. In the same line, political events are typically preceded by periods of heightened uncertainty, increased public mobilization, and media coverage, which may prompt firms to scale down their productive activities. By contrast, civil events are generally more localized and less foreseeable, reducing agents' ability and incentive to engage in anticipatory adjustments in economic activity. Finally, the inclusion of covariates and adjustment to more aggregated clustering levels do not alter our main conclusions.

6.3 Long-term

We finish this section by performing robustness checks to our long-term results. Here we focus on the following tests: analyzing the results for events and fatalities and event types, adding leads, adding covariates, clustering standard errors at the *arrondissement* level and using analytic weights corresponding to the population of each *commune* in 2020. Table D.33 shows that when we include one lead in our long-term regressions, we find no evidence of anticipation effects for either total events or total fatalities. Results contained in Table D.34 to D.37 and from Table D.41 to D.44 show that adding control variables do not generally alter our conclusions (however the coefficients for total fatalities become no statistically significant for real agriculture and total real production). Total real production seems to be more sensitive to events, whereas NTL are negatively affected by all the types of violence considered. Table D.38 and D.45 contain our baseline results when we cluster at the level of *arrondissement* instead of *commune*. With the exception of crop production, using a more aggregated clustering level for standard errors leaves our results largely unchanged, if anything it increases the number of coefficients that are statistically significant. Finally, Tables D.39 and D.46 confirm that our results are generally robust when accounting for differences in population size across *communes* (as in the case of adding control variables, here the coefficients of total fatalities for crop and total real production become no statistically significant).

7 Conclusion

This paper sheds light on the significant and lasting economic effects of rising political instability and social conflict in Haiti. We apply a two-way fixed effects approach to highly granular data—combining Facebook's Business Activity Trends with NASA's nighttime lights and other satellite imagery—to estimate the local economic impact of social conflict in a context where conventional economic data are scarce. This approach allows us to monitor subnational economic activity with high frequency and spatial precision, offering new insights into how conflict affects fragile economies. Our identification strategy exploits temporal and spatial variation in conflict exposure across *arrondissements*, comparing areas with differing intensities of unrest before and after episodes of violence. By controlling for time and subnational fixed effects, we isolate the localized impact of social conflict on economic activity.

The results indicate that conflict leads to large and persistent reductions in economic activity, particularly in sectors dependent on face-to-face interaction, such as professional services. In contrast, sectors tied to public goods appear more resilient. The effects are not short-lived—economic activity remains depressed for months following conflict events. Nighttime lights data mirror these trends, suggesting broader contractions in local economic intensity beyond what is visible in digital business data. Critically, we show that the economic damage of violence is cumulative and varies by type and timing. In the short term, total violent events reduce business activity by over 3% within ten days—more than three times the impact of fatalities. Medium-term effects persist over five months, particularly for repeated political violence. While civil events are less disruptive initially, they cause greater cumulative harm in the medium term. In the long run, violent events and fatalities significantly depress total real production and reduce nighttime luminosity—an indication of enduring structural disruptions.

These cumulative effects underscore the compounding nature of unrest: isolated events may cause modest economic setbacks, but sustained exposure leads to deeper, longer-term economic contractions. Moreover, strategic developments, battles and riots emerge as especially damaging, while civil disturbances—often dismissed as low-intensity—can accumulate into major economic drags in the medium and long-terms. These findings highlight the substantial economic costs of insecurity and the importance of measuring these impacts in data-poor environments. Without a clear understanding of how violence disrupts economic life—both immediately and over time—policy responses risk being poorly targeted or ineffective. By quantifying the short-, medium-, and long-term economic fallout of social conflict, this study supports the design of evidence-based interventions aimed at improving stability, encouraging investment, and promoting long-term economic resilience in fragile countries like Haiti.

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Appendices

A Additional satellite-based data

Additional satellite-based variables used in different extensions and robustness checks, and more details on the satellite images used in our baseline, are described in the paragraphs below.

MODIS/Terra Land Surface Temperature/Emissivity 8-Day L3 Global 1 km SIN Grid

These are approximate 1 km spatial resolution satellite data containing the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature/Emissivity 8-Day (version 6.1). According to NASA-DAAC, the 8 days version reflects the half of the ground track repeat cycle of the Terra and Aqua platforms (16 days). The default temperature measure units are Kelvins. We obtain the average temperature between day and night measures and convert the units of measure to degree Celsius. Surface temperature is often associated with variations in economic output and, in our approach, can serve as a control variable for environmental conditions that influence economic performance (Dell et al., 2012; Lanzafame, 2014).

GPM IMERG Final Precipitation L3 Half Hourly 0.1 degree x 0.1 degree V07

This product, developed under the Global Precipitation Measurement (GPM) mission, provides highly detailed global estimates of surface precipitation rates, offering fine spatial and temporal resolution (0.1 degree x 0.1 degree – approximately 10 km at the equator- every half-hour). This dataset allows for studying precipitation patterns and extreme weather events. Rainfall serves as a key proxy for natural irrigation, which is essential for successful crop cultivation in countries where agriculture heavily relies on precipitation due to limited irrigation infrastructure. In this line, Barrios et al. (2010) show that rainfall is important for economic growth in African countries where agriculture is one of the predominant economic activities.

The Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (MOD13Q1) Version 6.1

This dataset is compiled every 16 days from the Terra Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA's Terra satellite. The satellite imagery has a granular spatial resolution of 250 meters. It is comprised of two main indices: the Normalized Difference Vegetation Index (NDVI), which measures vegetation health and productivity, and the Enhanced Vegetation Index (EVI), designed for higher sensitivity in areas with dense vegetation and atmospheric interference. Covering global land areas, excluding regions with permanent snow or ice, the dataset is filtered out to include good quality pixels, providing reliability metrics to enhance usability and accuracy. We include the NDVI as an additional control variable, as it serves as a proxy for vegetation health and potential agricultural productivity.

Population counts

From WorldPop (2018), we obtain the annual gridded population counts for Haiti (more specifically the UN-adjusted 1 km resolution population counts available from 2000 to 2020). These time series are being estimated using the Haiti Population and Housing Census of 2003 (last census available) and a top-down modelling based on observable geospatialgeospatial covariate data (see Lloyd et al. (2019) for a detailed description). The authors calibrate a Random Forest model to spatially distribute population counts across space and time. The final product is a layer containing the number of people per pixel (with approximately 1km resolution) that is escalated to match the projected population estimates for Haiti produced by the Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat for 2019.

Reach of health services

The reach of health services (GeoAdaptive (2024) propietary data) is defined as the population accessibility to health services considering not only the location of health facilities, but also the time it takes for individuals to travel to the nearest healthcare facility. Therefore, providing a more precise analysis of healthcare accessibility. The mapping of healthcare facilities is based OpenStreetMap data for the years 2010–2022, while earlier data from 2005–2009 was sourced from a Pan American Health Organization (PAHO) master list and reformatted for consistency. To take into account real-world barriers, a custom temporal friction surface model was developed to calculate areas accessible within specific travel times. As such, the model adds to the spatial location of health infrastructure the following: information on terrain, road networks, and slope.[34]

Reach of education services

Educational facilities across Haiti were mapped using OpenStreetMap (OSM) data from 2010 to 2022, while the distribution of schools in 2005 was estimated through a combination of satellite imagery and advanced modeling. Changes in built structures between 2005 and 2010 were analyzed using the Global Human Settlement Layer (GHSL) to identify existing schools, and uncertainties were resolved using the Segment Anything Model (SAM), a deep learning approach applied to historical satellite imagery. Accessibility was modeled by calculating ar-

[34]This required the use of several datasets such as Globeland Land Cover, UNEP Protected Areas, CNIGS road data, and water bodies from OSM.

eas reachable within specific travel times based on a custom temporal friction surface model. This model integrates various datasets, including road networks from OSM and CNIGS, terrain data from ESRI, and hydrological data, to account for barriers like slope and impassable terrain. Demographic data from WorldPop (2018) provided age-disaggregated population estimates to calculate the share of school-age populations within educational catchment areas. Unlike simple buffers, this approach captures real-world accessibility dynamics, providing a more accurate representation of population reach and evolving infrastructure conditions between 2005 and 2022.

VNP46 products

NASA's BM-NTL data is available in three main VNP46 products: VNP46A2, which provides daily night-time lights (NTL) corrected for moonlight and atmospheric conditions; VNP46A3, which offers monthly composites based on daily radiance data corrected for atmospheric and lunar BRDF effects; and VNP46A4, which provides yearly composites using the same corrections applied to daily data. Important characteristics of the VNP46 products are (Román et al., 2018):

- Atmospheric correction: the VNP46 algorithm employs vector radiative transfer modelling to correct for the influence of aerosols, water vapor, and ozone on nighttime light radiance data.
- Bidirectional Reflectance Distribution Function (BRDF) correction: this correction improves the accuracy of nighttime light data by compensating for natural variations in lighting and reflectance, enabling more consistent and reliable comparisons across time and regions.
- Seasonal correction: NASA implements a correction that accounts for the density and vertical arrangement of leaves within each VIIRS DNB pixel.

The list of the 45 *communes* included in BM-NTL is: Anse-à-Pitre, Arcahaie, Belladère, Boucan-Carré, Cabaret, Cap-Haïtien, Capotille, Caracol, Carrefour, Cerca La Source, Croix-des Bouquets, Delmas, Dessalines, Dondon, Fort-Liberté, Ganthier, Gonaïves, Grand-Goâve, Hinche, Jacmel, Jérémie, Kenscoff, Lascahobas, Les Cayes, Limonade, Léogâne, Milot, Miragoâne, Mirebalais, Ouanaminthe, Petit-Goâve, Pignon, Plaine du Nord, Port-au-Prince, Port-de-Paix, Pétion-Ville, Quartier Morin, Saint-Marc, Saut-d'Eau, Terrier Rouge, Thomazeau, Trou du Nord, Verettes.

The list of the 23 *arrondissements* included in BM-NTL is: Cerca-la-Source, Hinche, Lascahobas, Mirebalais, Les Cayes, Jérémie, Gonaïves, Saint-Marc, Miragoâne, Fort-Liberté, Trou-du-Nord, Ouanaminthe, Port-de-Paix, Borgne, Acul-du-Nord, Cap-Haïtien, Saint-Raphaël, Croix-des-Bouquets, Arcahaie, Léogâne, Port-au-Prince, Belle-Anse, and Jacmel.

B Facebook's BAT additional information

The sample of Facebook pages used by Lam et al. (2022) to construct the BAT must comply with the following requisites:

- The page must have an administrator.
- The page must represent a local business with a physical location specified by the page administrators, including its latitude and longitude coordinates. Social media organisations and large companies are excluded.
- The page must have recorded admin activity within the 28 days preceding the crisis date.
- The physical location linked to the page must be situated within one of the administrative polygons designated for the crisis.
- The page must meet an internal quality standard and be searchable through Facebook's platform.
- The page must have been created prior to the baseline period (90 days before the specific date considered).

The list of the 22 *arrondissements* included in Facebook's BAT is: Hinche, Lascahobas, Mirebalais, Aquin, Les Cayes, Jérémie, Dessalines, Gonaïves, Saint-Marc, Trou-du-Nord, Ouanaminthe, Môle-Saint-Nicolas, Port-de-Paix, Borgne, Acul-du-Nord, Cap-Haïtien, Limbé, Croix-des-Bouquets, Arcahaie, Léogâne, Port-au-Prince, and Jacmel.

The following table summarizes the sectors considered in the data.

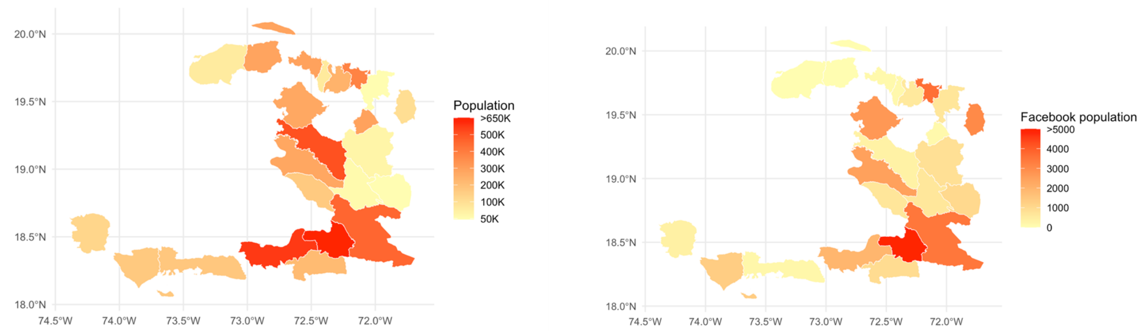
Table B.1: Business Verticals and Their Descriptions

Business Vertical	Description
Business & Utility Services	Business services offering business-to-business services like construction, office cleaning, advertising and marketing companies, and business software solutions. Utility services offer commodity services like electric, phone, internet, water, and energy.
Grocery & Convenience Stores	Retailers that sell everyday consumable goods including food (typically unprepared foods and ingredients) and a limited range of household goods (like toilet paper). These include grocery stores, convenience stores, pharmacies, and general stores.
Home Services	Services driven by demand from individual events at home, such as plumbing or electrical work. Examples include home repairs, photographers, cleaning, mechanics, plumbers, electricians, landscapers, and interior decorators.
Lifestyle Services	Specific to beauty, care, and fitness services. These businesses offer standardized services that are part of a customer's regular routines. Examples include gyms, salons, barbers, and nonmedical, noneducational supervision, like childcare nurseries and pet care.
Local Events	Events, activities, and businesses that sell real-life experiences, such as amusement parks, bowling alleys, concert venues, and social clubs.
Manufacturing	Businesses that manufacture durable goods (like furniture and cars) or consumable goods (like food and personal goods) with no or limited business-to-customer sales.
Professional Services	Services driven by demand from individual events such as legal needs or health issues that require high customization. Providers usually have advanced degrees or certifications and are considered experts and "knowledge workers." Examples include CPAs, lawyers, medical professionals, and architects.
Public Good	Includes government agencies, nonprofits, and religious organizations.
Restaurants	Businesses that sell prepared food and beverages for on-premise or off-premise dining.
Retail	Retail other than grocery and convenience stores, such as auto dealers, home goods stores, personal goods stores, and general merchandise/big-box stores like Walmart.
Travel	Businesses that provide or sell transportation or accommodation services, such as airlines, hotels, car rentals, and tour operators.
All	Includes all the previous categories and also those pages not included in the previous categories due to privacy thresholds at the cell level.

Source: Facebook's BAT.

To get a sense on how representative is the BAT data of the subnational distribution of economic activity, we get data on Facebook's network coverage and compare it with population counts for *arrondissements* (we would expect a high correlation between population counts and economic activity). Figure B.1 depicts an almost perfect overlap between the regional distribution of both data. This shows that Facebook's coverage is free from significant subnational biases and generally aligns with Haiti's subnational population distribution.

Figure B.1: Heat Map of the Spatial Distribution of Facebook's Network Coverage and Population Density



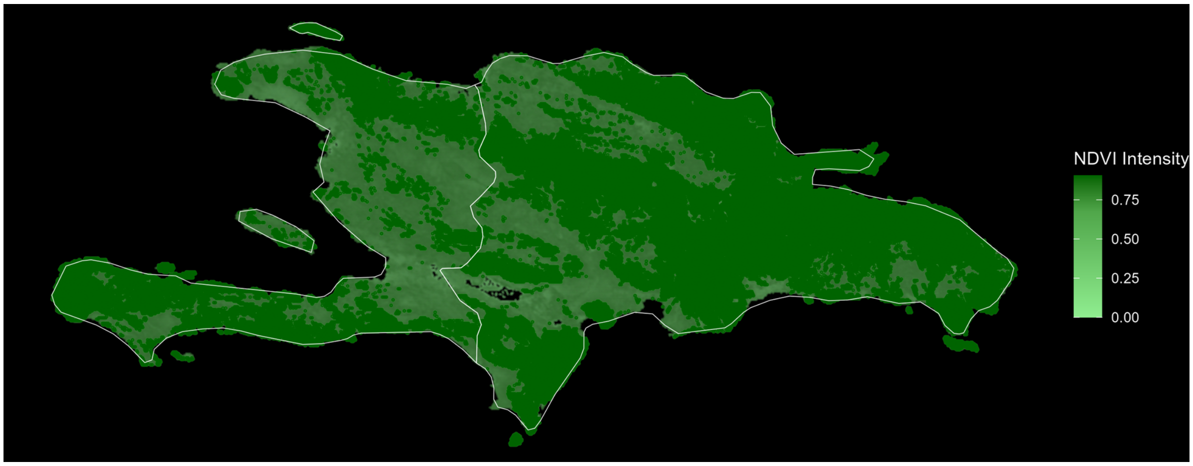
(a) Population 2020

(b) Facebook coverage - June 2023

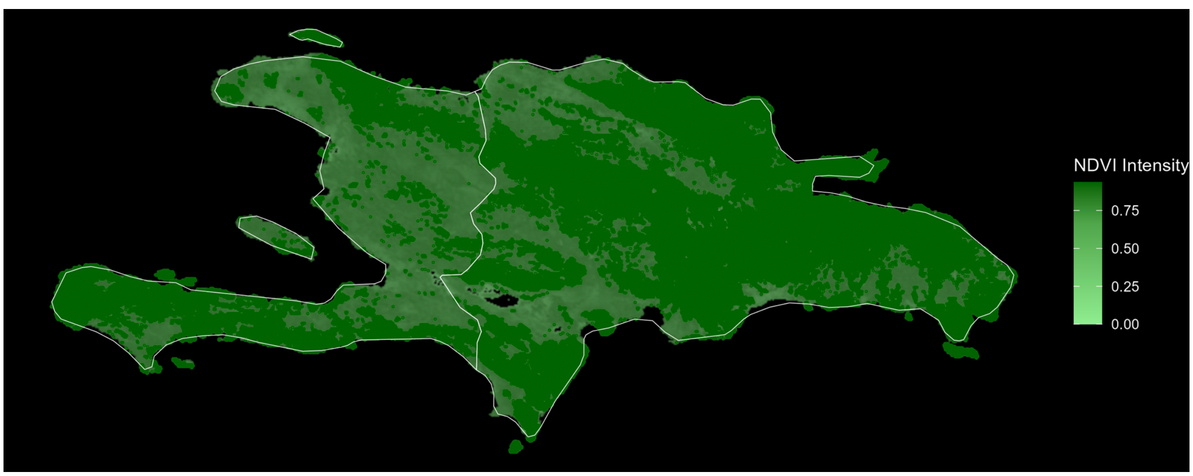
Notes: This figure presents heat maps with the geographical distribution (arrondissement) of the population counts and Facebook's network coverage. For population counts, 2020 is the last available year of the WorldPop (2018) time series, whereas the Facebook coverage is obtained from Facebook Population During Crisis, where June 2023 is the density of people who use Facebook with the Location Services device setting turned on after the June 2023 flooding that affected certain parts of Haiti. *Source:* WorldPop (2018) and Facebook's BAT, authors' own calculations.

C Additional tables and figures

Figure C.1: Map with the Spatial Distribution of Normalized Difference Vegetation Index (NDVI) – Island of Hispaniola (2018 vs 2023)



(a) 2018



(b) 2023

Notes: This figure presents the pixel-spatial distribution of the annual Normalized Difference Vegetation Index (NDVI) in 2018 and 2023 in the Island of Hispaniola, comprised by Haiti (left) and Dominican Republic (right). NDVI: vegetation indices 1-kilometer spatial resolution as a gridded level-3 product in the Sinusoidal projection. Notice that the index has not been aggregated at the level of arrondissement. The index normally ranges between 0 and 1, higher values indicating denser vegetation. *Source:* Atmosphere Archive & Distribution System Distributed Active Archive Center, authors' own calculations.

Table C.1: Activity Quantile (logs)

Lag Number	AIC	BIC
	Political Events	
1	66633.567	66651.896
2	66634.217	66661.710
3	66633.113	66669.771
4	66633.332	66679.154
5	66632.071	66687.057
6	66628.492	66692.643
7	**66627.275**	**66700.590**
8	66628.143	66710.623
9	66629.734	66721.378
10	66631.660	66732.469
	Civil Events	
1	**66633.226**	**66651.555**
2	66633.371	66660.865
3	66635.279	66671.937
4	66636.960	66682.782
5	66638.863	66693.850
6	66639.583	66703.734
7	66640.380	66713.695
8	66642.190	66724.670
9	66644.181	66735.825
10	66645.663	66746.471
	Political Fatalities	
1	147011.05	147029.85
2	146987.16	147015.35
3	146973.37	147010.96
4	146961.95	147008.95
5	146954.28	147010.66
6	146942.76	147008.55
7	146929.77	147004.95
8	146919.19	147003.77
9	146907.81	**147001.79**
10	**146898.74**	147002.12
	Civil Fatalities	
1	**66636.241**	**66654.570**
2	66638.173	66665.666
3	66639.646	66676.304
4	66641.285	66687.107
5	66641.483	66696.470
6	66642.367	66706.518
7	66644.360	66717.675
8	66646.359	66728.838
9	66648.344	66739.988
10	66650.323	66751.131

Table C.2: Nighttime Lights (logs)

Lag Number	AIC	BIC
	Political Events	
1	146970.47	146989.27
2	146912.45	146940.65
3	146866.98	146904.57
4	146845.69	146892.68
5	146825.97	146882.36
6	146812.81	146878.60
7	146791.59	146866.77
8	146779.20	146863.78
9	146752.74	**146846.72**
10	**146746.08**	146849.46
	Civil Events	
1	147002.96	147021.76
2	146964.82	146993.02
3	146941.01	146978.60
4	146933.58	146980.57
5	146926.23	146982.61
6	146916.04	146981.82
7	146902.91	146978.10
8	146895.92	146980.51
9	146883.25	**146977.23**
10	**146882.14**	146985.52
	Political Fatalities	
1	147011.05	147029.85
2	146987.16	147015.35
3	146973.37	147010.96
4	146961.95	147008.95
5	146954.28	147010.66
6	146942.76	147008.55
7	146929.77	147004.95
8	146919.19	147003.77
9	146907.81	**147001.79**
10	**146898.74**	147002.12
	Civil Fatalities	
1	147019.27	147038.07
2	147004.71	**147032.90**
3	146997.97	147035.56
4	146994.29	147041.28
5	146990.19	147046.58
6	146984.99	147050.77
7	146977.33	147052.52
8	146971.72	147056.31
9	146966.18	147060.16
10	**146962.27**	147065.65

Table C.3: Model Selection Based on Information Criteria

Table C.4: Activity Quantile (logs)

Lags	AIC	BIC
	Political Events	
1	546.50434	557.69411
2	544.94404	561.72869
3	487.90447	510.28400
4	423.79820	451.77262
5	**412.52194**	**446.09125**
	Civil Events	
1	544.84804	556.03781
2	546.82521	563.60986
3	508.81137	531.19091
4	468.36380	496.33822
5	**462.70885**	**496.27815**
	Political Fatalities	
1	543.69418	554.88395
2	537.20796	553.99262
3	485.52849	507.90803
4	457.71662	**485.69104**
5	**453.49795**	487.06725
	Civil Fatalities	
1	546.73073	557.92050
2	546.13800	**562.92266**
3	547.67331	570.05285
4	547.94464	575.91906
5	**538.69852**	572.26783

Table C.5: Nighttime Lights (logs)

Lags	AIC	BIC
	Political Events	
1	-3423.7561	-3411.9195
2	-3465.9356	-3448.1808
3	-3499.1721	-3475.4991
4	-3515.8979	-3486.3066
5	**-3544.4844**	**-3508.9748**
	Civil Events	
1	-3352.1098	-3340.2733
2	-3401.6552	-3383.9004
3	-3427.5043	-3403.8313
4	-3451.8692	-3422.2779
5	**-3466.8815**	**-3431.3719**
	Political Fatalities	
1	-3288.4938	-3276.6573
2	-3343.3727	-3325.6179
3	-3406.1679	-3382.4949
4	-3442.1442	-3412.5528
5	**-3506.4598**	**-3470.9502**
	Civil Fatalities	
1	-3269.0869	-3257.2504
2	-3300.1613	-3282.4065
3	-3333.4470	-3309.7739
4	-3366.4048	-3336.8135
5	**-3441.8597**	**-3406.3501**

D Robustness checks and extensions

Short-term

Table D.1: Robustness: Adding leads to baseline (10 leads)

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t+10}$	0.000	0.001*
	(0.002)	(0.000)
$v_{i,t+9}$	0.000	0.001*
	(0.001)	(0.000)
$v_{i,t+8}$	-0.000	0.000
	(0.001)	(0.000)
$v_{i,t+7}$	-0.001	0.001***
	(0.001)	(0.000)
$v_{i,t+6}$	0.001	0.001**
	(0.001)	(0.000)
$v_{i,t+5}$	0.001	0.001
	(0.001)	(0.000)
$v_{i,t+4}$	0.002	0.000
	(0.001)	(0.000)
$v_{i,t+3}$	0.001	0.000
	(0.001)	(0.000)
$v_{i,t+2}$	0.001	-0.000
	(0.001)	(0.000)
$v_{i,t+1}$	0.002	-0.000
	(0.002)	(0.001)
$v_{i,t-1}$	-0.002	-0.001
	(0.002)	(0.001)
$v_{i,t-2}$	-0.003**	-0.001
	(0.001)	(0.000)
$v_{i,t-3}$	-0.004***	-0.001***
	(0.001)	(0.000)
$v_{i,t-4}$	-0.004***	-0.001**
	(0.001)	(0.000)
$v_{i,t-5}$	-0.005***	-0.001***
	(0.001)	(0.000)
$v_{i,t-6}$	-0.006***	-0.001***
	(0.001)	(0.000)
$v_{i,t-7}$	-0.004***	-0.001
	(0.002)	(0.000)
$v_{i,t-8}$	-0.004**	-0.001*
	(0.002)	(0.000)
$v_{i,t-9}$	-0.003*	-0.001
	(0.002)	(0.000)
$v_{i,t-10}$	-0.001	-0.000
	(0.002)	(0.001)
$\sum_{k=1}^{10} v_{i,t-k}$	-0.036***	-0.008**
Wald test: p value	0.001	0.034
$\sum_{k=1}^{10} v_{i,t+k}$	0.006	0.004
Wald test: p value	0.587	0.238
Observations	61,202	61,202
R-squared	0.457	0.457
Average Y	-0.974	-0.974
Av. X	0.421	0.383

Notes: This table reports coefficients from estimating equation (1), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged and lead counts of total events and total fatalities, respectively, at $k = 1, \ldots, 10$ days. The row labelled $\sum_{k=1}^{10} v_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" is from a joint significance test of those ten lags. The row labelled $\sum_{k=1}^{10} v_{i,t+k}$ gives the cumulative effect of the 10 leads, and "Wald test: p-value" is from a joint significance test of those ten leads. All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*–sector level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.2: Robustness: Adding Controls to Baseline

	(1) *Total Events*	(2) *Total Fatalities*
$v_{i,t-1}$	-0.001	-0.000
	(0.002)	(0.001)
$v_{i,t-2}$	-0.002	-0.000
	(0.002)	(0.000)
$v_{i,t-3}$	-0.003**	-0.001**
	(0.001)	(0.000)
$v_{i,t-4}$	-0.003**	-0.001*
	(0.001)	(0.000)
$v_{i,t-5}$	-0.004***	-0.001***
	(0.001)	(0.000)
$v_{i,t-6}$	-0.006***	-0.001***
	(0.001)	(0.000)
$v_{i,t-7}$	-0.005***	-0.001
	(0.002)	(0.000)
$v_{i,t-8}$	-0.004**	-0.001*
	(0.002)	(0.000)
$v_{i,t-9}$	-0.003**	-0.001*
	(0.002)	(0.000)
$v_{i,t-10}$	-0.001	-0.000
	(0.002)	(0.001)
$\sum_{k=1}^{10} v_{i,t-k}$	-0.032***	-0.007*
Wald test: p value	0.004	0.065
Earthquake 2021	0.116**	0.115*
	(0.058)	(0.058)
Floods 2022	-0.092	-0.094
	(0.070)	(0.070)
Land Surface Temperature	-0.017	-0.017
	(0.012)	(0.012)
Precipitation	-0.325	-0.282
	(0.252)	(0.247)
Reach of Health Services	-43.366	-42.164
	(78.235)	(77.878)
Reach of Education Services	53.904	52.568
	(79.945)	(79.609)
Observations	61,912	61,912
R-squared	0.460	0.460
Average Y	-0.977	-0.977
Av. X	0.418	0.381

Notes: This table reports coefficients from estimating equation (1) adding control variables, not including γ_k and $\eta_{i,t}$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 10$ days. The row labelled $\sum_{k=1}^{10} v_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" is from a joint significance test of those ten lags. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake between August 14, 2021, and October 14, 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. Note activity quantile measures exclude the Nippes department which was mostly affected by the earthquake. *Floods 2022* is a binary variable indicating whether an area was affected by flooding between January 30, 2022, and March 30, 2022, in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*–sector level, are in parentheses. $* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$.

Table D.3: Robustness: SE clustered at department level

	(1) *Total events*	(2) *Total fatalities*
$\nu_{i,t-1}$	-0.001*	-0.000***
	(0.001)	(0.000)
$\nu_{i,t-2}$	-0.002**	-0.000***
	(0.001)	(0.000)
$\nu_{i,t-3}$	-0.003***	-0.001***
	(0.001)	(0.000)
$\nu_{i,t-4}$	-0.003***	-0.001***
	(0.001)	(0.000)
$\nu_{i,t-5}$	-0.004***	-0.001***
	(0.001)	(0.000)
$\nu_{i,t-6}$	-0.006***	-0.001***
	(0.001)	(0.000)
$\nu_{i,t-7}$	-0.005***	-0.001***
	(0.001)	(0.000)
$\nu_{i,t-8}$	-0.004**	-0.001***
	(0.001)	(0.000)
$\nu_{i,t-9}$	-0.003*	-0.001***
	(0.001)	(0.000)
$\nu_{i,t-10}$	-0.001	-0.000***
	(0.002)	(0.000)
$\sum_{k=1}^{10} \nu_{i,t-k}$	-0.031***	-0.007***
Wald test: p value	0.008	0.000
Observations	61,912	61,912
R-squared	0.457	0.457
Average Y	-0.977	-0.977
Av. X	0.418	0.381

Notes: This table reports coefficients from estimating equation (1), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 10$ days. The row labelled $\sum_{k=1}^{10} \nu_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" is from a joint significance test of those ten lags. All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the department level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.4: Robustness: Using arrondissement population as analytic weight

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t-1}$	-0.003	-0.001
	(0.002)	(0.001)
$v_{i,t-2}$	-0.003*	-0.000
	(0.002)	(0.000)
$v_{i,t-3}$	-0.004***	-0.001***
	(0.001)	(0.000)
$v_{i,t-4}$	-0.004**	-0.001***
	(0.001)	(0.000)
$v_{i,t-5}$	-0.004***	-0.001***
	(0.001)	(0.000)
$v_{i,t-6}$	-0.006***	-0.001***
	(0.002)	(0.000)
$v_{i,t-7}$	-0.005***	-0.001
	(0.002)	(0.000)
$v_{i,t-8}$	-0.004**	-0.001**
	(0.002)	(0.000)
$v_{i,t-9}$	-0.003**	-0.001**
	(0.001)	(0.000)
$v_{i,t-10}$	-0.001	-0.000
	(0.001)	(0.001)
$\sum_{k=1}^{10} v_{i,t-k}$	-0.036***	-0.008***
Wald test: p value	0.001	0.002
Observations	61,912	61,912
R-squared	0.545	0.544
Average Y	-0.977	-0.977
Av. X	0.418	0.381

Notes: This table reports coefficients from estimating equation (1) not including γ_k and $\eta_{i,t}$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1,\ldots,10$ days. The row labelled $\sum_{k=1}^{10} v_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" is from a joint significance test of those ten lags. All regressions are weighted using analytic weights based on the population of each arrondissement. This assumes that observations corresponding to larger populations are measured with greater precision (variance is inversely proportional to population size). All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*–sector level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.5: Robustness: Only including business vertical "All"

	Total events	*Total fatalities*
$v_{i,t-1}$	-0.001	0.000
	(0.004)	(0.001)
$v_{i,t-2}$	-0.005	-0.000
	(0.005)	(0.001)
$v_{i,t-3}$	-0.007	-0.002*
	(0.005)	(0.001)
$v_{i,t-4}$	-0.009	-0.002
	(0.005)	(0.001)
$v_{i,t-5}$	-0.014**	-0.003**
	(0.005)	(0.001)
$v_{i,t-6}$	-0.019***	-0.003**
	(0.006)	(0.001)
$v_{i,t-7}$	-0.018***	-0.002*
	(0.005)	(0.001)
$v_{i,t-8}$	-0.016**	-0.003**
	(0.006)	(0.001)
$v_{i,t-9}$	-0.014**	-0.003**
	(0.006)	(0.001)
$v_{i,t-10}$	-0.013	-0.002
	(0.008)	(0.001)
$\sum_{k=1}^{10} v_{i,t-k}$	-0.115**	-0.019*
Wald test: p value	0.038	0.069
Observations	19,184	19,184
R-squared	0.476	0.474
Average Y	-1.001	-1.001
Av. X	0.147	0.127

Notes: This table reports coefficients from estimating equation (1), not including γ_k and $\eta_{i,t}$ and only using the business vertical "All". The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i and day t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 10$ days. The row labelled $\sum_{k=1}^{10} v_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" is from a joint significance test of those ten lags. All specifications include *arrondissement* and year–month fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

Table D.6: Robustness: Wild cluster bootstrap test for individual and joint significance

	Total events	*Total fatalities*
$v_{i,t-1}$	-0.001	-0.000
p value	0.625	0.630
$v_{i,t-2}$	-0.002	-0.000
p value	0.269	0.484
$v_{i,t-3}$	-0.003*	-0.001**
p value	0.064	0.024
$v_{i,t-4}$	-0.003**	-0.001**
p value	0.042	0.036
$v_{i,t-5}$	-0.004***	-0.001**
p value	0.009	0.011
$v_{i,t-6}$	-0.006***	-0.001***
p value	0.001	0.001
$v_{i,t-7}$	-0.005**	-0.001
p value	0.0216	0.157
$v_{i,t-8}$	-0.004*	-0.001**
p value	0.074	0.010
$v_{i,t-9}$	-0.003*	-0.001
p value	0.073	0.106
$v_{i,t-10}$	-0.001	-0.000
p value	0.516	0.639
$\sum_{k=1}^{10} v_{i,t-k}$	-0.031**	-0.007**
WB joint test: p value	0.019	0.014
Observations	61,912	61,912
Average Y	-0.977	-0.977
Av. X	0.418	0.381

Notes: This table reports coefficients and corresponding wild cluster bootstrap p-values from estimating equation (1), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 10$ days. The row labelled $\sum_{k=1}^{10} v_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "WB joint test: p-value" is from a joint significance test of those ten lags. All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*–sector level. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.7: Robustness: Adding leads to violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t+10}$	0.001	0.008**	0.001	0.002*
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t+9}$	0.000	0.005	0.000	0.001
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t+8}$	-0.000	0.004	0.000	0.000
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t+7}$	0.002	0.005	0.001***	0.001*
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t+6}$	0.002	0.006	0.001**	0.001**
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t+5}$	0.001	0.005	0.000	0.001
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t+4}$	0.002	0.007*	0.000	0.001
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t+3}$	-0.000	0.006	0.000	-0.000
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t+2}$	0.000	0.009**	-0.000	0.001
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t+1}$	-0.000	0.008*	-0.000	0.000
	(0.003)	(0.004)	(0.001)	(0.001)
$v_{i,t-1}$	-0.004	0.007	-0.001	-0.002
	(0.003)	(0.004)	(0.001)	(0.001)
$v_{i,t-2}$	-0.002	0.006	-0.001*	-0.001
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t-3}$	-0.004**	0.003	-0.001***	-0.002**
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t-4}$	-0.002	0.006	-0.001**	-0.001*
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t-5}$	-0.003*	0.004	-0.001***	-0.003***
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-6}$	-0.004*	0.003	-0.001***	-0.001
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t-7}$	-0.003	0.003	-0.001	-0.000
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-8}$	-0.001	0.005	-0.001*	0.000
	(0.003)	(0.004)	(0.000)	(0.001)
$v_{i,t-9}$	0.001	0.006**	-0.001	0.000
	(0.003)	(0.003)	(0.000)	(0.001)
$v_{i,t-10}$	0.004	0.010***	-0.000	0.000
	(0.003)	(0.003)	(0.001)	(0.001)
$\sum_{k=1}^{10} v_{i,t-k}$	-0.019	0.052	-0.008**	-0.009
Wald test: p value	0.338	0.116	0.0257	0.232
$\sum_{k=1}^{10} v_{i,t+k}$	0.002	0.033*	0.000	0.003
Wald test: p value	0.835	0.0686	0.837	0.362
Observations	61,202	61,202	61,202	61,202
R-squared	0.457	0.458	0.460	0.457
Average Y	-0.974	-0.974	-0.974	-0.974
Av. X	0.239	0.141	0.374	0.126

Notes: This table presents the coefficient estimates of equation (1), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Column (1) shows the effect of lagged and lead political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1,\dots,10$ days. The row $\sum_{k=1}^{10} v_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those ten lags. The row labelled $\sum_{k=1}^{10} v_{i,t+k}$ gives the cumulative effect of the 10 leads, and "Wald test: p-value" is from a joint significance test of those ten leads. All regressions include *arrondissement* and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.8: Robustness: Adding controls to violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t-1}$	-0.002	0.009*	-0.000	-0.001
	(0.003)	(0.005)	(0.001)	(0.001)
$v_{i,t-2}$	-0.001	0.008*	-0.000	-0.001
	(0.003)	(0.004)	(0.000)	(0.001)
$v_{i,t-3}$	-0.003	0.004	-0.001**	-0.002**
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t-4}$	-0.002	0.007*	-0.001**	-0.001
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t-5}$	-0.003	0.004	-0.001***	-0.003**
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-6}$	-0.005**	0.002	-0.001***	-0.001
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-7}$	-0.003	0.002	-0.000	0.000
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-8}$	-0.001	0.004	-0.001	0.000
	(0.003)	(0.003)	(0.000)	(0.001)
$v_{i,t-9}$	0.000	0.005	-0.001	0.000
	(0.003)	(0.003)	(0.000)	(0.001)
$v_{i,t-10}$	0.003	0.008**	-0.000	0.000
	(0.003)	(0.003)	(0.001)	(0.001)
$\sum_{k=1}^{10} v_{i,t-k}$	-0.017	0.052	-0.007*	-0.008
Wald test: p value	0.452	0.106	0.065	0.334
Earthquake 2021	0.115*	0.119**	0.118**	0.115*
	(0.058)	(0.058)	(0.058)	(0.058)
Floods 2022	-0.091	-0.088	-0.110	-0.095
	(0.070)	(0.070)	(0.071)	(0.070)
Land Surface Temperature	-0.018	-0.018	-0.018	-0.017
	(0.012)	(0.012)	(0.012)	(0.012)
Precipitation	-0.346	-0.356	-0.299	-0.283
	(0.247)	(0.251)	(0.248)	(0.248)
Reach of Health Services	-45.383	-44.758	-40.734	-42.043
	(78.856)	(78.775)	(77.485)	(77.841)
Reach of Education Services	55.864	55.217	50.786	52.450
	(80.584)	(80.479)	(79.207)	(79.570)
Observations	61,912	61,912	61,912	61,912
R-squared	0.460	0.461	0.463	0.460
Average Y	-0.977	-0.977	-0.977	-0.977
Av. X	0.238	0.140	0.373	0.127

Notes: This table presents the coefficient estimates of equation (1), separately for each type of event and adding control variables (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 10$ days. The row $\sum_{k=1}^{10} v_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those ten lags. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake between August 14, 2021, and October 14, 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. Note activity quantile measures exclude the Nippes department which was mostly affected by the earthquake. *Floods 2022* is a binary variable indicating whether an area was affected by flooding between January 30, 2022, and March 30, 2022, in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.9: Robustness: SE clustered at department level in violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t-1}$	-0.002***	0.009***	-0.000***	-0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
$v_{i,t-2}$	-0.001**	0.008***	-0.000***	-0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
$v_{i,t-3}$	-0.003***	0.004***	-0.001***	-0.002***
	(0.000)	(0.001)	(0.000)	(0.000)
$v_{i,t-4}$	-0.002***	0.007***	-0.001***	-0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
$v_{i,t-5}$	-0.003***	0.004***	-0.001***	-0.002***
	(0.001)	(0.001)	(0.000)	(0.000)
$v_{i,t-6}$	-0.005***	0.002**	-0.001***	-0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
$v_{i,t-7}$	-0.003***	0.002*	-0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
$v_{i,t-8}$	-0.001	0.004**	-0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
$v_{i,t-9}$	0.001	0.005***	-0.001***	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
$v_{i,t-10}$	0.003**	0.009***	-0.000**	0.000
	(0.001)	(0.002)	(0.000)	(0.000)
$\sum_{k=1}^{10} v_{i,t-k}$	-0.017***	0.053***	-0.007***	-0.008***
Wald test: p value	0.007	0.000	0.000	0.005
Observations	61,912	61,912	61,912	61,912
R-squared	0.457	0.458	0.460	0.457
Average Y	-0.977	-0.977	-0.977	-0.977
Av. X	0.238	0.140	0.373	0.127

Notes: This table presents the coefficient estimates of equation (1), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 10$ days. The row $\sum_{k=1}^{10} v_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those ten lags. All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the department level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.10: Robustness: Analytic population weights in violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t-1}$	-0.005	0.005	-0.001	-0.002*
	(0.003)	(0.004)	(0.001)	(0.001)
$v_{i,t-2}$	-0.003	0.004	-0.001	-0.001*
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-3}$	-0.006***	-0.001	-0.001***	-0.002***
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-4}$	-0.004**	0.002	-0.001***	-0.002**
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-5}$	-0.006***	-0.001	-0.001***	-0.003***
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-6}$	-0.006***	-0.002	-0.001***	-0.002**
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-7}$	-0.004*	-0.003	-0.000	-0.000
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-8}$	-0.002	-0.001	-0.001*	-0.000
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-9}$	-0.001	0.001	-0.001*	-0.000
	(0.002)	(0.002)	(0.000)	(0.001)
$v_{i,t-10}$	0.001	0.004*	-0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)
$\sum_{k=1}^{10} v_{i,t-k}$	-0.035*	0.007	-0.007***	-0.013*
Wald test: p value	0.062	0.767	0.004	0.078
Observations	61,912	61,912	61,912	61,912
R-squared	0.545	0.546	0.548	0.544
Average Y	-0.977	-0.977	-0.977	-0.977
Av. X	0.238	0.140	0.373	0.127

Notes: This table presents the coefficient estimates of equation (1), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1,\dots,10$ days. The row $\sum_{k=1}^{10} v_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those ten lags. All regressions are weighted using analytic weights based on the population of each arrondissement. This assumes that observations corresponding to larger populations are measured with greater precision (variance is inversely proportional to population size). All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.11: Robustness: Only including business vertical "All"

	Violence Type			
	Political Events	Civil Events	Political Fatalities	Civil Fatalities
$\nu_{i,t-1}$	-0.001	0.015	0.000	-0.003
	(0.004)	(0.012)	(0.001)	(0.002)
$\nu_{i,t-2}$	-0.003	0.012	-0.001	-0.004
	(0.004)	(0.010)	(0.001)	(0.003)
$\nu_{i,t-3}$	-0.008*	0.004	-0.002*	-0.006**
	(0.004)	(0.009)	(0.001)	(0.002)
$\nu_{i,t-4}$	-0.006*	0.008	-0.002	-0.005
	(0.003)	(0.009)	(0.001)	(0.003)
$\nu_{i,t-5}$	-0.010***	0.000	-0.003***	-0.007***
	(0.003)	(0.010)	(0.001)	(0.002)
$\nu_{i,t-6}$	-0.016***	-0.006	-0.003**	-0.005
	(0.005)	(0.012)	(0.001)	(0.003)
$\nu_{i,t-7}$	-0.011**	-0.001	-0.002*	-0.002
	(0.004)	(0.009)	(0.001)	(0.002)
$\nu_{i,t-8}$	-0.009*	-0.001	-0.003*	-0.001
	(0.005)	(0.009)	(0.001)	(0.002)
$\nu_{i,t-9}$	-0.004	0.002	-0.002**	0.000
	(0.005)	(0.011)	(0.001)	(0.002)
$\nu_{i,t-10}$	0.001	0.006	-0.002	-0.000
	(0.005)	(0.014)	(0.001)	(0.003)
$\sum_{k=1}^{10} \nu_{i,t-k}$	-0.067*	0.040	-0.019*	-0.033
Wald test: p value	0.070	0.697	0.063	0.143
Observations	19,184	19,184	19,184	19,184
R-squared	0.476	0.477	0.482	0.474
Average Y	-1.001	-1.001	-1.001	-1.001
Av. X	0.080	0.046	0.124	0.045

Notes: This table presents the coefficient estimates of equation (1), separately for each type of event and only using business vertical "All" (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $\nu_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 10$ days. The row $\sum_{k=1}^{10} \nu_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those ten lags. All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table D.12: Robustness: Wild cluster bootstrap test for individual and joint significance

	Violence Type			
	Political Events	Civil Events	Political Fatalities	Civil Fatalities
$\nu_{i,t-1}$	-0.002	0.009*	-0.000	-0.001
p value	0.529	0.108	0.668	0.369
$\nu_{i,t-2}$	-0.001	0.008*	-0.000	-0.001
p value	0.586	0.0863	0.326	0.267
$\nu_{i,t-3}$	-0.003	0.004	-0.001**	-0.002**
p value	0.171	0.325	0.0130	0.0189
$\nu_{i,t-4}$	-0.002	0.007*	-0.001**	-0.001
p value	0.353	0.0825	0.0204	0.165
$\nu_{i,t-5}$	-0.003	0.004	-0.001***	-0.002**
p value	0.146	0.231	0.00600	0.0291
$\nu_{i,t-6}$	-0.005*	0.002	-0.001***	-0.001
p value	0.0599	0.553	0.000900	0.209
$\nu_{i,t-7}$	-0.003	0.002	-0.001	0.000
p value	0.264	0.517	0.162	0.891
$\nu_{i,t-8}$	-0.001	0.004	-0.001	0.000
p value	0.764	0.265	0.132	0.707
$\nu_{i,t-9}$	0.001	0.005	-0.001	0.000
p value	0.856	0.126	0.138	0.642
$\nu_{i,t-10}$	0.003	0.009**	-0.000	0.000
p value	0.303	0.0248	0.707	0.716
$\sum_{k=1}^{10} \nu_{i,t-k}$	-0.017	0.053	-0.007**	-0.008
WB joint test: p value	0.0214	0.0169	0.0235	0.0742
Observations	61,912	61,912	61,912	61,912
Average Y	-0.977	-0.977	-0.977	-0.977
Av. X	0.238	0.140	0.373	0.127

Notes: This table reports the coefficient estimates and corresponding wild cluster bootstrap p-values of equation (1), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and day t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $\nu_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 10$ days. The row $\sum_{k=1}^{10} \nu_{i,t-k}$ gives the cumulative effect over the ten-day horizon, and "WB joint test: p-value" reports the p-value from the joint significance test of those ten lags. All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Medium-term

Activity Quantile

Table D.13: Robustness 1: Add leads to baseline (5 leads)

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t+5}$	0.000	0.000
	(0.001)	(0.000)
$v_{i,t+4}$	-0.002*	-0.001***
	(0.001)	(0.000)
$v_{i,t+3}$	-0.001	-0.000
	(0.001)	(0.000)
$v_{i,t+2}$	-0.000	0.000
	(0.001)	(0.000)
$v_{i,t+1}$	0.001	-0.000
	(0.001)	(0.000)
$v_{i,t-1}$	-0.003**	-0.002***
	(0.001)	(0.000)
$v_{i,t-2}$	0.005***	-0.000
	(0.001)	(0.000)
$v_{i,t-3}$	0.001	-0.000
	(0.001)	(0.000)
$v_{i,t-4}$	-0.002***	-0.000
	(0.001)	(0.001)
$v_{i,t-5}$	0.001	-0.001*
	(0.001)	(0.000)
$\sum_{k=1}^{5} v_{i,t-k}$	0.001	-0.003*
Wald test: p value	0.712	0.073
$\sum_{k=1}^{5} v_{i,t+k}$	-0.002	-0.000
Wald test: p value	0.652	0.699
Observations	1,349	1,349
R-squared	0.684	0.683
Average Y	-0.921	-0.921
Av. X	12.26	10.08

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged and lead counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. The row labelled $\sum_{k=1}^{5} v_{i,t+k}$ gives the cumulative effect of the five leads, and "Wald test: p-value" is from a joint significance test of those five leads. All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*–sector level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.14: Robustness: Add controls to Baseline

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t-1}$	-0.003***	-0.000**
	(0.001)	(0.000)
$v_{i,t-2}$	0.000	-0.001*
	(0.001)	(0.000)
$v_{i,t-3}$	-0.002***	-0.002***
	(0.001)	(0.000)
$v_{i,t-4}$	-0.005***	-0.001**
	(0.001)	(0.001)
$v_{i,t-5}$	-0.005***	-0.001***
	(0.001)	(0.000)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.016***	-0.006***
Wald test: p value	0.001	0.001
Earthquake 2021	-0.035	-0.108
	(0.066)	(0.069)
Lag Earthquake 2021	0.196**	0.103
	(0.086)	(0.091)
Floods 2022	-0.155*	-0.122
	(0.089)	(0.090)
Lag Floods 2022	-0.082	-0.026
	(0.061)	(0.062)
Land Surface Temperature	-0.025*	-0.033**
	(0.014)	(0.014)
Precipitation	-0.355	0.053
	(0.393)	(0.372)
Reach of Health Services	-25.217	-6.656
	(73.366)	(67.370)
Reach of Education Services	44.186	23.201
	(75.391)	(69.628)
Observations	1,704	1,704
R-squared	0.655	0.663
Average Y	-0.977	-0.977
Av. X	12.94	12.38

Notes: This table reports coefficients from estimating equation (2) adding control variables, not including γ_k and $\eta_{i,t}$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1,\dots,5$ months. The row labelled $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable that equals 1 only in August 2021 if the area was affected by the earthquake. Affected areas include Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Côteaux, and Port-Salut. Otherwise, it takes a value of 0. Note activity quantile measures exclude the Nippes department which was mostly affected by the earthquake. *Floods 2022* is a binary variable that equals 1 only in February 2022 if the area was affected by flooding. Affected regions include Nord, Nord-Est, Nippes, and Nord-Ouest. Otherwise, it takes a value of 0. All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*–sector level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.15: Robustness: SE clustered at department level

	(1) *Total events*	(2) *Total fatalities*
$\nu_{i,t-1}$	-0.003***	-0.000***
	(0.001)	(0.000)
$\nu_{i,t-2}$	0.001	-0.001***
	(0.001)	(0.000)
$\nu_{i,t-3}$	-0.002***	-0.002***
	(0.000)	(0.000)
$\nu_{i,t-4}$	-0.005***	-0.001***
	(0.001)	(0.000)
$\nu_{i,t-5}$	-0.005***	-0.001***
	(0.001)	(0.000)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.015***	-0.005***
Wald test: p value	0.000	0.000
Observations	1,704	1,704
R-squared	0.648	0.657
Average Y	-0.977	-0.977
Av. X	12.94	12.38

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta i, t$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the department level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.16: Robustness: Adding population as analytic weight

	(1) *Total events*	(2) *Total fatalities*
$\nu_{i,t-1}$	-0.004***	-0.000***
	(0.001)	(0.000)
$\nu_{i,t-2}$	0.000	-0.001*
	(0.001)	(0.000)
$\nu_{i,t-3}$	-0.003***	-0.002***
	(0.001)	(0.000)
$\nu_{i,t-4}$	-0.005***	-0.001**
	(0.002)	(0.001)
$\nu_{i,t-5}$	-0.005***	-0.001***
	(0.001)	(0.000)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.016***	-0.005***
Wald test: p value	0.002	0.001
Observations	1,704	1,704
R-squared	0.706	0.716
Average Y	-0.977	-0.977
Av. X	12.94	12.38

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. All regressions are weighted using analytic weights based on the population of each arrondissement. This assumes that observations corresponding to larger populations are measured with greater precision (variance is inversely proportional to population size). All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*–sector level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.17: Robustness: Only including business vertical "All"

	(1) *Total events*	(2) *Total fatalities*
$\nu_{i,t-1}$	-0.003**	-0.000**
	(0.001)	(0.000)
$\nu_{i,t-2}$	0.001	-0.001*
	(0.001)	(0.000)
$\nu_{i,t-3}$	-0.002***	-0.002***
	(0.001)	(0.000)
$\nu_{i,t-4}$	-0.005***	-0.001**
	(0.001)	(0.001)
$\nu_{i,t-5}$	-0.005***	-0.001***
	(0.001)	(0.000)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.015***	-0.005***
Wald test: p value	0.003	0.001
Observations	1,704	1,704
R-squared	0.648	0.657
Average Y	-0.977	-0.977
Av. X	12.94	12.38

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$, and only using the business vertical "All". The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*–sector level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.18: Robustness: Wild cluster bootstrap test for individual and joint significance

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t-1}$	-0.003**	-0.000*
p value	0.021	0.059
$v_{i,t-2}$	0.001	-0.001
p value	0.579	0.127
$v_{i,t-3}$	-0.002**	-0.002***
p value	0.012	0.002
$v_{i,t-4}$	-0.005***	-0.001*
p value	0.007	0.0503
$v_{i,t-5}$	-0.005***	-0.001***
p value	0.003	0.007
$\sum_{k=1}^{5} v_{i,t-k}$	-0.015***	-0.005***
WB joint test: p value	0.001	0.009
Observations	1,704	1,704
Average Y	-0.977	-0.977
Av. X	12.94	12.38

Notes: This table reports coefficients and corresponding wild cluster bootstrap p-values from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "WB joint test: p-value" is from a joint significance test of those five lags. All specifications include *arrondissement*–sector and year–month fixed effects. Standard errors, clustered at the *arrondissement*–sector level. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table D.19: Robustness: Add leads to violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t+5}$	-0.001	0.001	0.000	-0.000
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t+4}$	-0.000	-0.003	-0.001***	0.001
	(0.001)	(0.003)	(0.000)	(0.001)
$v_{i,t+3}$	0.004***	-0.003	-0.000	-0.001
	(0.001)	(0.003)	(0.000)	(0.001)
$v_{i,t+2}$	-0.004**	-0.005	0.000	0.000
	(0.002)	(0.003)	(0.000)	(0.003)
$v_{i,t+1}$	-0.000	-0.005	0.001	0.002
	(0.002)	(0.004)	(0.001)	(0.003)
$v_{i,t-1}$	0.003	-0.000	-0.001**	0.000
	(0.003)	(0.005)	(0.001)	(0.003)
$v_{i,t-2}$	0.001	0.007	-0.000	0.003
	(0.002)	(0.005)	(0.001)	(0.004)
$v_{i,t-3}$	-0.011**	-0.007	-0.000	-0.004
	(0.004)	(0.006)	(0.001)	(0.005)
$v_{i,t-4}$	0.003	0.001	-0.000	-0.007
	(0.004)	(0.006)	(0.001)	(0.006)
$v_{i,t-5}$	0.004	0.006	-0.000	0.003
	(0.003)	(0.005)	(0.001)	(0.002)
$\sum_{k=1}^{5} v_{i,t-k}$	0.001	0.007	-0.002	-0.004
Wald test: p value	0.863	0.716	0.387	0.756
$\sum_{k=1}^{5} v_{i,t+k}$	-0.004	-0.009	0.001	0.002
Wald test: p value	0.231	0.115	0.380	0.623
Observations	1,349	1,349	1,349	1,349
R-squared	0.690	0.689	0.688	0.688
Average Y	-0.921	-0.921	-0.921	-0.921
Av. X	7.269	4.212	9.919	3.763

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement i*, sector s and month t (period July 2020 – November 2022). Column (1) shows the effect of lagged and lead political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \dots, 5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. The row labelled $\sum_{k=1}^{5} v_{i,t+k}$ gives the cumulative effect of the five leads, and "Wald test: p-value" is from a joint significance test of those five leads. All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.20: Robustness: Add controls to violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t-1}$	0.003*	0.003	-0.001***	-0.000
	((0.001)	(0.003)	(0.000)	(0.001)
$v_{i,t-2}$	-0.000	-0.002	-0.001*	0.000
	(0.001)	(0.002)	(0.000)	(0.001)
$v_{i,t-3}$	-0.007***	-0.009***	-0.002***	0.001
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-4}$	-0.009***	-0.012**	-0.001*	0.003*
	(0.002)	(0.005)	(0.000)	(0.002)
$v_{i,t-5}$	-0.002	-0.004	-0.002***	0.000
	(0.002)	(0.004)	(0.000)	(0.001)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.016***	-0.025*	-0.006***	0.005
Wald test: p value	0.004	0.079	0.000	0.193
Earthquake 2021	-0.058	-0.055	-0.104	-0.106
	(0.068)	(0.064)	(0.066)	(0.069)
Lag Earthquake 2021	0.171*	0.215**	0.110	0.118
	(0.088)	(0.086)	(0.089)	(0.089)
Floods 2022	-0.116	-0.131	-0.100	-0.134
	(0.091)	(0.090)	(0.089)	(0.089)
Lag Floods 2022	-0.033	-0.054	-0.090	-0.038
	(0.063)	(0.061)	(0.064)	(0.062)
Land Surface Temperature	-0.035**	-0.021	-0.030**	-0.036**
	(0.014)	(0.014)	(0.013)	(0.014)
Precipitation	-0.237	-0.341	-0.030	0.001
	(0.367)	(0.375)	(0.372)	(0.370)
Reach of Health Services	6.530	-6.186	-2.320	1.125
	(63.808)	(68.586)	(67.042)	(66.626)
Reach of Education Services	10.700	24.109	17.646	13.668
	(65.818)	(70.647)	(69.297)	(68.964)
Observations	1,704	1,704	1,704	1,704
R-squared	0.672	0.662	0.670	0.668
Average Y	-0.977	-0.977	-0.977	-0.977
Av. X	7.529	4.323	12.13	3.987

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event and adding control variables (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1,\ldots,5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. For a description of the variables *land surface temperature, precipitation, reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable that equals 1 only in August 2021 if the area was affected by the earthquake. Affected areas include Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Côteaux, and Port-Salut. Otherwise, it takes a value of 0. Note activity quantile measures exclude the Nippes department which was mostly affected by the earthquake. *Floods 2022* is a binary variable that equals 1 only in February 2022 if the area was affected by flooding. Affected regions include Nord, Nord-Est, Nippes, and Nord-Ouest. Otherwise, it takes a value of 0. All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.21: Robustness: SE clustered at department level in violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$\nu_{i,t-1}$	0.003***	0.003***	-0.001***	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)
$\nu_{i,t-2}$	-0.000	-0.002	-0.001***	0.001
	(0.001)	(0.001)	(0.000)	(0.000)
$\nu_{i,t-3}$	-0.007***	-0.009***	-0.002***	0.001*
	(0.001)	(0.002)	(0.000)	(0.001)
$\nu_{i,t-4}$	-0.009***	-0.012***	-0.001***	0.004**
	(0.001)	(0.003)	(0.000)	(0.001)
$\nu_{i,t-5}$	-0.001	-0.004**	-0.002***	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.015***	-0.025***	-0.006***	0.005***
Wald test: p value	0.000	0.004	0.000	0.033
Observations	1,704	1,704	1,704	1,704
R-squared	0.666	0.656	0.666	0.663
Average Y	-0.977	-0.977	-0.977	-0.977
Av. X	7.529	4.323	12.13	3.987

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $\nu_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1,\ldots,5$ months. The row $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the department level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.22: Robustness: Analytic weights in violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t-1}$	0.003**	0.003	-0.001***	-0.000
	(0.001)	(0.003)	(0.000)	(0.001)
$v_{i,t-2}$	-0.001	-0.004	-0.001*	0.001
	(0.001)	(0.003)	(0.000)	(0.001)
$v_{i,t-3}$	-0.008***	-0.009***	-0.002***	0.001
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-4}$	-0.009***	-0.014**	-0.001*	0.004**
	(0.003)	(0.005)	(0.000)	(0.002)
$v_{i,t-5}$	0.000	-0.004	-0.001***	0.000
	(0.002)	(0.004)	(0.000)	(0.001)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.015***	-0.029*	-0.006***	0.006*
Wald test: p value	0.009	0.061	0.001	0.069
Observations	1,704	1,704	1,704	1,704
R-squared	0.724	0.715	0.720	0.722
Average Y	-0.977	-0.977	-0.977	-0.977
Av. X	7.529	4.323	12.13	3.987

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions are weighted using analytic weights based on the population of each arrondissement. This assumes that observations corresponding to larger populations are measured with greater precision (variance is inversely proportional to population size). All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.23: Robustness: Only including business vertical "All"

	(1) Political Events	(2) Civil Events	(3) Political Fatalities	(4) Civil Fatalities
$\nu_{i,t-1}$	0.005*	0.008*	-0.002***	-0.001
	(0.002)	(0.005)	(0.001)	(0.002)
$\nu_{i,t-2}$	0.000	-0.001	-0.002***	0.001
	(0.002)	(0.005)	(0.000)	(0.002)
$\nu_{i,t-3}$	-0.014***	-0.017***	-0.004***	0.000
	(0.003)	(0.005)	(0.000)	(0.003)
$\nu_{i,t-4}$	-0.018***	-0.021**	-0.002**	0.006
	(0.004)	(0.009)	(0.001)	(0.005)
$\nu_{i,t-5}$	-0.009*	-0.015***	-0.006**	-0.003
	(0.005)	(0.004)	(0.002)	(0.003)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.036***	-0.045**	-0.015***	0.0029
Wald test: p value	0.000	0.048	0.000	0.842
Observations	528	528	528	528
R-squared	0.694	0.672	0.707	0.676
Average Y	-0.998	-0.998	-0.998	-0.998
Av. X	2.536	1.430	4.123	1.483

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event and only using the business vertical "All" (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $\nu_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 5$ months. The row $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

Table D.24: Robustness: Wild cluster bootstrap test for individual and joint significance

	(1) Political Events	(2) Civil Events	(3) Political Fatalities	(4) Civil Fatalities
$v_{i,t-1}$	0.003**	0.003	-0.001***	-0.000
p value	0.049	0.220	0.003	0.864
$v_{i,t-2}$	-0.000	-0.002	-0.001*	0.001
p value	0.996	0.356	0.098	0.462
$v_{i,t-3}$	-0.007***	-0.009***	-0.002***	0.001
p value	0.001	0.006	0.003	0.249
$v_{i,t-4}$	-0.009***	-0.012**	-0.001*	0.004*
p value	0.008	0.044	0.098	0.081
$v_{i,t-5}$	-0.001	-0.004	-0.002***	0.000
p value	0.589	0.290	0	0.873
$\sum_{k=1}^{5} v_{i,t-k}$	-0.015**	-0.024*	-0.006***	0.005
WB joint test: p value	0.024	0.071	0.004	0.306
Observations	1,704	1,704	1,704	1,704
Average Y	-0.977	-0.977	-0.977	-0.977
Av. X	7.529	4.323	12.13	3.987

Notes: This table presents the coefficient estimates and corresponding wild cluster bootstrap p-values of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of the activity quantile $Y_{i,s,t}$ in *arrondissement* i, sector s and month t (period July 2020 – November 2022). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "WB joint test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *arrondissement*–sector and year–month fixed effects. Standard errors are clustered at the *arrondissement*–sector level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Night-Time Lights

Table D.25: Robustness: Add leads to baseline (5 leads)

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t+5}$	-0.001	-0.003**
	(0.004)	(0.001)
$v_{i,t+4}$	-0.005**	-0.001
	(0.002)	(0.001)
$v_{i,t+3}$	-0.000	-0.002**
	(0.002)	(0.001)
$v_{i,t+2}$	0.002	-0.002***
	(0.003)	(0.001)
$v_{i,t+1}$	-0.005***	-0.004***
	(0.002)	(0.001)
$v_{i,t-1}$	-0.014***	-0.007***
	(0.004)	(0.002)
$v_{i,t-2}$	-0.009***	-0.005***
	(0.003)	(0.001)
$v_{i,t-3}$	-0.006	-0.004***
	(0.004)	(0.001)
$v_{i,t-4}$	-0.001	-0.001
	(0.004)	(0.001)
$v_{i,t-5}$	-0.005	-0.004
	(0.005)	(0.003)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.036**	-0.021***
Wald test: p value	0.018	0.009
$\sum_{k=1}^{5} v_{i,t+k}$	-0.009	-0.012***
Wald test: p value	0.304	0.002
Observations	2,790	2,790
R-squared	0.876	0.876
Average Y	3.929	3.929
Av. X	1.655	1.305

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of nighttime lights $Y_{i,t}$ in *commune* i and month t (period January 2018 – December 2023). Columns (1) and (2) show the effects of lagged and lead counts of total events and total fatalities, respectively, at $k = 1,\ldots,5$ months. The row labelled $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. The row labelled $\sum_{k=1}^{5} v_{i,t+k}$ gives the cumulative effect of the five leads, and "Wald test: p-value" is from a joint significance test of those five leads. All specifications include *commune* and year–month fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.26: Robustness: Add controls to baseline

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t-1}$	-0.008**	-0.002
	(0.004)	(0.002)
$v_{i,t-2}$	-0.006**	-0.001
	(0.003)	(0.002)
$v_{i,t-3}$	-0.008*	-0.002
	(0.004)	(0.004)
$v_{i,t-4}$	-0.002	-0.001
	(0.003)	(0.003)
$v_{i,t-5}$	-0.004	-0.001
	(0.003)	(0.003)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.028*	-0.008
Wald test: p value	0.052	0.560
Earthquake 2021	0.099	0.108
	(0.130)	(0.132)
Lag Earthquake 2021	-0.082	-0.078
	(0.134)	(0.135)
Floods 2022	0.112	0.128
	(0.151)	(0.151)
Lag Floods 2022,	0.120	0.134
	(0.120)	(0.119)
Land Surface Temperature	0.045**	0.044**
	(0.021)	(0.021)
Precipitation	-0.261	-0.236
	(0.448)	(0.449)
Reach of Health Services	-0.262	-0.566
	(5.538)	(5.552)
Reach of Education Services	-10.043*	-10.137*
	(5.521)	(5.506)
Observations	2,365	2,365
R-squared	0.897	0.897
Average Y	3.934	3.934
Av. X	1.636	1.046

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of nighttime lights $Y_{i,t}$ in *commune* i and month t (period January 2018 – December 2022, as variables Reach of health Services and Reach of Education Services are available from 2018 to 2022). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable that equals 1 only in August 2021 if the area was affected by the earthquake. Affected areas include Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Côteaux, and Port-Salut. Otherwise, it takes a value of 0. *Floods 2022* is a binary variable that equals 1 only in February 2022 if the area was affected by flooding. Affected regions include Nord, Nord-Est, Nippes, and Nord-Ouest. Otherwise, it takes a value of 0. All specifications include *commune* and year–month fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.27: Robustness: SE clustered at *arrondissement* level

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t-1}$	-0.015***	-0.007***
	(0.002)	(0.001)
$v_{i,t-2}$	-0.009***	-0.005***
	(0.002)	(0.001)
$v_{i,t-3}$	-0.011***	-0.004***
	(0.002)	(0.001)
$v_{i,t-4}$	-0.002	-0.002
	(0.003)	(0.002)
$v_{i,t-5}$	-0.007	-0.006**
	(0.006)	(0.003)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.044***	-0.025***
Wald test: p value	0.000	0.000
Observations	2,881	2,881
R-squared	0.873	0.873
Average Y	4.037	4.037
Av. X	1.805	1.460

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of nighttime lights $Y_{i,t}$ in *commune* i and month t (period January 2018 – December 2023). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. All specifications include *commune* and year–month fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table D.28: Robustness: Adding population as analytic weight

	(1) *Total events*	(2) *Total fatalities*
$\nu_{i,t-1}$	-0.015***	-0.006***
	(0.005)	(0.002)
$\nu_{i,t-2}$	-0.006*	-0.003**
	(0.003)	(0.001)
$\nu_{i,t-3}$	-0.011**	-0.004**
	(0.005)	(0.002)
$\nu_{i,t-4}$	-0.006*	-0.004*
	(0.004)	(0.002)
$\nu_{i,t-5}$	-0.008*	-0.006***
	(0.005)	(0.002)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.046***	-0.024***
Wald test: p value	0.000	0.001
Observations	3,015	3,015
R-squared	0.871	0.870
Average Y	3.982	3.982
Av. X	1.725	1.395

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of nighttime lights $Y_{i,t}$ in *commune* i and month t (period January 2018 – December 2023). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. All regressions are weighted using analytic weights based on the population of each *commune*. This assumes that observations corresponding to larger populations are measured with greater precision (variance is inversely proportional to population size). All specifications include *commune* and year–month fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.29: Robustness: Add leads to violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t+5}$	-0.003	0.002	-0.003**	-0.004**
	(0.004)	(0.008)	(0.001)	(0.002)
$v_{i,t+4}$	-0.003	0.002	-0.001	-0.002
	(0.003)	(0.006)	(0.001)	(0.002)
$v_{i,t+3}$	-0.004*	0.006	-0.002*	-0.002
	(0.002)	(0.007)	(0.001)	(0.001)
$v_{i,t+2}$	-0.004*	0.001	-0.003***	-0.000
	(0.002)	(0.013)	(0.001)	(0.001)
$v_{i,t+1}$	-0.009***	0.002	-0.003***	-0.005**
	(0.003)	(0.010)	(0.001)	(0.002)
$v_{i,t-1}$	-0.023***	-0.017*	-0.007***	-0.008***
	(0.005)	(0.010)	(0.002)	(0.002)
$v_{i,t-2}$	-0.013***	-0.016	-0.005***	-0.007*
	(0.004)	(0.011)	(0.001)	(0.003)
$v_{i,t-3}$	-0.008***	-0.005	-0.004***	-0.007**
	(0.003)	(0.006)	(0.001)	(0.003)
$v_{i,t-4}$	-0.004	0.002	-0.000	0.000
	(0.004)	(0.007)	(0.001)	(0.001)
$v_{i,t-5}$	-0.004	-0.009	-0.006	-0.009
	(0.007)	(0.007)	(0.005)	(0.006)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.053***	-0.045*	-0.022**	-0.030**
Wald test: p value	0.000	0.073	0.014	0.029
$\sum_{k=1}^{5} v_{i,t+k}$	-0.0223***	0.0126	-0.0117***	-0.0132**
Wald test: p value	0.003	0.747	0.001	0.011
Observations	2,790	2,790	2,790	2,790
R-squared	0.877	0.876	0.877	0.876
Average Y	3.929	3.929	3.929	3.929
Av. X	0.849	0.480	1.244	0.547

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *commune* i, and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged and lead political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1,\ldots,5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. The row labelled $\sum_{k=1}^{5} v_{i,t+k}$ gives the cumulative effect of the five leads, and "Wald test: p-value" is from a joint significance test of those five leads. All regressions include *commune* and year–month fixed effects. Standard errors are clustered at the *commune* level and are in parentheses. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

Table D.30: Robustness: Add controls to violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t-1}$	-0.006	-0.006	-0.002	-0.004*
	(0.004)	(0.010)	(0.002)	(0.002)
$v_{i,t-2}$	-0.008**	-0.001	-0.001	0.000
	(0.003)	(0.008)	(0.002)	(0.004)
$v_{i,t-3}$	-0.007	-0.000	-0.002	0.001
	(0.005)	(0.009)	(0.004)	(0.004)
$v_{i,t-4}$	-0.010*	-0.002	-0.002	-0.001
	(0.006)	(0.007)	(0.003)	(0.003)
$v_{i,t-5}$	-0.004	-0.006	-0.001	0.000
	(0.003)	(0.007)	(0.003)	(0.003)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.034**	-0.015	-0.008	-0.004
Wald test: p value	0.0414	0.619	0.521	0.820
Earthquake 2021	0.097	0.093	0.110	0.109
	(0.134)	(0.126)	(0.133)	(0.132)
Lag Earthquake 2021	-0.077	-0.089	-0.076	-0.079
	(0.133)	(0.136)	(0.136)	(0.135)
Floods 2022	0.120	0.115	0.126	0.126
	(0.152)	(0.151)	(0.151)	(0.151)
Lag Floods 2022	0.113	0.124	0.131	0.136
	(0.118)	(0.119)	(0.119)	(0.119)
Land Surface Temperature	0.045**	0.045**	0.046**	0.045**
	(0.021)	(0.021)	(0.021)	(0.021)
Precipitation	-0.271	-0.270	-0.236	-0.238
	(0.452)	(0.448)	(0.450)	(0.451)
Reach of Health Services	-0.209	-0.301	-0.566	-0.580
	(5.551)	(5.554)	(5.545)	(5.563)
Reach of Education Services	-10.087*	-10.165*	-10.145*	-10.158*
	(5.513)	(5.532)	(5.516)	(5.513)
Observations	2,365	2,365	2,365	2,365
R-squared	0.898	0.897	0.897	0.897
Average Y	3.934	3.934	3.934	3.934
Av. X	0.772	0.450	0.975	0.433

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event and adding control variables (coefficients γ_k are not presented). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *commune* i, and month t (period January 2018 – December 2022, as variables Reach of health Services and Reach of Education Services are available from 2018 to 2022). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable that equals 1 only in August 2021 if the area was affected by the earthquake. Affected areas include Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Côteaux, and Port-Salut. Otherwise, it takes a value of 0. *Floods 2022* is a binary variable that equals 1 only in February 2022 if the area was affected by flooding. Affected regions include Nord, Nord-Est, Nippes, and Nord-Ouest. Otherwise, it takes a value of 0. All regressions include *commune* and year–month fixed effects. Standard errors are clustered at the *commune* level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.31: Robustness: SE clustered at *arrondissement* level in violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t-1}$	-0.018***	-0.015**	-0.007***	-0.008***
	(0.004)	(0.006)	(0.001)	(0.001)
$v_{i,t-2}$	-0.013***	-0.017**	-0.005***	-0.008***
	(0.003)	(0.006)	(0.001)	(0.002)
$v_{i,t-3}$	-0.012***	-0.011**	-0.004***	-0.006***
	(0.003)	(0.005)	(0.001)	(0.002)
$v_{i,t-4}$	-0.006*	-0.002	-0.002	-0.005
	(0.003)	(0.008)	(0.002)	(0.003)
$v_{i,t-5}$	-0.012*	-0.012	-0.007**	-0.011**
	(0.007)	(0.010)	(0.003)	(0.005)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.061***	-0.056***	-0.025***	-0.039***
Wald test: p value	0.000	0.026	0.000	0.003
Observations	2,881	2,881	2,881	2,881
R-squared	0.874	0.873	0.873	0.873
Average Y	4.037	4.037	4.037	4.037
Av. X	0.933	0.519	1.387	0.579

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *commune* i, and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1,\dots,5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *commune* and year–month fixed effects. Standard errors are clustered at the *arrondissement* level and are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table D.32: Robustness: Analytic weights in violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t-1}$	-0.014*	-0.009	-0.007***	-0.006
	(0.007)	(0.011)	(0.002)	(0.003)
$v_{i,t-2}$	-0.006	-0.007	-0.003**	-0.004
	(0.005)	(0.010)	(0.001)	(0.003)
$v_{i,t-3}$	-0.012**	-0.010	-0.003*	-0.003
	(0.005)	(0.008)	(0.002)	(0.002)
$v_{i,t-4}$	-0.008**	-0.012	-0.004**	-0.008*
	(0.004)	(0.013)	(0.002)	(0.004)
$v_{i,t-5}$	-0.011**	-0.013	-0.006***	-0.011***
	(0.005)	(0.012)	(0.002)	(0.004)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.051	-0.051	-0.023	-0.032
Wald test: p value	0.000	0.166	0.001	0.004
Observations	3,015	3,015	3,015	3,015
R-squared	0.872	0.871	0.871	0.870
Average Y	3.982	3.982	3.982	3.982
Av. X	0.891	0.496	1.325	0.553

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *commune* i, and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions are weighted using analytic weights based on the population of each *commune*. This assumes that observations corresponding to larger populations are measured with greater precision (variance is inversely proportional to population size). All regressions include *commune* and year–month fixed effects. Standard errors are clustered at the *commune* level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Long-term

Table D.33: Add leads to baseline (1 lead)

	Violence type	
	Total events	*Total fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)		
$v_{i,t+1}$	0.000	0.000
	(0.001)	(0.000)
$v_{i,t-1}$	-0.001	-0.001*
	(0.001)	(0.001)
Observations	471	471
R-squared	0.993	0.993
Average Y	-0.0139	-0.0139
Av. X	6.495	5.282
Panel B: Real Textile Production (effect sizes in standard deviations)		
$v_{i,t+1}$	-0.001	0.000
	(0.002)	(0.000)
$v_{i,t-1}$	-0.015	-0.004
	(0.010)	(0.005)
Observations	471	471
R-squared	0.953	0.944
Average Y	-0.0123	-0.0123
Av. X	6.495	5.282
Panel C: Total Real Production (in logs)		
$v_{i,t+1}$	-0.000	-0.000
	(0.001)	(0.000)
$v_{i,t-1}$	-0.005***	-0.002***
	(0.001)	(0.001)
Observations	471	471
R-squared	0.997	0.997
Average Y	7.173	7.173
Av. X	6.495	5.282
Panel D: Nighttime Lights (in logs)		
$v_{i,t+1}$	-0.001	-0.001
	(0.002)	(0.001)
$v_{i,t-1}$	-0.009***	-0.012***
	(0.003)	(0.003)
Observations	168	168
R-squared	0.950	0.949
Average Y	3.854	3.854
Av. X	13.92	7.875

Notes: This table reports coefficients from estimating equation (3), not including γ_k and $\eta_{i,t}$. The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *commune* i and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. All specifications include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.34: Robustness: Real Agricultural production with control variables

	(1) *Total Events*	(2) *Total Fatalities*
Events last year	-0.000	0.001
	(0.001)	(0.001)
Land Surface Temperature	-0.044**	-0.044**
	(0.019)	(0.018)
Precipitation	2.204***	2.208***
	(0.674)	(0.661)
Reach of Health Services	-0.123	-0.121
	(0.084)	(0.084)
Reach of Education Services	0.268	0.284
	(0.389)	(0.386)
Earthquake 2021	-0.025	-0.024
	(0.034)	(0.034)
Floods 2022	0.009	0.011
	(0.009)	(0.009)
Observations	444	444
R-squared	0.993	0.993
Average Y	0.0360	0.0360
Av. X	5.775	3.559

Notes: This table reports coefficients from estimating equation (3) adding control variables, not including γ_k and $\eta_{i,t}$. The dependent variable is real crop production in standard deviations $Y_{i,t}$ in *commune* i and year t (period 2018–2022). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.35: Robustness: Real Textile production with control variables

	(1) *Total Events*	(2) *Total Fatalities*
Events last year	-0.019	-0.016
	(0.012)	(0.016)
Land Surface Temperature	0.068	0.045
	(0.068)	(0.069)
Precipitation	0.290	1.141
	(0.487)	(0.959)
Reach of Health Services	0.296	0.360*
	(0.181)	(0.211)
Reach of Education Services	1.154*	1.490
	(0.656)	(0.948)
Earthquake 2021	0.017	0.007
	(0.026)	(0.022)
Floods 2022	-0.068	-0.031
	(0.050)	(0.060)
Observations	444	444
R-squared	0.955	0.947
Average Y	-0.0148	-0.0148
Av. X	5.775	3.559

Notes: This table reports coefficients from estimating equation (3) adding control variables, not including γ_k and $\eta_{i,t}$. The dependent variable is real textile production in standard deviations $Y_{i,t}$ in *commune* i and year t (period 2018–2022). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.36: Robustness: Total Real Production (in logs) with control variables

	(1) *Total Events*	(2) *Total Fatalities*
Events last year	-0.004**	-0.003
	(0.002)	(0.002)
Land Surface Temperature	0.002	-0.003
	(0.019)	(0.019)
Precipitation	0.825***	1.008***
	(0.303)	(0.319)
Reach of Health Services	0.049	0.065
	(0.055)	(0.064)
Reach of Education Services	0.611**	0.696**
	(0.293)	(0.334)
Earthquake 2021	0.023**	0.020**
	(0.010)	(0.009)
Floods 2022	-0.009	0.000
	(0.014)	(0.016)
Observations	444	444
R-squared	0.998	0.997
Average Y	7.166	7.166
Av. X	5.775	3.559

Notes: This table reports coefficients from estimating equation (3) adding control variables, not including γ_k and $\eta_{i,t}$. The dependent variable is the logarithm of real total production in thousands USD $Y_{i,t}$ in *commune* i and year t (period 2018–2022). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. For a description of the variables *land surface temperature, precipitation, reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.37: Robustness: Nighttime Lights (in logs) with control variables

	(1) *Total Events*	(2) *Total Fatalities*
Events last year	-0.010***	-0.013***
	(0.003)	(0.004)
Land Surface Temperature	-0.091	-0.153
	(0.231)	(0.229)
Precipitation	4.181	5.030
	(5.090)	(5.288)
Reach of Health Services	19.284**	19.821**
	(7.186)	(7.415)
Reach of Education Services	-27.230***	-26.471***
	(6.588)	(6.768)
Earthquake 2021	0.194	0.220
	(0.237)	(0.207)
Floods 2022	0.068	0.097
	(0.135)	(0.138)
Observations	160	160
R-squared	0.958	0.958
Average Y	3.916	3.916
Av. X	14.62	8.269

Notes: This table reports coefficients from estimating equation (3) adding control variables, not including γ_k and $\eta_{i,t}$. The dependent variable is the logarithm of nighttime lights $Y_{i,t}$ in *commune* i and year t (period 2018–2023). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. For a description of the variables *land surface temperature, precipitation, reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table D.38: Robustness: SE clustered at *arrondissement* level

	Violence type	
	Total events	*Total fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)		
Events last year	-0.001	-0.001*
	(0.001)	(0.001)
Observations	484	484
R-squared	0.993	0.993
Average Y	-0.0234	-0.0234
Av. X	6.320	5.140
Panel B: Real Textile Production (effect sizes in standard deviations)		
Events last year	-0.015**	-0.004***
	(0.008)	(0.001)
Observations	484	484
R-squared	0.952	0.944
Average Y	-0.0164	-0.0164
Av. X	6.320	5.140
Panel C: Total Real Production (in logs)		
Events last year	-0.005**	-0.002***
	(0.002)	(0.000)
Observations	484	484
R-squared	0.997	0.997
Average Y	7.162	7.162
Av. X	6.320	5.140
Panel D: Nighttime Lights (in logs)		
Events last year	-0.010***	-0.007**
	(0.002)	(0.003)
Observations	200	200
R-squared	0.935	0.936
Average Y	4.078	4.078
Av. X	16.23	12.86

Notes: This table reports coefficients from estimating equation (3), not including γ_k and $\eta_{i,t}$. The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *commune* i and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. All specifications include *commune* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

Table D.39: Robustness: Adding population as analytic weight

	Violence type	
	Total events	*Total fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)		
Events last year	0.000	0.000
	(0.001)	(0.000)
Observations	448	448
R-squared	0.994	0.994
Average Y	0.0311	0.0311
Av. X	5.752	3.540
Panel B: Real Textile Production (effect sizes in standard deviations)		
Events last year	-0.004	-0.001
	(0.003)	(0.002)
Observations	448	448
R-squared	0.945	0.943
Average Y	-0.0161	-0.0161
Av. X	5.752	3.540
Panel C: Total Real Production (in logs)		
Events last year	-0.004**	-0.003
	(0.002)	(0.002)
Observations	448	448
R-squared	0.998	0.997
Average Y	7.162	7.162
Av. X	5.752	3.540
Panel D: Nighttime Lights (in logs)		
Events last year	-0.008***	-0.005***
	(0.002)	(0.001)
Observations	210	210
R-squared	0.924	0.921
Average Y	4.022	4.022
Av. X	15.46	12.25

Notes: This table reports coefficients from estimating equation (3), not including γ_k and $\eta_{i,t}$. The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *commune* i and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. All regressions are weighted using analytic weights based on the population of each commune. This assumes that observations corresponding to larger populations are measured with greater precision (vari- ance is inversely proportional to population size). All specifications include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.40: Add leads to baseline (1 lead)

	Violence type			
	Political Events	*Civil Events*	*Political Fatalities*	*Civil Fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)				
$v_{i,t+1}$	-0.000	-0.001	0.000	0.000
	(0.001)	(0.002)	(0.000)	(0.001)
$v_{i,t-1}$	-0.002	-0.005	-0.001*	-0.002*
	(0.002)	(0.003)	(0.001)	(0.001)
Observations	471	471	471	471
R-squared	0.993	0.993	0.993	0.993
Average Y	-0.0139	-0.0139	-0.0139	-0.0139
Av. X	3.197	1.777	5.042	2.098
Panel B: Real Textile Production (effect sizes in standard deviations)				
$v_{i,t+1}$	0.002	0.007	0.001	-0.005
	(0.002)	(0.007)	(0.001)	(0.005)
$v_{i,t-1}$	-0.006	-0.005	-0.006	-0.017
	(0.009)	(0.012)	(0.007)	(0.017)
Observations	471	471	471	471
R-squared	0.956	0.954	0.947	0.946
Average Y	-0.0123	-0.0123	-0.0123	-0.0123
Av. X	3.197	1.777	5.042	2.098
Panel C: Total Real Production (in logs)				
$v_{i,t+1}$	0.000	0.004**	-0.000	-0.000
	(0.001)	(0.002)	(0.000)	(0.001)
$v_{i,t-1}$	-0.004*	-0.005	-0.002**	-0.000
	(0.002)	(0.004)	(0.001)	(0.003)
Observations	471	471	471	471
R-squared	0.997	0.997	0.997	0.997
Average Y	7.173	7.173	7.173	7.173
Av. X	3.197	1.777	5.042	2.098
Panel D: Nighttime Lights (in logs)				
$v_{i,t+1}$	-0.004	-0.018*	-0.000	-0.006**
	(0.003)	(0.010)	(0.001)	(0.002)
$v_{i,t-1}$	-0.013**	-0.008	-0.016***	-0.006
	(0.005)	(0.010)	(0.005)	(0.005)
Observations	168	168	168	168
R-squared	0.951	0.951	0.949	0.950
Average Y	3.854	3.854	3.854	3.854
Av. X	6.196	3.536	7.286	3.399

Notes: This table presents the coefficient estimates of equation (3), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *commune* i, and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. All regressions include *commune* and year fixed effects. Standard errors are clustered at the *commune* level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.41: Robustness: Real Agricultural production with control variables

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
Events last year	0.000	-0.001	0.001	0.000
	(0.002)	(0.005)	(0.001)	(0.003)
Land Surface Temperature	-0.044**	-0.044**	-0.044**	-0.045**
	(0.019)	(0.019)	(0.018)	(0.018)
Precipitation	2.199***	2.206***	2.208***	2.204***
	(0.676)	(0.682)	(0.664)	(0.662)
Reach of Health Services	-0.123	-0.123	-0.121	-0.122
	(0.084)	(0.084)	(0.084)	(0.084)
Reach of Education Services	0.268	0.269	0.278	0.283
	(0.389)	(0.391)	(0.383)	(0.386)
Earthquake 2021	-0.024	-0.025	-0.025	-0.025
	(0.034)	(0.034)	(0.034)	(0.034)
Floods 2022	0.009	0.009	0.010	0.011
	(0.009)	(0.009)	(0.009)	(0.009)
Observations	444	444	444	444
R-squared	0.993	0.993	0.993	0.993
Average Y	0.0360	0.0360	0.0360	0.0360
Av. X	2.655	1.509	3.329	1.536

Notes: This table reports coefficients from estimating equation (3) adding control variables (coefficients γ_k are not presented in this table). The dependent variable is real crop production in standard deviations $Y_{i,t}$ in *commune* i and year t (period 2018 –2022). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. For a description of the variables *land surface temperature, precipitation, reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table D.42: Robustness: Real Textile production with control variables

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
Events last year	-0.014	-0.014	-0.018	-0.055*
	(0.014)	(0.021)	(0.016)	(0.029)
Land Surface Temperature	0.068	0.069	0.053	0.021
	(0.068)	(0.068)	(0.069)	(0.075)
Precipitation	0.245	0.243	1.134	0.921
	(0.469)	(0.452)	(0.957)	(0.824)
Reach of Health Services	0.295	0.297	0.362*	0.290
	(0.180)	(0.182)	(0.204)	(0.188)
Reach of Education Services	1.156*	1.144*	1.375*	1.407
	(0.640)	(0.636)	(0.807)	(0.895)
Earthquake 2021	0.018	0.018	-0.006	-0.008
	(0.028)	(0.028)	(0.030)	(0.026)
Floods 2022	-0.065	-0.068	-0.040	-0.014
	(0.048)	(0.049)	(0.058)	(0.066)
Observations	444	444	444	444
R-squared	0.955	0.955	0.950	0.953
Average Y	-0.0148	-0.0148	-0.0148	-0.0148
Av. X	2.655	1.509	3.329	1.536

Notes: This table reports coefficients from estimating equation (3) adding control variables (coefficients γ_k are not presented in this table). The dependent variable is real textile production in standard deviations $Y_{i,t}$ in *commune* i and year t (period 2018 –2022). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. For a description of the variables *land surface temperature, precipitation, reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$.

Table D.43: Robustness: Total Real Production (in logs) with control variables

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
Events last year	-0.003	-0.005	-0.003	-0.007**
	(0.003)	(0.005)	(0.002)	(0.003)
Land Surface Temperature	0.002	0.002	-0.002	-0.005
	(0.019)	(0.019)	(0.019)	(0.020)
Precipitation	0.814***	0.829***	1.007***	0.986***
	(0.301)	(0.298)	(0.323)	(0.316)
Reach of Health Services	0.049	0.049	0.065	0.058
	(0.055)	(0.055)	(0.063)	(0.064)
Reach of Education Services	0.611**	0.612**	0.683**	0.687**
	(0.292)	(0.292)	(0.324)	(0.330)
Earthquake 2021	0.023**	0.022**	0.019**	0.019**
	(0.011)	(0.010)	(0.009)	(0.009)
Floods 2022	-0.009	-0.010	-0.001	0.002
	(0.014)	(0.014)	(0.016)	(0.017)
Observations	444	444	444	444
R-squared	0.998	0.998	0.997	0.997
Average Y	7.166	7.166	7.166	7.166
Av. X	2.655	1.509	3.329	1.536

Notes: This table reports coefficients from estimating equation (3) adding control variables (coefficients γ_k are not presented in this table). The dependent variable is the logarithm of real total production in thousands USD $Y_{i,t}$ in *commune* i and year t (period 2018 –2022). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table D.44: Robustness: Nighttime Lights (in logs) with control variables

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
Events last year	-0.012**	-0.012*	-0.013***	-0.009
	(0.004)	(0.007)	(0.004)	(0.006)
Land Surface Temperature	-0.091	-0.092	-0.151	-0.150
	(0.230)	(0.232)	(0.228)	(0.230)
Precipitation	4.220	4.269	5.026	5.026
	(5.080)	(5.119)	(5.299)	(5.299)
Reach of Health Services	19.421***	19.324**	19.811**	19.820**
	(7.169)	(7.189)	(7.445)	(7.475)
Reach of Education Services	-27.214***	-27.218***	-26.503***	-26.335***
	(6.618)	(6.601)	(6.812)	(6.823)
Earthquake 2021	0.205	0.199	0.220	0.222
	(0.234)	(0.234)	(0.206)	(0.209)
Floods 2022	0.066	0.067	0.096	0.094
	(0.136)	(0.136)	(0.142)	(0.139)
Observations	160	160	160	160
R-squared	0.958	0.958	0.958	0.958
Average Y	3.916	3.916	3.916	3.916
Av. X	6.506	3.712	7.650	3.569

Notes: This table reports coefficients from estimating equation (3) adding control variables (coefficients γ_k are not presented in this table). The dependent variable is the logarithm of nighttime lights $Y_{i,t}$ in *commune* i and year t (period 2018 –2023). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *commune* and year fixed effects. Standard errors, clustered at the *commune* level, are in parentheses. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

Table D.45: Robustness: SE clustered at *arrondissement* level in violence type specification

	Violence type			
	Political Events	*Civil Events*	*Political Fatalities*	*Civil Fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)				
Events last year	-0.002	-0.004	-0.001*	-0.002***
	(0.003)	(0.005)	(0.001)	(0.000)
Observations	484	484	484	484
R-squared	0.993	0.993	0.993	0.993
Average Y	-0.0234	-0.0234	-0.0234	-0.0234
Av. X	3.112	1.729	4.907	2.041
Panel B: Real Textile Production (effect sizes in standard deviations)				
Events last year	-0.009	-0.007	-0.004***	-0.008***
	(0.006)	(0.009)	(0.001)	(0.000)
Observations	484	484	484	484
R-squared	0.953	0.953	0.946	0.944
Average Y	-0.016	-0.016	-0.016	-0.016
Av. X	3.112	1.729	4.907	2.041
Panel C: Total Real Production (in logs)				
Events last year	-0.005	-0.005	-0.002***	-0.001*
	(0.003)	(0.004)	(0.000)	(0.001)
Observations	484	484	484	484
R-squared	0.997	0.997	0.997	0.997
Average Y	7.162	7.162	7.162	7.162
Av. X	3.112	1.729	4.907	2.041
Panel D: Nighttime Lights (in logs)				
Events last year	-0.011**	-0.015	-0.007**	-0.007
	(0.004)	(0.011)	(0.003)	(0.007)
Observations	200	200	200	200
R-squared	0.935	0.935	0.936	0.936
Average Y	4.078	4.078	4.078	4.078
Av. X	8.235	4.570	12.140	5.555

Notes: This table presents the coefficient estimates of equation (3), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *commune* i, and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. All regressions include *commune* and year fixed effects. Standard errors are clustered at the *commune* level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table D.46: Robustness: Analytic weights in violence type specification

	Violence type			
	Political Events	*Civil Events*	*Political Fatalities*	*Civil Fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)				
Events last year	-0.000	-0.003	-0.000	-0.003
	(0.001)	(0.003)	(0.001)	(0.004)
Observations	448	448	448	448
R-squared	0.994	0.994	0.994	0.994
Average Y	0.0311	0.0311	0.0311	0.0311
Av. X	2.654	1.511	3.313	1.533
Panel B: Real Textile Production (effect sizes in standard deviations)				
Events last year	-0.001	0.001	-0.001	-0.020
	(0.003)	(0.006)	(0.002)	(0.015)
Observations	448	448	448	448
R-squared	0.946	0.945	0.943	0.945
Average Y	-0.0161	-0.0161	-0.0161	-0.0161
Av. X	2.654	1.511	3.313	1.533
Panel C: Total Real Production (in logs)				
Events last year	-0.000	-0.000	-0.000	-0.003*
	(0.001)	(0.003)	(0.000)	(0.002)
Observations	448	448	448	448
R-squared	0.996	0.996	0.996	0.996
Average Y	7.162	7.162	7.162	7.162
Av. X	2.654	1.511	3.313	1.533
Panel D: Nighttime Lights (in logs)				
Events last year	-0.007***	-0.005	-0.005***	0.002
	(0.002)	(0.012)	(0.001)	(0.004)
Observations	210	210	210	210
R-squared	0.924	0.924	0.921	0.923
Average Y	4.022	4.022	4.022	4.022
Av. X	7.843	4.352	11.570	5.290

Notes: This table presents the coefficient estimates of equation (3), separately for each type of event (coefficients γ_k are not included in this table). The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *commune* i, and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. All regressions are weighted using analytic weights based on the population of each commune. This assumes that observations corresponding to larger populations are measured with greater precision (variance is inversely proportional to population size). All regressions include *commune* and year fixed effects. Standard errors are clustered at the *commune* level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Online Appendix

Economic Fallout of Social Conflict: Evidence from Social Media and Satellite Images

Matteo Grazzi, Paola Llamas, Giulia Lotti, Werner Peña

Medium-term impacts for nighttime lights using *arrondissement*

Table OA.1: Medium-term effects of violence on Nighttime Lights (logs)

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t-1}$	-0.008***	-0.003***
	(0.001)	(0.000)
$v_{i,t-2}$	-0.005***	-0.002**
	(0.002)	(0.001)
$v_{i,t-3}$	-0.003	-0.002**
	(0.002)	(0.001)
$v_{i,t-4}$	-0.001	-0.001
	(0.001)	(0.001)
$v_{i,t-5}$	-0.002	-0.002*
	(0.003)	(0.001)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.0198***	-0.00989***
Wald test: p value	0.00667	0.00958
Observations	1,541	1,541
R-squared	0.894	0.894
Average Y	2.234	2.234
Av. X	3.891	3.631

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i and month t (period January 2018 – December 2023). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. All specifications include *arrondissement* and year–month fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Heterogeneity analysis by event type for nighttime lights using *arrondissement*

Table OA.2: Medium-term effects of violence on Nighttime Lights (logs)

	(1) Political Events	(2) Civil Events	(3) Political Fatalities	(4) Civil Fatalities
$v_{i,t-1}$	-0.011***	-0.010***	-0.003***	-0.005***
	(0.001)	(0.002)	(0.001)	(0.001)
$v_{i,t-2}$	-0.005***	-0.009***	-0.002***	-0.005**
	(0.001)	(0.003)	(0.001)	(0.003)
$v_{i,t-3}$	-0.004*	0.000	-0.002**	-0.004
	(0.002)	(0.004)	(0.001)	(0.003)
$v_{i,t-4}$	-0.000	0.003	-0.001	-0.003
	(0.001)	(0.006)	(0.001)	(0.003)
$v_{i,t-5}$	-0.003	-0.002	-0.002*	-0.010*
	(0.003)	(0.005)	(0.001)	(0.005)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.023***	-0.018	-0.010***	-0.028*
Wald test: p value	0.000	0.252	0.006	0.056
Observations	1,541	1,541	1,541	1,541
R-squared	0.894	0.894	0.894	0.895
Average Y	2.234	2.234	2.234	2.234
Av. X	2.066	1.134	3.482	1.380

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i, and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \dots, 5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *arrondissement* and year–month fixed effects. Standard errors are clustered at the *arrondissement* level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.3: Event Type Effect on Nighttime Lights (in logs)

	(1) *Battles*	(2) *Protests*	(3) *Riots*	(4) *Strategic Developments*	(5) *Violence Against Civilians*
$v_{i,t-1}$	-0.016***	0.005	-0.003	-0.002	-0.010***
	(0.004)	(0.008)	(0.005)	(0.008)	(0.002)
$v_{i,t-2}$	-0.005**	0.001	-0.003	-0.008	-0.009***
	(0.002)	(0.010)	(0.006)	(0.005)	(0.003)
$v_{i,t-3}$	-0.008**	-0.001	0.000	-0.020**	0.000
	(0.004)	(0.013)	(0.004)	(0.008)	(0.004)
$v_{i,t-4}$	-0.004*	0.003	0.001	0.005	0.003
	(0.002)	(0.009)	(0.005)	(0.010)	(0.006)
$v_{i,t-5}$	-0.006*	-0.015*	0.005**	-0.008	-0.002
	(0.003)	(0.008)	(0.002)	(0.016)	(0.005)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.039***	-0.007	0.002	-0.034	-0.018
Wald test: p value	0.002	0.854	0.938	0.115	0.252
Observations	1,541	1,541	1,541	1,541	1,541
R-squared	0.894	0.894	0.894	0.894	0.894
Average Y	2.234	2.234	2.234	2.234	2.234
Av. X	0.781	0.738	0.874	0.364	1.134

Notes: This table presents coefficient estimates from equation (2), separately by event type at the most disaggregated level (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged battles $v_{i,t-k}$; column (2), protests; column (3), riots; column (4), strategic developments; and column (5), violence against civilians, for $k = 1, \ldots, 5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *arrondissement* and year–month fixed effects. Regressions for each event type exclude *arrondissements* without any occurrences of that event type. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Long-term impacts for nighttime lights and production using *arrondissement*

Table OA.4: Long-term Effects of Violence on Economic Activity

	Violence type	
	Total events	*Total fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)		
Events last year	-0.0001	-0.0002**
	(0.0001)	(0.0001)
Observations	164	164
R-squared	0.993	0.993
Average Y	-0.0289	-0.0289
Av. X	26.55	21.09
Panel B: Real Textile Production (effect sizes in standard deviations)		
Events last year	-0.006***	-0.006***
	(0.0004)	(0.0003)
Observations	164	164
R-squared	0.977	0.966
Average Y	-0.0232	-0.0232
Av. X	26.55	21.09
Panel C: Total Real Production (in logs)		
Events last year	-0.001***	-0.001***
	(0.000)	(0.000)
Observations	164	164
R-squared	0.997	0.997
Average Y	8.352	8.352
Av. X	26.55	21.09
Panel D: Nighttime Lights (in logs)		
Events last year	-0.003***	-0.002***
	(0.001)	(0.001)
Observations	115	115
R-squared	0.945	0.948
Average Y	2.321	2.321
Av. X	49.48	46.77

Notes: This table reports coefficients from estimating equation (3). The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *arrondissement* i and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Heterogeneity analysis by event type for nighttime lights and production using *arrondissement*

Table OA.5: Long-term effects of violence on economic activity

	Violence type			
	Political Events	*Civil Events*	*Political Fatalities*	*Civil Fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)				
Events last year	-0.001	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Observations	164	164	164	164
R-squared	0.993	0.993	0.993	0.993
Average Y	-0.0289	-0.0289	-0.0289	-0.0289
Av. X	13.46	7.677	20.20	8.116
Panel B: Real Textile Production (effect sizes in standard deviations)				
Events last year	-0.003***	-0.000	-0.007***	-0.004***
	(0.001)	(0.002)	(0.002)	(0.000)
Observations	164	164	164	164
R-squared	0.978	0.979	0.966	0.966
Average Y	-0.0232	-0.0232	-0.0232	-0.0232
Av. X	13.46	7.677	20.20	8.116
Panel C: Total Real Production (in logs)				
Events last year	-0.001***	-0.001**	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	164	164	164	164
R-squared	0.997	0.997	0.997	0.997
Average Y	8.352	8.352	8.352	8.352
Av. X	13.46	7.677	20.20	8.116
Panel D: Nighttime Lights (in logs)				
Events last year	-0.003***	-0.003	-0.003***	-0.006*
	(0.001)	(0.003)	(0.001)	(0.004)
Observations	115	115	115	115
R-squared	0.946	0.945	0.948	0.949
Average Y	2.321	2.321	2.321	2.321
Av. X	26.75	14.70	45.15	17.50

Notes: This table presents the coefficient estimates of equation (3), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *arrondissement* i, and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. All regressions include *arrondissement* and year fixed effects. Standard errors are clustered at the *arrondissement* level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.6: Heterogeneity of long-term effects by event type

	Event type				
	Battles	*Protests*	*Riots*	*Strategic Developments*	*Violence against civilians*
Panel A: Agriculture Production Real (effect sizes in standard deviations)					
Events last year	-0.002	0.004	0.000	-0.000	-0.001
	(0.004)	(0.007)	(0.001)	(0.002)	(0.001)
Observations	164	164	164	164	164
R-squared	0.993	0.993	0.993	0.993	0.993
Average Y	-0.0289	-0.0289	-0.0289	-0.0289	-0.0289
Av. X	5.061	5.457	6.585	1.768	7.677
Panel B: Textile Production Real (effect sizes in standard deviations)					
Events last year	0.008	0.009*	-0.015***	-0.002	0.000
	(0.011)	(0.005)	(0.002)	(0.006)	(0.002)
Observations	164	164	164	164	164
R-squared	0.978	0.978	0.981	0.977	0.979
Average Y	-0.0232	-0.0232	-0.0232	-0.0232	-0.0232
Av. X	5.061	5.457	6.585	1.768	7.677
Panel C: Total real production (in logs)					
Events last year	-0.000	-0.001	-0.002***	-0.001	-0.001**
	(0.001)	(0.002)	(0.000)	(0.001)	(0.000)
Observations	164	164	164	164	164
R-squared	0.997	0.997	0.997	0.997	0.997
Average Y	8.352	8.352	8.352	8.352	8.352
Av. X	5.061	5.457	6.585	1.768	7.677
Panel D: Nighttime Lights (in logs)					
Events last year	-0.011***	-0.006	0.004**	0.001	-0.003
	(0.002)	(0.014)	(0.002)	(0.006)	(0.003)
Observations	115	115	115	115	115
R-squared	0.947	0.945	0.947	0.945	0.945
Average Y	2.321	2.321	2.321	2.321	2.321
Av. X	10.15	8.957	10.85	4.817	14.70

Notes: This table presents coefficient estimates from equation (3), separately by event type at the most disaggregated level (coefficients γ_k are not presented in this table). The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *arrondissement* i and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Column (1) shows the effect of one year lag of battles $v_{i,t-k}$; column (2), protests; column (3), riots; column (4), strategic developments; and column (5), violence against civilians. All regressions include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$.

Robustness check for nighttime lights and production using arrondissement

Medium term

Table OA.7: Add leads to baseline (5 leads)

	(1) *Total events*	(2) *Total fatalities*
$\nu_{i,t+5}$	0.002	-0.001*
	(0.003)	(0.000)
$\nu_{i,t+4}$	-0.002	-0.000
	(0.001)	(0.001)
$\nu_{i,t+3}$	0.002	-0.001**
	(0.002)	(0.001)
$\nu_{i,t+2}$	0.003	-0.001
	(0.002)	(0.001)
$\nu_{i,t+1}$	-0.004**	-0.002**
	(0.001)	(0.001)
$\nu_{i,t-1}$	-0.008***	-0.003***
	(0.002)	(0.000)
$\nu_{i,t-2}$	-0.005**	-0.002***
	(0.002)	(0.000)
$\nu_{i,t-3}$	-0.004	-0.002**
	(0.003)	(0.001)
$\nu_{i,t-4}$	-0.001	0.000
	(0.002)	(0.001)
$\nu_{i,t-5}$	-0.001	-0.001
	(0.003)	(0.001)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.0187*	-0.00738**
Wald test: p value	0.0977	0.0106
$\sum_{k=1}^{5} \nu_{i,t+k}$	0.000421	-0.00472**
Wald test: p value	0.957	0.0288
Observations	1,426	1,426
R-squared	0.902	0.902
Average Y	2.192	2.192
Av. X	3.727	3.363

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i and month t (period January 2018 – December 2023). Columns (1) and (2) show the effects of lagged and lead counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. The row labelled $\sum_{k=1}^{5} \nu_{i,t+k}$ gives the cumulative effect of the five leads, and "Wald test: p-value" is from a joint significance test of those five leads. All specifications include *arrondissement* and year–month fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table OA.8: Robustness: Add controls to baseline

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t-1}$	-0.004*	-0.001***
	(0.002)	(0.000)
$v_{i,t-2}$	-0.004*	-0.001
	(0.002)	(0.000)
$v_{i,t-3}$	-0.006*	-0.002**
	(0.003)	(0.001)
$v_{i,t-4}$	-0.003	-0.001**
	(0.002)	(0.000)
$v_{i,t-5}$	-0.003	-0.001**
	(0.002)	(0.000)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.0200***	-0.00532***
Wald test: p value	0.00101	0.00153
Earthquake 2021	-0.179	-0.193
	(0.167)	(0.164)
Lag Earthquake 2021	-0.345***	-0.360***
	(0.111)	(0.115)
Floods 2022	-0.120	-0.101
	(0.185)	(0.184)
Lag Floods 2022,	-0.118	-0.102
	(0.148)	(0.148)
Land Surface Temperature	0.138***	0.133***
	(0.040)	(0.040)
Precipitation	1.318**	1.530***
	(0.499)	(0.527)
Reach of Health Services	-61.791	-68.093
	(59.149)	(58.532)
Reach of Education Services	57.000	62.715
	(62.297)	(61.973)
Observations	828	828
R-squared	0.921	0.920
Average Y	2.040	2.040
Av. X	3.905	3.351

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i and month t (period January 2018 – December 2023). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable that equals 1 only in August 2021 if the area was affected by the earthquake. Affected areas include Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Côteaux, and Port-Salut. Otherwise, it takes a value of 0. *Floods 2022* is a binary variable that equals 1 only in February 2022 if the area was affected by flooding. Affected regions include Nord, Nord-Est, Nippes, and Nord-Ouest. Otherwise, it takes a value of 0. All specifications include *arrondissement* and year–month fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.9: Robustness: SE clustered at department level

	(1) *Total events*	(2) *Total fatalities*
$\nu_{i,t-1}$	-0.008***	-0.003***
	(0.001)	(0.001)
$\nu_{i,t-2}$	-0.005***	-0.002***
	(0.002)	(0.000)
$\nu_{i,t-3}$	-0.003*	-0.002**
	(0.002)	(0.001)
$\nu_{i,t-4}$	-0.001	-0.001**
	(0.001)	(0.000)
$\nu_{i,t-5}$	-0.002*	-0.002***
	(0.001)	(0.000)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.0198***	-0.00989***
Wald test: p value	0.00286	0.000283
Observations	1,541	1,541
R-squared	0.894	0.894
Average Y	2.234	2.234
Av. X	3.891	3.631

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i and month t (period January 2018 – December 2023). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. All specifications include *arrondissement* and year–month fixed effects. Standard errors, clustered at the department level, are in parentheses. $*\ p < 0.10$, $**\ p < 0.05$, $***\ p < 0.01$.

Table OA.10: Robustness: Adding population as analytic weight

	(1) *Total events*	(2) *Total fatalities*
$\nu_{i,t-1}$	-0.008***	-0.002***
	(0.001)	(0.000)
$\nu_{i,t-2}$	-0.003***	-0.001***
	(0.001)	(0.000)
$\nu_{i,t-3}$	-0.001*	-0.001**
	(0.001)	(0.000)
$\nu_{i,t-4}$	-0.000	-0.001*
	(0.001)	(0.000)
$\nu_{i,t-5}$	0.000	-0.001**
	(0.001)	(0.000)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.0118***	-0.00638***
Wald test: p value	0.00251	0.000417
Observations	1,206	1,206
R-squared	0.964	0.963
Average Y	2.614	2.614
Av. X	4.847	4.587

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i and month t (period January 2018 – December 2023). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. All regressions are weighted using analytic weights based on the population of each arrondissement. This assumes that observations corresponding to larger populations are measured with greater precision (variance is inversely proportional to population size). All specifications include *arrondissement* and year–month fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.11: Robustness: NTL - Wild cluster bootstrap test for individual and joint significance

	(1) *Total events*	(2) *Total fatalities*
$v_{i,t-1}$	-0.008*	-0.003*
p value	0.0739	0.0755
$v_{i,t-2}$	-0.005	-0.002
p value	0.210	0.127
$v_{i,t-3}$	-0.003	-0.002
p value	0.157	0.132
$v_{i,t-4}$	-0.001	-0.001
p value	0.564	0.179
$v_{i,t-5}$	-0.002	-0.002
p value	0.328	0.127
$\sum_{k=1}^{5} v_{i,t-k}$	-0.0198	-0.00989
WB joint test: p value	0.173	0.176
Observations	1,541	1,541
R-squared	0.894	0.894
Average Y	2.234	2.234
Av. X	3.891	3.631

Notes: This table reports coefficients from estimating equation (2), not including γ_k and $\eta_{i,t}$. The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i and month t (period January 2018 – December 2023). Columns (1) and (2) show the effects of lagged counts of total events and total fatalities, respectively, at $k = 1, \ldots, 5$ months. The row labelled $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" is from a joint significance test of those five lags. All specifications include *arrondissement* and year–month fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $* \, p < 0.10$, $** \, p < 0.05$, $*** \, p < 0.01$.

Table OA.12: Robustness: Add leads to violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$\nu_{i,t+5}$	0.003	0.002	-0.001*	-0.003**
	(0.002)	(0.003)	(0.000)	(0.001)
$\nu_{i,t+4}$	-0.002	-0.004	-0.000	-0.004***
	(0.002)	(0.006)	(0.001)	(0.001)
$\nu_{i,t+3}$	-0.001	0.002	-0.001***	-0.003**
	(0.002)	(0.004)	(0.001)	(0.001)
$\nu_{i,t+2}$	0.002	-0.000	-0.001	-0.002
	(0.002)	(0.006)	(0.001)	(0.001)
$\nu_{i,t+1}$	-0.005**	-0.004	-0.002***	-0.006***
	(0.002)	(0.005)	(0.000)	(0.002)
$\nu_{i,t-1}$	-0.013***	-0.006*	-0.004***	-0.005***
	(0.002)	(0.003)	(0.000)	(0.001)
$\nu_{i,t-2}$	-0.005**	-0.008	-0.002***	-0.006**
	(0.002)	(0.004)	(0.000)	(0.002)
$\nu_{i,t-3}$	-0.008***	0.002	-0.002**	-0.005
	(0.003)	(0.007)	(0.001)	(0.003)
$\nu_{i,t-4}$	0.000	0.009	0.000	-0.000
	(0.002)	(0.010)	(0.000)	(0.001)
$\nu_{i,t-5}$	0.003	0.002	-0.001	-0.010
	(0.004)	(0.006)	(0.001)	(0.006)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.0222***	8.24e-05	-0.00825***	-0.0253**
Wald test: p value	0.002	0.862	0.004	0.044
$\sum_{k=1}^{5} \nu_{i,t+k}$	-0.004	-0.004	-0.005**	-0.017***
Wald test: p value	0.354	0.997	0.016	0.000
Observations	1,426	1,426	1,426	1,426
R-squared	0.903	0.903	0.903	0.903
Average Y	2.192	2.192	2.192	2.192
Av. X	1.976	1.100	3.231	1.374

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i, and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged and lead political events $\nu_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1,\dots,5$ months. The row $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. The row labelled $\sum_{k=1}^{5} \nu_{i,t+k}$ gives the cumulative effect of the five leads, and "Wald test: p-value" is from a joint significance test of those five leads. All regressions include *arrondissement* and year–month fixed effects. Standard errors are clustered at the *arrondissement* level and are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table OA.13: Robustness: Add controls to violence type specification

	(1) Political Events	(2) Civil Events	(3) Political Fatalities	(4) Civil Fatalities
$v_{i,t-1}$	-0.006**	-0.006	-0.002***	-0.001
	(0.003)	(0.005)	(0.000)	(0.002)
$v_{i,t-2}$	-0.002	-0.001	-0.001*	0.001
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t-3}$	-0.007***	-0.004	-0.002**	-0.002
	(0.002)	(0.005)	(0.001)	(0.002)
$v_{i,t-4}$	-0.006***	-0.001	-0.001*	-0.000
	(0.002)	(0.006)	(0.000)	(0.002)
$v_{i,t-5}$	-0.002	-0.003	-0.000	-0.003
	(0.002)	(0.005)	(0.000)	(0.002)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.022***	-0.014	-0.005***	-0.005
Wald test: p value	0.000	0.467	0.003	0.511
Earthquake 2021	-0.180	-0.177	-0.194	-0.193
	(0.168)	(0.166)	(0.161)	(0.164)
Lag Earthquake 2021	-0.348***	-0.350***	-0.360***	-0.362***
	(0.114)	(0.113)	(0.112)	(0.116)
Floods 2022	-0.122	-0.122	-0.093	-0.102
	(0.188)	(0.186)	(0.184)	(0.186)
Lag Floods 2022	-0.126	-0.115	-0.113	-0.100
	(0.149)	(0.145)	(0.152)	(0.150)
Land Surface Temperature	0.138***	0.138***	0.135***	0.133***
	(0.041)	(0.041)	(0.041)	(0.041)
Precipitation	1.380**	1.302**	1.474**	1.538***
	(0.498)	(0.483)	(0.531)	(0.527)
Reach of Health Services	-61.446	-61.435	-67.327	-68.207
	(59.405)	(58.957)	(58.615)	(58.793)
Reach of Education Services	56.812	56.634	61.731	62.774
	(62.430)	(62.149)	(62.112)	(62.341)
Observations	828	828	828	828
R-squared	0.921	0.921	0.920	0.920
Average Y	2.040	2.040	2.040	2.040
Av. X	2.161	1.248	3.286	1.267

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event and adding control variables (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i, and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \ldots, 5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable that equals 1 only in August 2021 if the area was affected by the earthquake. Affected areas include Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Côteaux, and Port-Salut. Otherwise, it takes a value of 0. *Floods 2022* is a binary variable that equals 1 only in February 2022 if the area was affected by flooding. Affected regions include Nord, Nord-Est, Nippes, and Nord-Ouest. Otherwise, it takes a value of 0. All regressions include *arrondissement* and year–month fixed effects. Standard errors are clustered at the *arrondissement* level and are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table OA.14: Robustness: SE clustered at department level in violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$v_{i,t-1}$	-0.011***	-0.010***	-0.003***	-0.005***
	(0.002)	(0.003)	(0.001)	(0.001)
$v_{i,t-2}$	-0.005***	-0.009*	-0.002***	-0.005***
	(0.002)	(0.004)	(0.000)	(0.001)
$v_{i,t-3}$	-0.004*	0.000	-0.002***	-0.004***
	(0.002)	(0.006)	(0.001)	(0.001)
$v_{i,t-4}$	-0.000	0.003	-0.001**	-0.003**
	(0.001)	(0.008)	(0.000)	(0.001)
$v_{i,t-5}$	-0.003**	-0.002	-0.002***	-0.010***
	(0.001)	(0.006)	(0.000)	(0.001)
$\sum_{k=1}^{5} v_{i,t-k}$	-0.0234	-0.0178	-0.0102	-0.0282
Wald test: p value	0.001	0.456	0.000	0.000
Observations	1,541	1,541	1,541	1,541
R-squared	0.894	0.894	0.894	0.894
Average Y	2.234	2.234	2.234	2.234
Av. X	2.066	1.134	3.482	1.380

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i, and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1,\dots,5$ months. The row $\sum_{k=1}^{5} v_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *arrondissement* and year–month fixed effects. Standard errors are clustered at the department level and are in parentheses. $* \; p < 0.10$, $** \; p < 0.05$, $*** \; p < 0.01$.

Table OA.15: Robustness: Analytic weights in violence type specification

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
$\nu_{i,t-1}$	-0.010***	-0.008***	-0.003***	-0.004***
	(0.002)	(0.002)	(0.000)	(0.001)
$\nu_{i,t-2}$	-0.003***	-0.008***	-0.001***	-0.002**
	(0.001)	(0.002)	(0.000)	(0.001)
$\nu_{i,t-3}$	-0.004**	-0.001	-0.001***	-0.001
	(0.001)	(0.003)	(0.000)	(0.001)
$\nu_{i,t-4}$	-0.001	-0.003*	-0.001**	-0.001
	(0.001)	(0.002)	(0.000)	(0.001)
$\nu_{i,t-5}$	-0.002	-0.003	-0.001***	-0.003*
	(0.001)	(0.003)	(0.000)	(0.001)
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.019***	-0.024**	-0.007***	-0.012***
Wald test: p value	0.000	0.022	0.000	0.004
Observations	1,206	1,206	1,206	1,206
R-squared	0.965	0.964	0.963	0.963
Average Y	2.614	2.614	2.614	2.614
Av. X	2.600	1.434	4.400	1.749

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i, and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged political events $\nu_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1,\dots,5$ months. The row $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "Wald test: p-value" reports the p-value from the joint significance test of those five lags. All regressions are weighted using analytic weights based on the population of each arrondissement. This assumes that observations corresponding to larger populations are measured with greater precision (variance is inversely proportional to population size). All regressions include *arrondissement* and year–month fixed effects. Standard errors are clustered at the *arrondissement* level and are in parentheses. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Table OA.16: Robustness: NTL - Wild cluster bootstrap test for individual and joint significance

	(1) Political Events	(2) Civil Events	(3) Political Fatalities	(4) Civil Fatalities
$\nu_{i,t-1}$	-0.011**	-0.010	-0.003*	-0.005*
p value	0.0190	0.155	0.0704	0.0988
$\nu_{i,t-2}$	-0.005	-0.009	-0.002*	-0.005**
p value	0.111	0.185	0.106	0.0654
$\nu_{i,t-3}$	-0.004	0.000	-0.002	-0.004
p value	0.266	0.942	0.130	0.161
$\nu_{i,t-4}$	-0.000	0.003	-0.001	-0.003
p value	0.838	0.549	0.181	0.308
$\nu_{i,t-5}$	-0.003	-0.002	-0.002	-0.010*
p value	0.144	0.655	0.166	0.0783
$\sum_{k=1}^{5} \nu_{i,t-k}$	-0.023	-0.018	-0.010*	-0.028
WB joint test: p value	0.179	0.371	0.0696	0.564
Observations	1,541	1,541	1,541	1,541
R-squared	0.894	0.894	0.894	0.895
Average Y	2.234	2.234	2.234	2.234
Av. X	2.066	1.134	3.482	1.380

Notes: This table presents the coefficient estimates of equation (2), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variable is the log of nighttime lights $Y_{i,t}$ in *arrondissement* i, and month t (period January 2018 – December 2023). Column (1) shows the effect of lagged political events $\nu_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities, for $k = 1, \dots, 5$ months. The row $\sum_{k=1}^{5} \nu_{i,t-k}$ gives the cumulative effect over the five-month horizon, and "WB joint test: p-value" reports the p-value from the joint significance test of those five lags. All regressions include *arrondissement* and year–month fixed effects. Standard errors are clustered at the *arrondissement* level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Long term

Table OA.17: Add leads to baseline (1 lead)

	Violence type	
	Total events	*Total fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)		
$v_{i,t+1}$	0.001	0.001*
	(0.001)	(0.000)
$v_{i,t-1}$	-0.001	-0.002**
	(0.001)	(0.001)
Observations	123	123
R-squared	0.992	0.992
Average Y	-0.0432	-0.0432
Av. X	24.50	15.54
Panel B: Real Textile Production (effect sizes in standard deviations)		
$v_{i,t+1}$	-0.004	0.001
	(0.004)	(0.001)
$v_{i,t-1}$	-0.004**	-0.006***
	(0.002)	(0.002)
Observations	123	123
R-squared	0.983	0.971
Average Y	-0.00327	-0.00327
Av. X	24.50	15.54
Panel C: Total Real Production (in logs)		
$v_{i,t+1}$	-0.001	0.000
	(0.001)	(0.000)
$v_{i,t-1}$	-0.001**	-0.001***
	(0.000)	(0.000)
Observations	123	123
R-squared	0.998	0.998
Average Y	8.349	8.349
Av. X	24.50	15.54
Panel D: Nighttime Lights (in logs)		
$v_{i,t+1}$	0.000	0.000
	(0.002)	(0.000)
$v_{i,t-1}$	-0.003	-0.002***
	(0.002)	(0.000)
Observations	115	115
R-squared	0.945	0.94
Average Y	2.321	2.321
Av. X	49.48	46.77

Notes: This table reports coefficients from estimating equation (3), not including γ_k and $\eta_{i,t}$. The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *arrondissement* i and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.18: Robustness: Real Agricultural production with control variables

	(1) *Total Events*	(2) *Total Fatalities*
Events last year	-0.0001	-0.0003***
	(0.000)	(0.000)
Land Surface Temperature	-0.112	-0.114
	(0.082)	(0.083)
Precipitation	1.974	2.008
	(3.470)	(3.497)
Reach of Health Services	8.871**	8.913**
	(4.004)	(4.063)
Reach of Education Services	-11.265**	-11.371**
	(5.546)	(5.622)
Earthquake 2021	-0.050	-0.051
	(0.059)	(0.059)
Floods 2022	0.007	0.004
	(0.012)	(0.012)
Observations	123	123
R-squared	0.994	0.994
Average Y	0.00732	0.00732
Av. X	27.49	24.29

Notes: This table reports coefficients from estimating equation (3) adding control variables, not including γ_k and $\eta_{i,t}$. The dependent variable is real crop production in standard deviations $Y_{i,t}$ in *arrondissement* i and year t (period 2018–2022). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table OA.19: Robustness: Real Textile production with control variables

	(1) *Total Events*	(2) *Total Fatalities*
Events last year	-0.004***	-0.002***
	(0.000)	(0.000)
Land Surface Temperature	-0.025	-0.048
	(0.070)	(0.090)
Precipitation	2.730	1.227
	(5.289)	(6.462)
Reach of Health Services	1.666	0.916
	(3.276)	(2.571)
Reach of Education Services	-1.460	0.292
	(4.478)	(3.061)
Earthquake 2021	-0.063	-0.073
	(0.047)	(0.057)
Floods 2022	-0.047	-0.021
	(0.045)	(0.060)
Observations	123	123
R-squared	0.984	0.984
Average Y	-0.0510	-0.0510
Av. X	27.49	24.29

Notes: This table reports coefficients from estimating equation (3) adding control variables, not including γ_k and $\eta_{i,t}$. The dependent variable is real textile production in standard deviations $Y_{i,t}$ in *arrondissement* i and year t (period 2018–2022). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.20: Robustness: Total Real Production (in logs) with control variables

	(1) *Total Events*	(2) *Total Fatalities*
Events last year	-0.001***	-0.001***
	(0.000)	(0.000)
Land Surface Temperature	0.024	0.015
	(0.024)	(0.026)
Precipitation	1.816	1.422
	(1.134)	(1.278)
Reach of Health Services	1.274	1.112
	(2.089)	(2.107)
Reach of Education Services	-1.558	-1.188
	(2.965)	(2.981)
Earthquake 2021	0.000	-0.004
	(0.009)	(0.010)
Floods 2022	-0.028	-0.023
	(0.022)	(0.023)
Observations	123	123
R-squared	0.999	0.999
Average Y	8.365	8.365
Av. X	27.49	24.29

Notes: This table reports coefficients from estimating equation (3) adding control variables, not including γ_k and $\eta_{i,t}$. The dependent variable is the logarithm of real total production in thousands USD $Y_{i,t}$ in *arrondissement* i and year t (period 2018–2022). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. For a description of the variables *land surface temperature, precipitation, reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table OA.21: Robustness: Nighttime Lights (in logs) with control variables

	(1) *Total Events*	(2) *Total Fatalities*
Events last year	-0.002**	-0.001**
	(0.001)	(0.001)
Land Surface Temperature	0.465	0.450
	(0.686)	(0.685)
Precipitation	1.286	-0.375
	(17.519)	(17.582)
Reach of Health Services	-47.278	-53.388
	(46.844)	(48.023)
Reach of Education Services	45.011	51.834
	(50.232)	(51.717)
Earthquake 2021	0.099	0.103
	(0.278)	(0.267)
Floods 2022	0.126	0.149
	(0.140)	(0.146)
Observations	69	69
R-squared	0.974	0.974
Average Y	2.142	2.142
Av. X	46.86	40.22

Notes: This table reports coefficients from estimating equation (3) adding control variables, not including γ_k and $\eta_{i,t}$. The dependent variable is the logarithm of nighttime lights $Y_{i,t}$ in *arrondissement* i and year t (period 2018–2023). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table OA.22: Robustness: SE clustered at department level

	Violence type	
	Total events	*Total fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)		
Events last year	-0.000	-0.0002*
	(0.000)	(0.000)
Observations	164	164
R-squared	0.993	0.993
Average Y	-0.0289	-0.0289
Av. X	26.55	21.09
Panel B: Real Textile Production (effect sizes in standard deviations)		
Events last year	-0.006***	-0.006***
	(0.0004)	(0.0003)
Observations	164	164
R-squared	0.977	0.966
Average Y	-0.0232	-0.0232
Av. X	26.55	21.09
Panel C: Total Real Production (in logs)		
Events last year	-0.001***	-0.001***
	(0.000)	(0.000)
Observations	164	164
R-squared	0.997	0.997
Average Y	8.352	8.352
Av. X	26.55	21.09
Panel D: Nighttime Lights (in logs)		
Events last year	-0.003***	-0.002***
	(0.001)	(0.001)
Observations	115	115
R-squared	0.945	0.948
Average Y	2.321	2.321
Av. X	49.48	46.77

Notes: This table reports coefficients from estimating equation (3), not including γ_k and $\eta_{i,t}$. The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *arrondissement* i and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the department level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.23: Robustness: Adding population as analytic weight

	Violence type	
	Total events	*Total fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)		
Events last year	-0.0003***	-0.0004***
	(0.000)	(0.000)
Observations	88	88
R-squared	0.994	0.995
Average Y	0.331	0.331
Av. X	47.09	38.02
Panel B: Real Textile Production (effect sizes in standard deviations)		
Events last year	-0.006***	-0.006***
	(0.000)	(0.000)
Observations	88	88
R-squared	0.990	0.975
Average Y	0.161	0.161
Av. X	47.09	38.02
Panel C: Total Real Production (in logs)		
Events last year	-0.002***	-0.002***
	(0.000)	(0.000)
Observations	88	88
R-squared	0.999	0.999
Average Y	8.820	8.820
Av. X	47.09	38.02
Panel D: Nighttime Lights (in logs)		
Events last year	-0.002***	-0.002***
	(0.000)	(0.000)
Observations	90	90
R-squared	0.979	0.983
Average Y	2.681	2.681
Av. X	61.74	59.12

Notes: This table reports coefficients from estimating equation (3), not including γ_k and $\eta_{i,t}$. The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *arrondissement* i and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. All regressions are weighted using analytic weights based on the population of each arrondissement. This assumes that observations corresponding to larger populations are measured with greater precision (vari- ance is inversely proportional to population size). All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.24: Robustness: NTL - Wild cluster bootstrap test for individual and joint significance

	(1) *Total Events*	(2) *Total Fatalities*
Events last year	-0.003	-0.002
WB joint test: p-value	0.408	0.266
Observations	115	115
Average Y	2.321	2.321
Av. X	49.48	46.77

Notes: This table reports coefficients from estimating equation (3), not including γ_k and $\eta_{i,t}$. The dependent variable is the logarithm of nighttime lights $Y_{i,t}$ in *arrondissement* i and year t (period 2018–2023). Columns (1) and (2) show the effects of one lag count of total events and total fatalities. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.25: Add leads to baseline (1 lead)

	Violence type			
	Political Events	*Civil Events*	*Political Fatalities*	*Civil Fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)				
$v_{i,t+1}$	0.002***	0.003	0.001*	0.001
	(0.000)	(0.003)	(0.000)	(0.001)
$v_{i,t-1}$	-0.002**	-0.002	-0.001	-0.005
	(0.001)	(0.002)	(0.001)	(0.005)
Observations	126	126	126	126
R-squared	0.992	0.992	0.992	0.992
Average Y	-0.0415	-0.0415	-0.0415	-0.0415
Av. X	11.05	6.492	14.24	5.770
Panel B: Real Textile Production (effect sizes in standard deviations)				
$v_{i,t+1}$	0.001	0.016***	0.001	0.009**
	(0.001)	(0.005)	(0.001)	(0.004)
$v_{i,t-1}$	-0.007***	-0.007***	-0.008	-0.003
	(0.001)	(0.002)	(0.005)	(0.010)
Observations	126	126	126	126
R-squared	0.989	0.988	0.972	0.983
Average Y	-0.00323	-0.00323	-0.00323	-0.00323
Av. X	11.05	6.492	14.24	5.770
Panel C: Total Real Production (in logs)				
$v_{i,t+1}$	0.000	0.002	0.000	0.002***
	(0.001)	(0.002)	(0.000)	(0.001)
$v_{i,t-1}$	-0.002***	-0.002***	-0.002**	0.000
	(0.000)	(0.001)	(0.001)	(0.003)
Observations	123	123	123	123
R-squared	0.998	0.998	0.998	0.998
Average Y	8.349	8.349	8.349	8.349
Av. X	11.32	6.650	14.59	5.911
Panel D: Nighttime Lights (in logs)				
$v_{i,t+1}$	0.002	0.005	-0.000	-0.003***
	(0.002)	(0.003)	(0.000)	(0.001)
$v_{i,t-1}$	-0.004***	-0.003*	-0.003***	-0.007*
	(0.001)	(0.001)	(0.001)	(0.004)
Observations	115	115	115	115
R-squared	0.946	0.946	0.948	0.950
Average Y	2.321	2.321	2.321	2.321
Av. X	26.75	14.70	45.15	17.50

Notes: This table presents the coefficient estimates of equation (3), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *arrondissement* i, and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. All regressions include *arrondissement* and year fixed effects. Standard errors are clustered at the *arrondissement* level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.26: Robustness: Real Agricultural production with control variables

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
Events last year	-0.001	-0.001	-0.000	-0.002*
	(0.000)	(0.001)	(0.000)	(0.001)
Land Surface Temperature	-0.112	-0.113	-0.112	-0.121
	(0.082)	(0.082)	(0.082)	(0.084)
Precipitation	1.819	1.812	1.980	1.584
	(3.383)	(3.412)	(3.542)	(3.495)
Reach of Health Services	8.422**	8.473**	8.767**	8.906**
	(3.945)	(3.941)	(3.991)	(4.041)
Reach of Education Services	-10.631*	-10.655*	-11.186*	-11.212**
	(5.444)	(5.420)	(5.538)	(5.517)
Earthquake 2021	-0.051	-0.051	-0.050	-0.056
	(0.059)	(0.059)	(0.058)	(0.059)
Floods 2022	0.006	0.007	0.004	0.009
	(0.012)	(0.013)	(0.012)	(0.013)
Observations	123	123	123	123
R-squared	0.994	0.994	0.994	0.994
Average Y	0.0438	0.0438	0.0438	0.0438
Av. X	15.39	8.862	23.85	9.252

Notes: This table reports coefficients from estimating equation (3) adding control variables (coefficients γ_k are not presented in this table). The dependent variable is real crop production in standard deviations $Y_{i,t}$ in *arrondissement* i and year t (period 2018 –2022). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table OA.27: Robustness: Real Textile production with control variables

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
Events last year	-0.001	0.003**	-0.004*	0.012***
	(0.001)	(0.001)	(0.002)	(0.002)
Land Surface Temperature	-0.010	0.002	-0.077	0.047
	(0.054)	(0.046)	(0.114)	(0.042)
Precipitation	3.622	3.895	-0.045	5.255
	(5.078)	(5.020)	(7.100)	(5.152)
Reach of Health Services	3.820	3.908	1.650	-0.472
	(4.406)	(4.114)	(3.077)	(2.516)
Reach of Education Services	-4.641	-5.220	0.011	0.551
	(6.853)	(6.393)	(4.131)	(3.861)
Earthquake 2021	-0.053	-0.048	-0.061	-0.018
	(0.039)	(0.039)	(0.045)	(0.034)
Floods 2022	-0.046	-0.053	-0.029	-0.069
	(0.042)	(0.042)	(0.052)	(0.044)
Observations	123	123	123	123
R-squared	0.993	0.993	0.986	0.994
Average Y	-0.0459	-0.0459	-0.0459	-0.0459
Av. X	15.39	8.862	23.85	9.252

Notes: This table reports coefficients from estimating equation (3) adding control variables (coefficients γ_k are not presented in this table). The dependent variable is real textile production in standard deviations $Y_{i,t}$ in *arrondissement* i and year t (period 2018 –2022). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.28: Robustness: Total Real Production (in logs) with control variables

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
Events last year	-0.001***	-0.001***	-0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Land Surface Temperature	0.024	0.025	0.007	0.028
	(0.024)	(0.024)	(0.024)	(0.025)
Precipitation	1.859	1.858	1.079	1.987
	(1.149)	(1.162)	(1.236)	(1.203)
Reach of Health Services	1.380	1.356	1.305	0.915
	(2.103)	(2.110)	(2.009)	(2.094)
Reach of Education Services	-1.715	-1.697	-1.264	-1.153
	(2.965)	(2.985)	(2.779)	(3.036)
Earthquake 2021	0.001	0.001	-0.001	0.004
	(0.009)	(0.009)	(0.009)	(0.009)
Floods 2022	-0.027	-0.028	-0.025	-0.030
	(0.022)	(0.023)	(0.023)	(0.023)
Observations	123	123	123	123
R-squared	0.999	0.999	0.999	0.999
Average Y	8.365	8.365	8.365	8.365
Av. X	15.39	8.862	23.85	9.252

Notes: This table reports coefficients from estimating equation (3) adding control variables (coefficients γ_k are not presented in this table). The dependent variable is the logarithm of real total production in thousands USD $Y_{i,t}$ in *arrondissement* i and year t (period 2018 –2022). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.29: Robustness: Nighttime Lights (in logs) with control variables

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
Events last year	-0.001	-0.001	-0.002	-0.001
	(0.001)	(0.002)	(0.002)	(0.003)
Land Surface Temperature	0.467	0.468	0.442	0.457
	(0.699)	(0.695)	(0.705)	(0.689)
Precipitation	1.860	1.745	-0.502	0.058
	(17.882)	(17.913)	(17.680)	(18.328)
Reach of Health Services	-45.333	-46.813	-53.992	-53.997
	(46.483)	(46.788)	(48.215)	(48.411)
Reach of Education Services	42.679	44.211	52.486	52.252
	(49.553)	(49.999)	(52.318)	(52.117)
Earthquake 2021	0.095	0.099	0.103	0.108
	(0.282)	(0.283)	(0.269)	(0.271)
Floods 2022	0.125	0.123	0.147	0.144
	(0.141)	(0.139)	(0.142)	(0.146)
Observations	69	69	69	69
R-squared	0.974	0.974	0.974	0.974
Average Y	2.142	2.142	2.142	2.142
Av. X	25.93	14.97	39.43	15.20

Notes: This table reports coefficients from estimating equation (3) adding control variables (coefficients γ_k are not presented in this table). The dependent variable is the logarithm of nighttime lights $Y_{i,t}$ in *arrondissement* i and year t (period 2018 –2023). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. For a description of the variables *land surface temperature*, *precipitation*, *reach of health services* and *reach of education services* see Appendix A. *Earthquake 2021* is a binary variable indicating whether an area was affected by the earthquake in 2021, in the affected areas—Baradères, Miragoâne, L'Anse-à-Veau, Jérémie, Anse d'Hainault, Corail, Les Cayes, Aquin, Les Chardonnières, Les Côteaux, or Port-Salut. *Floods 2022* is a binary variable indicating whether an area was affected by flooding in 2022 in the affected regions—Nord, Nord-Est, Nippes, or Nord-Ouest. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.30: Robustness: SE clustered at department level in violence type specification

	Violence type			
	Political Events	*Civil Events*	*Political Fatalities*	*Civil Fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)				
Events last year	-0.001	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Observations	168	168	168	168
R-squared	0.993	0.993	0.993	0.993
Average Y	-0.0277	-0.0277	-0.0277	-0.0277
Av. X	13.14	7.494	19.71	7.923
Panel B: Real Textile Production (effect sizes in standard deviations)				
Events last year	-0.003**	-0.000	-0.007***	-0.004***
	(0.001)	(0.002)	(0.002)	(0.000)
Observations	168	168	168	168
R-squared	0.978	0.979	0.967	0.966
Average Y	-0.0229	-0.0229	-0.0229	-0.0229
Av. X	13.14	7.494	19.71	7.923
Panel C: Total Real Production (in logs)				
Events last year	-0.001***	-0.001**	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	164	164	164	164
R-squared	0.997	0.997	0.997	0.997
Average Y	8.352	8.352	8.352	8.352
Av. X	13.46	7.677	20.20	8.116
Panel D: Nighttime Lights (in logs)				
Events last year	-0.003***	-0.003	-0.003***	-0.006***
	(0.001)	(0.003)	(0.000)	(0.001)
Observations	115	115	115	115
R-squared	0.946	0.945	0.948	0.949
Average Y	2.321	2.321	2.321	2.321
Av. X	26.75	14.70	45.15	17.50

Notes: This table presents the coefficient estimates of equation (3), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *arrondissement* i, and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. All regressions include *arrondissement* and year fixed effects. Standard errors are clustered at the department level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.31: Robustness: Analytic weights in violence type specification

	Violence type			
	Political Events	*Civil Events*	*Political Fatalities*	*Civil Fatalities*
Panel A: Real Agricultural Production (effect sizes in standard deviations)				
Events last year	-0.001***	-0.002***	0.001**	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	88	88	88	88
R-squared	0.996	0.996	0.996	0.995
Average Y	0.362	0.362	0.362	0.362
Av. X	24.06	13.74	36.41	14.66
Panel B: Real Textile Production (effect sizes in standard deviations)				
Events last year	-0.002***	0.003***	-0.012***	-0.004***
	(0.000)	(0.000)	(0.004)	(0.000)
Observations	88	88	88	88
R-squared	0.995	0.995	0.978	0.975
Average Y	0.168	0.168	0.168	0.168
Av. X	24.06	13.74	36.41	14.66
Panel C: Total Real Production (in logs)				
Events last year	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	88	88	88	88
R-squared	0.999	0.999	0.999	0.999
Average Y	8.820	8.820	8.820	8.820
Av. X	24.06	13.74	36.41	14.66
Panel D: Nighttime Lights (in logs)				
Events last year	-0.003***	-0.005***	-0.002***	-0.001
	(0.000)	(0.001)	(0.000)	(0.002)
Observations	90	90	90	90
R-squared	0.982	0.980	0.984	0.983
Average Y	2.681	2.681	2.681	2.681
Av. X	33.70	18.60	57.07	22.16

Notes: This table presents the coefficient estimates of equation (3), separately for each type of event (coefficients γ_k are not presented in this table). The dependent variables are real crop production in standard deviations (Panel A), real textile production in standard deviations (Panel B), the log of total real production (Panel C) and the log of nighttime lights (Panel D) $Y_{i,t}$ in *arrondissement* i, and year t (period 2018 – 2023 for nighttime lights and 2018 –2022 for production variables). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. All regressions are weighted using analytic weights based on the population of each arrondissement. This assumes that observations corresponding to larger populations are measured with greater precision (variance is inversely proportional to population size). All regressions include *arrondissement* and year fixed effects. Standard errors are clustered at the *arrondissement* level and are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table OA.32: Robustness: NTL - Wild cluster bootstrap test for individual and joint significance

	(1) *Political Events*	(2) *Civil Events*	(3) *Political Fatalities*	(4) *Civil Fatalities*
Events last year	-0.003	-0.003	-0.003	-0.006
WB joint test: p-value	0.166	0.667	0.138	0.172
Observations	115	115	115	115
R-squared	0.492	0.487	0.516	0.521
Average Y	2.321	2.321	2.321	2.321
Av. X	26.75	14.70	45.15	17.50

Notes: This table reports coefficients from estimating equation (3) adding control variables (coefficients γ_k are not presented in this table). The dependent variable is the logarithm of nighttime lights $Y_{i,t}$ in *arrondissement* i and year t (period 2018 –2023). Column (1) shows the effect of one year lag of political events $v_{i,t-k}$; column (2), civil events; column (3), political fatalities; and column (4), civil fatalities. All specifications include *arrondissement* and year fixed effects. Standard errors, clustered at the *arrondissement* level, are in parentheses. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.