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Poverty and Violence

The Immediate Impact of Terrorist Attacks against Civilians in Somalia

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Abstract

Somalia, one of the poorest countries in Sub-Saharan Africa, still faces many challenges as it remains fragile. Terrorist groups and their attacks are threatening the government and limiting its capacity to implement effective development policies. Using difference-in-difference and instrumental variables approaches with micro-data from two waves of the Somali High Frequency Survey, this paper estimates the immediate (within a week) impact of terrorist attacks on households. The consumption of households exposed to terrorist incidents decreases by 33 percent, mainly on food items. As a result, poverty and the depth of poverty among the poor increases. The decline in consumption seems to be explained by a smaller share of household members working and earning income after an attack. In addition, the effect on consumption is restricted to a 4-kilometer radius from incidents and has a heterogeneous impact, not affecting households in the top 20 percent of the consumption distribution. The paper also finds a deterioration in people's perception of police competence. Achieving peace is a fundamental first step to increase welfare conditions that will also bring other wider long-term benefits in Somalia.

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Poverty and Violence: The Immediate Impact of Terrorist Attacks against Civilians in Somalia[1]

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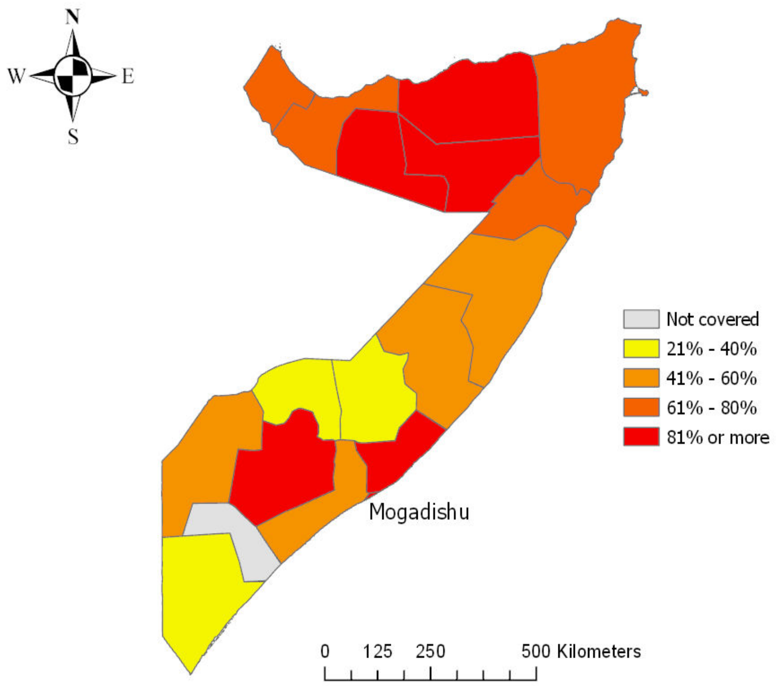
1. Introduction

Somalia is one of the poorest countries in Sub-Saharan Africa, with 69% of the population living under the standard international poverty line of US$1.90 in 2017-18 (Figure 1).[3] In 2004, an interim central state was established with the aim of bringing political stability across Somali regions. The political transition culminated with the establishment of the Federal Government of Somalia in 2012 and a first electoral process in 2017. The elected government has aimed to improve national security conditions, yet the opportunity to ensure a development trajectory still faces many challenges, among them terrorist attacks (World Bank, 2018).

Figure 1: Poverty incidence in 2017-18 across
Somali regions (% of poor population)



Source: Authors' calculations based on data from the SHFS. Note: The boundaries on the map show approximate borders of Somali pre-war regions and do not necessarily reflect official borders, nor imply the expression of any opinion concerning the status of any territory or the delimitation of its boundaries.

At a first glance, the consequences of a terrorist attack might seem small and contained given that they usually affect a small fraction of the population and the economy. Yet, several studies suggest sizable effects on economic outcomes (Abadie and Gardeazabal, 2008). Further, nearly two-thirds of the poor around the world are projected

[3] See Pape and Karamba (2019) for a comprehensive overview of poverty and vulnerability in Somalia.

to live in conflict-affected countries by 2030, including Somalia.[4] Therefore, it is important to shed light and improve our understanding on the links between conflict and poverty.

This paper estimates the immediate (within a week) impact of terrorist attacks from Al-Shabaab against civilians in Somalia using micro-data from two waves of the Somali High Frequency Survey (SHFS), combined with geo-tagged information on attacks.[5] We exploit the spatial and time variation of interviews through a difference-in-difference identification strategy that compares outcomes of control and exposed households, before and after terrorist incidents. We also derive a shift-share instrument using changes in the number of US air/drone attacks against Al-Shabaab and employ an instrumental variables approach. We provide evidence to support the validity of our identification strategies and that our estimates are robust to different specifications, samples considered and several sensitivity checks.

Our results suggest that consumption of households exposed to terrorist incidents decreases by 33%, mainly driven by a decline in food consumption. The reduction in consumption increases poverty and the depth of poverty among the poor. The impact on consumption seems to be associated to a smaller share of household members (aged 15 to 50) working and earning income after an attack. In addition, we document that the negative impact on consumption is clustered within a 4 kilometer radius from the incident and has a heterogeneous impact, not affecting households in the top 20% of the consumption distribution. The perception of police competence also worsens as a result of a terrorist incident.

The literature models terrorists as rational actors, with terrorism having large consequences on economic outcomes, besides the loss of life, damage to persons and negative psychological effects.[6] Conflict can also lead to sharp increases in poverty and vulnerability and other adverse outcomes.[7] Our findings are in line with the disruption that could be expected from a terrorist attack. We contribute to the literature on the intersection between poverty and adverse shocks in developing countries, as well as to the policy debate by quantifying the impact of terrorist attacks on consumption and poverty,

[4] World Bank (2020).

[5] Somalia has a strong presence of Al-Shabaab, the largest militant organization seeking to control the territory with the goal of establishing an Islamic State based on its interpretation of Shariah Law. The United States Department of State declared Al-Shabaab a foreign terrorist organization in February 2008. The group has engaged in bombings, suicide attacks and armed assaults.

[6] In Europe alone, the impact of terrorism has been estimated at around €180 billion between 2004 and 2016 (RAND 2018).

[7] In South Sudan, conflict combined with a macroeconomic crisis brought into poverty an additional 16 percent of the population in a single year (Pape et al. 2018).

describing which households are affected by such incidents and the mechanisms through which this is likely to occur. Most of the empirical literature on the effects of terrorism on economic outcomes has relied on data aggregated at some geographical level (district, region or country), while the growing body of research exploiting micro-data to understand the effect of various shocks on poverty has not analyzed the effect of terrorism. To our knowledge, this is the first study to measure the causal impact of terrorism on consumption and poverty using household-level data in a fragile and conflict-affected country.

The paper is structured as follows: The next section discusses the related literature on the effects of terrorism and multiple shocks on welfare conditions for households. Section 3 describes the data sources, sample considered and the definition of households exposed to terrorist incidents, besides specifying the identification strategies. Section 4 presents the results and extensions. Section 5 discusses multiple robustness checks and supplementary OLS estimates, while Section 6 contains our concluding remarks.

2. Literature

Terrorist incidents are different from other types of events since terrorist organizations use violence –or the threat of violence– against civilians as a tool for achieving political change (Crenshaw 1981; Kydd and Walter 2006). Under this characterization, terrorists are rational actors making tactical and strategic decisions while inflicting terror among citizens (Cornish and Clarke 2014). The United States Department of State defined terrorism in 1983 as "means premeditated, politically motivated violence perpetrated against noncombatant targets by subnational groups or clandestine agents, usually intended to influence an audience". Terrorist attacks are then part of a broader strategy with the ultimate goal of undermining the government's authority, publicizing an agenda and/or creating a sense of instability (Crenshaw 1981). Therefore, terrorist incidents do not occur at random and are usually clustered in time and space (LaFree et al. 2012).

Poverty conditions are thought to be a catalyst to develop and foster terrorist organizations. In fragile and conflict-affected situations, terrorist groups can establish themselves as alternatives to democratically elected governments, especially if governments cannot provide basic services and social safety nets.[8] However, Krueger and

[8] In Somalia, Al-Shabaab has filled this vacuum of political power and service delivery by bringing order and –to some extent– services in regions underserved by the government (Bronwyn 2015).

Malečková (2003) refute this notion as they find no evidence of a causal connection from poverty to terrorism. The authors claim terrorist activities are more likely to be associated with political conditions and social frustration, than with suboptimal welfare conditions. In line with this finding, Abadie (2004) shows that the risk of terrorism is relatively similar between developed and developing countries, after considering country-specific characteristics, and concludes that the level of political freedom is better at explaining terrorist incidents compared to economic and poverty conditions of the population.

Moreover, the consequences of a terrorist attack could be underestimated as they appear to affect only some parts of the economy. Becker and Murphy (2001) claimed that the attacks on the World Trade Center on September 11th in New York would barely affect economic outcomes since they only represented a loss of 0.06% of the stock of capital in the US. Yet, several studies indicate large effects on the economy. Abadie and Gardeazabal (2008) show that even if the threat of an attack only accounts for a small share of the overall risk, terrorism can have a substantial impact on the allocation of productive capital across nations. The risk of an attack increases uncertainty, reduces expected return to investments and induces a decline in net foreign direct investment (FDI).

Empirical research has documented the effect of terrorism on consumption and gross domestic product (GDP) due to increased uncertainty and disruption to the markets. Eckstein and Tsiddon (2004) use a long time series data and find a decrease in annual consumption per capita of around 5% after a year from a terrorist incident. Fielding (2003) describes how violence in Israel explains reductions on aggregate consumption and savings between 1987 and 1999. Using a synthetic control method, Abadie and Gardeazabal (2003) estimate a decline of 10% in GDP per capita over two decades as a result of terrorism in the Basque Country. Some authors have analyzed the consequences of terrorism on other outcomes. Nitsch and Schumacher (2004) associate terrorist actions with a reduced volume of trade across various countries, while Enders and Sandler (1991) report an annual reduction of FDI inflows by 13.5% and a loss of 140,000 tourists between 1970 and 1988 in Spain. All these negative effects can ultimately limit economic growth of a country. Gaibulloev and Sandler (2009) use panel data for Asian countries and find that terrorist incidents reduce private sector investment and increase government spending, which leads to a decline in GDP per capita growth by 1.5%. Similarly, Ruiz Estrada, Park, and Khan (2018) conclude that terrorist attacks have slowed economic growth in Turkey between 1990 and 2016.[9]

[9] See Frey, Luechinger, and Stutzer (2007) for a summary of the literature on the economic impact of terrorism.

Another stream of the literature has exploited micro-data to investigate the effect of various shocks, such as conflict and weather conditions, on multiple socio-economic characteristics. Several studies document how adverse weather conditions reduce agricultural incomes and can push households into poverty. Hill and Mejia-Mantilla (2017) describe the negative effects from droughts in Uganda. Porter (2012) finds that weather shocks reduce consumption in the long run among rural households in Ethiopia. Similarly, Hill and Porter (2016) conclude that in Ethiopia consumption declined by 9% in rural areas due to a moderate drought. For the case of Somalia, Pape and Wollburg (2019) estimate an increase in poverty of 9 percentage points among rural households attributed to a drought shock.

In terms of the drivers of conflict, Dube and Vargas (2006) use municipality-level data in a difference-in-difference framework to understand the dynamics of Colombia's civil war. They find a negative relationship between coffee prices and the incidence and intensity of conflict, while a positive relationship between oil prices and violence. Besides, large evidence supports the adverse impact of conflict-related violence on welfare conditions. Mercier, Ngenzebuke, and Philip (2016) use household-level panel data for Burundi and conclude that exposure to violence condemns vulnerable households into chronic poverty. Hill and Mejia-Mantilla (2017) find a negative effect from conflict and prices on poverty in Uganda. In South Sudan, Müller, Pape, and Ralston (2019a) investigate the effects of conflict-induced cancellation of programs on their designated beneficiaries and describe the welfare status of households displaced by violence. In the same country, Pape and Phipps (2018) analyze the impact of conflict on the socio-economic and psychosocial well-being of teenage girls, including on income opportunities, aspirations and marriage. Other authors provide evidence on how conflict increases the likelihood of chronic poverty due to disruption of income-generating activities and depletion of infrastructure and basic services (Bratti, Mariapia, and Alfonso 2009; Bozzoli and Brück 2009; Bozzoli, Brueck, and Muhumuza 2016).

3. Empirical analysis

The World Bank implemented Wave 1 (2016) and Wave 2 (2017-18) of the Somali High Frequency Survey to better understand livelihoods, vulnerabilities and poverty across

Somali regions.[10] Several terrorist attacks occurred during fieldwork of the SHFS.[11] The analysis exploits detailed household data with dates of interviews and GPS positions to evaluate the immediate impact of attacks against civilians in Somalia. The types of incidents considered correspond to attacks from Al-Shabaab against civilians.[12] We concentrate on measuring the effect within a week due to data availability given that i) the questionnaires used a recall period of 7 days for food items, which is the main component of the consumption aggregate; and ii) only one household was interviewed 8 days or more after an incident.

3.1 Data sources

The main sources of data correspond to detailed household information on socio-demographic characteristics, perceptions and poverty conditions from Waves 1 and 2 of the Somali High Frequency Survey, as well as location and time of attacks from The Armed Conflict Location & Event Data Project (ACLED). In this way, household data from the SHFS is combined with geo-tagged information on attacks to identify households exposed to terrorist incidents.

Wave 1 includes 4,117 households interviewed between February and March 2016, which are representative of 9 of the 18 Somali pre-war regions, as the remaining areas were inaccessible for security reasons at the time of fieldwork. Wave 2 expanded the coverage to 17 pre-war regions, interviewing 6,092 households between December 2017 and January 2018.[13] ACLED data records locations and intensity of armed conflict coded by researchers who collect information from secondary sources, NGO reports, local and international news reports and research publications (Raleigh and Dowd 2015). The database is unique due to its geographical level of precision when reporting the latitude and longitude of the attacks, indicating the location of an incident (Figure 2). All the violent incidents reported in ACLED that occurred a week before the start and end of data collection of Wave 2 of the SHFS were considered as consumption data is recorded for the week preceding the interview. Attacks from Al-Shabaab against civilians were manually identified.

[10] Interviews were conducted between the February 10 and March 17, 2016 for Wave 1, while between the December 4, 2017 and January 16, 2018 for Wave 2.

[11] The incidents did not affect data collection plans of Wave 2. The share of completed interviews increases across weeks during fieldwork, as it would be expected.

[12] Al-Shabaab perpetrated attacks outside Somalia for the first time in 2010 in Kampala, and a few years later on the Westgate mall in Nairobi, suggesting that the organization is part of the global network with strong connections to Al-Qaeda (Varin and Dauda 2017).

[13] The SHFS was not designed as a panel survey. Waves 1 and 2 correspond to repeated cross-sections, representative of Somali regions.

Figure 2: Terrorist attacks in Mogadishu during data collection of Wave 2

Source: Authors' calculations based on data from the SHFS and ACLED. Note: The boundaries on the map show approximate borders of districts within Mogadishu and do not necessarily reflect official borders, nor imply the expression of any opinion concerning the status of any territory or the delimitation of its boundaries.

3.2 Definition of treatment and sample considered

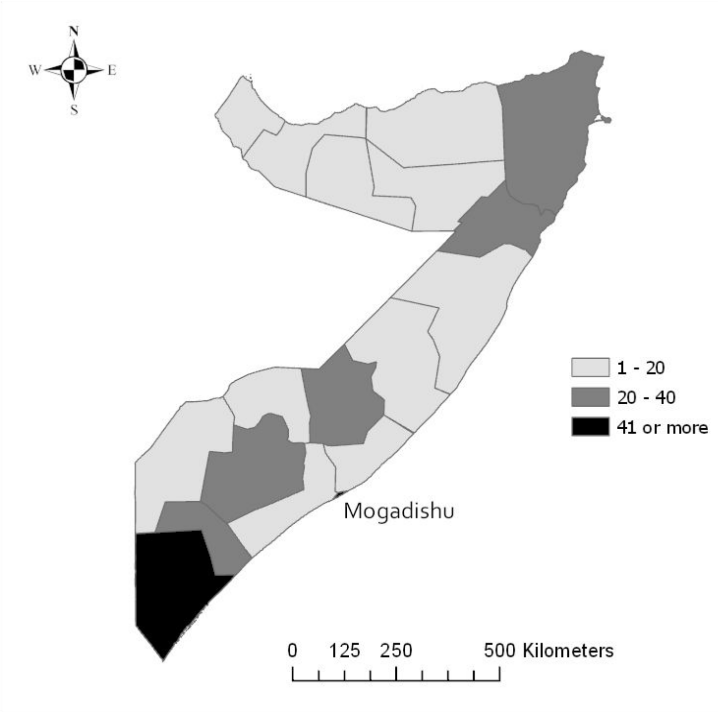
For the econometric analysis, treated or exposed households are defined as those which meet the following criteria in time and space: i) households whose interview was conducted between 1 and 7 days after an incident occurred during data collection of Wave 2; and ii) those within a radius of 1 kilometer from the terrorist attack.[14]

From this definition we identify four groups of households. Exposed households before (2016) and after a terrorist attack (2017-18). The latter group corresponds to exposed households in Wave 2 meeting the space and time criteria, while the former group to households that are also located within 1 kilometer from the incident, but that were interviewed in Wave 1.[15] Similarly, we identify control households before and after an attack. Control households in Wave 2 are those interviewed in 2017-18 that do not meet the time and space criteria of treatment or exposed status, while control households in Wave 1 are those located more than 1 kilometer away from the incidents and that were interviewed in 2016.[16] Moreover, some households interviewed in Wave 1 were also close

[14] We consider a period of 7 days because the consumption module of the questionnaire from the SHFS used a recall period of 1 week for food items, which is the main component of the consumption aggregate.
[15] The average distance from incidents is 1.09 kilometers for exposed households interviewed in Wave 1, while 1.12 kilometers for exposed households interviewed in Wave 2.
[16] The definition of control group does not consider an upper bound limit in terms of how far households are located from incidents.

in time and space but to incidents that occurred in Wave 1. Those Wave 1 households interviewed up to a week after the incidents and within a 10 kilometers radius are excluded from the analysis as they are likely to be affected by a terrorist incident in a previous period.[17]

Figure 3: Number of violent incidents during data collection of Wave 2



Source: Authors' calculations based on data from the SHFS and ACLED. Note: The boundaries on the map show approximate borders of Somali pre-war regions and do not necessarily reflect official borders, nor imply the expression of any opinion concerning the status of any territory or the delimitation of its boundaries.

During fieldwork of Wave 2, a large proportion of violent incidents took place in Mogadishu, since it is home to potential targets such as government actors and international organizations (Figure 3). In particular, terrorist attacks from Al-Shabaab during data collection were concentrated in urban areas, mainly in Mogadishu. Furthermore, a security assessment was carried out before data collection of the SHFS and incorporated into the sampling frame such that Primary Sampling Units (PSUs) were drawn only from accessible areas, to ultimately ensure PSUs visited by enumerators were safe on the day of fieldwork (Pape and Wollburg 2019b). As a result of both, the geographical clustering of incidents and the sampling strategy of the survey, only in two

[17] We adopt a cautionary approach and consider a larger radius of 10 kilometers to avoid including 'contaminated' households by previous incidents in our Wave 1 control group.

Somali regions interviews were conducted during Wave 2 after an incident and close to it (Table 7 in the Appendix).

Table 1: Number of households by group and Wave for each sample alternative

	Alternative	Group	Wave 1	Wave 2
(1)	Mogadishu	Exposed	21	113
		Control	664	775
(2)	Mogadishu with overlapping exposed households in Wave 1 and 2	Exposed	21	78
		Control	664	775
(3)	Mogadishu with overlapping districts in Wave 1 and 2	Exposed	21	113
		Control	519	775
(4)	All urban areas	Exposed	21	135
		Control	2,712	3,876
(5)	Urban areas with exposed and control households in Wave 1 and 2	Exposed	21	135
		Control	664	1,468

Source: Authors' calculations based on data from the SHFS and ACLED.

The main sample considered in the econometric analysis corresponds to Mogadishu. The capital of Somalia is one of the most fragile cities in the world (Pape and Karamba 2019). It concentrates 16 percent of Somali households and poverty is higher in Mogadishu than in other urban areas of Somalia. A few additional samples are used to provide further robustness to the results from the econometric analysis (Table 1). We consider a few variations within Mogadishu; one restricting the group of exposed households to overlapping Wave 1 and 2 areas (Figure 6 in the Appendix), and another option restricting the sample to overlapping Wave 1 and 2 districts. Then, we consider all urban households across Somali regions. This alternative includes exposed households from Mogadishu and South West urban, as well as control households from all urban areas of Somalia. Finally, the other sample considered in the econometric analysis refers to only urban areas with exposed households in Wave 2; that is, exposed and control households only from Mogadishu and South West urban.

All these different alternatives have a relatively small sample size for the group of exposed households in Waves 1 and 2. This is determined by the location and timing of interviews in relation to attacks. Further, the sampling strategy clustered households into PSUs, with a target of 12 interviews per PSU. Households within each of these geographical areas are likely to have a similar set of characteristics. Our sample of households from Mogadishu belongs to four PSUs in Wave 1 and ten in Wave 2. The small size of our exposed group of households introduces an important caveat to our estimates and findings. Nonetheless, we try to ease such concerns by considering different identification strategies and robustness checks.

3.3 Identification strategy

Using the four groups of households identified (exposed and control households before and after the incidents), we first employ a difference-in-difference (DiD) approach with repeated cross-sections to compare outcomes of households exposed to the terrorist attack against households who were not exposed to the incidents (Imbens and Wooldridge 2007). The identification strategy exploits spatial and time variation of the data. For this, we estimate the following equation:

$$Y_{it} = \alpha + \lambda Wave_t + \mu Exposed_i + \beta(Wave_t * Exposed_i) + \eta L_a + \varphi X_{it} + u_{it} \qquad (1)$$

where Y_{it} refers to the outcome of interest for household i in period t, $Wave$ to the period t of data collection (Wave 1 in 2016 or Wave 2 in 2017-18). $Exposed$ corresponds to the status of household i according to our definition of treatment, L_a to location fixed effects for geography a –which refers regions or districts– and X_{it} to a vector of covariates capturing characteristics of the household and household head, dwelling characteristics, exposure to drought, as well as humanitarian aid received.[18]

Moreover, the probability of being exposed to an incident is likely to be associated to the location of households and the composition of regions or districts. Hence, we focus on regional comparisons (i.e., within-location variation) through the inclusion of location fixed effects.[19] For the DiD analysis we use the sample of households from Mogadishu as we can include fixed effects at the district level –which is the lowest geographical level available– providing a more precise comparison of households, as opposed to including region fixed effects.[20] Yet, we expand the analysis to the other samples as a robustness check.

[18] Drought exposure corresponds to drought affected status from the Standardized Precipitation Index. Humanitarian aid is the percentage of beneficiaries reached through food aid and livelihood inputs by region.
[19] It is unlikely the composition of neighborhoods changed substantially after a terrorist attack in the period of analysis. Only 1.6% of the Wave 2 sample of households in Mogadishu reported they were forced to leave their previous place of residence and moved to another region.
[20] The delimitation of PSUs was different in Wave 1 and Wave 2, in part due to the lack of census data in Somalia. As a result, PSUs from Wave 1 and Wave 2 are not comparable nor mutually exclusive. Therefore, the lowest level of aggregation comparable across surveys corresponds to districts in Mogadishu.

Our empirical strategy relies on the parallel trend assumption of the difference-in-difference approach. It assumes that the difference in the outcome among exposed and control households would be similar had the attacks not occurred. Any difference between treatment and control is unlikely to have changed over 22 months –between Waves 1 and 2– since the identification strategy compares households within districts of Mogadishu and any other shock is likely to have affected in a similar way both exposed and control households. We also provide evidence to support the conditional independence assumption. Table 8 in the Appendix presents an OLS regression for the exposure of households to attacks in Mogadishu. The consumption level of households, their location and socio-economic characteristics are not associated with the propensity from being exposed to an incident. This suggests that terrorist incidents are likely to be exogenous, conditioned on location fixed effects and household characteristics.

In addition, we employ an instrumental variables (IV) identification strategy to further validate the results from the difference-in-difference approach. For this, we obtain a shift-share type of instrument based on Bartik (1991), exploiting the spatial variation of incidents against civilians and changes in the number of US air/drone attacks against Al-Shabaab in Somalia.[21] US air/drone attacks against Al-Shabaab were manually identified from ACLED data among all events recorded between Waves 1 and 2 of the SHFS. The US air/drone activity against Al-Shabaab is mainly concentrated on South West Somalia, with the number of attacks increasing from 4 in the first semester of 2015 to 21 in the last semester of 2017 (Figure 7 in the Appendix).

To support the validity of the instrument, we examine the location of both, US air/drone strikes against Al-Shabaab, and attacks from Al-Shabaab against civilians in Somalia, with an emphasis on Southern Somalia (Figure 8 in the Appendix). The locations of these two types of incidents are not spatially correlated. US air/drone attacks occurred in locations which are different to those of incidents against civilians. This could be because US air/drone strikes usually target high-profile members of Al-Shabaab and operation centers that are based in areas they already control, which is less often the case for the location of attacks against civilians.[22] US air/drone attacks are thus likely to increase the number of attacks from Al-Shabaab against civilians –as terrorist

[21] Bartik (1991) combines national changes in employment with the composition of local industry to capture local demand shocks in the labor market.

[22] The lack of spatial correlation between the location of US air/drone strikes against Al-Shabaab and attacks from the latter against civilians, as well as the different nature of these incidents suggest it is unlikely that causality runs in the opposite direction, such that US air/drone strikes target regions with high activity from Al-Shabaab against civilians.

organizations rely on violence to achieve political gains– partially explaining the exposure of households to terrorist attacks, while being independent from locations where Al-Shabaab commits an attack.

For each region in Somalia, the instrument was derived as the product of i) the exposure to attacks against civilians, and ii) the rate of growth of US air/drone attacks against Al-Shabaab. We first obtain the 'initial' share of attacks on civilians as the proportion of incidents in each region from the total number of events in the period covering from Wave 1 to the mid-point between Waves 1 and 2. We then obtain the rate of growth of US air/drone attacks against Al-Shabaab between this period and the end of Wave 2 for each region. Finally, we obtain the instrument from multiplying the exposure of attacks on civilians (share) and the rate of growth of US air/drone attacks against Al-Shabab (the shift).

The IV strategy estimates the causal effect of incidents through the variation in the probability of households being exposed to an incident in Wave 2 explained by the shift-share instrument. In this way, the first stage of the IV approach is the following:

$$P_i = \omega + \theta V_i + \eta L_i + \gamma X_i + u_i \qquad (2)$$

where P_i measures the likelihood of being exposed to an incident in Wave 2 for household i, while L_i and X_i corresponds to the same set of covariates included in the DiD approach (i.e., fixed effects, characteristics of the household and household head, dwelling characteristics, exposure to drought and humanitarian aid). V_i refers to the shift-share instrument, capturing the exposure to attacks against civilians and the growth of US air/drone attacks against Al-Shabaab, which takes the same value for all households within the same region. The second stage regression for any outcome Y corresponds to:

$$Y_i = \alpha + \delta \hat{P}_i + \eta L_i + \rho X_i + \varepsilon_i \qquad (3)$$

where $\hat{P}_i$ is the predicted likelihood of household i being exposed to an incident in Wave 2. In this context, the coefficient of interest is δ which provides an estimate of the average effect of terrorist attacks against civilians. To obtain IV estimates we cannot use the sample of households from Mogadishu since the instrument is calculated at the region level and does not vary across households from the capital. Thus, we use the group of households from urban areas with exposed households in Wave 2 as our main IV sample, which includes Mogadishu and South West urban. However, we also expand the analysis to all urban areas as a robustness check.

Our shift-share instrument and the likelihood of households being exposed to an incident in Wave 2 show a quadratic pattern (Figure 9 in the Appendix). Therefore, we consider a quadratic term of the instrument in all our IV specifications. Table 2 presents the first stage of the IV regression. Column 1 is our basic specification, which only includes fixed effects and uses sampling weights to derive standard errors. Our most complete specification, including the full set of controls, corresponds to column 4. The estimated coefficient for the quadratic term of the shift-share instrument is always positive and statistically significant at the 1% level. Column 5 presents the coefficient with standard errors clustered at the PSU level. In all cases the F-statistic is greater than 10, which is the cutoff value for considering the instrument as weak.[23] Overall, the instrument is strong at explaining the likelihood of being exposed to an incident in Wave 2 across these specifications among households in the main IV sample.

Table 2: First stage of the instrumental variables approach

	Urban areas with exposed and control households in Wave 1 and 2				
	(1)	(2)	(3)	(4)	(5)
Instrument (θ)	0.0001*** (<0.001)	0.0001*** (<0.001)	0.0001*** (<0.001)	0.0001*** (<0.001)	0.0001*** (<0.001)
Fixed effects	Region	Region	Region	Region	Region
Characteristics of household & head	No	Yes	Yes	Yes	Yes
Dwelling characteristics	No	No	Yes	Yes	Yes
Drought affected status	No	No	No	Yes	Yes
F-statistic	34.9	34.6	37.7	49.8	10.7
Standard errors	Sampling weights	Sampling weights	Sampling weights	Sampling weights	Clustered by PSU
Observations	2,272	2,249	2,241	2,241	2,241

Source: Authors' calculations based on data from the SHFS and ACLED. Note: Estimated coefficients from the 1st stage of the IV regression. The dependent variable corresponds to exposure to incidents in Wave 2. Characteristics of household refer to size and receiving remittances, while those from household head refer to age, sex and literacy. Dwelling characteristics include tenure, roof and floor material, water source and sanitation type. Humanitarian assistance is not included due to collinearity with the region fixed effects. Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

In terms of statistical inference, the estimates from both the difference-in-difference and instrumental variables approaches are obtained with standard errors that consider the sampling weights of the surveys in all specifications, mainly due to the different sampling frame and design between Wave 1 and 2. One of the key differences is that the sampling strategy of Wave 2 included an oversampling of households in Mogadishu (Pape and Wollburg 2019b). Hence, using sampling weights to derive the standard errors is

[23] Staiger and Stock (1994) proposed a rule of thumb cutoff of 10 for the first-stage F-statistic of an IV regression, below which the instrument is considered as weak.

needed to correct for the endogenous sampling and avoid obtaining inconsistent estimates (Solon, Haider, and Wooldridge 2013). Yet, we expand the analysis and consider clustered standard errors at the PSU level, since household-level error terms within these small geographical units are likely to be correlated, given households could have a similar set of characteristics. Further, we also derive heteroskedasticity and autocorrelation-consistent (HAC) standard errors to account for spatial correlation in the data, in line with Conley (1999) and Conley (2010).

4. Results and extensions

For the impact on household consumption in Mogadishu, Table 9 in the Appendix presents various specifications with different covariates considered. Our preferred specification corresponds to column 6, which includes district fixed effects, characteristics of the household, household head and dwelling. The results indicate a decline of 33% in core consumption –an aggregate that includes both food and non-food items– after a week caused by a terrorist attack from Al-Shabaab.[24]

Table 3 presents the estimates for various outcomes using our preferred DiD specification from equation (1) for the sample of households in Mogadishu. The negative effect of 33% on consumption (per capita deflated) from terrorist attacks seems to be concentrated on food items, as the results suggest an immediate negative effect on food consumption of around 42%.[25] Furthermore, for some households this decline in consumption brings their expenditure level below the poverty line, ultimately increasing the proportion of population living in poverty, as indicated by a positive and significant coefficient from the respective probit regression (column 3 in Table 3). This estimate implies an average increase of 0.3 point in the predicted probability of exposed households being poor. Among poor households, the negative effect on consumption results in consumption levels further from the poverty line due to the disruption caused by the incident. The poverty gap increases by 12% (column 4); that is, the average difference between consumption levels and the poverty line –measured as a proportion of the poverty line– increases by 12% among the poor in Mogadishu.

[24] The SHFS used a rapid consumption methodology where only a group of core food and non-food items, identified based on their consumption share, were asked to every household, while the rest of the items were algorithmically partitioned into optional modules and randomly distributed across households. After data collection, consumption of optional modules was imputed for all households (Pape and Mistiaen 2018). Thus, we use core consumption per capita deflated and not total imputed consumption in the econometric analysis. The core consumption aggregate represents around 75% of total consumption of Somali households.

[25] The food consumption aggregate represents almost 70% of total consumption of Somali households.

Table 3: DiD estimates for the effect of terrorist attacks against civilians in Mogadishu

	Log of core consumption (1)	Log of food consumption (2)	Poverty status (3)	Poverty gap (4)	Experienced hunger (5)	Police competence (6)
Diff-in-diff coefficient (β)	-0.326*** (0.118)	-0.415** (0.159)	1.617*** (0.597)	0.115*** (0.039)	0.813 (0.659)	-0.881** (0.365)
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Exposed/control	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Characteristics of household & head	Yes	Yes	Yes	Yes	Yes	Yes
Dwelling characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,532	1,532	1,532	1,532	1,516	1,498

Source: Authors' calculations based on data from the SHFS and ACLED. Note: Estimated coefficients from an OLS or probit regression. Characteristics of household refer to size and receiving remittances, while those from household head refer to age, sex and literacy. Dwelling characteristics include tenure, roof and floor material, water source and sanitation type. Drought affected status and humanitarian assistance are not included due to the lack of variation in the data within Mogadishu. Standard errors considering sampling weights in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

In terms of the effect of incidents on self-reported outcomes, the coefficient for experiencing hunger is positive but not statistically significant (column 5 in Table 3). A reduction of food consumption is likely to be associated with a larger share of household reporting to have experienced hunger. However, a non-significant result could be explained by the recall period considered in the survey instrument. The question asked to households referred to whether they had experienced hunger over the last month. As such, hunger reported by households covers between 1 and 7 days after an incident and at least 3 weeks before. We also find a deterioration of perception on police competence (column 6 in Table 3). The predicted probability of households perceiving police as being competent decreases on average by 0.34 point among exposed households in Mogadishu.

For the IV estimates, we use the same preferred specification as in the DiD approach, which includes fixed effects, characteristics of the household, household head and dwelling, as well as the drought affected status of households. The results also show a negative immediate effect on core consumption (per capita deflated) attributable to terrorist attacks from Al-Shabaab against civilians (column 1 in Table 4).

Overall, point estimates are larger with the IV approach compared to DiD estimates. Yet, the former estimates are less precise and have larger standard errors in the second stage since it only considers part of the variation in the treatment status of households, which is induced by the instrument (the exposure to attacks combined with the rate of growth of US air/drone attacks against Al-Shabaab). Nevertheless, the IV estimates (Table 4) reinforce the DiD results: a negative immediate effect on consumption in urban areas with exposed and control households in Waves 1 and 2, mainly driven by a reduction of food consumption. The decline in consumption also increases the share of population with a consumption level below the poverty line, which has a similar magnitude between the IV and DiD estimates.

Table 4: IV estimates for the effect of terrorist attacks against civilians in urban areas with exposed and control households in Wave 1 and 2

	Log of core consumption (1)	Log of food consumption (2)	Poverty status (3)	Poverty gap (4)	Experienced hunger (5)	Police competence (6)
IV coefficient (δ)	-1. 715*** (0.540)	-1.924*** (0.692)	1.564*** (0.371)	0.248 (0.208)	2.688*** (0.667)	-0.710 (0.478)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Characteristics of household & head	Yes	Yes	Yes	Yes	Yes	Yes
Dwelling characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Drought affected status	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,241	2,241	2,241	2,241	2,234	2,167

Source: Authors' calculations based on data from the SHFS and ACLED. Note: Estimated coefficients from an IV regression. Characteristics of household refer to size and receiving remittances, while those from household head refer to age, sex and literacy. Dwelling characteristics include tenure, roof and floor material, water source and sanitation type. Humanitarian assistance is not included due to collinearity with the region fixed effects. Standard errors considering sampling weights in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

The estimated coefficient for the effect on the poverty gap is positive and larger with the IV approach (Table 4), compared to the DiD result (Table 3). Despite this, the IV estimate is not statistically significant. Contrary to this result, the IV coefficient of hunger is positive and statistically significant, unlike the DiD estimate. For the perception of police competence, the IV result also suggests a negative effect, as our DiD estimate, but the coefficient is not significant. Even though the IV and DiD coefficients are estimated from different samples of households, the differences in results seem to be related to larger standard errors from the IV approach. For the effect of incidents on the poverty gap and police competence, the 95% confidence interval of the DiD coefficient lies within the confidence interval of the respective IV estimate. The imprecision of IV estimates, combined with the fact that the point estimates are consistent on the direction on the effect, could suggest the result might not be different between DiD and IV, ultimately pointing to a positive effect of incidents on the poverty gap and a deterioration of perception of police competence.

Table 5: DiD and IV estimates for the effect on employment and earnings

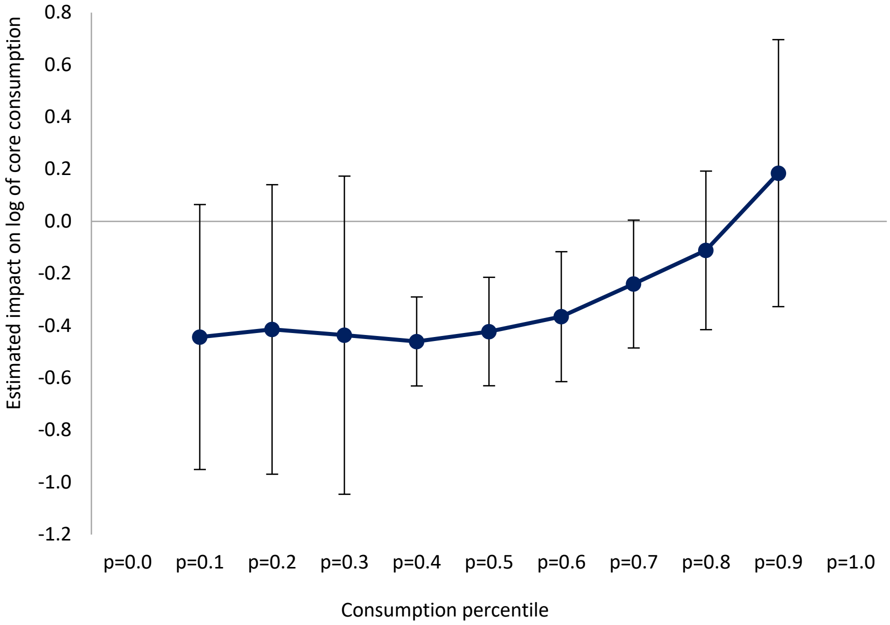
	Proportion of household members (aged 15-50) employed in the previous week		Proportion of household members (aged 15-50) earning income in the previous week	
	DiD (1)	IV (2)	DiD (3)	IV (4)
DiD or IV coefficient	-0.147** (0.066)	-1.952*** (0.326)	-0.150* (0.086)	-1.682*** (0.285)
Fixed effects	District	Region	District	Region
Full set of controls	Yes	Yes	Yes	Yes
Observations	1,525	2,221	1,525	2,221

Source: Authors' calculations based on data from the SHFS and ACLED. Note: Estimated coefficients from an OLS regression for Mogadishu and IV regression for urban areas with exposed and control households in Wave 1 and 2. Estimates obtained from our most complete specification including household size, receiving remittances, age, sex and literacy of the household head, tenure, roof and floor material of the dwelling, water source and sanitation type. Drought affected status and humanitarian assistance are not included in the OLS regression due to the lack of variation in the data within Mogadishu. Humanitarian assistance is not included in the IV regression due to collinearity with the region fixed effects. Standard errors considering sampling weights in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

We further explore the mechanisms through which a terrorist attack from Al-Shabaab against civilians can lead to a decrease in consumption. Table 5 presents the results for the impact on the proportion of household members aged 15 to 50 that were employed and earned income after an incident. The DiD coefficients are obtained from the sample of households in Mogadishu, while the IV coefficients from urban areas with exposed and control households in Waves 1 and 2; both from our most complete specification. All estimates are negative and statistically significant. Similar to other outcomes, IV point estimates are larger and have bigger standard errors. However, the IV estimates also reinforce the DiD findings, which indicate a decrease of around 15% in the share of both, household members working and earning income between 1 and 7 days after an incident. A reduction in employment and income could lead to a decline in consumption and exacerbate poverty and vulnerability among households exposed to an incident.

There are other supply-side mechanisms, such as limited availability of food items and higher prices, which could help explain how a terrorist attack disrupts the economy and affects welfare conditions of the population. To assess this, we compare the cost of the consumption basket –made out of 38 core food items– of exposed households from Mogadishu in Wave 2 against that from a group of households also in Wave 2 located within 1 kilometer from incidents in Mogadishu but that were interviewed before the attacks. The consumption basket of exposed households was 3% more expensive for these items, providing some evidence that higher food prices could also be another relevant mechanism through which a terrorist incident affects consumption levels.[26]

Figure 4: Distributional effect across consumption percentiles in Mogadishu



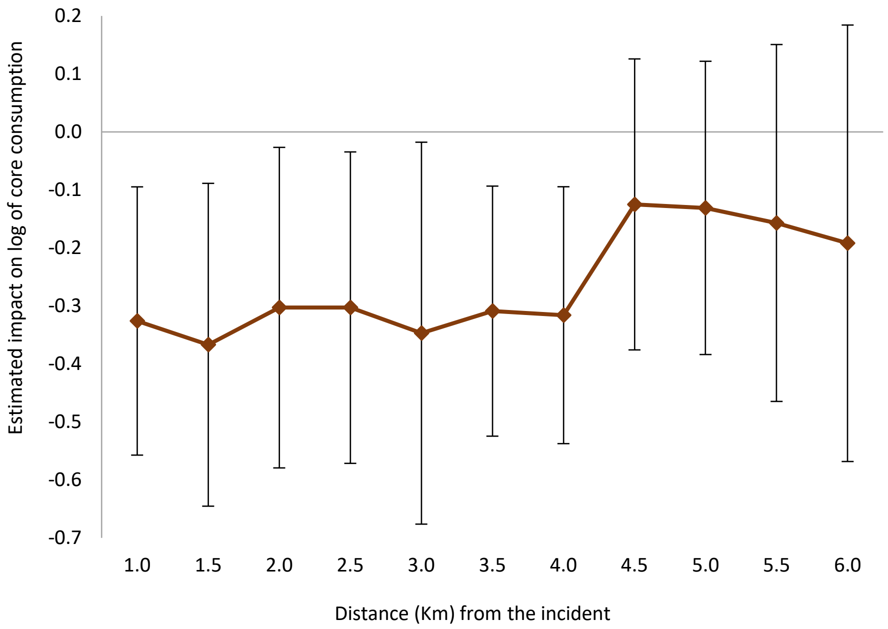
Source: Authors' calculations based on data from the SHFS and ACLED. Note: The vertical lines depict 95% confidence intervals.

We extend the analysis to investigate how the impact on consumption differs across consumption percentiles and the spatial variation of this negative effect.[27] For these extensions, we use our most complete specification from the DiD approach, the sample of households from Mogadishu and the sampling weights of surveys. Figure 4 plots the point estimates for the effect of incidents on core consumption from a quantile regression. For the negative and immediate impact of terrorist attacks on consumption, we find a heterogeneous effect across different parts of the consumption distribution. The point estimates increase with the consumption decile. Incidents affect exposed households from most of the consumption distribution, except those in the top 20%. The estimates for deciles 1, 2 and 3 are either significant at the 10% level or not significant because these groups are underrepresented in the survey sample considered.[28] Most of the households

[26] It is unlikely that the difference in cost of consumption baskets is explained by a seasonal pattern as all interviews of households in these groups were conducted within a period of 13 days.
[27] We cannot extend the analysis to measure the effect beyond 7 days after an incident occurred as only one exposed household was interviewed in this period during data collection of Wave 2.
[28] Households in the bottom 30% of the consumption distribution accumulate 40% of the sum of sampling weights from the total sample, ultimately indicating they are underrepresented in the survey data.

affected experienced a decrease in consumption of similar magnitude and mainly correspond to poor households since the incidence of poverty in Mogadishu was 74% in 2017-18. Households in the top 20% of the consumption distribution are likely to have savings or other sources of income, allowing them to smooth the shock from a terrorist attack and preventing them from reducing their consumption levels.

Figure 5: Spatial variation of the impact on consumption in Mogadishu



Source: Authors' calculations based on data from the SHFS and ACLED. Note: The vertical lines depict 95% confidence intervals.

Finally, we also relax the spatial criterion for the definition of treated households and classify as exposed or treated those households located from 1 to 6 kilometers away from the incidents.[29] Figure 5 presents the estimated coefficients for the effect on core consumption, considering as exposed those households located within the radius of each cutoff point.[30] The impact on consumption is similar for households located between 1 and 4 kilometers from the incident. After this threshold, the estimates become insignificant. The results suggest the immediate negative effect is clustered within a 4 kilometer radius from the attack. Households located within this radius suffer a decrease in consumption of similar magnitude. Conversely, those households located more than 4 kilometers away from an incident seem to be far enough, such that their consumption levels are not directly

[29] We only consider households between 1 and 6 kilometers since there are no Wave 2 households interviewed beyond a radius of 6 kilometers from where the attacks took place.
[30] The cutoff points of the different spatial criteria used to identify exposed households correspond to geodetic distances from incidents.

affected within a week. The impact encompasses around 10% of the area of Mogadishu and 25% of its population. Only part of the city is affected within a week, which could be associated to a localized disruption of roads and markets. Also, households located further away from the attack could still be affected after a week.

5. Robustness checks and additional OLS estimates

The estimated effect on consumption from our preferred DiD specification (-33%) is robust to i) the use of clustered standard errors at the PSU level and HAC standard errors (columns 3 and 4 of Table 9 in the Appendix); ii) seasonal patterns, after including year-month fixed effects (column 5 of Table 9 in the Appendix); and iii) the different samples and control groups considered (Table 10 in the Appendix).[31] The IV coefficients are also robust to the inclusion of clustered standard errors at the PSU level and HAC standard errors, as well as to the different samples and control groups considered; our main IV sample, composed of urban areas with exposed and control households in Waves 1 and 2, and all urban areas (Table 11 in the Appendix).

In addition, there is a low risk of obtaining biased DiD results due to compositional differences from using a repeated-cross section (Waves 1 and 2) representative of Mogadishu. Table 12 in the Appendix shows that the composition of the sample is relatively similar with respect to time-invariant characteristics when comparing exposed and control households between Wave 1 and Wave 2. Besides, we conduct a falsification test, measuring the impact before the events occurred. For this, we use the same definition for each group, and estimate equation (1) but substituting exposed households with those that were interviewed in Wave 2 before the incident took place (Table 13 in the Appendix). The results indicate no impact on this group of households, validating the DiD empirical strategy and the results.

To further support our findings, we employ another alternative empirical strategy. We restrict the analysis to households from Mogadishu in Wave 2 and compare exposed households –using the same definition in time and space– against a control group made of only those located within a 1 kilometer radius from an incident but that were interviewed before the attack. This alternative includes a sample of 113 exposed and 67 control households from Mogadishu in Wave 2. All households are located within the same

[31] All estimates with HAC standard errors consider a spatial correlation within 0.5 km to allow for variation in the group of exposed households, which is defined as those within a radius of 1 km from terrorist incidents.

distance from the attacks. The difference between exposed and control households is the timing of their interview in relation to when an attack occurred. However, fieldwork of Wave 2 is likely to have followed a geographical pattern or strategy when conducting interviews, due to logistical considerations. Thus, exposed and control groups and unlikely to be random but determined by the data collection schedule, which implies that households interviewed before and after the incidents are likely to be different. Yet, we find that they do not differ much in terms of observable characteristics. Exposed and control groups are relatively comparable or balanced on key observable dimensions (Table 14 in the Appendix).

Table 6: OLS estimates for the effect of terrorist attacks against civilians considering Wave 2 households from Mogadishu interviewed before and after the incidents

	Log of core consumption (per capita deflated)			
	(1)	(2)	(3)	(4)
Exposed/control	-0.215* (0.107)	-0.458*** (0.117)	-0.458*** (0.142)	-0.458*** (0.124)
District fixed effects	Yes	Yes	Yes	Yes
Characteristics of household & head	Yes	Yes	Yes	Yes
Dwelling characteristics	Yes	Yes	Yes	Yes
Standard errors	Sampling weights	Clustered by district	Clustered by PSU	HAC
Observations	180	180	180	180

Source: Authors' calculations based on the SHFS and ACLED. Note: Estimated coefficients from an OLS regression. Characteristics of household refer to size and receiving remittances, while those from household head refer to age, gender and literacy. Dwelling characteristics include tenure, roof and floor material, water source and sanitation type. Drought affected status and humanitarian assistance are not included due to the lack of variation in the data within Mogadishu. Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

We estimate a linear regression model using ordinary least squares (OLS). The coefficient of interest corresponds to the exposed or control dummy variable capturing the effect of terrorist incidents. Our specification includes district fixed effects to account for time-invariant unobservable factors. Also, there is a small risk that time-varying unobservables could affect the estimates as all interviews were conducted within a 6-week period. This alternative strategy produces similar results for Mogadishu, which are also robust to the inclusion of clustered standard errors and HAC standard errors (Table 6). The OLS estimate suggests a decline in core consumption of 22% attributable to attacks that occurred during data collection of Wave 2. Our main DiD estimate from the preferred specification (-33%) lies within the 95% confidence interval of this OLS point estimate.

6. Conclusions

After more than two decades of civil war and conflict, Somalia remains a fragile state subject to conflict and violence. The Federal Government of Somalia aims to provide the political and security conditions for improving the development trajectory of the country and increasing the welfare conditions of its population. The challenge of improving security conditions will be larger in the coming years as countries participating in The African Union Mission in Somalia (AMISOM) are considering whether to withdraw from Somalia.[32] Terrorist groups and their attacks are one of the threats to the government and its stability, representing a risk for the well-being of the population and limiting the capacity of the government and international partners to design and implement effective development policies.

This paper documents the immediate (within a week) impact of terrorist attacks from Al-Shabaab against civilians in Somalia. We combine micro-data from two waves of the Somali High Frequency Survey and employ a difference-in-difference approach comparing outcomes of households exposed to terrorist attacks against households who were not exposed to the incidents, before and after the events. Our estimates are robust to the use of clustered and HAC standard errors, different samples and control groups considered, besides that a similar composition of repeated-cross sections and a falsification test –measuring the impact before the events occurred– support the validity of our empirical strategy. We further confirm the results through an instrumental variables approach, for which we obtain a valid shift-share type of instrument that exploits the spatial variation of incidents and changes in the number of US air/drone attacks against Al-Shabaab.

Our estimates indicate a sizable immediate effect on consumption for households exposed to attacks with a decrease of 33%, mainly driven by a decline in food consumption. For some households, the reduced consumption brings their expenditure level below the poverty line, increasing the share of poor population. Among the poor, the negative effect results in consumption levels further away from the poverty line. The impact on consumption seems to be explained by a smaller share of household members (aged 15 to 50) working and earning income after an attack. In addition, we document that the negative impact on consumption is clustered within a 4 kilometer radius from the incident and has a heterogeneous effect, not affecting households in the top 20% of the consumption distribution. Besides, OLS estimates –comparing Wave 2 households in Mogadishu before

[32] The African Union Mission in Somalia is an active, regional peacekeeping mission operated by the African Union with the approval of the United Nations Security Council.

and after incidents but all within 1 kilometer from them– further support our findings. We also find that perceptions of police competence worsen, which could erode trust in formal institutions and ultimately hinder the government's legitimacy and capability for implementing policies.

The results are in line with the disruption that could be expected from a terrorist attack against civilians. However, these findings cannot necessarily be extrapolated to other contexts or periods due to differences in the size, structure and operation of other criminal organizations. The stage and duration of the conflict could also lead to different results. Moreover, we only capture immediate impacts due to data limitations. Further research is needed to assess if the effect on consumption and poverty is transitory or permanent and if it varies depending on whether attacks are more common in certain regions, as well as to understand displacement and other longer term effects on welfare.

Nearly two-thirds of the world's poor will be concentrated in conflict-affected countries by 2030.[33] Therefore, it is important to shed light and improve our understanding on the links between conflict and poverty. We contribute to the literature and policy debate by quantifying the impact on consumption and poverty, describing which households are affected by such incidents and the mechanisms through which this is likely to occur. A terrorist attack against civilians can lead to increases in poverty and vulnerability, among other adverse outcomes. In this context, policies could provide support to affected households through a combination of cash and in-kind food assistance to ameliorate the sharp decrease in consumption, mainly of food items. Beneficiaries can be identified using geographical targeting, covering those within 4 kilometers from the incident. Effective labor market interventions that support continuous employment could help by providing certainty and stability to households' incomes. Nevertheless, accelerating poverty reduction will be challenging until security conditions improve. Al-Shabaab has filled a vacuum of political power and gained control over several towns and villages across Somalia. National and international efforts should prioritize achieving peace, which is a fundamental first step for increasing welfare conditions that will also bring other wider long-term benefits in Somalia.

[33] World Bank (2020).

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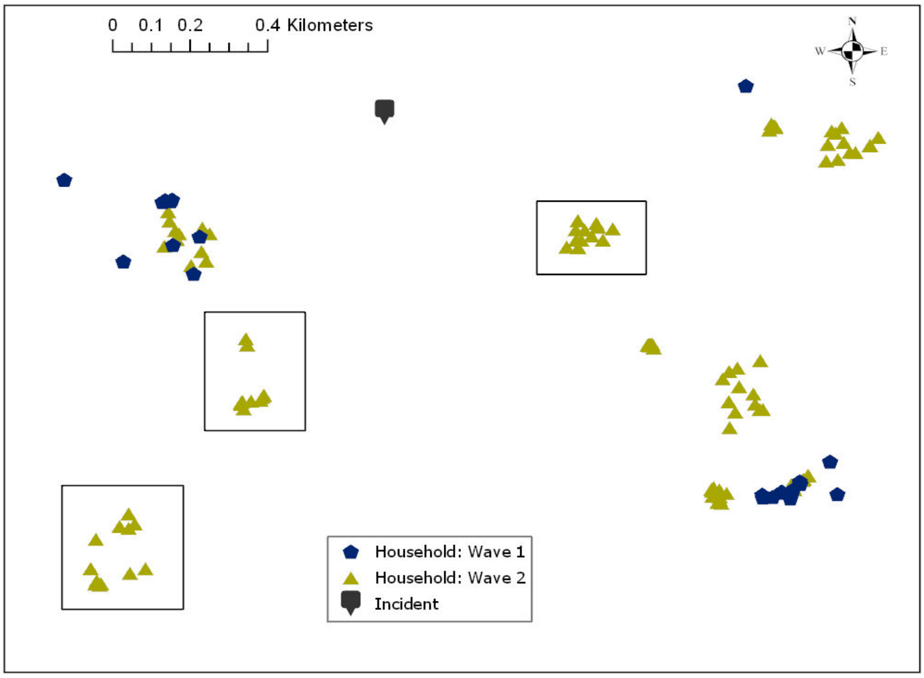
Appendix

Table 7: Wave 2 exposed households by urban region

Somali region	Number of exposed households
Mogadishu	113
North-east Urban	0
North-east Urban	0
Central regions	0
Jubbaland Urban	0
South West Urban	22

Source: Authors' calculations based on data from the SHFS and ACLED.

Figure 6: Interviewed households closed to an incident in Wave 1 and 2



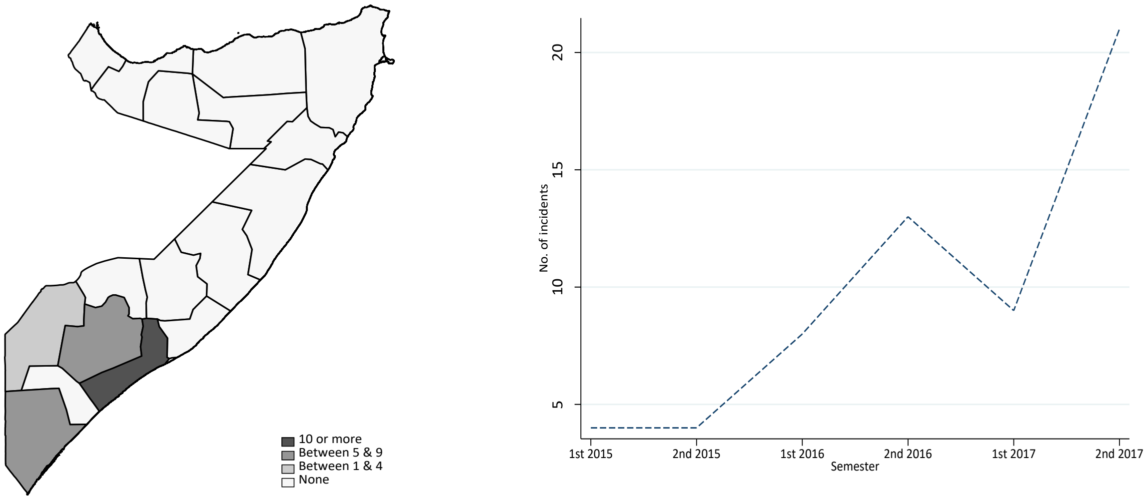
Source: Authors' calculations based on the SHFS and ACLED. Note: Solid rectangles correspond to Wave 2 exposed households without an overlapping cluster of Wave 1 households in Mogadishu.

Table 8: Correlates of terrorist attacks in Mogadishu

	Exposure of households to Wave 2 incidents		
	(1)	(2)	(3)
Log of core consumption (per capita deflated)	0.346 (0.326)	0.029 (0.036)	0.029 (0.032)
No. of members in the household	0.002 (0.007)	0.007 (0.007)	0.007 (0.006)
Household head: sex	-0.048 (0.068)	-0.042 (0.041)	-0.042 (0.036)
Household head: literate	0.013 (0.051)	0.042 (0.037)	0.042 (0.036)
Received remittances	-0.030 (0.051)	-0.033 (0.029)	-0.033 (0.025)
Tenure of the dwelling	-0.066 (0.072)	-0.042 (0.093)	-0.042 (0.087)
Floor of cement	0.066* (0.039)	0.038 (0.039)	0.038 (0.036)
Roof of metal	0.040 (0.034)	0.001 (0.045)	0.001 (0.038)
Access to piped water	-0.029 (0.074)	0.059 (0.046)	0.059 (0.044)
Improved sanitation	0.013 (0.039)	0.022 (0.043)	0.022 (0.042)
District in Mogadishu	Yes	Yes	Yes
Standard errors	Sampling weights	Clustered by PSU	HAC
Adjusted R-squared	0.062	0.017	0.017
Observations	885	885	885

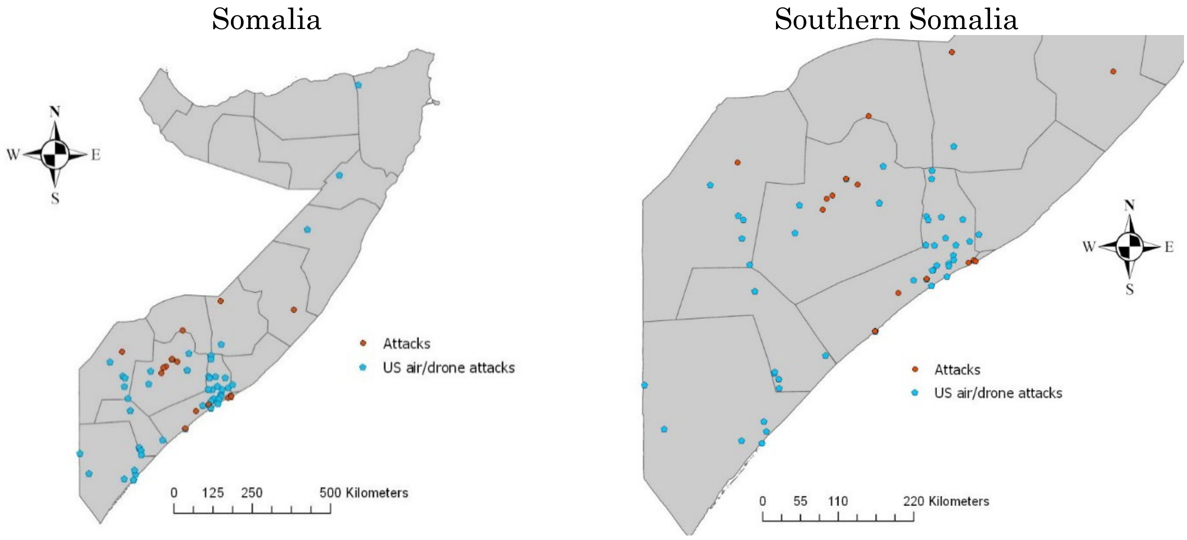
Source: Authors' calculations based on data from the SHFS and ACLED. Note: Estimated coefficients from an OLS regression. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Figure 7: Number of US air/drone attacks against Al-Shabaab between February 2015 and November 2017



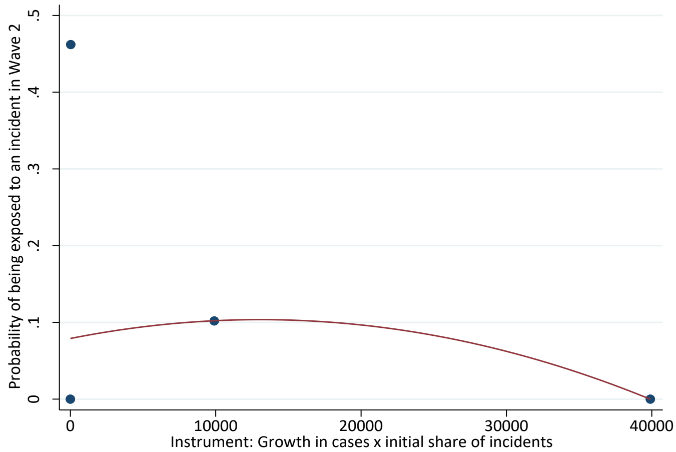
Source: Authors' calculations based on data from ACLED. Note: The boundaries on the map show approximate borders of Somali pre-war regions and do not necessarily reflect official borders, nor imply the expression of any opinion concerning the status of any territory or the delimitation of its boundaries.

Figure 8: Location of incidents and US air/drone attacks against Al-Shabaab during data collection of Wave 2



Source: Authors' calculations based on data from ACLED. Note: The boundaries on the map show approximate borders of Somali pre-war regions and do not necessarily reflect official borders, nor imply the expression of any opinion concerning the status of any territory or the delimitation of its boundaries.

Figure 9: Instrument and exposure to incidents in Wave 2 for urban areas with exposed and control households in Wave 1 and 2



Source: Authors' calculations based on data from the SHFS and ACLED. Note: The figure presents a binned scatterplot for the relationship between the instrument and the probability of households from being exposed to an incident in Wave 2.

Table 9: Different DiD specifications for the effect of terrorist attacks against civilians in Mogadishu

	Log of core consumption (per capita deflated)					
	(1)	(2)	(3)	(4)	(5)	(6)
Diff-in-diff coefficient (β)	-0.502*** (0.143)	-0.542*** (0.166)	-0.279** (0.130)	-0.279** (0.118)	-0.321*** (0.118)	-0.326*** (0.118)
Wave	Yes	Yes	Yes	Yes	Yes	Yes
Exposed/control	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	No	Yes	Yes	Yes	Yes	Yes
Characteristics of household & head	No	No	No	No	Yes	Yes
Dwelling characteristics	No	No	No	No	Yes	Yes
Year-month fixed effects	No	No	No	No	Yes	No
Standard errors	Sampling weights	Sampling weights	Clustered by PSU	HAC	Sampling weights	Sampling weights
Adjusted R-squared	0.018	0.045	0.100	0.100	0.342	0.342
Observations	1,557	1,557	1,557	1,557	1,532	1,532

Source: Authors' calculations based on data from the SHFS and ACLED. Note: Estimated coefficients from an OLS regression. Characteristics of household refer to size and receiving remittances, while those from household head refer to age, sex and literacy. Dwelling characteristics include tenure, roof and floor material, water source and sanitation type. Drought affected status and humanitarian assistance are not included due to the lack of variation in the data within Mogadishu. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: DiD estimates from different samples for the effect of terrorist attacks against civilians in Mogadishu

	Log of core consumption (per capita deflated)				
	Mogadishu (1)	Mogadishu with overlapping exposed households in Wave 1 and 2 (2)	Mogadishu with overlapping districts in Wave 1 and 2 (3)	All urban areas (4)	Urban areas with exposed and control households in Wave 1 and 2 (5)
Diff-in-diff coefficient (β)	-0.326*** (0.118)	-0.299** (0.144)	-0.324*** (0.118)	-0.159* (0.091)	-0.315*** (0.083)
Wave	Yes	Yes	Yes	Yes	Yes
Exposed/control	Yes	Yes	Yes	Yes	Yes
Fixed effects	District	District	District	Region	Region
Characteristics of household & head	Yes	Yes	Yes	Yes	Yes
Dwelling characteristics	Yes	Yes	Yes	Yes	Yes
Drought affected status	No	No	No	Yes	Yes
Humanitarian assistance	No	No	No	Yes	Yes
Adjusted R-squared	0.342	0.344	0.329	0.333	0.368
Observations	1,532	1,497	1,396	6,560	2,241

Source: Authors' calculations based on data from the SHFS and ACLED. Note: Estimated coefficients from an OLS regression. Characteristics of household refer to size and receiving remittances, while those from household head refer to age, sex and literacy. Dwelling characteristics include tenure, roof and floor material, water source and sanitation type. Drought affected status and humanitarian assistance are not included in the first three columns due to the lack of variation in the data within Mogadishu. Standard errors considering sampling weights in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: IV estimates from different samples for the effect of terrorist attacks against civilians

	Log of core consumption (per capita deflated)					
	Urban areas with exposed and control households in Wave 1 and 2			All urban areas		
	(1)	(2)	(3)	(1)	(2)	(3)
IV coefficient (δ)	-1.715*** (0.540)	-2.391*** (0.857)	-2.391** (1.178)	-1.508*** (0.523)	-2.217*** (0.801)	-2.217** (1.091)
Fixed effects	Region	Region	Region	Region	Region	Region
Characteristics of household & head	Yes	Yes	Yes	Yes	Yes	Yes
Dwelling characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Drought affected status	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors	Sampling weights	Clustered by PSU	HAC	Sampling weights	Clustered by PSU	HAC
Observations	2,241	2,241	2,241	6,560	6,560	6,560

Source: Authors' calculations based on data from the SHFS and ACLED. Note: Estimated coefficients from an IV regression. Characteristics of household refer to size and receiving remittances, while those from household head refer to age, sex and literacy. Dwelling characteristics include tenure, roof and floor material, water source and sanitation type. Humanitarian assistance not included due to collinearity with fixed effects by region. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Composition of Wave 1 and 2 samples for Mogadishu

Household characteristic	Exposed households			Control households		
	Difference (W2 - W1)	Significant	Obs.	Difference (W2 - W1)	Significant	Obs.
Household head without education (%)	11.9	No	134	-2.1	No	1,423
Access to piped water (%)	15.4	No	134	4.5	*	1,423
Improved sanitation (%)	-4.0	*	134	-3.7	No	1,423
Floor of cement (%)	3.9	No	134	3.4	No	1,421
Floor of tiles or mud (%)	0.6	No	134	5.3	No	1,421
Floor of wood or other material (%)	-4.0	No	134	-8.7	**	1,421
Roof of metal (%)	17.7	No	134	-5.7	No	1,423

Source: Authors' calculations based on data from the SHFS and ACLED. Note: Each row corresponds to an OLS regression of the Wave dummy over a household characteristic. Standard errors derived considering the sampling weights of the surveys. *** p<0.01, ** p<0.05, * p<0.1.

Table 13: DiD falsification test measuring the impact before the terrorist attacks occurred

	Log of core consumption (per capita deflated)			
	Exposed: Households interviewed up to a week before the incident		Exposed: All households interviewed before the incident	
	Mogadishu (1)	Urban areas with exposed and control households in Wave 1 & 2 (2)	Mogadishu (3)	Urban areas with exposed and control households in Wave 1 & 2 (4)
Diff-in-diff coefficient (β)	0.262 (0.167)	0.199 (0.131)	0.367 (0.316)	0.366 (0.343)
Wave	Yes	Yes	Yes	Yes
Exposed/control	Yes	Yes	Yes	Yes
Fixed effects	District	Region	District	Region
Characteristics of household & head	Yes	Yes	Yes	Yes
Dwelling characteristics	Yes	Yes	Yes	Yes
Drought affected status	No	Yes	No	Yes
Humanitarian assistance	No	Yes	No	Yes
Adjusted R-squared	0.346	0.362	0.341	0.361
Observations	1,419	2,106	1,419	2,106

Source: Authors' calculations based on data from the SHFS and ACLED. Note: Estimated coefficients from an OLS regression. Characteristics of household refer to size and receiving remittances, while those from household head refer to age, sex and literacy. Dwelling characteristics include tenure, roof and floor material, water source and sanitation type. Drought affected status and humanitarian assistance are not included in column 1 and 3 due to the lack of variation in the data within Mogadishu. Standard errors considering sampling weights in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Composition of treatment and control groups considering Wave 2 households from Mogadishu interviewed before and after the incidents

Household characteristic	Difference (Exposed-Control)	Significant	Obs.
No. of dependents in the household	0.3	No	180
Share of working-age members in the household (%)	1.0	No	180
Age of household head (years)	1.3	No	180
Household head without education (%)	5.6	No	180
Access to piped water (%)	0.4	No	180
Improved sanitation (%)	13.8	**	180
Floor of cement (%)	9.7	No	180
Floor of tiles or mud (%)	-11.3	No	180
Floor of wood or other material (%)	1.6	No	180
Roof of metal (%)	-2.5	No	180

Source: Authors' calculations based on data from the SHFS and ACLED. Note: Each row corresponds to an OLS regression of the exposed/control dummy over a household characteristic. Standard errors derived considering the sampling weights of the surveys. *** p<0.01, ** p<0.05, * p<0.1.