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Terrorism, education, and the role of perceptions: Evidence from al-Shabaab attacks in Kenya

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HiCN Working Paper 309

August 2019

Abstract: This paper investigates how terrorism alters human capital investment through perceived uncertainty. Using various estimators, we identify a causal negative effect of terrorism on Kenyan school enrolment. Among these, we exploit al-Shabaab's revenue streams and position in the al-Qaeda network to predict attacks. To isolate the significant contribution of behavioural responses to changes in the perceived risk of going to school, we estimate the effect of media reporting about terrorism exploiting house- hold variation in radio signal coverage. Evidence from finely geo-coded data further suggests that attacks occurring some distance from children's way to school or even on the other side of an international border still decrease school enrolment. Finally, we evaluate risk perception within a structural model, and use it to predict individuals' earnings loss arising from the reduction in schooling.

JEL Classifications: D74, I21, O15

Keywords: terrorism, education, expectations

Acknowledgements: For helpful comments we would like to thank Jerome Adda, Vittorio Bassi, Sascha Becker, Christian Dustmann, Thiemo Fetzer, Markus Gehrsitz, Pamela Giustinelli, Selim Gulesci, Hyejin Ku, Marinella Leone, Attila Lindner, Eliana La Ferrara, Thomas LeBarbanchon, Edwin Leuven, Nicola Limodio, Stuart McIntyre, Stelios Michalopoulos, Sebastian Otten, Uta Schöonberg, Diego Ubfal, Christopher Udry, Fernando Vega-Redondo and participants at various seminars and workshops. We would also like to thank Günter Lorenz and Peer-Axel Kroeske for providing a map of radio coverage.

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1 Introduction

Among respondents surveyed in Europe and North America, 58 percent are "a good deal" or "very much worried" about terrorist attacks, on par with concerns about job loss or war (World Value Survey, 2010-2013). In Africa, the share is 74 percent. The observed risks of dying in terrorist attacks in both regions are relatively low, $9.2 \cdot 10^{-5}$ percent and $9.6 \cdot 10^{-4}$ percent, respectively.[1] Such concerns can, nevertheless, affect decisions regarding the future. For physical capital, Abadie and Gardeazabal (2003, 2008) argue that terrorism affects the economy not through its impact on infrastructure, which is likely to be small. Even so, economic costs can be large if agents react and divert foreign direct investment. We extend this logic to human capital formation.

In this paper, we highlight the importance of individual perceptions and awareness of the risks associated with terrorism as a mechanism through which terrorist attacks affect primary school enrolment. Different from many other types of violence, such as gun crime or civil war, the explicit purpose of terrorism is the spread of fear and disruption beyond the violent act itself (see Krueger and Maleckova, 2003; for a detailed discussion). As such, terrorism can affect educational outcomes in two ways. Like other types of violence, terrorist attacks can affect educational outcomes *directly* by destroying infrastructure and killing school personnel. However, terrorist attacks are likely to affect educational choices also *indirectly* by changing the risks associated with school attendance. As *indirect*, we define any channel other than *immediate physical* harm to school infrastructure or personnel caused by terrorist attacks. The fact that intimidation is the motive behind many terrorist attacks may induce fear and thus trigger an endogenous individual response that exacerbates the effect of terrorism above and beyond any direct physical impact. In particular, any such effect on forward looking decisions like human capital investment implies that the mere threat of terrorism may have long term economic consequences.

The setting for our analysis is Kenya, where parts of the country have seen a stark increase in terrorist activity from the late 2000s onwards. The vast majority of attacks are carried out by al-Shabaab, an Islamist terror organisation based in Somalia with links to al-Qaeda. We explore the importance of perceived risk and the mechanisms at play by exploiting media reporting on attacks together with radio signal coverage to investigate the importance of salience. We further use finely geo-coded data to isolate attacks that do not occur on children's way to school or even in the administrative area they reside in. Moreover, we estimate a behavioural model of activity choices for children in the presence of terrorist

[1] The percentages reported are the annual risk of dying from terrorist attacks in 2015. Numbers for terrorist fatalities are drawn from the Global Terror Database (own calculations). Population numbers are drawn from UN data, see `https://population.un.org/wpp/DataQuery/`, accessed January 2019.

attacks. This allows us to evaluate agents' perception of fatality risk, and to quantify the economic cost of terrorism arising from its effect on education decisions.

Before turning our attention to the mechanisms at play, we establish a causal effect of terrorism on school enrolment, applying a range of estimators to several independent data sources. Estimates using enrolment data for school children digitised from reports by the ministry of education suggest that between 2009 and 2014 each attack kept 243 children out of school. Data from the Demographic Health Survey (DHS) allow us to construct enrolment rates at official school entry age back to 2001, before terrorist attacks had started. We use the unique concentration of attacks in spacetime to estimate various difference-in-differences and event study specifications, and to test for parallel trends between affected and unaffected areas before the sharp increase in attacks. We corroborate our results by zooming into two of the counties hardest hit by terrorist attacks. Using longitudinal household data collected as part of the Hunger Safety Net Programme (HSNP), we find very similar effects, even after we condition on household fixed effects.

A potential identification challenge is that terrorists select when and where to attack. We cannot reject parallel trends during the early 2000s. Nevertheless, we exploit three features unique to the Kenyan setting to obtain plausibly exogenous variation in al-Shabaab attacks. First, we use al-Shabaab's position within the al-Qaeda network. Al-Shabaab has particularly strong links to the Yemeni branch of al-Qaeda, al-Qaeda in the Arabian Peninsula (AQAP), from which it receives support and strategic guidance. We document not only that al-Shabaab closely follows AQAP in its timing of attacks, but also that it chooses similar targets. Second, we exploit the fact that revenue streams for al-Qaeda derived from Yemen's exports of hydrocarbons increase the intensity of attacks by both AQAP and al-Shabaab. Finally, we look at al-Shabaab's main source of income directly: the export of charcoal. A major trading partner for Somalia's coal are the United Arab Emirates (UAE) where it is mainly used to smoke water pipe. Accordingly, we use tobacco imports into the UAE as an exogenous shifter of its demand for coal and thus al-Shabaab's revenues. Estimates obtained from IV and OLS are of similar magnitude and we cannot reject the validity of the instruments.

Since the causal reduced form estimates capture both direct physical effects and behavioural responses to terrorism that operate via agents' expectations, we provide three pieces of evidence all pointing towards a crucial role of the latter. First, we show that media coverage of terrorist activity in Kenyan regions is negatively associated with enrolment in those areas, conditional on attacks carried out. To approximate household level exposure to media we obtained geo-coded data on the location of broadcasting antennas and on radio signal coverage across Kenya. The estimates show a negative effect of media only for households with access to wireless broadcasting. As a more direct measure, we also use self-reported radio ownership and find similar results. This variation across households further suggests that the reduction in enrolment is not driven by school closures or teacher absence. We also consider media mentions of “guns”, and do not find any significant correlations. These results highlight the importance of salience, which may alter agents’ expectations about the risk of going to school.

Second, to fully rule out a direct effect through damage to Kenyan infrastructure or personnel, we use the fact that the responsibility and provision of education vary discretely at the border between two countries. We find that even attacks on Somali soil that are geographically close have a strong and significant effect on school enrolment of Kenyan children in the border region, even after controlling for attacks in a child’s Kenyan county of residence. Moreover, we find that terrorist threats issued against Somalia impact negatively on educational enrolment in Kenyan counties adjacent to the Somali border.

Finally, to focus more narrowly on the specific risk faced by school children, we use the geographic coordinates of individuals, schools and attacks to identify terrorist incidences, which occur between a child’s residence and the closest primary school. Comparing the responses of children residing at different distances from school, we find large negative effects for attacks that occur on the way to school. In a second step, we estimate how this effect dissipates with longer distances from children’s school. Attacks *in the proximity of but not immediately on* the way to school are unlikely to cause physical damage, but may well be perceived as a threat and alter agents’ risk assessment. Correspondingly we find smaller yet still significant effects—even after controlling for attacks on the immediate way to school. Moreover, we show that the effect of attacks elsewhere in a child’s county of residence is stronger for children who live at a longer distance from school.

Based on these insights about the importance of indirect effects, we formulate a simple structural model of activity choices for children. We employ moments constructed from the HSNP data, and maintain a close link with the reduced form estimation by exploiting the quasi-experimental variation in attacks also for identification in the structural estimation. By estimating the model’s parameters, we can calculate the perceived fatality risk that is implied by observed choices. The estimated probability is 45 times higher than the actual number of deaths for the same period. This suggests that parents significantly over-estimate death risks. Our estimate is in line with studies documenting individuals’ over-estimation of mortality risk in various contexts (see e.g. Fischhoff et al., 2000; Delavande et al., 2017). Finally, we use the model to obtain an estimate of the individual-level cost of terrorism arising from its effect on education choices. Our estimate for the discounted expected earnings loss over individuals’ adult life corresponds to approximately one year’s average earnings of an adult without any schooling.

Our analysis complements the literature on the consequences of violence on education by documenting the importance of non-physical aspects as a mechanism through which behaviour is affected. Several studies estimate either the total reduced form impact of violence (e.g. Justino et al., 2013; Khan and Seltzer, 2016; Singh and Shemyakina, 2016; Koppensteiner and Menezes, 2018; Bertoni et al., 2018; Brück et al., forthcoming), explicitly model the physical impacts such as destruction of infrastructure (Akbulut-Yuksel, 2014) or the effect on education personnel (Monteiro and Rocha, 2017), or evaluate the effect of psychological distress (Shany, 2018). A separate body of work, in turn, analyses the importance of subjective expectations for educational decisions (Dominitz and Manski, 1996; Jensen, 2010; Lekfuangfu, 2016; Giustinelli and Pavoni, 2017; Boneva and Rauh, 2018; Attanasio et al., 2019; Duncan et al., 2019; Delavande and Zafar, forthcoming; see Hartog and Diaz-Serrano, 2014, and Giustinelli and Manski, 2018, for overviews). We draw on insights from both of these literatures and provide evidence that terrorism affects behaviour also by changing expected risks associated with attending school. In addition, by integrating the reduced form evidence in a structurally estimated behavioural model, we can quantify the effect of different mechanisms.

This paper also contributes to the knowledge base on the workings of terrorist networks. Part of our strategy to identify the causal effect of terrorist attacks exploits al-Shabaab's revenues and its position within the al-Qaeda network. The descriptive analysis leading to our first stage thus provides novel empirical evidence on the strong correlation between attacks by al-Shabaab on the one hand, and its revenues and attacks carried out by AQAP on the other. The workings of terrorist organisations have already been documented in qualitative analyses (see Zimmermann, 2013; for instance). We provide a quantitative analysis of these links. As such, the paper contributes on the growing literature on the determinants of violence, like media access (Yanagizawa-Drott, 2014), resources and economic conditions (Miguel et al., 2004; Chassang and Padró i Miquel, 2009; Gehring et al., 2018; Adhvaryu et al., 2019), climate and weather conditions (Burke et al., 2015; Condra et al., 2018; Harari and La Ferrara, 2018), colonial history (Michalopoulos and Papaioannou, 2016) and ethnic composition (Amodio and Chiovelli, 2017), commodity prices (Brückner and Ciccone, 2010; Dube and Vargas, 2013; Bazzi and Blattman, 2014; Berman et al., 2017; Ciccone, 2018), social insurance (Fetzer, 2014), and collusion between politicians and paramilitaries (Acemoglu et al., 2013); see also the recent machine learning exercises by Mueller and Rauh (2018) and Blattman et al. (2019), who use large sets of potential determinants to predict violence. More specifically on terrorist organizations, studies have investigated for instance the role of donations (Limodio, 2018) and resource constraints (Koehler-Derrick and Milton, 2017), of unobserved coalitions between factions (Trebbi and Weese, 2019), as well as agency problems within organizations (Shapiro and Siegel, 2007). For wider surveys, also on both the determinants and the effects of terrorism, see Berman (2009) and Gaibulloev and Sandler (2019).

After first describing the context and data sources used, we estimate in Section 3 the causal effect of terrorist attacks on school enrolment. In Section 4, we bring additional data to the analysis to investigate the mechanisms driving the estimated reduced form effects. Finally, Section 5 presents the structurally estimated behavioural model together with its estimates and counterfactual analysis.

2 Background and data

The setting for our analysis is Kenya, which experienced a sharp increase in terrorist activity. The majority of attacks were carried out from 2010 onwards by al-Shabaab in Kenya's northeastern region, bordering Somalia.

2.1 Terrorism in Kenya

Information on terrorist attacks is drawn from the Global Terrorism Database (GTD). The GTD defines a terrorist attack as the use of *illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation.*[2] For each incident in the data, the GTD collects information on, among other things, the geographic coordinate of the incident's location, the target, number of casualties and injuries, the weapons used and the group responsible.

The vast majority of terrorist attacks in Kenya are carried out by al-Shabaab, an Islamist terror organisation based in Somalia with the aim of overthrowing governments in the Horn of Africa region and to install Islamic rule. The organisation traces its origins back to the early 2000s, when radical young Islamists merged with a group of sharia courts, the Islamic Courts Union, to serve as a youth militia. During the last two decades, al-Shabaab has been present in large parts of Somalia.[3]

Al-Shabaab is an affiliate of al-Qaeda with particularly strong ties to al-Qaeda in the Arabian Peninsula (AQAP). Al-Qaeda operates in a network structure with al-Qaeda core, led directly by the "emir", at its centre along with sets of affiliates. Closest to the core are the regional affiliates, such as al-Qaeda in Iraq, al-Qaeda in the Islamic Maghreb and

[2] The data are available under `https://www.start.umd.edu/gtd/about/`.

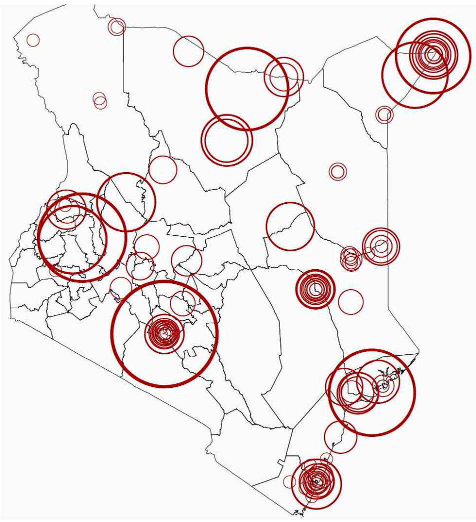
[3] See for instance Anderson and McKnight (2015) for an overview.

al-Qaeda in the Arabian Peninsula. Next, are affiliates, which are organisations subscribing to al-Qaeda's ideology and influence. These are officially recognised by al-Qaeda core, have pledged allegiance to the "emir", and al-Shabaab is one of them. Furthest away are associates that have not been publicly recognised as al-Qaeda but are close in terms of ideology. These include, for instance, Boko Haram in Nigeria or the so-called Movement for Tawhid and Jihad in West Africa. See Zimmermann (2013) for a detailed description of the al-Qaeda network. See appendix A for the geographical distribution.

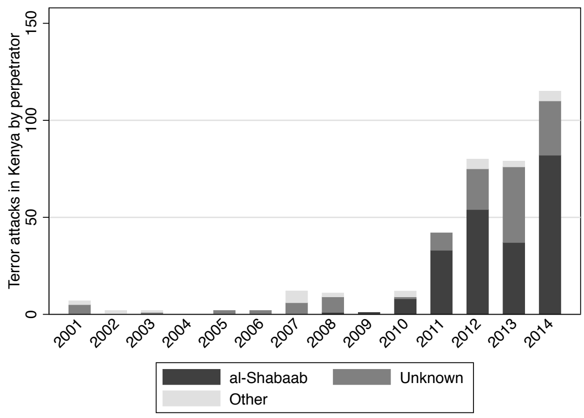
Between the years 2001 and 2014, Kenya experienced 367 terrorist attacks (see panel A of table 1). Figure 1a reports the geographical distribution terrorist attacks in Kenya. Most attacks are concentrated in the three northeastern counties of Kenya, which border Somalia.[4] The two largest towns, Nairobi and Mombasa also experience considerable number of attacks. Figure 1b shows the temporal variation in terrorist attacks. Between the years 2001 and 2007, Kenya experienced relatively few attacks. From then onwards, the intensity increases sharply, reaching 82 attacks in 2014. The maps in appendix B further show the geographical distribution of attacks over time for the years 2010 to 2014.

Figure 1: Terrorist attacks in Kenya

(a) Casualties of terrorist attacks in Kenya



(b) Terrorist attacks over time in Kenya



Notes: The figure reports total number of casualties and attacks in Kenya by perpetrator during the years 2001-2014; radii indicate number of casualties per attack; Source: Global Terrorism Database; own calculations.

In contrast to Boko Haram in Nigeria and favourable to our purposes, al-Shabaab barely targets educational institutions (see panel B of table 1). The most common targets for al-Shabaab are the police (96 attacks), citizens (74 attacks), businesses (53 attacks) and the

[4]These are Mandera, Wajir and Garissa.

military (22 attacks). Between 2001 and 2014, educational institutions were targeted only 5 times, corresponding to 1.4 percent of all attacks.

In fact, al-Shabaab attacks are only a relatively small proportion of violent incidences occurring in Kenya. Armed Conflict Location & Event Data (ACLED) reports that al-Shabaab attacked 215 times between 2001 and 2014. Over the same time period there were 3,759 other types of violent events.

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Terrorist attacks in Kenya 2001-2014						
Organisation	All	al-Shabaab	un-known	other			
Attacks	367	216	122	29			
Casualties	931	523	313	95			
	Panel B: Terrorist attacks in Kenya 2001-2014 by target (source: GTD)						
Target	All	Police	Citizens	Business	Military	Education	Other
Attacks	367	96	74	53	22	5	117
Casualties	931	165	292	154	29	51	240
	Panel C: Characteristics of individuals in Kenya						
Data source	DHS	DHS	DHS	HSNP			
Sample	All	North-east	Mandera & Wajir	Mandera & Wajir			
Year	2009	2009	2009	2010			
Children (6-14) currently at school	93.1	60.2	56.9	55.3			
Girls (6-14) currently at school	93.4	55.7	50.7	46.7			
Boys (6-14) currently at school	92.9	64.0	62.0	62.4			
Adults (18+) ever in school	84.7	23.7	19.7	18.9			
Women (18+) ever in school	79.3	11.7	8.4	7.6			
Men (18+) ever in school	90.8	37.5	32.7	29.1			
Members per household	4.3	5.4	5.7	6.2			

Notes: Panel A: reports the total number and casualties of terrorist attacks by organisation in Kenya occurring 2001 to 2014; Source: Global Terrorism Database; own calculations. Panel B: reports the total number of terrorist attacks by target of attack in Kenya occurring 2001 to 2014; Source: Global Terrorism Database; own calculations. Panel C: reports characteristics of respondents; column 1 is drawn from the 2009 DHS for the whole of Kenya; column 2 is drawn from the 2009 DHS for the northeast of Kenya (Mandera, Wajir and Garissa) only; column 3 is drawn from the 2009 DHS for counties Mandera and Wajir only; column 4 is drawn from the 2010 HSNP Baseline survey for counties Mandera and Wajir.

2.2 Education in Kenya and summary statistics

Data on education in Kenya: We measure school enrolment in three different ways using three distinct and independent data sources. First, we employ two rounds of the Kenyan Demographic Health Surveys (DHS), 2009 and 2014, two nationally representative surveys of Kenyan households.[5] The 2009 and 2014 rounds of the Kenyan DHS interviewed all members of 9,057 and 36,430 households, respectively (Kenya National Bureau of Statistics, 2009, 2014). In addition to many other subjects, the questionnaires collect extensive information on educational enrolment and years spent in school.

We complement these data with official information on the total number of children enrolled in primary school for each county from the Kenyan Ministry of Education. We digitised these figures from the Statistical Abstract published annually by the Kenya National Bureau of Statistics.

Finally, we use a household panel dataset collected to evaluate the Hunger Safety Net Programme (HSNP) to focus on Mandera and Wajir, where a disproportionately high number of terrorist attacks occur. In order to evaluate the HSNP, data were collected on 2,436 households in the counties Mandera, Marsabit, Turkana and Wajir (see appendix A for a map of these) over three years between August 2009 and November 2012. This dataset also records children's major activity (school attendance, work or staying at home), and thus allows us to assess how other activities are affected by the presence of terrorist attacks. It further lets us confirm the estimated effects not only for school enrolment, but also for attendance.

The educational situation in Kenya: Primary school covers eight years, and the school year runs from January to November. At the end of each year, children automatically advance to the next year. According to the 2009 DHS, 93.1 percent of children aged 6 to 14 are currently in school. The corresponding figure for northeastern Kenya is lower, 60.2 percent, see panel C of table 1. The quality of primary schooling in terms of teacher presence and knowledge has been shown to be relatively high compared to other African countries (Bold et al., 2017). We use retrospective information on school enrolment contained in the DHS to calculate whether each child enrolled in school at the age of 7. The school entry age set by the government is 6. We include children aged 7 at the time of interview since these children may have turned 7 between enrolling in school and being interviewed by the DHS. Our overall focus on enrolment better reflects parents' choice, and is unlikely to be affected by, for instance, teacher absenteeism (Glewwe et al., 2010; Duflo et al., 2012).[6] For

[5] The data are publicly available at `dhsprogram.com`.

[6] We consider children who at the time of the interview were below 14 years old. For each child, we use information on time spent in school to construct a dummy variable taking the value 1 if the child enrolled

the years 2010 and 2014, 79.2 percent enrolled by the age of 7. Our figure tallies with other measurements of education for similar years. The World Bank, for instance, reports a net primary school enrolment rate of 81 percent in 2012 (the last year available).[7]

3 The effect of terrorism on schooling

Before examining in detail the role of perceived risk for individuals' response to terrorist threats, this section estimates the causal effect of terrorism on school enrolment. We employ a range of estimators including difference-in-differences, instrumental variables and household fixed effects on the three completely separate data sources outlined above.

3.1 OLS and difference-in-differences estimations

Ordinary Least Squares: In our most basic specification we regress school enrolment in county c and year t ($school_{ct}$) on the number of terrorist attacks in that county ($attacks_{ct}$). We estimate the following specification using various measures of educational enrolment and find consistently negative effects.

$$school_{ct} = \alpha \ attacks_{ct} + \gamma_c + \tau_t + u_{ct}, \tag{1}$$

where we control for unobserved heterogeneity across counties c in factors determining the level of enrolment, as well as country-wide variation in aggregate conditions over time t. Table 2 reports the results. In columns (1) and (2), we measure school enrolment as the total number of children enrolled in primary school in each county, digitised from reports by the Kenyan Ministry of Education. The parameter estimate suggests that each attack decreases the number of pupils by 243 (controlling for the total population). In columns (3) and (4) we use retrospective information on school enrolment contained in the DHS to construct a panel of the percentage of children enrolled by age 7 described in Section 2.2, and to evaluate the relation between attacks and enrolling in school on time. We estimate equation (1) both at the county level, and using individual data that allow us to control for household and child characteristics. Columns (5) and (6) show the individual level

in school at age 7. For each year and county, we then match the fraction of children to which this applies to the number of terrorist attacks in the same year and county.We drop the small percentage (6%) of children who either dropped out of school or repeated (despite it being banned), since for them we cannot correctly calculate the age at which they enrolled.

[7]Data were downloaded from `https://data.worldbank.org/`; accessed November 2018. Net enrolment is defined as *the ratio of children of official school age who are enrolled in school to the population of the same age.*

estimates. Including the number of attacks during the previous year in columns (2), (4) and (6) shows that correlations are consistently driven by contemporaneous attacks, pointing towards agents' immediate fear rather longer-term considerations. Columns (7) and (8) show that there is no significant difference across gender. Instead of attacks within a child's county of residence, we also consider attacks within a given radius around the geographic coordinate of respondents' residence. This definition of treated areas is similar to the one adopted in a recent study by Bertoni et al. (2018). The estimate for attacks occurring within 10km of a respondent's home (reported in column (9) of table 2) is of similar magnitude as the county-level treatment estimates.

Finally, to examine whether staying out of school until at least age 7 translates into lower school enrolment later on, column (10) take current school enrolment at the time of the interview as the dependent variable. A comparison of columns (5) and (10) shows that the effect of attacks when a child is of age 7 equally carries over to later enrolment. Finally, in column (11) we restrict our attention to attacks occuring only during the last three months prior to each DHS interview.[8] Overall, the estimated coefficients exhibit a remarkable robustness across definitions and specifications.

Difference-in-differences: One concern is that al-Shabaab attacks occur in regions that are characterised by both weak institutions as well as low school enrolment. To investigate this possibility, we exploit the unique concentration of al-Shabaab attacks in spacetime and estimate various difference-in-differences and event study specifications. We start by comparing—over time—counties hardest hit by terrorist attacks to the rest of the country using the following difference-in-differences specification

$$school_{ct} = \delta\ post_t \times affected_c + \kappa_c + \theta_t + \upsilon_{ct}, \tag{2}$$

To ensure that our results are not driven by an arbitrary specification, we vary both the definitions of regions experiencing terrorism ($affected_c$) and of the time period when terrorist attacks occur ($post_t$). In particular, we vary the cutoffs for $post_t = 1$ between 2007 and 2011. Similarly, we define $affected_c = 1$ for the three northeastern regions, and alternatively also add Nairobi and Mombasa (see appendix E). We estimate equation (2) at the county level using the same school enrolment measure as in column (4) in table 3A. The estimates in table 3 show a reduction in school enrolment of about 14 percentage points in regions experiencing terrorist attacks compared to those that do not.

Event studies: To investigate parallel trends between areas affected and unaffected by terrorist incidences, we analyse enrolment before the sharp increase in terrorist activity. In

[8]The 2009 DHS was implemented October 2008 to March 2009 and the 2014 DHS between April and October 2014.

Table 2: Effect of terrorism on school enrolment: different specifications and measurements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Different measures of educational enrolment										
Dependent variable	No. of in school prim. school admin data (county)		% of kids in school by age 7 DHS (county)		=100 if kid in school by age 7 DHS (individual)		(girl)	(boy)	(individual)	=100 if kid is currently attending school DHS (individual)	
# attacks in same c, t	−243.37	−211.10	−0.890	−0.829	−0.664	−0.631	−0.581	−0.764			
	(81.83)***	(74.35)***	(0.196)***	(0.251)***	(0.192)***	(0.265)**	(0.115)***	(0.265)***			
lagged # attacks		−70.92		−0.106		−0.060					
		(77.08)		(0.197)		(0.170)					
# attacks within 10km of residence									−1.115		
									(0.168)***		
# attacks in same c when child was 7										−0.673	
										(0.326)**	
# attacks in 3 months prior to interview											−0.953
											(0.366)**
county population	YES	YES									
c and t effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
indiv. characteristics					YES	YES	YES	YES	YES	YES	YES
R squared	0.99	0.99	0.78	0.78	0.24	0.24	0.27	0.22	0.24	0.24	0.23
Observations	282	282	658	658	40,657	40,657	20,168	20,489	40,657	41,000	41,000

Notes: table reports OLS estimates; # *attacks* is the number of attacks classified as terrorist per county and year; columns (1) and (2) dependent variable is total number of children in school, drawn from official reports by Kenyan Ministry of education (2009-14); columns (3) and (4) dependent variable is the county average of children enrolled in school by age 7, sample consists of 6 to 14 year olds for 2009 and 2014 round of DHS, one observation per county year; columns (5) to (9) dependent variable takes value 100 if child enrolled in school by age 7, sample consists of 6 to 14 year olds for 2009 and 2014 round of DHS, one observation per child; columns (10) and (11) dependent variable takes value 100 if child currently in school, sample consists of 6 to 14 year olds for 2009 and 2014 round of DHS, one observation per child; individual characteristics include dummies for child's gender, rural location, household having electricity, radio and TV and for whether household head has secondary education; standard errors are clustered at the county level.

Table 3: Effect of terrorism on school enrolment: difference-in-differences

	(1)	(2)	(3)	(4)	(5)
Dependent variable	% of kids in school by age 7				
Mean in pre-period	57.2	57.9	59.2	60.6	55.9
Post × Affected	$-14.72**$	$-14.80**$	$-14.03**$	$-14.17***$	
	(5.65)	(5.64)	(6.00)	(5.21)	
Trend × Affected					-0.590
					(0.730)
c and t effects	YES	YES	YES	YES	YES
Post=1 for	≥ 2008	≥ 2009	≥ 2010	≥ 2011	
Years	2001-14	2001-14	2001-14	2001-14	≤ 2007
Observations	658	658	658	658	329
R squared	0.78	0.78	0.782	0.78	0.78

Notes: table reports difference-in-differences estimates comparing the northeast (Mandera, Wajir and Garissa) to the rest of Kenya; dependent variable is the county average of children enrolled in school by age 7; data structure is a panel for the 47 counties for the years 2001-14; $post = 1$ for years after (and including) 2008 (column 1), 2009 (column 2), 2010 (column 3) and 2011 (column 4); $Affected = 1$ for northeastern Kenya (Mandera, Wajir and Garissa) data are drawn from 2009 and 2014 Kenyan DHS; column 5 shows that parallel trends for the pre-period cannot be rejected; standard errors are clustered at the county level.

column (5) of table 3, we test for a difference in pre-trends and cannot reject that trends are indeed parallel. We complement this finding with a detailed event study analysis. In panel (a) of figure 2 we plot the proportion of children enrolling in school by age 7 for two regions of Kenya: the northeast —where most of terrorist attacks occur—and the remainder of the country. Although enrolment is considerably lower in Northeastern Kenya, the trends before the sharp rise in terrorist activity appear parallel. In panel b of figure 2 we statistically test the effect suggested in panel (a) by substituting the $post_t$ dummy in equation (2) with dummies for each year between 2002 and 2014. The results confirm large and statistically significant differences, which start to appear only from 2007 onwards. Before that year, the trend appears parallel, which tallies with our estimates from column (5) of table 3.

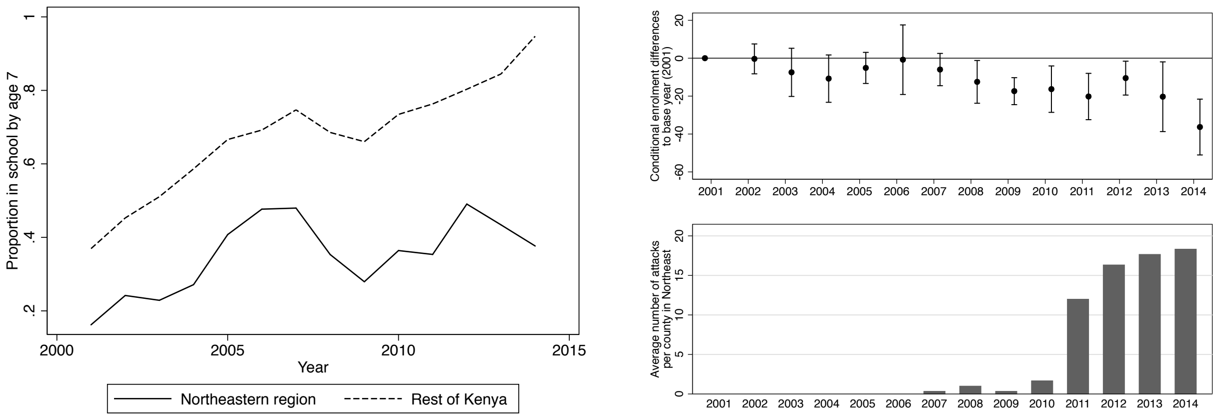
3.2 Instrumenting terrorist attacks

Although we do not find evidence for a violation of the parallel trend assumption required for consistency of the difference-in-differences estimates, the estimator would be biased if al-Shabaab targets areas that experience shocks which are correlated with enrolment decisions.

One possible concern might be that it is al-Shabaab's strategy to target areas experiencing positive economic shocks, possibly in order to maximise impact and social distress. This

Figure 2: Terrorist attacks and schooling over time

(a) Unconditional means (b) Conditional differences



Notes: Panel a reports proportion of children enrolling in school by age 7 for northeastern Kenya (Mandera, Wajir and Garissa) and the rest of the country by year; Panel b reports conditional yearly differences in the proportion of children enrolling in school by age 7 between northeastern Kenya (Mandera, Wajir and Garissa) and the rest of the country; lower panel shows number of attacks carried out in northeastern Kenya by year; Sources: Demographic Health Surveys and Global Terrorism Database.

would induce an upward bias in estimates of the effect of terrorism on school enrolment. Another possibility is related to findings by Limodio (2018), who documents the importance of donations for the funding of Islamist organizations in Pakistan. If al-Shabaab can raise higher donations in more affluent areas and is more active there, this would again induce an upward bias.

We address these concerns by exploiting some unique features of the context in which al-Shabaab operates in order to instrument its choice of both timing and location of attacks. To predict the geographical location of terror incidences, we show that the probability of attacks decreases with distance to the Somali border. We combine this insight with three factors which influence the timing of attacks but are plausibly exogenous to the Kenyan context: al-Shabaab's affiliation to al-Qaeda, and revenue streams arising from hydrocarbon and coal exports, both known to be major sources of revenues for these terrorist organisations. With three resulting instruments, we have over-identification and can test instrument validity.

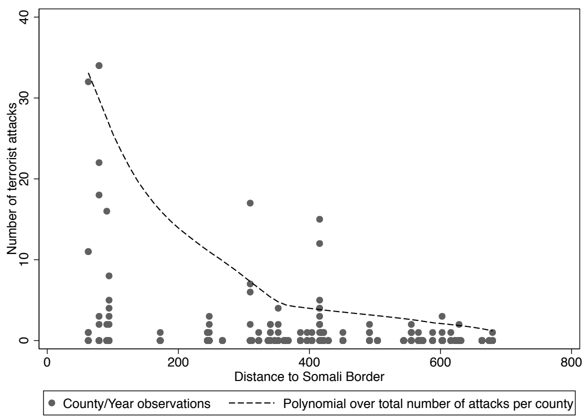
Location of attacks — Distance to Somali border: Carrying out terrorist attacks is expensive[9] and this cost is likely to increase with the distance from the area controlled by the organisation in question. In the Kenyan case, this corresponds to distance from the Somali border. An additional factor decreasing the costs of attacks close to the border in our

[9]See, for instance: `https://www.cfr.org/backgrounder/tracking-down-terrorist-financing` (accessed December 2018)

setting derives from the population in the border region being primarily of Somali ethnicity, implying a lower cost for maintaining network structures and carrying out attacks. Distance to border has also been used in other contexts as an instrument for terrorist attacks (Rehman and Vanin, 2017).

We illustrate the predictive power of distance to the border by plotting the total number of terrorist attacks each county experienced between 2001 and 2014 against the distance between that county's centroid and the Somali border. Figure 3 shows a clear negative correlation and a hyperbolic shape. We provide further evidence on the importance of distance to the border controlling for other county characteristics in appendix C, confirming that distance to border is by far the strongest predictor for the location of terrorist attacks.

Figure 3: Terrorist attacks and distance to Somali border



Notes: The figure shows total number of attacks occurring in each of the 47 counties of Kenya between 2001 and 2014 by distance between the county and the Kenyan/Somali border; Source: Global Terrorism Database.

To predict terrorist attacks in spacetime, we combine distance to border with three factors that affect the *timing* of al-Shabaab attacks. We interact each of these with distance to the Somali border as follows

$$attacks_{ct} = \phi \; timing_t / distance_c + \lambda_c + \iota_t + w_{ct},$$

where $distance_c$ is the aerial distance between county c's centroid and the closest point on the Somali border. For $timing_t$ we use three separate instruments that we detail in turn.

Timing of attacks (I) — Al-Shabaab's affiliation to al-Qaeda: We use al-Shabaab's position in the al-Qaeda network to obtain plausibly exogenous variation in the timing of terrorist attacks carried out by al-Shabaab in Kenya. Al-Shabaab is an affiliate of al-Qaeda with particularly strong ties to al-Qaeda in the Arabian Peninsula (AQAP). With encouragement of al-Qaeda core, AQAP established and maintained close links with al-Shabaab (Rollins, 2011; Zarif, 2011). In practice, AQAP supports al-Shabaab in several ways. First, AQAP provides al-Shabaab with financial help and it is believed that access to al-Qaeda's resources was one of the reasons for al-Shabaab's loyalty pledge (Keatinge, 2014). Second, AQAP provides al-Shabaab directly with weapons and military training (Zimmermann, 2013). Third, AQAP shares personnel with al-Shabaab. It is known, for instance, that fighters have crossed the gulf of Aden to Somalia (Hansen, 2013). AQAP itself operates in a completely different geographical region to al-Shabaab, almost exclusively in the Arabian peninsula, and never in Africa.[10]

Unsurprisingly, there is no systematic data on the documented financial, material and training support between terrorist organisations. Nonetheless, we do observe data patterns that are highly consistent with the qualitative evidence provided in the literature. The strong degree of coordination between the two organizations is supported by the high correlation in the timing of attacks that we highlight in figure 4a, which reports the frequency of al-Shabaab and AQAP attacks, grouped into 4 week intervals. Given its global standing, the hierarchy plausibly puts AQAP above al-Shabaab in this relation (see also Lahoud, 2012; Zimmermann, 2013). In table 4 we investigate these correlations further. We construct a weekly time series and regress the number of al-Shabaab attacks on attacks carried out by AQAP.[11] The parameter estimates not only show strong and robust correlations in attacks (column 2) by the two organisations but also that when AQAP attacks public (private) targets, so does al-Shabaab (columns 3 and 4).

Timing of attacks (II) — Natural gas exports from Yemen: Our second source of plausibly exogenous variation in the timing of terrorist attacks carried out by al-Shabaab in Kenya is the volume of Yemen's exports of liquid natural gas. Besides ransom and extortions, AQAP derives a large part of its income from those exports (Fanusie and Entz, 2017a). Since, as mentioned before, AQAP provides financial assistance to al-Shabaab, part of these gas revenues may indirectly be channelled to al-Shabaab. This financial resource channel is particularly important since terrorist organisations cannot easily save or borrow over time (Limodio, 2018). The pipeline to Balhaf from where natural gas from Yemen is exported in fact falls within territory controlled by AQAP, see map in appendix A.

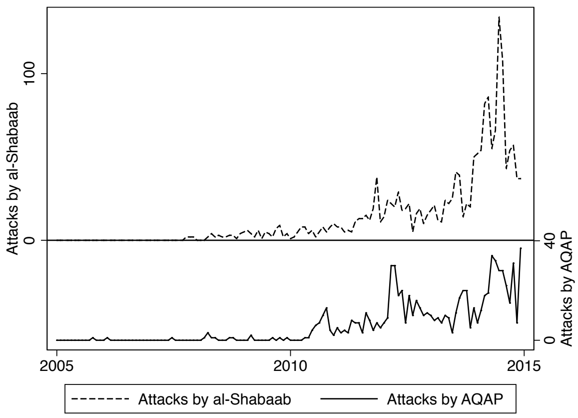
Figure 4b illustrates the strong correlation between attacks by AQAP and liquid natural gas exports. In 2014, less than 0.01 percent of Yemen's natural gas are exported to Africa,

[10]The only terrorist incidences outside the Arabian peninsula attributed to AQAP were in the United Kingdom, the United States, and most recently the Charlie Hebdo attack in Paris 2015.

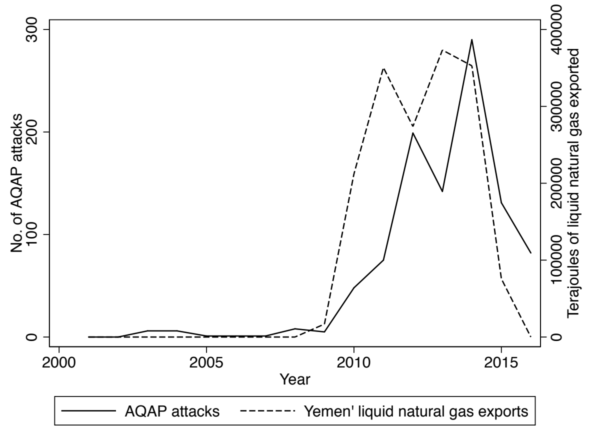
[11]We carry out Dickey-Fuller tests using various lags and reject the hypothesis of non-stationarity throughout.

Figure 4: Natural gas, tobacco, coal and terrorist attacks by AQAP and al-Shabaab

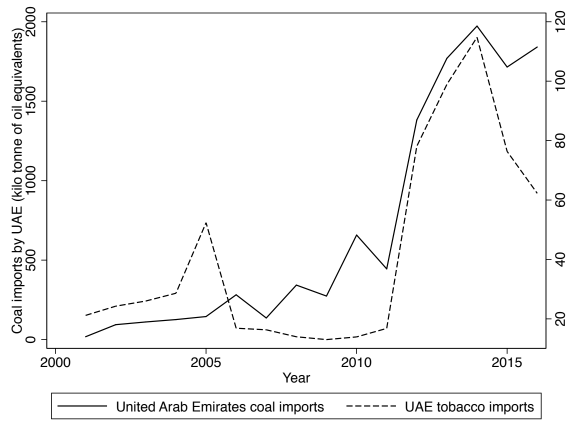
(a) Attacks by AQAP and al-Shabaab



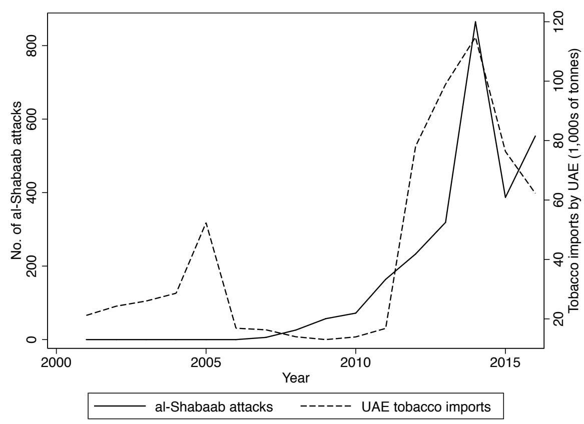
(b) Yemen's gas exports and AQAP attacks



(c) UAE's tobacco and coal imports



(d) UAE's tobacco imports & al-Shabaab attacks



Notes: Panel a shows attacks by al-Shabaab and AQAP for 4 week time periods; Panel b shows attacks by AQAP for each year and terajoules of natural liquid gas exported by Yemen; Panel c shows coal imports by United Arab Emirates in kilo tonne of oil equivalents and tobacco imports in kilo tonnes; Panel d shows attacks by al-Shabaab for each year and tobacco imports by United Arab Emirates in kilo tonnes; Sources: Global Terrorism Database and International Energy Agency, own calculations.

Table 4: Attacks by AQAP and al-Shabaab

	(1)	(2)	(3)	(4)
	Dependent variable: Number of weekly al-Shabaab attacks by target			
Target	Any	Any	Public	Private
Means	2.39	2.39	1.60	0.80
AQAP attacks	0.184 ∗ ∗	0.212∗∗∗		
	(0.074)	(0.079)		
AQAP attacks (t-1)		0.070		
		(0.077)		
AQAP attacks (t-2)		0.046		
		(0.077)		
AQAP attacks (t+1)		0.077		
		(0.077)		
AQAP attacks (t+2)		0.003		
		(0.076)		
AQAP attacks on "public" targets			0.295∗∗∗	−0.037
			(0.072)	(0.037)
AQAP attacks on "private" targets			−0.191	0.157 ∗ ∗
			(0.135)	(0.070)
R squared	0.740	0.753	0.707	0.593
Observations	728	726	728	728

Notes: The table reports correlations between al-Shabaab and al-Qaeda in the Arabian Peninsula (AQAP) activity, measured as the total number of attacks carried out by al-Shabaab and AQAP per week; public targets are police, military, governments and educational institutions; private tagets are civilians, religious leaders and businesses; data are drawn from Global Terrorism Database.

so that we can rule out any direct link with outcomes in Kenya.[12] Our second instrument thus predicts the timing of attacks by using Yemen's exports of natural gas in hepta tons.

Timing of attacks (III) — Tobacco imports by the United Arab Emirates: Exporting and trading charcoal is one of the largest sources of funding for al-Shabaab, which generated an estimated USD 83 million per annum between 2012 and 2014 (Fanusie and Entz, 2017b; United Nations Security Council, 2012). Due to the close link between coal exports and al-Shabaab's revenues, United Nations Security Council (2012) Resolution 2036 banned coal exports from Somalia in 2012. Despite this resolution, however, Somali coal exports continue illicitly and remain a major source of income for al-Shabaab (United Nations Security Council, 2018). Gulf Countries are the main destination for Somali charcoal, with around 33 percent of Somali exports going the United Arab Emirates (UAE) alone.

Made from acacia trees growing abundantly across the Horn of Africa, this charcoal is particularly prized for its long burning quality, which makes it well suited for smoking water pipe. We thus use imports of tobacco to the UAE as an exogenous shift in the demand for Somali coal and thus for al-Shabaab's finances. We collected the UAE's tobacco imports from the United Arab Emirates Federal Competitiveness and Statistics Authority[13] and plot these against the country's coal imports as reported by the International Energy Agency. Figure 4c shows a strong correlation. Tobacco imports, moreover, map very closely to al-Shabaab's activity—see figure 4d. Again, demand for tobacco in the UAE is arguably driven by factors exogenous to school enrolment choices by parents in Kenya. In fact, figures from the United Nations Conference on Trade and Development (UNCTAD) show that Somali coal makes up only 6 percent of the UAE's coal imports for the most recent years for which data is available (2010 to 2012).

Results: Columns (2) to (4) of table 5 we use each instrument separately. Using all three instrument simultaneously in column (4) render very similar results. The slightly more negative 2SLS coefficients may point to the suspected upward bias in OLS estimates in column (1), though the bias appears modest. The high F-statistics suggest that our three instruments have a strong predictive power. Moreover, we cannot reject the validity of our instruments. The very similar estimates under each of the three different instruments are reassuring. In appendix D we report the first stage results.

Robustness: In appendix E we test the robustness of our estimates. Among other things, we find that

- there is no statistically significant response in migration to attacks

[12] Trade data reported in the section are retrieved from UNCTAD webpage `https://unctadstat.unctad.org`. Own calculations. Accessed February 2019.

[13] Available on `http://fcsa.gov.ae/`; accessed April 2019.

Table 5: Effect of terrorism on school enrolment: Instrumental variables estimates

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: % of kids in school by age 7				
Mean in pre-period			65.5		
# terrorist attacks	-0.890^{***}	-1.318^{***}	-1.510^{***}	-1.006^{***}	-1.346^{***}
	(0.196)	(0.254)	(0.344)	(0.206)	(0.265)
***c* and *t* effects**	YES	YES	YES	YES	YES
F-Statistic		21.3	12.1	20.2	71.6
Instrument	OLS	AQAP	Gas	Tobacco	All 3
Observations			658		
R squared	0.78	0.78	0.78	0.78	0.78

Notes: The table reports the effect of terrorist attacks on school enrolment; # *attacks* is the number of attacks classified as terrorist per county and year; dependent variable is the county average of children enrolled in school by age 7; data structure is a panel for the 47 counties for the years 2001-14; column 1 reports OLS estimates; column 2 instruments # *attacks* with interaction of 1/distance and attacks by AQAP; column 3 instruments # *attacks* with interaction of 1/distance and Yemen's exports of hydrocarbons; column 4 instruments # *attacks* with interaction of 1/distance and tobacco imports by United Arab Emirates; column 5 uses all three instruments simultaneously; *distance* is the areal distance in km between a county's centroid and the Somali border; data are drawn from 2009 and 2014 Kenyan DHS; standard errors clustered at county level.

- the estimated effect is robust both to controlling for public expenditure on security and for education expenditure
- conditional on county effects, school closures do not correlate with proximity to terrorist attacks
- results are robust to several variations in the definition of treatment as well as to different sample restrictions.
- the effects are driven by contemporaneous rather than by lagged attacks

3.3 Panel estimates

Finally, we re-estimate the effect of terrorism using disaggregate data from the Hunger Safety Net Programme (HSNP) household panel. This allows us to focus on variation within a subset of affected counties, controlling for unobserved household characteristics. We also will use this data source for our structural estimation in section 5.

In panel C of table 1 we compare characteristics of children and adults from the HSNP in 2010 (its baseline) with individuals drawn from the 2009 round of the representative Kenyan DHS. Although the HSNP was not designed as a representative sample of the counties it surveyed, the characteristics of its respondents are remarkably similar to the overall populations in those counties.

The HSNP reports the location of respondents' residence. We use this information to define a location to be *affected* by terrorism if it is located within 25km of an attack. Appendix A shows attacks as red points, affected municipalities in yellow and unaffected ones in green. We estimate a model based on equation (1), for which we count the number of attacks in the 12 months prior to interview. The estimation sample includes children aged 6 to 14 at the time of interview.

The HSNP records the main activity of all household members. We use this information to classify the activities of children aged 6 to 14 into three groups: i) the child is currently attending school, ii) the child is working outside of the household and iii) the child is staying at home. We incorporate these categories explicitly in the behavioural model of Section 5. This information allows us to corroborate our results for attendance rather than enrolment, which we have used so far. Notice that given our focus on within-household variation, here we consider school attendance of children of any age.

The parameter estimates in columns (1) and (2) of panel A in table 6 show a significant negative impact of terrorism of a magnitude comparable to the DHS estimates in table 5, which persists even conditional on household fixed effects. In columns (3) and (4), we estimate the effect on the probability of working outside of the house (which excludes unpaid

Table 6: Effect of terrorism on child activities: household panel data from northeastern Kenya

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Effect of terrorist attacks on schooling and work					
	Dependent variable = 100 if child is currently					
	Enrolled in school		Working outside house		Staying at home	
Means	61.2		14.9		23.8	
# terrorist attacks	-1.216^{***}	-0.885^{**}	0.096	-0.045	1.120^{**}	0.930^{**}
	(0.321)	(0.326)	(0.236)	(0.200)	(0.432)	(0.395)
R squared	0.092	0.094	0.057	0.059	0.123	0.142
Covariates	YES	YES	YES	YES	YES	YES
Time effects	YES	YES	YES	YES	YES	YES
Cluster FE	YES		YES		YES	
Household FE		YES		YES		YES
Observations	7,078					
	Panel B: Effect of terrorist attacks by age					
	Dependent variable = 100 if child is currently					
	Enrolled in school		Working outside house		Staying at home	
Means	59.8	67.1	13.4	21.1	26.9	11.8
# terrorist attacks	-1.198^{***}	-1.150^{***}	-0.058	0.613	1.257^{**}	0.536
	(0.388)	(0.303)	(0.270)	(0.532)	(0.468)	(0.468)
R squared	0.085	0.119	0.053	0.049	0.114	0.055
Covariates	YES	YES	YES	YES	YES	YES
Cluster and time effects	YES	YES	YES	YES	YES	YES
Age	6-12	13-14	6-12	13-14	6-12	13-14
Observations	5,640	1,438	5,640	1,438	5,640	1,438

Notes: The table reports the effect of terrorism on primary school attendance and child labour; # *attacks* denotes the number of terrorist attacks in the last 12 months wihtin a 25km radius of the municipality in which the child resides; data are drawn from Hunger Safety Net Programme (HSNP) for counties Mandera and Wajir; columns 1-2: dependent variable takes 100 if child reports to be currently enrolled in school; columns 3-4: dependent variable takes 100 if child reports to be currently working outside the house; columns 5-6: dependent variable takes 100 if child reports neither to be currently working outside the house nor to be attending school; sample in panel A consists of children aged 6-14 at time of interview; samples in panel B consist of children aged 6-12 in columns 1, 3 and 5 and 13 to 14 in columns 2, 4 and 6; all standard errors are clustered at municipality level.

domestic work). The effect is estimated equally precisely, though closer to zero. Finally, columns (5) and (6) of panel A show a stark increase in the percentage of children staying at home. Taken together, these estimates suggest that rather than increasing the tendency to work for a wage outside the home, the lower school attendance due to terrorist attacks coincides with an increase in the number of children staying home. Thus, the reduction in school enrolment is unlikely to be driven by economic needs. In the next section, we explore the mechanisms behind the observed effects in more detail.

We also use the detailed information of the HSNP to investigate the effect of terrorist attacks on school attendance of children in the last few years of primary school. Any drop-out of school for these cohorts could affect children's likelihood to transit to secondary school and thus have consequences for long term human capital formation. In panel B of table 16 we distinguish children aged 6 to 12 from 13 to 14 year olds and find large negative effects for school attendance for both cohorts. These findings point towards long term effects of terrorism. Finally, we find no effect on the probability of working throughout.

4 The role of fear and awareness as a mechanism

Terrorism differs from other types of violence, such as civil war or gun crime, in as much as its direct effect on infrastructure and casualties is relatively low. Yet, its economic impact can be severe. In a commentary for the Wall Street Journal, Becker and Murphy (2001) predicted terrorism to only have a limited economic impact, due to the small share of capital stock it destroys. Abadie and Gardeazabal (2008) instead provide evidence for a more substantial effect. They contend that terrorism reduces expected returns, which in turn may lower foreign direct investment and hamper economic growth.

We extend this logic to human capital investment. Rather than through a direct physical impact, terrorism primarily alters expectations about the risks associated with schooling. The reduced form effects of terrorism based on equations (1) and (2) capture the sum of such *indirect* effects and a potential *direct* physical impact that terrorism shares with other forms of violence. A key empirical challenge is to disentangle these two, which we address in this section. In fact, estimates based on Afrobarometer data reported in table 7 suggest that individuals exposed to terrorist attacks are more afraid of crime, less satisfied with their living situation and less optimistic regarding future economic conditions.

In this section we explore this issue further by providing three pieces of evidence which all point towards a crucial role of *awareness* about terrorism in households' schooling decisions. First, *media coverage* of terrorist attacks, which by themselves do not affect infrastructure or school personnel directly, are strongly and negatively associated with enrolment. This correlation persists even after controlling for attacks actually carried out. Crucially, this is driven by households owning a radio or within reach of ratio broadcasting antennas, and thus with plausibly better access to media reporting. Second, taking a geographically wider perspective, we find that for children living close to the Kenyan/Somali border, attacks in Somali soil affect educational choices in Kenya (again after controlling for attacks in Kenya). This also extends to mere *threats* voiced by terrorist organisations for Somalia. Third, zooming in, we find that attacks in Kenya have a stronger impact the closer to children's way to school they are, which dissipates with further distance. Furthermore, attacks, including those occurring at a longer distance have a stronger effect the longer is a child's way to school.

Table 7: Effect of terrorism on attitudes

	(1)	(2)	(3)
	Dependent variable: = 100 if respondent states that		
	Is afraid of crime	Own situation better than others	Economic conditions will improve
Mean	14.1	22.7	36.9
# terrorist attacks	0.956***	−0.663 * *	−0.514 * *
	(0.207)	(0.273)	(0.252)
c **and** t **effects**	YES	YES	YES
individual charactersitics	YES	YES	YES
Observations		7,178	
R squared	0.092	0.070	0.114

Notes: The table reports the effect of terrorist attacks on attitudes; # *attacks* is the number of attacks classified as terrorist per county and year; dependent variable in column (1) takes value 100 if respondent answers question *Over the past year, how often, if ever, have you or anyone in your family: Feared crime in your own home?* with *many times* or *always*; dependent variable in column (2) takes value 100 if respondent answers question *In general, how do you rate your living conditions compared to those of other Kenyans?* with *better* or *much better*; dependent variable in column (3) takes value 100 if respondent answers question *Looking ahead, do you expect economic conditions in this country to be better or worse in twelve months time?* with *better* or *much better*; data structure is one observation per person; sample consists of individuals aged 21 to 53 drawn from 2005, 2008, 2011 and 2015 rounds of Afrobarometer; individuals characteristics controlled for are age of respondent, and dummies for individual being female, having at least completed primary education and being muslim; standard errors are clustered at county level.

4.1 Media coverage of terrorist attacks

In this section we first shed light on the importance of indirect mechanisms by examining the role of *media coverage* of terrorist attacks, for which we can plausibly rule out any direct effect on infrastructure or the number of casualties.[14] We find a negative relation, which is robust to the inclusion of the number of attacks actually carried out. Importantly, we find large and significant effects only for households with access to media.

The data for this analysis are drawn from the Global Database of Events, Language, and Tone (GDELT) project. The GDELT monitors media outlets such as print, broadcast and web news worldwide, and provides information on organisations, people, themes, quotes, images and many more in almost real time.[15] For Kenya, the GDELT records to which of the country's 8 regions an event refers (see map in appendix A). We use this information to construct a region/year panel, which we then match with primary school information on the 47 counties used so far, which are sub-strata of the 8 regions.

The GDELT records and classifies violent events. We define the following events as occurrences of terrorism: bombing (whether suicide, car or other non-military), abductions (including hijacking and taking of hostages) and assassinations of a known person (whether successful or not). In general, the GDELT classifies these events as uses of *unconventional* violence as opposed to uses of violence that are conventional in the sense of using military force. For each region and year, we sum media mentions across all of GDELT's source documents.[16] Figure 5a shows the evolution of media coverage of terrorist attacks Kenya. The GDELT also keeps a record of threats made. These are defined as exclusively verbal acts. The two sub-categories of threats most relevant for the present purpose are threats of "unconventional forms of violence", which the GDELT stipulates include terrorist threats, and threats of "unconventional forms of mass violence". We will make use of this additional information in Section 4.2.

To model the effect on educational enrolment empirically, we start by summing all media mentions per region/year, match these to the 47 counties and add the resulting variable to the OLS specification in equation (1). Column (1) of table 8 highlights a strong negative relationship between media mentions and the percentage of children in school by age 7. Part of this relation vanishes when we control for attacks carried out in the same region (column

[14]Whereas the effect of media coverage of terrorist attacks on education has not been investigated so far, the literature has considered the role of media on various economic and social outcomes, see DellaVigna and La Ferrara (2015) for a survey.

[15]The data are freely available under `https://www.gdeltproject.org/`.

[16]We follow GDELT's suggested practice and adjust the mentions of terrorist attacks by taking out variation in the total coverage for Kenya across all subjects. For easier interpretation, we report effect per 100s of mentions.

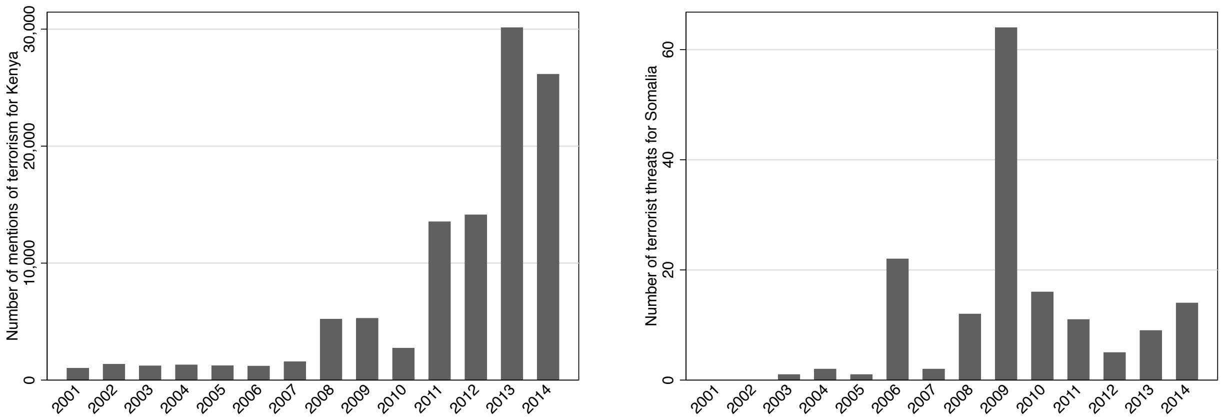
Table 8: Media coverage of attacks, media exposure and school enrolment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable:							
Dependent variable	Percentage of children in school by age 7		=100 if child in school by age 7			% in school by age 7	=100 if child in school by age 7	
Mean	65.5		69.8			65.5	69.8	
Mentions of terrorism (in 100s)	−0.326***	−0.169*	0.031	0.311	0.227			
	(0.063)	(0.091)	(0.103)	(0.194)	(0.147)			
Mentions of terrorism (in 100s) × Owns radio			−0.120**					
			(0.057)					
Mentions of terrorism (in 100s) × Close to antenna				−0.387**				
				(0.192)				
Mentions of terrorism (in 100s) × Radio coverage					−0.292**			
					(0.142)			
Mentions of guns (in 100s)						−0.064	0.170	0.148
						(0.071)	(0.139)	(0.128)
Mentions of guns (in 100s) × Close to antenna							−0.164	
							(0.138)	
Mentions of guns (in 100s) × Radio coverage								−0.132
								(0.122)
# terrorist attacks		−0.815***	−0.841***	−0.655***	−0.683***	−0.675***	−0.713***	−0.711***
		(0.091)	(0.201)	(0.204)	(0.210)	(0.214)	(0.216)	(0.223)
Owns radio			7.943***					
			(0.851)					
Close to antenna				1.807			1.359	
				(1.763)			(1.688)	
Radio coverage					6.881***			6.459***
					(2.181)			(2.054)
c **and** t **effects**	YES	YES	YES	YES	YES	YES	YES	YES
Individual characteristics			YES	YES	YES		YES	YES
R squared	0.775	0.781	0.242	0.244	0.244	0.775	0.244	0.244
Unit of observation	county		child			county	child	
Observations	658		40,657	40,486	40,657	658	40,486	40,657

Notes: The table reports relation between media coverage of attacks and educational enrolment in Kenya; *Mentions of terrorism (in 100s)* is the number of mentions in international media on Kenyan regions that cover terrorism; *Mentions of terrorism (in 100s)* × *Radio* is the number of mentions in international media on Kenyan regions that cover terrorism interacted with dummy for whether household child resides in owns a radio (*Radio*); *Mentions of terrorism (in 100s)* × *Close to antenna* is the number of mentions in international media on Kenyan regions that cover terrorism interacted with dummy for whether household child resides within 40km of a radio antenna; *Mentions of terrorism (in 100s)* × *Radio coverage* is the number of mentions in international media on Kenyan regions that cover terrorism interacted with dummy for whether the household resides in an area that `fmscan.org` confirms has radio coverage, *# terrorist attacks* is the number of attacks classified as terrorist per county and year; *Mentions of guns (in 100s)* is the number of mentions in international media on Kenyan regions that cover gun crime; dependent variable in columns (1), (2) and (6) is the county average of children enrolled in school by age 7 (data structure: one observation per county/year); dependent variable in columns (3), (4), (5), (7) and (8) takes value 100 if child enrolled in school by age 7 (data structure: one observation per child); individual characteristics are dummies for child's gender, rural location, household having electricity, radio and TV and for whether household head has secondary education; data are drawn from 2009 and 2014 round of DHS; all standard errors are clustered at county level.

Figure 5: Threat of terrorism and media coverage of terrorist attacks

(a) Media coverage (b) Terrorist threats



Notes: Panel (a) the yearly number of mentions in international media on terrorism in Kenya; panel (b) shows yearly totals of terror threats in Somalia; see text for definitions; Source: Global Database of Events, Language, and Tone (GDELT).

2).

An effect of media coverage of terrorist events on agents' behaviour requires access to media. We focus on wireless broadcasting, which is both cheap and widely used in Kenya; according to the DHS around two thirds of households report to own a radio. We measure radio access in three different ways. First, we use self-reported information on wireless receiver ownership to distinguish households with and without a radio. We also use information on the geographical location of governmental radio antennae from the Communication Authority of Kenya to calculate the distance between each household and the closest public antenna. See map (g) in appendix A. The average reach of antennae in Kenya is around 40km, which we use as a cut-off.[17] The results are robust to a variety of similar values. Since radio signal is likely to vary with terrain surface (see Yanagizawa-Drott, 2014), we also use direct information areas with wireless reception provided by `fmscan.org`, which supplies worldwide radio frequencies and transmitter maps. We distinguish areas at signal level 45 $dB\mu V$, which generally is regarded as providing good signal reception in and outside of buildings for a variety of different types of terrain. See map (h) in appendix A for the coverage areas. One possible concern is that households with and without radio reception exhibit different trends in primary school enrolment. The graphs in appendix G, however, show that—before the sharp increase in terrorist activity—both samples exhibit very parallel trends. If anything, the enrolment trend for areas with radio coverage is slightly steeper,

[17]See `fmscan.org`.

which would imply an even stronger effect than suggested by our estimates.

An advantage of using the three aforementioned cross-household variations is that the estimated effect (within counties) on schooling is unlikely to be driven by school closures or teacher absence.[18] Using each source separately, we define three dummies for radio reception and interact each of these with the total number of terrorism related media items in each region in columns (3) to (5) of table 8. The parameter estimates suggest that the influence of terrorist mentions is indeed considerably stronger for households with likely better access to media. This suggests an effect of media coverage of terrorist activity on educational outcomes above and beyond the number of attacks actually carried out in a given region. In columns (6) to (9), we conduct a placebo test and use the number of mentions of "guns" rather than "terrorism". The results show small and insignificant results.

4.2 Attacks and threats in Somalia

In this section we consider the broader context, examining the effect of attacks on Somali soil on education outcomes in Kenya. This, at the same time, allows us to rule out that the effect operates, for instance, via casualties among teachers and a disruption of educational services, we note the fact that the provision of education changes discretely at international borders. We focus on north-eastern Kenya, and estimate whether attacks occurring in Somalia but close to the border have an effect on enrolment in Kenya. Given the geographic proximity and shared ethnicity in the border region, Kenyans likely are well aware of violent events across the border.[19] An effect of terrorist attacks in Somalia on Kenyan infrastructure or education personnel, however, is improbable.

Using respondents' geographic coordinates, we define a variable, which counts the number of attacks in each year occurring within a given radius around each child *and* which were carried out on Somali soil. To again condition on attacks in each county, we add this variable to equation (1).

Columns (1) and (3) of table 9 show that Somali attacks have a large and significant negative effect on school enrolment among Kenyan children living within 250km and 100km from the attack. Each attack decreases the probability of enrolling in school on time by close to 0.2 percentage points and 0.4 percentage points respectively. As would be expected, for both radii the effect is considerably smaller than the effect of attacks occurring in the child's own county. Columns (2) and (4) select only children living in eastern Kenya (highlighted

[18] This also is supported by directly using school data in column (6) of appendix table 14.

[19] Overlaying Kenyan administrative boundaries with ethnographic maps based on the classical Soviet Atlas Narodov Mira shows that the three northeastern regions fall into the ethnic homeland of *Somalis*, which make up almost all of Somalia as well (Weidmann et al., 2010).

in yellow in map (f) of appendix A).[20] The estimates remain robust for this sub-sample.[21]

Table 9: Effect of terrorist attacks and threats in *Somalia* on education in *Kenya*

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable = 100 if child in school by age 7					
Means	69.6	61.5	69.6	61.5	69.6	61.5
# attacks in Somalia ≤100km	−0.385***	−0.399 **				
	(0.138)	(0.177)				
# attacks in Somalia ≤250km			−0.179***	−0.176 **		
			(0.065)	(0.072)		
# threats for Somalia × NE					−0.107***	−0.131***
					(0.028)	(0.039)
# attacks in same county	−0.723***	−0.618***	−0.603***	−0.506***	−0.700***	−0.602
	(0.138)	(0.170)	(0.119)	(0.113)	(0.192)	(0.196)
***c* and *t* effects**	YES	YES	YES	YES	YES	YES
individual characteristics			YES	YES	YES	YES
R squared	0.229	0.231	0.230	0.229	0.242	0.240
Unit of observation	Child					
Sample	all	East	all	East	all	East
Observations	40,657	15,204	40,657	15,204	40,657	15,204

Notes: The table reports the effect of terrorist attacks in Somalia on educational enrolment in Kenya; *# attacks in Somalia ≤100km* are attacks on Somali soil occurring within 100km of child i per year; *# attacks in Somalia ≤250km* are attacks on Somali soil occurring within 250km of child i per year; *# threats in Somalia × NE* is the number of verbal threats issued by terrorist organisations for the whole of Somalia interacted with a dummy for the three northeastern Kenyan counties (*NE*) bordering Somalia (Mandera, Wajir and Garissa); *# attacks in same county* is the number of attacks classified as terrorist per county and year; dependent variable takes value 100 if child enrolled in school by age 7 (data structure: one observation per child); individual characteristics are dummies for child's gender, rural location, household having electricity, radio and TV and for whether household head has secondary education; data are drawn from 2009 and 2014 round of DHS; East of Kenya consists of three regions: Eastern, Coast and Northeastern region; all standard errors are clustered at county level.

Besides actual attacks carried out in Somalia, we find that threats voiced by terrorist organisations for Somalia affect schooling in the Northeastern Kenyan counties differently from other parts of the country. Figure 5b shows how threats of terrorist attacks in Somalia, as reported in the GDELT database, vary over time.

To test this, we interact the Somalia specific variable counting the number of threats with a dummy for the three Kenyan counties bordering Somalia. Columns (5) and (6) of

[20]We use counties in the three regions: Northeast, East and Coast

[21]We also estimate the same specification using a radius of 50km around each child and the results remain robust, although the number of treated observation becomes rather small. The estimates are available from the authors upon request.

table 9 show a strong negative relation, which is stable to controlling for attacks actually carried out in a child's Kenyan county. These latter results are noteworthy. It is possible that threats regarding a Kenyan region are determined by unobservable shocks in that same region (which in turn also affect education). The effect of threats issued against another country, by contrast, are less likely to suffer from the same bias. Hence these results can be plausibly interpreted as causal.

4.3 Attacks on the way to school

As a further corroboration of the importance of agents' perceived risk, we analyse the proximity of attacks to the way to the closest primary school and to respondents' homes. We use the same data and outcome measure as in column (3) of table 2 and the difference-in-differences and IV estimations. Our focus on school enrolment rather than attendance in this section makes it unlikely that results are driven by teacher absence.

Both sets of estimations show the same pattern: Attacks occurring between respondents' homes and the closest primary school have the strongest impact on educational choices. Nonetheless, incidences further away and not on the way to the closest primary school retain a strong and significant negative impact.The latter shows that indirect channels, such as changes in perceived risk, have an effect that cannot be explained by direct physical impacts.

Attacks on the way to school: To focus on terrorism's impact on education, we isolate attacks occurring along and at a distance from each child's way to school. For this, we follow the methodology proposed by Koppensteiner and Menezes (2018), who use detailed information on children's way to school to estimate the effect of gun violence in Rio de Janeiro. Urban gun crime typically is highly localised, with a rather direct impact on children. Our emphasis instead is on understanding whether children with a longer way to school, which implies a higher risk, respond more strongly to terrorist attacks elsewhere in the county. First, however, we will show that effects are strongest for attacks occurring along the way to school than attacks that are further away.

To measure which attacks occur on the way to school, we overlay the geographic coordinates of children's residences with the coordinates of all 31,231 primary schools in Kenya, provided by the Kenya Open Data Initiative (KODI) Primary Schools dataset.[22] See appendix A for a map of the DHS clusters and of Kenya's primary schools. For each child, we identify the closest school. The mean distance to the closest school is 1.98km. We start by investigating whether the effect of terrorist attacks in the same administrative unit highlighted in table 2 varies with the distance between a child and its closest school. As panel

[22] Available under `https://hub.arcgis.com/datasets/66cfcf6d3724405bb15b0099faa46142_0`.

A of table 10 shows, the effect of terrorist attacks is larger for children living further away from their closest school, consistent with longer journeys to school making terrorist attacks a stronger concern.[23]

To investigate the effect of attacks that occur on the way to school, we draw corridors around the line connecting each child's home and the closest primary school. To account for possible detours on the way to school, we create corridors of different breadths. For each year we count the number of attacks falling within each area (coefficients for different sizes are reported as $\leq 1km$, $\leq 2.5km$ and $\leq 5km$ under the heading *# terrorist attacks between child and closest school by size of corridor* in table 10). These corridors include radii around the school and thus capture any attacks occurring in the vicinity of the school. To exclude attacks on the immediate way to school, which may affect enrolment decisions via physical destruction, we overlay these three corridors and count the number of attacks occurring exclusively between 1km and 2.5km on the one hand and 2.5km and 5km on the other (denoted as as *1km-2.5km* and *2.5km-5km* under the heading *# terrorist attacks between child and closest school by size of corridor* in table 10), controlling also for attacks within a 1km corridor. Attacks occurring more than 1km (or respectively 2.5km) off a child's way to school are less likely to affect enrolment decisions via physical destruction. Nonetheless, they may well be perceived as threats and trigger an endogenous response as parents update their risk assessment.

Column (1) of in panel B of table 10 suggests that attacks occurring within 1km between the child and the closest school have a strong effect, with each attack decreasing the probability of a child enrolling by around 1.8 percentage points. The effect diminishes as we increase the size of the corridor in columns (2) and (3). Crucially, the results in column (4) show that attacks occurring 1km to 2.5km away from the child's way to school decrease enrolment by around 0.9 percentage points. This conditions on attacks closer to the way to school. Yet, the magnitude is barely smaller than the effect of the overall number of attacks in a county reported in table 2. As expected, for attacks even further away (2.5km to 5km) the effect becomes smaller yet remains statistically and economically significant. To allow for spatial dependence amongst children, we also computed Conley standard errors (Conley, 1999). The results remain significant and are available upon request.

[23]Note that all regressions control for a number of household characteristics, such as whether the household lives in a rural or an urban area.

Table 10: Effect of terrorist attacks on way to school

	(1)	(2)	(3)	(4)
	Dependent variable = 100 if child in school by age 7			
	Panel A: Effect of attacks by distance to school			
Mean	80.3	75.5	70.2	45.1
# terrorist attacks in child's county	-0.554^{***}	-0.681^{***}	$-0.746**$	$-0.837**$
	(0.153)	(0.195)	(0.320)	(0.343)
Distance to closest school	< 0.5km	0.5-1km	1-2km	> 2km
c and t effects	YES	YES	YES	YES
individual characteristics	YES	YES	YES	YES
R squared	0.197	0.199	0.218	0.195
Observations	10,014	13,542	9,171	7,759
	Panel B: Attacks on way to school			
Mean	69.6			
# terrorist attacks between child and closest school by breadth of corridor				
≤ 1km	-1.757^{***}			-1.714^{***}
	(0.236)			(0.263)
≤ 2.5km		-1.149^{***}		
		(0.388)		
≤ 5km			-1.018^{***}	
			(0.244)	
1km - 2.5km				$-0.883**$
				(0.432)
2.5km - 5km				-0.733^{***}
				(0.246)
c and t effects	YES	YES	YES	YES
individual characteristics	YES	YES	YES	YES
R squared	0.241	0.241	0.241	0.242
Observations	40,486			

Notes: The table reports the effect of terrorist attacks on school enrolment by precise geographical location of attacks; dependent variable takes value 100 if child enrolled in school by age 7; Panel A: shows results by distance to closest primary school; distances are 0 to 0.5km in column 1, distances are 0.5 to 1km in column 2, distances are 1 to 2km in column 3 and distances are more than 2km in column 4; Panel B: shows results by attacks on way to school; # *terrorist attacks between child and closest school by size of corridor* is constructed as follows: for each child we draw a straight line between its residence and the closest primary school; around this line, we draw corridors of different sizes (1km, 2.5km and 5km) either side of the line and count the number of attacks per year, which fall in this area; individual characteristics are dummies for child's gender, rural location, household having electricity, radio and tv and for whether household head has secondary education; all standard errors are clustered at county level.

5 A model of expectations and school attendance

Having provided evidence supporting the importance of indirect effects in the previous section, we estimate a behavioural model in which parents choose an activity for their children subject to expected risk and returns to schooling. Our model incorporates parental risk aversion and expectations regarding the risk associated with schooling in the presence of terrorism. The model's structural parameters are estimated using choices observed in the household panel described in Section 3.3. To keep the structural estimation both credible and close to the reduced-form estimates above, we exploit some of the same quasi-experimental variation for identification as before. Our model has three main purposes. First, we evaluate the degree of agents' misperception regarding the risk of dying in a terrorist attack. Second, we simulate outcomes under different counterfactual degrees of fatality risk. Finally, we use the model to obtain an estimate of the longer-term cost of terrorism.

5.1 Model

In line with the analysis in Section 3.3, we distinguish choices made by parents of child i in two types of location l_i of north-eastern Kenya: those that after 2010 experience a terrorist attack, and those that do not; hence, $l_i \in \{NT, T\}$.

Childhood: When children are of age six, parents decide whether to enroll them in school. If children do attend school, households face a location-specific monetary cost c^{l_i}. If not in school, children either work to earn a wage $w_c^{l_i}$ or stay at home. Like wage and schooling cost, the value of a child staying at home may vary across locations. This value is denoted as η^{l_i}. It measures the total mean benefit from children being at home relative to the other choice options, and includes—among other things—home production, like caring for younger siblings or helping with chores, as well as the utility parents derive from having children at home. We label the three activities as S(chool), W(ork) and H(ome). Household income without a child's earnings is y^{l_i}, and the household derives utility $u(x,n) = ((x/n)^{1-\gamma} - 1)/(1-\gamma)$ from disposable household income x, where n is the number of household members and γ is the coefficient of relative risk aversion. In addition to the monetary payoffs associated with each activity, parents are heterogeneous in terms of their preference v_S^i, v_W^i and v_H^i for each option.

The payoffs in location l_i associated with these three options during childhood are thus given by

$$\begin{aligned}
U_{iS}^{l_i} &= \sum_{t=1}^{\tau_c} \beta^{t-1} u(y^{l_i} - c^{l_i}, n^{l_i}) + v_S^i && \text{if in school} \\
U_{iW}^{l_i} &= \sum_{t=1}^{\tau_c} \beta^{t-1} u(y^{l_i} + w_c^{l_i}, n^{l_i}) + v_W^i && \text{if working} \\
U_{iH}^{l_i} &= \sum_{t=1}^{\tau_c} \beta^{t-1} u(y^{l_i} + \eta^{l_i}, n^{l_i}) + v_H^i && \text{if staying home,}
\end{aligned}$$

where β is an annual discount factor, and τ_c is the duration of childhood post age six.

Adult life: Positive returns to education imply that the schooling decision during childhood affects continuation values during adult life. For individuals with and without school education in location l_i, these continuation values are given by

$$V_{e_i}^{l_i} = \sum_{t=1}^{\tau_a} \beta^{\tau_c+t-1} \mathrm{E}[u(w_{e_i}^{l_i}, n^{l_i})],$$

where $e_i = \{E, NE\}$ indicates whether individual i has attended school, $w_{e_i}^{l_i}$ is the corresponding wage as an adult, and τ_a denotes the duration of adult working life. The expectations operate $\mathrm{E}[\cdot]$ accounts for the fact that the wage $w_{e_i}^{l_i}$ is realized with a several year lag and that there is considerably more variation in adults' than in children's wages.

Payoffs under terrorism: In the presence of terrorist attacks, parents form an expectation about fatality risk π to which children are exposed if not staying at home, and alter children's activity choice accordingly. To mirror the difference-in-differences setup used above, we distinguish agents' decisions in two locations before and after the start of terrorist attacks. As explained below, we estimate the model on the HSNP data, and take its last wave in 2012 as the post-period, after terrorist attacks have had their steepest increase. The payoffs for agents facing terrorist attacks in location $l_i = T$ in 2012 thus become:

$$\begin{aligned}
U_{iS}^{T,2012} &= \sum_{t=1}^{\tau_c} \beta^{t-1} (1-\pi)^t u(y^T - c^T, n^T) + v_S^i && \text{if in school} \\
U_{iW}^{T,2012} &= \sum_{t=1}^{\tau_c} \beta^{t-1} (1-\pi)^t u(y^T + w_c^T, n^T) + v_W^i && \text{if working} \\
U_{iH}^{T,2012} &= \sum_{t=1}^{\tau_c} \beta^{t-1} u(y^T + \eta^T, n^T) + v_H^i && \text{if staying home}
\end{aligned}$$

during childhood, and

$$V_{e_i}^{T,2012} = \sum_{t=1}^{\tau_a} \beta^{\tau_c+t-1}(1-\pi)^t \mathrm{E}[u(w_{e_i}^T, n^T)],$$

with $e_i \in \{NE, E\}$, during adult life. Taken together, an agent's welfare is given by

$$W^{l_i} = \max_{a\in\{S,W,H\}} \left\{ U_{iS}^{l_i} + V_E^{l_i}, U_{iW}^{l_i} + V_{NE}^{l_i}, U_{iH}^{l_i} + V_{NE}^{l_i} \right\}.$$

Under the assumption that preference shocks v^i are independent and extreme value distributed, the choice probabilities have a closed for solution.[24] This allows a straight forward solution of the model by backward induction. To estimate the model's parameters, we draw both on estimates of the kind reported in Section 3.3, and a number of additional moments detailed below.

5.2 Identification and Estimation

In the Hunger Safety Net Programme evaluation data (see Section 3.3), we directly observe wages for adults with and without schooling, wages earned by children, as well as the cost of schooling, which includes fees and expenses for supplies, transport and uniform (see table 17 in appendix H). Since here we focus on households in only two counties, regional differences largely reflect rural-urban gaps in wages and schooling costs. These, together with the different values of staying at home (η^{NT} and η^T) to be estimated can explain the enrolment difference across areas. As we demonstrate below, the model is over-identified, and able to replicate this difference very precisely.

The parameters to be estimated are the values η^{NT} and η^T of staying at home in the two types of location, the spread parameter σ_v of preference heterogeneity, the coefficient of relative risk aversion γ, as well as the perceived fatality risk π in the presence of terrorism. We estimate these parameters by general method of moments (GMM), exploiting for identification amongst others the quasi-experimental variation induced by terrorist attacks across regions and time.[25]

To identify the values of staying at home η^{NT} and η^T, as well as the spread parameter σ_v, we use the observed school attendance rates of children in different regions, as well as the

[24] The distribution of preference realizations v^i has an estimated spread parameter σ_v. Additivity of v in the utility function, independence and extreme value distribution imply that the location choice probabilities take a logistic form (see e.g. Rust, 1987).

[25] Primary school in Kenya covers ages 6 to 14, and so in the estimation, we set $\tau_c = 8$. Life expectancy in Kenya in the middle of our sample period for the HSNP (2011) was 64 years. Correspondingly, we set $\tau_a = 64 - 14 = 50$. The discount factor is set to $\beta = 0.9$.

share of children who are working. Empirically, wages for adults who have attended school are considerably more dispersed than for those who have not, and more so in region T by (see figure 13 in appendix H). Everything else equal, a higher risk aversion thus decreases the incentive to attend school, and more so in the latter type of locations. This implies that a regional difference in school attendance rates also is informative about agents' risk aversion γ.[26]

Identification of the perceived fatality risk π arising from terrorist attacks requires additional information. To identify this parameter, we closely follow the spirit of the reduced-form estimation of Section 3, where we have used a variety of estimators to establish that terrorist attacks have a negative effect on school enrollment in Kenya. We use difference-in-differences estimates of the effect of terrorism on both school attendance and on the propensity to work as moments for which the model predicts a direct counterpart. A more negative effect on these choices implies a higher level of perceived fatality risk π. While the effect on either activity would be sufficient for identification of π, we use the effect on both as over-identifying information to assess the model's validity. We obtain a p-value for the Sargan-Hansen over-identification test of 0.45, and are thus far from rejecting the model.[27] Our simple model is able to closely replicate most of these quantities, and appendix H provides further details on the estimation. In particular, table 18 shows the fit for the targeted model moments, while table 19 displays the gradient matrix and shows for each parameter which moments contribute to its identification.

5.3 Results and Interpretation

Structural estimates: Table 11 lists the structural estimates of the model's parameters.[28] The perceived probability π of a child dying in a terrorist attack exceeds the objective probability $2 \cdot 10^{-5}$ by about a factor 45. This strong discrepancy is in line with directly elicited subjective expectations suggesting that individuals tend to strongly over-estimate mortality risk. For instance, comparing directly elicited subjective expectations about mortality

[26]Implicitly, this assumes that other relevant differences across regions are incorporated in the model. The most obvious difference that locations in T experience a terrorist attack, but also that the earnings distributions, including earnings levels, differ, as well as different costs schooling costs, child wages, values of home production and household sizes are all part of the model and thus accounted for explicitly.

[27]A restriction this also tests is whether the perceived fatality risk is indeed the same for when going to school as when going to work, as assumed in the baseline model. When we re-estimate the model allowing for different risk perceptions for these activities, we obtain a very similar fatality risk when going to school as when going to work (0.123% vs 0.085%). In this case all moments listed in table 18 in appendix H are matched perfectly.

[28]We also display the inter-quartile range for each estimate, computed based on 500 bootstrap replications. Note that asymptotic standard errors are not meaningful in this context, as for instance the standard deviation σ_v is defined only on $\mathbb{R}^+$.

risk to the objective risk for teenagers in the United States, Fischhoff et al. (2000) report a median expected probability of dying from violent causes that exceeds the objective probability by a factor 125. It also is in line with the evidence on the effect of media coverage provided in Section 4.1. We estimate a relative risk aversion of 1.20, very close to the average experiment-based estimate by Gandelman and Hernández-Murillo (2015) for a set of East African countries.[29] The relatively high value attributed to staying at home reflects the large fraction (about 30 percent in both types of location) of children who are reported to neither attend school nor work for a wage outside the house. Possibly, many of these children perform essential duties such as looking after younger siblings.

Table 11: Structural parameter estimates.

Parameter	Point est.	inter-quart. range
perceived fatality risk, π	0.089%	[0.05% — 0.17%]
risk aversion, γ	1.204	[0.94 — 1.39]
value of staying at home in non-terror region, η_{NT}	460.242	[453.24 — 475.47]
value of staying at home in terror region, η_T	528.337	[522.88 — 569.77]
std. dev. of preferences, σ_v	0.267	[0.12 — 0.98]

Notes: GMM estimates for the structural model parameters detailed in Section 5.1, based on HSNP (2010-2012) data. Bootstrapped inter-quartile range of the estimates (500 replications) in brackets.

Counterfactual analysis - The effect of risk: With these estimates at hand, the model can be used for out-of-sample predictions and to quantify the importance of misperceptions. Figure 6a shows the effect of perceived fatality risk on by plotting the fraction of children attending school as a function of the subjective probability π. We numerically estimate an elasticity of school attendance with respect to a change in the perceived risk of leaving the house of -0.13. To assess this quantity in comparison to a possibly better understood policy variable, figure 6b shows how the fraction of children in primary school varies with the monetary cost of schooling. At the actually observed cost of 75 USD in locations close to terrorist attacks, school attendance would rise by 7 percentage points if the misperception about fatality risk from terrorist attacks could be eliminated. A similarly large increase in schooling would require a reduction in the schooling cost by a considerable amount, 79 percent.

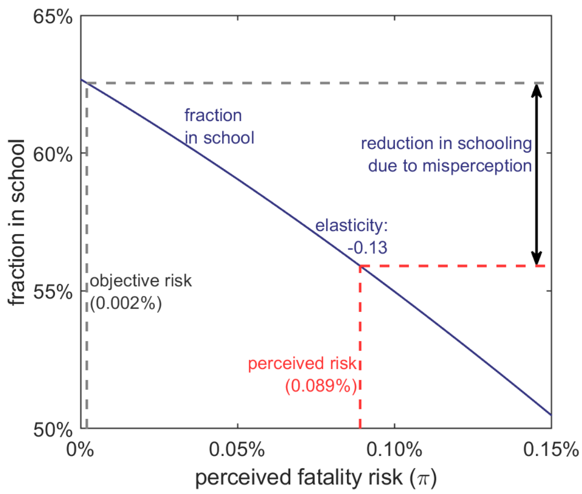
The costs of terrorism: The threat of terrorism induces a sizable reduction in school attendance, as Section 3 has shown, with lasting consequences for individuals' earnings potential. The estimated model can be used for a back of the envelope calculation of the

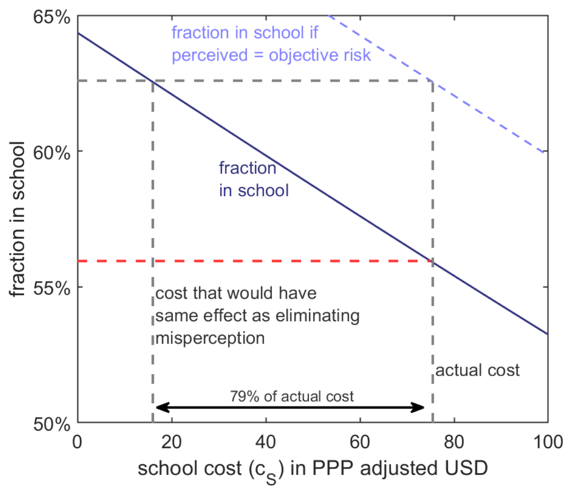
[29] While Gandelman and Hernández-Murillo (2015) do not provide estimates of relative risk aversion for Kenya, the average level for the East African countries they consider (Burundi, Madagascar, Mozambique, Tanzania and Uganda) lies at 1.19.

Figure 6: Fatality risk and school attendance

(a) Effect of fatality risk

(b) Comparison to schooling cost





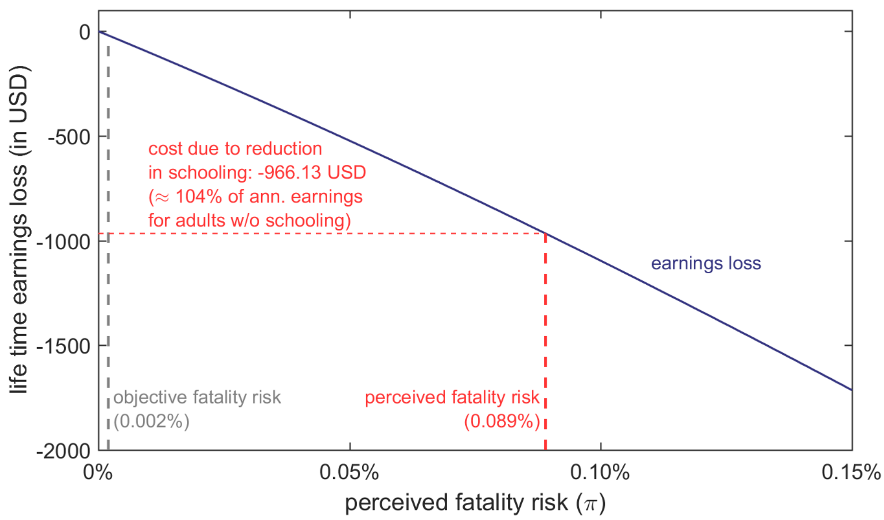
Notes: Model simulations based on GMM estimates for the structural model parameters detailed in the text, using HSNP (2010-2012) data. Panel (a) shows school attendance for varying fatality risks. Panel (b) illustrates how this compares to a reduction in schooling costs. The dashed curve in panel (b) depicts school attendance in a counterfactual situation with zero fatality risk.

cost of terrorism in terms of earnings. We estimate that the discounted loss in earnings during an individual's adult life time amounts to almost 1,000 USD, corresponding to about one year's average earnings of an adult without any schooling in a location experiencing terrorist attacks. Figure 7 shows how this value varies for different probabilities π.

6 Conclusion

Besides a potential direct physical impact on school infrastructure or personnel that terrorism shares with other forms of violence, we show that indirect mechanisms like fear and changes in expected risk contribute significantly to the reduction in primary school enrolment of Kenyan children. In particular, threats of and media reporting on terrorist acts reduce school enrolment above and beyond the effect of attacks carried out, and effect that is driven by households with access to this information. These findings highlight the importance of salience and point towards an interesting avenue for future research regarding the channels through which violence more generally affects individual behaviour. In addition to this, our results can be considered as a caution against sensationalism and in favour of moderate fact-based reporting of terrorist events. Based on the evidence for the importance

Figure 7: Fatality risk and earnings loss



Notes: Model simulations based on GMM estimates for the structural model parameters detailed in the text, using HSNP (2010-2012) data. The figure shows the change in discounted earnings during an individual's adult life in locations experiencing terrorist attacks.

of indirect channels, we structurally estimate a behavioural model in which terrorist attacks alter the expected costs of schooling. A comparison of our estimation results to actual casualty numbers suggests that the perceived fatality risk may substantially exceed the objective rate, resulting in an inefficiently low level of school attendance. The stronger effects of terrorist attacks for children with a longer way to school that we document further suggest that policy may play a role. Providing children living far away from schools with fast, reliable and secure transport to school may mitigate some of terrorism's negative effects on human capital investment

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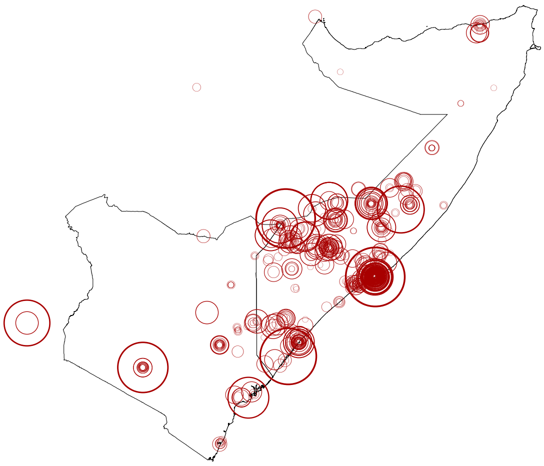
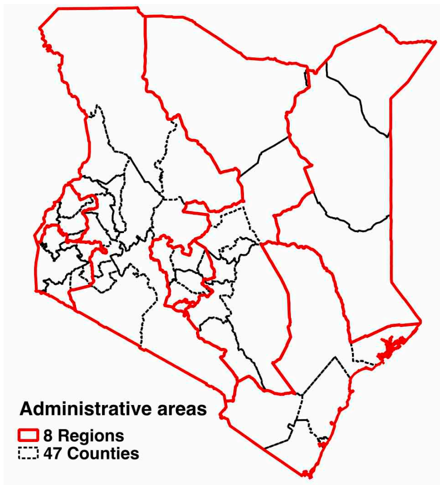
Appendices - for online publication

A Additional maps

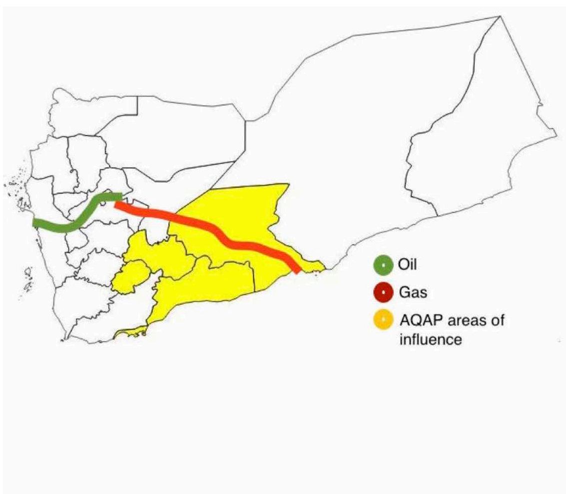
(a) Casualties of al-Shabaab attacks



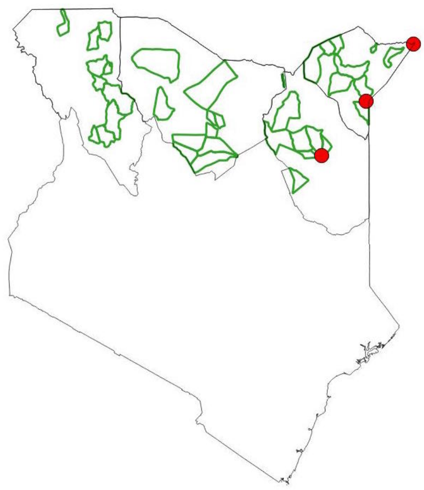
(b) Kenya's administrative areas

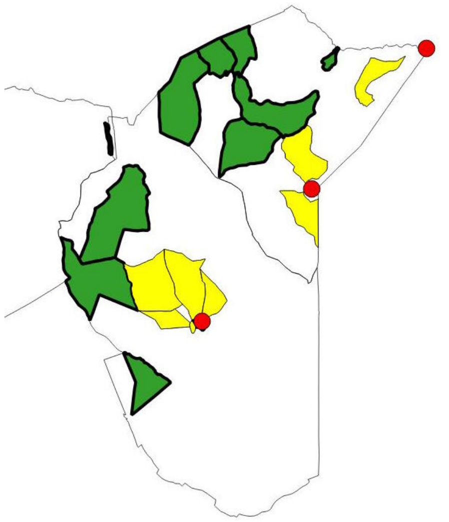


(c) Yemen - Natural gas and terrorism

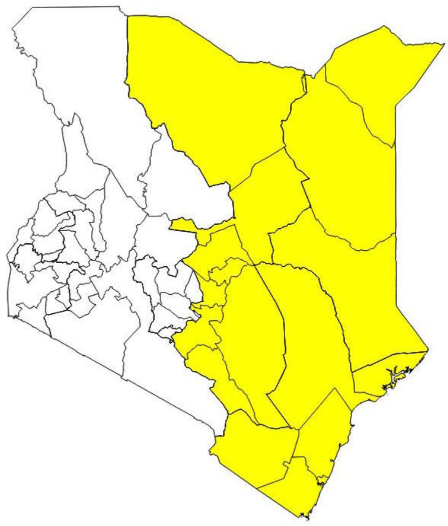


(d) HSNP clusters and terrorist attacks

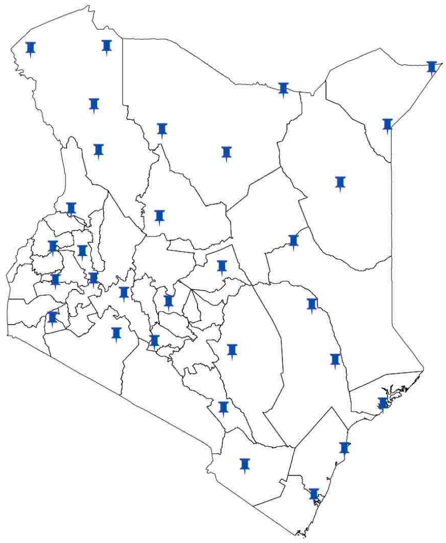




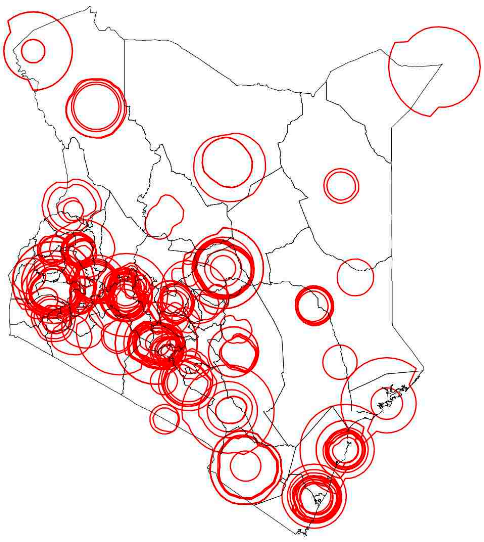
(e) HSNP - Treated and control clusters



(f) East of Kenya

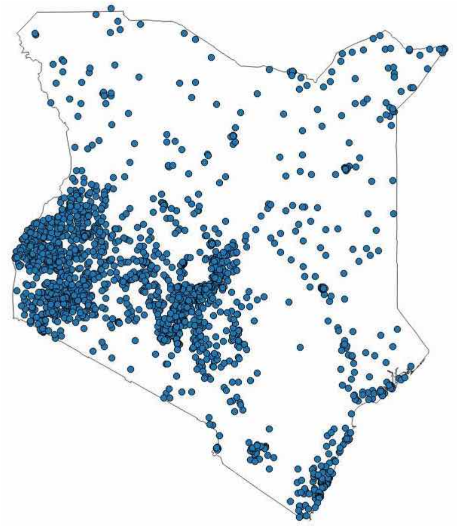


(g) Location of governmental antennae

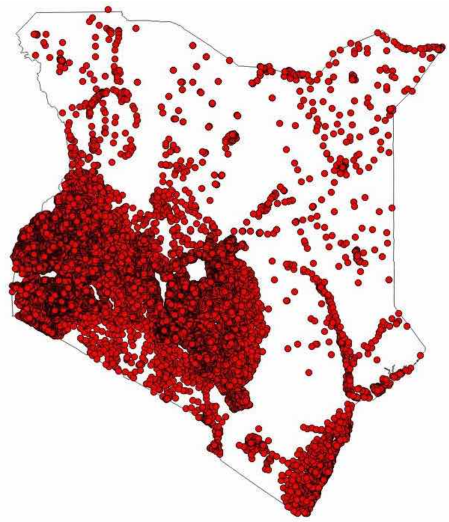


(h) Radio coverage

(i) DHS respondents



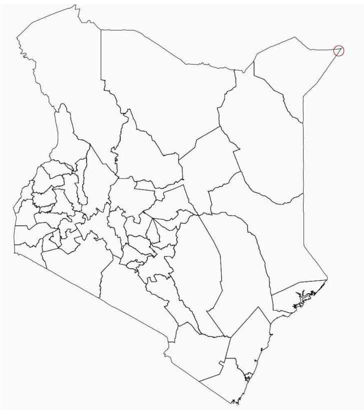
(j) Primary schools in Kenya



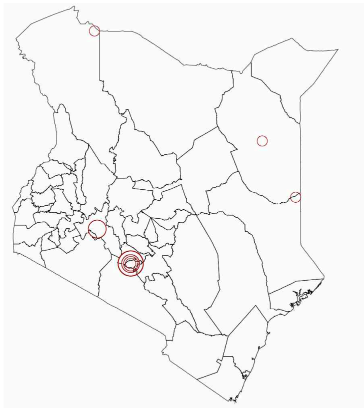
Notes: Map a: shows attacks by al-Shabaab, including in Somalia, Map b: shows Kenya's 8 regions and 47 counties, Map c: show's Yemen's gas and petrol pipelines and AQAP controlled areas, Map d: shows municipalities interviewed under HSNP, Map e: shows municipalities interviewed under HSNP by terror status (red=attacks, yellow=experienced terror, green=did not experience terror), Map f: shows 3 most eastern regions of Kenya (East of Kenya), Map g: shows geographical location of governmental antennae (source: Communication Authority of Kenya), Map h: shows geographical location radio coverage (source: `fmscan.org`), Map i: shows the geographical coordinates of respondents for the DHS 2009 and 2014, Map j: shows the geographical coordinates all 31,231 primary schools in Kenya.

B Temporal and geographical variation

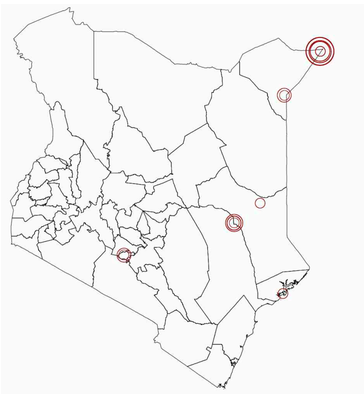
2009



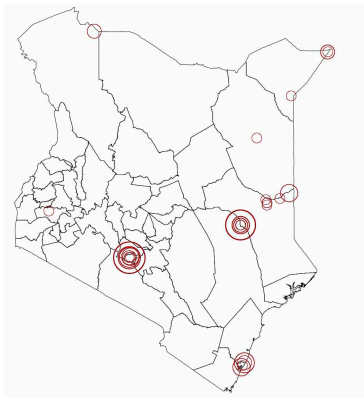
2010



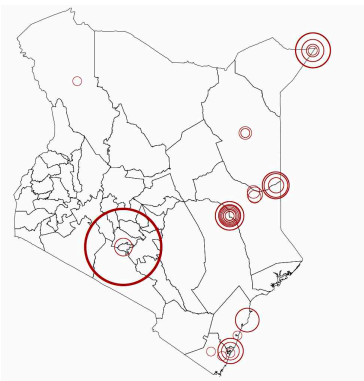
2011



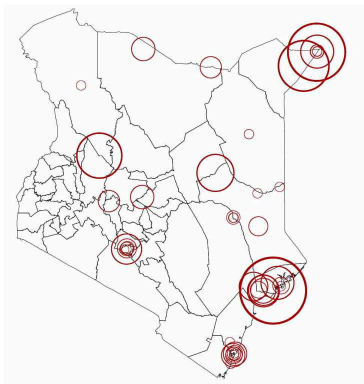
2012



2013



2014



Notes: Maps show location of terrorist attacks in Kenya between 2009 and 2014, radii indicate number of casualties. Source: Global Terrorism Database.

C Distance to the border

	(1)	(2)	(3)	(4)
	Dependent variable:			Means
	Number of terrorist attacks		Percent explained	
One over distance	5,003.8***	5,374.7***	64.5%	0.032
	(660.9)	(831.3)		
Population in 2014		3.7	5.6%	0.91
		(6.7)		
Change in population 2009 to 2014		43.2	7.9%	0.11
		(29.1)		
Land area		31.4	4.3%	0.01
		(149.6)		
Per capita govt revenues		66.4	14.7%	0.01
		(1,075.5)		
Per capita govt expenditures		89.9	3.1%	0.004
		(1,315.0)		
Counties	47	47		47
R squared	0.560	0.691		

Notes: The table reports parameter estimates and means for terrorist attacks and county characteristics; covariates are defined as follows, one over distance: is one divided by the distance between a county's centroid and the nearest point of the border between Somalia and Kenya, Population in 2014: population of county in year 2014, Change in population 2009 to 2014: population of county in year 2014 minus population of county in year 2009, Land area: area covered by county, Per capita govt revenues: county revenues in 2014 divided by population of county in year 2014, Per capita govt expenditures: county expenditures in 2014 divided by population of county in year 2014.

D Effect of terrorism on school enrolment: First stages

	(1)	(2)	(3)	(4)
	Dependent variable: # terrorist attacks			
Mean	0.541			
$AQAP_t/distance_c$	6.090***			3.219
	(1.319)			(2.467)
$Gas/distance_c$		3.345***		1.402
		(0.962)		(1.491)
$Tobacco/distance_c$			14.470***	2.559
			(3.221)	(3.076)
c **and** t **effects**	YES	YES	YES	YES
F-statistic	21.3	12.1	20.2	71.6
Observations	658			
R squared	0.627	0.595	0.558	0.640

Notes: The table reports first stage estimates for IV estimations; dependent variable, *# terrorist attacks* is the number of attacks classified as terrorist per county and year; $AQAP_t/distance_c$ is interaction of 1/distance to Somali border and attacks by AQAP; $Gas/distance_c$ is interaction of 1/distance to Somali border and Yemen's exports of hydrocarbons; $Tobacco/distance_c$ is interaction of 1/distance to Somali border and tobacco imports by United Arab Emirates; data are drawn from 2009 and 2014 Kenyan DHS; data structure is a panel for the 47 counties for the years 2001-14; standard errors clustered at county level.

E Effect of terrorism on school enrolment: Robustness

This appendix addresses a number of identification concerns.

Alternative treatment group for the difference-in-differences specification: The difference-in-differences specification in equation (2) uses the three northeastern counties (Mandera, Wajir and Garissa) as the treatment group (*affected*). In table 12 we add the largest cities of Nairobi and Mombasa to the treatment group.

Table 12: Effect of terrorism on school enrolment: difference-in-differences

	(1)	(2)	(3)	(4)
	Dependent variable: percentage of children in school by age 7			
Mean in pre-period	57.2	57.9	59.2	60.6
Post × Affected	$-15.58***$	$-15.27***$	$-15.24***$	$-14.90***$
	(4.00)	(4.09)	(4.25)	(4.07)
c **and** t **effects**	YES	YES	YES	YES
R squared	0.777	0.782	0.782	0.781
Observations	658			
Post=1 for	≥ 2008	≥ 2009	≥ 2010	≥ 2011

Notes: The table reports difference-in-differences estimates comparing the northeast (Mandera, Wajir and Garissa) and Nairobi and Mombasa to the rest of Kenya; dependent variable is the county average of children enrolled in school by age 7; data structure is a panel for the 47 counties for the years 2001-14; $post = 1$ for years after (and including) 2008 (column 1), 2009 (column 2), 2010 (column 3) and 2011 (column 4); $Affected = 1$ for Nairobi, Mombasa, Mandera, Wajir and Garissa; standard errors are clustered at the county level.

Distinguishing between perpetrators and types of violence: The GTD cannot attribute every attack unambiguously to an actor or organisation. As shown in figure 1, for some attacks the perpetrators are unknown. To illustrate the effect of attacks attributable to al-Shabaab only, we use only confirmed attacks. Column (1) of table 13 shows a negative effect, the magnitude of which exceeds the corresponding one for all attacks shown in column (3) of table 3A. In column (2) we compare these estimates with conflict data from the ACLED project. The ACLED reports actors of incidences of violence and we select al-Shabaab attacks only. The estimates are remarkably similar across both data sources. In column (3) we use information on other incidences of violence contained in the ACLED to compare the effect of terrorism to that of other types of violence. The estimates show that once we control for terrorist attacks, other incidences of violence have a very small impact on schooling.

Leads and lags: In column 4 of table 13 we disnguish attacks occurring during the school year and attacks carried out during the previous and successive summer holidays (in Kenya these are in November and December). We find that the effect entirely driven by attacks carried out during the school year, and again suggests an important role for immediate fear rather than longer-term considerations by parents.

Table 13: Effect of terrorism - robustness (I)

	(1)	(2)	(3)	(4)
	Dependent variables:			
	% of kids in school by age 7			=100 if kid in school by age 7
Means	65.5	65.5	65.5	69.6
Attacks by al-Shabaab	−1.285***	−1.403***	−1.377***	
	(0.253)	(0.246)	(0.248)	
Incidences of other violence			−0.023	
			(0.082)	
# attacks within 10km				−1.171***
				(0.205)
# attacks during previous summer holidays				−0.399
				(0.577)
# attacks during successive summer holidays				−0.580
				(0.361)
c **and** t **effects**	YES	YES	YES	YES
R squared	0.781	0.780	0.780	0.24
Source of violence data	GTD	ACLED	ACLED	GTD
Observations	658	658	658	40,657

Notes: The table reports the effect of terrorist attacks on school enrolment; *Attacks by al-Shabaab* is the number of attacks attributed to al-Shabaab per county and year; *Incidences of other violence* is the number of incidences of violence not attributed to al-Shabaab per county and year; data structure is a panel for the 47 counties for the years 2001-14; all standard errors are clustered at county level; *# terrorist attacks within 10km* is the number of attacks classified as terrorist within 10km of a respondent's residence in a given year; Columns (1) to (3): dependent variable is the percentage of children enrolled in school per county and year; data structure is one observation per county and per year. Column (4): dependent variable = 100 if a child is in school by age 7; summer holidays in Kenya cover November and December; all standard errors are clustered at county level.

Government responses to terrorist attacks and other robustness checks: We further digitised data from official government reports to investigate the robustness of our results with respect to two different types of expenditure. It is possible, for instance, that the central government responds to the rise in terrorist attacks by increasing expenditure on security. Kenya provides a contingent for the African Union Mission to Somalia (AMISOM), which fights, amongst others, al-Shabaab. An increased presence of security forces in the border region, in turn, could affect education. To investigate this, we use information on the government's expenditure on "Public Order and Safety" we digitised from official government reports. Any effect of these expenditures on the whole of Kenya would be picked up by the time effect. To allow for the possibility that safety expenditure has a particularly strong effect on border regions, we interact the federal expenditure data with a dummy for the northeast of Kenya and include it as a covariate in the estimation of equation (1).

Column (1) of table 14 shows that controlling for a differential effect of safety expenditure in northeastern Kenya hardly changes the coefficient on terrorist attacks. The parameter estimate is almost identical to the baseline result in column (4) of table 3A. We also control for education expenditure having a disproportionate effect in the northeast in column (2). Again, the coefficient on terrorist attacks hardly changes. Finally, we control for both safety and education expenditure (column 3). As before, the results remain robust.

Table 14: Effect of terrorism - robustness (II)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variables:					
		% of children in school by age 7		% of women migrating	Total population	School is closed
Means		65.5		3.44	785.68	0.049
# attacks in county	−0.866***	−0.824***	−0.761***	0.0176	1.689	0.004
	(0.200)	(0.199)	(0.208)	(0.0570)	(6.359)	(0.012)
c **effects**	YES	YES	YES	YES	YES	YES
t **effects**	YES	YES	YES	YES	YES	YES
R squared	0.780	0.780	0.781	0.016	0.974	0.063
Security spending × NE	YES		YES			
Education spending × NE		YES	YES			
Observations		658		14,731	658	31,229

Notes: The table reports the effect of terrorist attacks on migration and school enrolment; *# terrorist attacks in county* is the number of attacks classified as terrorist per county and year; data structure is a panel for the 47 counties for the years 2001-14; columns (1) to (3) dependent variable is the county average of children enrolled in school by age 7; column (1) controls for percentage of government spending used for safety interacted with dummy for northeastern Kenya (Mandera, Wajir and Garissa); column (2) controls for percentage of government spending used for education interacted with dummy for northeastern Kenya (Mandera, Wajir and Garissa); column (3) controls for both interactions; column (4) has dependent variable = 100 if woman reports having moved to current residence in year t data drawn from 2014 round of DHS; column (5) has as dependent variable the total population per county and year, data drawn from Kenyan Bureau of Statistics (KStat); column (6) has dependent variable = 1 if primary school reports total number of children enrolled to be equal to zero; for this column *# terrorist attacks* is the total number of attacks classified as terrorist within 20km of the school; all standard errors are clustered at county level.

The effect of terrorism on migration: To investigate whether the increase in terrorist activity led individuals to migrate out of affected areas, we use information contained in the 2014 DHS on past migration. The survey reports the number of years respondents have been living at their current residence. Using this information, we create a panel for each woman, where the dependent variable takes the value 100 if she moved to her current residence in any given year t. Regressing this on the number of attacks within the same county and year shows that terrorist attacks have no impact on in-migration (see table 14). As an alternative measure, we digitised county populations from official records for the years 2001 to 2014. The estimates show no significant effect of terrorist attacks on the number of residents either.

The effect of terrorism on school closures: In column 6 of table 14 we use information on schools drawn from the Kenya Open Data Initiative (KODI) Primary Schools dataset laid out in section 4.2 to estimate whether proximity to terrorist attacks causes school closures. We classify a school as closed if the reported total number of pupils is zero. This occurs for around 5 percent of schools. The explanatory variable is the number of terrorist attacks in 2016, which occur within 20km of each school. The coefficient is small and statistically insignificant.

Other robustness checks: Finally, we show OLS and IV estimates for different subsamples in table 15. Specifically, we exclude the largest cities Nairobi and Mombasa from the sample; we only use the years 2009-14 for which school enrolment rates can be constructed from the 2014 round of the DHS, i.e. without using the data from different waves; and allow for a separate time trend for northeastern Kenya (the counties Mandera, Wajir and Garissa).

Table 15: Effect of terrorism on school enrolment: Robustness (III)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: percentage of children in school by age 7					
	OLS	IV	OLS	IV	OLS	IV
Means	64.5		76.6		65.5	
# terrorist attacks	-0.813***	-1.366***	-0.388	-0.698***	$-0.640**$	-1.183***
	(0.190)	(0.278)	(0.238)	(0.218)	(0.245)	(0.392)
c and t effects	YES	YES	YES	YES	YES	YES
F-statistic		16.8		29.1		17.0
R squared	0.785	0.782	0.896	0.895	0.781	0.780
	excl. Nairobi & Mombasa		2009-14 only		separate time trends	
Observations	630		238		658	

Notes: The table reports the effect of terrorist attacks on school enrolment; *Terrorist attacks* is the number of attacks classified as terrorist per county and year; dependent variable is the county average of children enrolled in school by age 7; data structure is a panel for the 47 counties for the years 2001-14; columns 2, 4 and 6 use 3 instruments: interaction of 1/distance and attacks by AQAP, Yemen's exports of hydrocarbons in previous year and tobacco imports by United Arab Emirates in previous year; data are drawn from 2009 and 2014 Kenyan DHS; standard errors are clustered at county level; Columns 1-2: exclude Nairobi and Mombasa; Columns 3-4: only use years 2009-14 drawn from 2014 DHS; Columns 5-6: include a linear time trend specific for the three Northeastern counties (Mandera, Wajir and Garissa).

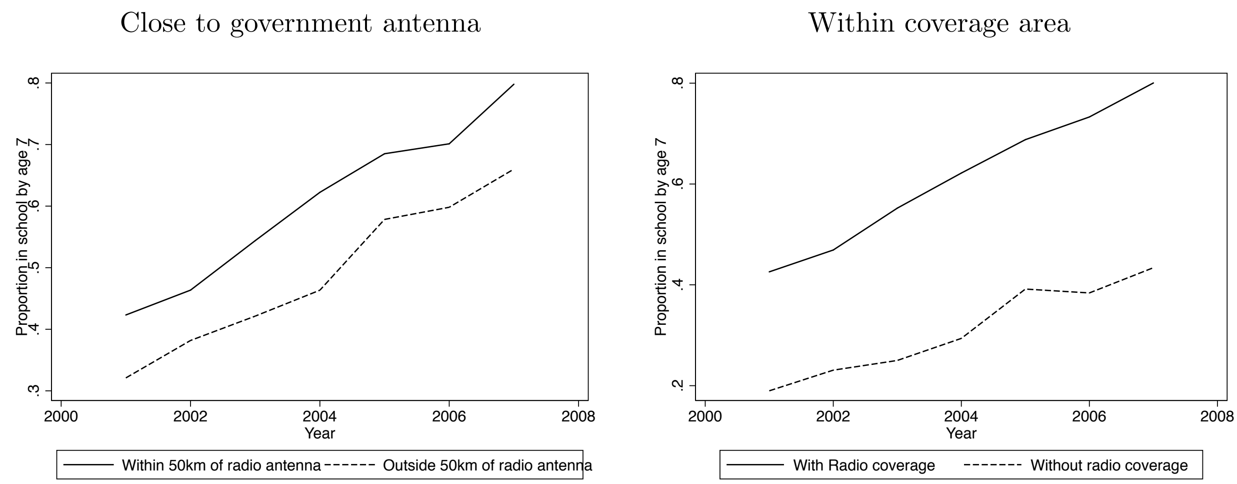
F HSNP adults

Table 16: Effect of terrorism on parents' activities: household panel data from northeastern Kenya

	(1)	(2)	(3)
	Dependent variable = 100 if respondent is Currently working outside house		
Means			
# terrorist attacks	−0.258	−0.624	0.098
	(0.479)	(0.851)	(0.244)
R squared	0.316	0.080	0.310
Covariates	YES	YES	YES
Time effects	YES	YES	YES
Cluster FE	YES	YES	YES
Sample	All	Women	Men
Observations	7,246	3,496	3,750

Notes: The table reports the effect of terrorism on whether adults work outside the house; # *attacks* denotes the number of terrorist attacks in the last 12 months within a 25km radius of the municipality in which the household resides; data are drawn from Hunger Safety Net Programme (HSNP) for counties Mandera and Wajir; dependent variable takes 100 if an individual works; all standard errors are clustered at municipality level.

G Trends for households with and without radio reception



Notes: Panel (a) shows enrolment trends separately for areas within 40km of a radio antenna and further away; panel (b) shows enrolment trends separately for areas that fmscan.org confirms have radio coverage and for areas that do not. The small divergence in panel (b) works against us in the sense that in table 8 we may slightly underestimate the full effect that coverage has on the degree that households respond to media coverage of terrorist events.

H Data and identification in the structural model

Most model components are observed directly in the survey data from the Hunger Safety Net Program. Table 17 lists the means of these variables as they are fed into the model.

Table 17: Model variables observed in the HSNP data.

	Mean	Std.err.
household income, non-terror region, y^{NT}	1,036.14	(27.18)
household income, terror region, y^{T}	1,333.40	(40.71)
adult wage, non-educated, non-terror region, w_{NE}^{NT}	802.68	(20.91)
adult wage, educated, non-terror region, w_{E}^{NT}	1,505.00	(134.80)
adult wage, non-educated, terror region, w_{NE}^{T}	927.56	(28.80)
adult wage, educated, terror region, w_{E}^{T}	1,518.32	(95.27)
child wage, non-terror region, w_{c}^{NT}	391.42	(29.72)
child wage, terror region, w_{c}^{T}	376.38	(30.32)
schooling costs, non-terror region, c_{S}^{NT}	39.20	(5.03)
schooling costs, terror region, c_{S}^{T}	75.46	(7.40)
household size, non-terror region, n^{NT}	6.07	(0.09)
household size, terror region, n^{T}	6.40	(0.10)

Notes: Areas experiencing terrorist attacks (T) include locations within a 25km radius of a terrorist attack. Non-terror areas (NT) include locations outside this radius. Numbers refer to the first round of the HSNP survey (2010), before the increase in the number of attacks the counties Madera and Wajir. Source: Hunger Safety Net Programme evaluation data.

We estimate the structural parameter vector $\theta = (\pi, \gamma, \eta_{NT}, \eta_T, \sigma_v)'$ of the behavioural model in Section 5 by GMM, minimizing the distance between theoretical moments m_t implied by the model and the corresponding data moments m_d from the HSNP sample. Specifically, we minimize the estimation criterion

$$crit(\theta) = (m_d - m_t(\theta))' \, W \, (m_d - m_t(\theta)) \, ,$$

where W is a weighting matrix with the inverse empirical variances on the diagonal. The moments targeted are listed in Table 18.

Table 18: Targeted moments and model fit.

	Data	Std.err.	Model
Pre-terror enrolment in NT locations	48.69%	(0.014)	48.87%
Pre-terror enrolment in T locations	62.94%	(0.014)	62.68%
Pre-terror fraction working in NT locations	20.11%	(0.011)	19.75%
Pre-terror fraction working in T locations	10.04%	(0.009)	10.32%
Change in fraction enrolled (DiD coefficient)	-8.11pp	(0.044)	-6.77pp
Change in fraction working (DiD coefficient)	-0.73pp	(0.025)	-2.19pp

Notes: Areas experiencing terrorist attacks (T) include locations within a 25km radius of a terrorist attack. Non-terror areas (NT) include locations outside this radius. The fractions enrolled and working refer to the first round of the HSNP survey (2010), before the increase in the number of attacks the counties Madera and Wajir. The Difference-in-difference (DiD) coefficients are based on the change 2010-2012 in T relative to NT locations. Source: Hunger Safety Net Programme evaluation data.

Identification of risk aversion in the structural model of Section 5 exploits differences in the wage dispersion of adults with and without schooling across areas. The variance in wages is higher for schooled individuals, and more so in areas within a 25km radius to a terrorist attack. Figure 13 shows this graphically.

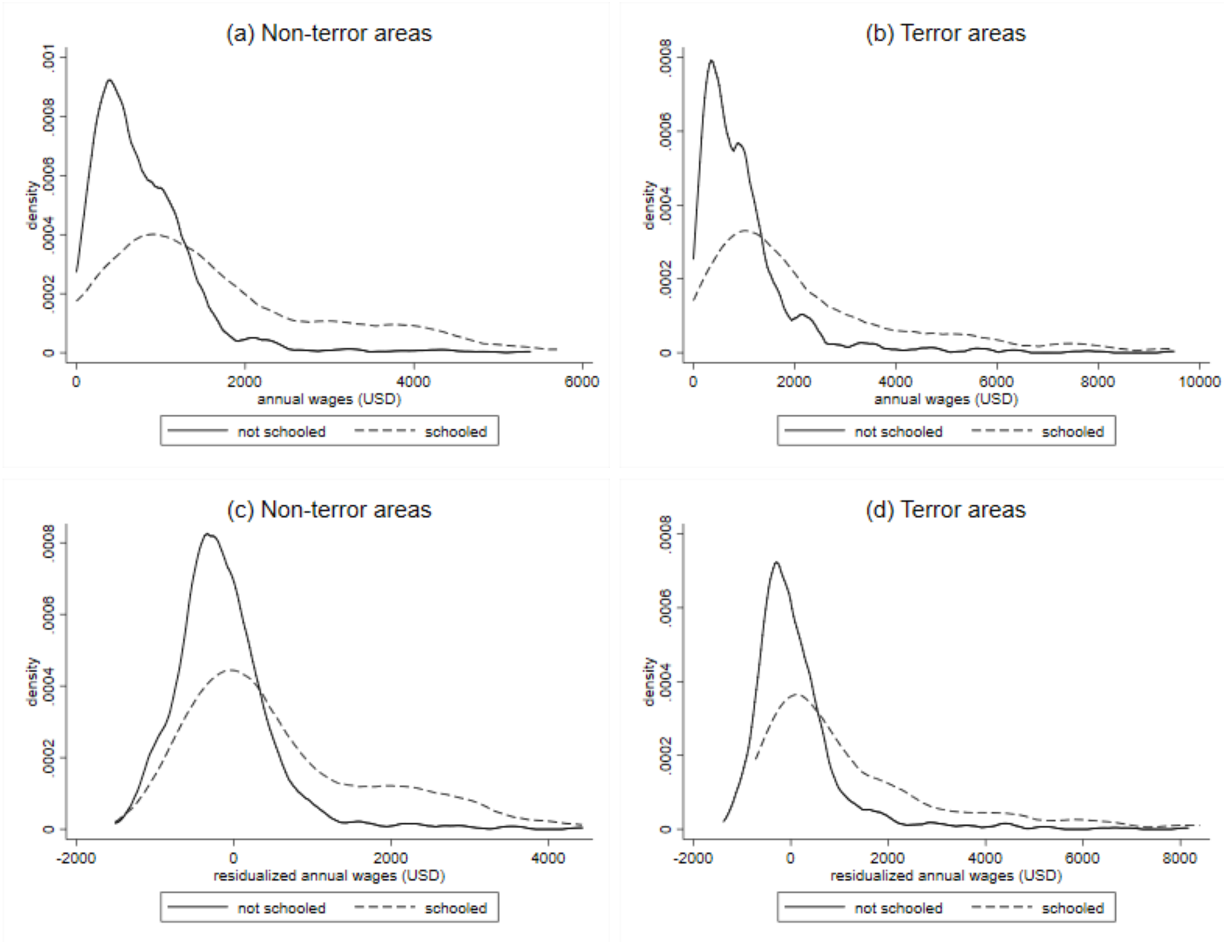


Figure 13: Source: Hunger Safety Net Program evaluation data for the districts Mandera and Wajir. The figure shows 2010 annual wages (in PPP adjusted USD) for adults in locations that have experienced a terrorist attack between 2010 and 2012, and in locations that have not. Panels (a) and (b) show the distributions of wage levels, whereas panels (c) and (d) show residualized annual wages after eliminating non education related individual characteristics.

In order to show local identification of the model parameters through our set of moments more formally, Table 19 lists the gradient matrix, expressed as elasticities of moments with respect to parameters, $\frac{\partial \mathbf{m_s}'}{\partial \theta} / \frac{\mathbf{m_s}'}{\theta}$. Identification requires that none of the parameters has a zero gradient vectors, and that gradient vectors are linearly independent. In our gradient matrix this is the case, so that our set of moments point identifies the structural parameters under the model. Finally, figure 14, which plots the estimation criterion $crit(\theta)$ against different values of the structural parameters in θ, shows that the criterion obtains a clear local minimum at the given parameter values.

	Moments					
Parameters	school$_{NT}$	school$_T$	work$_{NT}$	work$_T$	DiD$_{school}$	DiD$_{work}$
π	0.00000	0.00000	0.00000	0.00000	-84.15117	-23.39792
γ	-0.60725	-0.79370	0.55925	0.65861	-0.01925	-0.06687
η_{NT}	-0.00049	0.00000	-0.00058	0.00000	0.00000	0.00000
η_T	0.00000	-0.00039	0.00000	-0.00029	-0.00008	0.00004
σ_v	-0.52987	-0.63441	0.44396	0.49723	0.10677	0.00061

Table 19: Gradient matrix, expressed as elasticities of moments with respect to parameters, $\frac{\partial \mathbf{m_s}'}{\partial \theta} / \frac{\mathbf{m_s}'}{\theta}$.

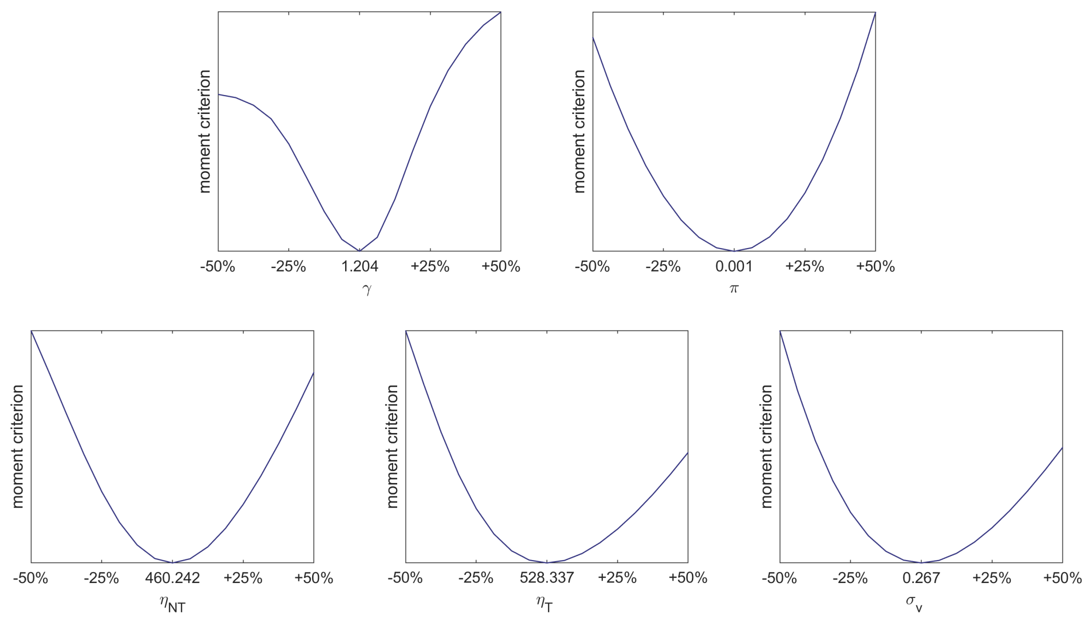


Figure 14: Local minima of the criterion with respect to values of structural parameters.