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# TERRORISM, EDUCATION, AND THE ROLE OF EXPECTATIONS: EVIDENCE FROM AL-SHABAAB ATTACKS IN KENYA


BY

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

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**Abstract**

This paper explores how terrorism alters human capital investment by affecting expectations. Using different estimators, we identify a negative causal effect of terrorism on Kenyan primary school enrolment and attendance. 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 indirect mechanisms—like expectations—we use finely geo-coded data on children and their closest schools as well as border discontinuities in educational provision, combined with media and attitudinal data. Moreover, we evaluate the degree and effect of the discrepancy between objective and subjective expectations in a structural model.

**JEL Classifications:** D74, I21, O15

**Keywords:** terrorism, education, expectations

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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. These fears seem at odds with the observed risks of dying in terrorist attacks in both regions, $9.2 \cdot 10^{-5}$ percent and $9.6 \cdot 10^{-4}$ percent respectively.[1] However well founded concerns may be, they can nevertheless affect decisions regarding the future, including investments in human capital.

In this paper, we examine the impact of terrorist attacks on primary school enrolment and attendance. Specifically, we highlight the importance of expectations as a mechanism through which terrorism affects behaviour. 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 a consequence of this strategy, terrorism can impact on 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, because intimidation is the motive behind many terrorist attacks, they are likely to affect educational choices also *indirectly* by changing expectations regarding the future; even for individuals physically unaffected by attacks.

We investigate this in the Kenyan setting, which lends itself to a causal analysis, as 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 expectations and the mechanisms at play by exploiting the fact that many attacks do not occur on children's way to school or even in the administrative area they reside in. To further investigate the importance of terrorism's salience we draw on data on media coverage of attacks and individual attitudes to violence. Moreover, we estimate a behavioural model of activity choices for children in the presence of terrorist attacks. This allows us to evaluate the importance of different mechanisms, and to obtain an estimate for the discrepancy between objective mortality risk and the subjective risk perceived by agents.

Before turning our attention to the role of expectations, fears and attitudes, we establish a causal effect of terrorism on school enrolment, applying a range of estimators to several independent data sources. In a first instance, we use the unique concentration of attacks in spacetime to estimate various difference-in-differences specifications. Estimates using Demo-

[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.

graphic Health Survey (DHS) data suggest that counties continuously exposed to terrorist attacks experience a decrease in enrolment of around 15 percentage points, corresponding to circa 25 percent. Each attack is found to decrease enrolment by 0.9 percentage points. We do not find significant gender differences in the parameter estimates. Estimates using enrolment data digitised from reports by the ministry of education suggest that each attack keeps 243 children out of school.

A potential identification challenge is that terrorists select when and where to attack. We cannot reject parallel trends during the early 2000s (before the sharp increase in terrorist activity). 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 guidance. We document not only that al-Shabaab closely follows AQAP in its timing of attacks, but also that it chooses similar targets for its attacks. 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), and we use coal imports by the UAE as a third exogenous variation. Estimates obtained from IV and OLS are of similar magnitude and we cannot reject the validity of the instruments.

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 that geographically close attacks reduce school attendance of primary school aged children even conditional on household fixed effects. We also compare the effect of terrorism with other types of violence, and find no influence of incidences of violence unrelated to terrorism, such as protests, riots or general violence.

Since the causal reduced form estimates capture both *direct* physical effects, and *indirect* effects of terrorism that operate via agents' expectations, we provide three pieces of evidence all pointing towards a crucial role of the latter. First, we use the exact geographic coordinates of individuals, schools and attacks and juxtapose two types of attacks: attacks close to children's residences or on their way to school on the one hand, and attacks further away (but still in the same county) on the other. The relative importance of direct and indirect pathways differs for the two, with attacks not in the immediate vicinity unlikely to affect behaviour through physical damage. Although the effect of attacks in proximity to schools or residences is considerably larger, attacks occurring elsewhere retain a significant effect. 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 administrative borders. 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, controlling for attacks in a child's Kenyan county of residence.

Second, we examine the influence of two factors that—by themselves—do not affect infrastructure or personnel directly: *threats* made by terrorist organisations and *media coverage* of terrorist attacks. The correlations with enrolment are large and significant for both, again conditional on the incidence of actual attacks carried out in any given county. Moreover, we find that terrorist threats and media coverage of terrorist attacks regarding Somalia impact negatively on educational enrolment in Kenyan counties adjacent to the Somali border. Finally, we investigate attitudes directly. Using self-reported data from the Afrobarometer we find no effect of terrorist attacks on self-reported *experiences* of violence but large effects on *concerns* about violence.

Based on these insights about the importance of expectations, we formulate a simple structural model of activity choices for children. Indirect effects include on the one hand a change in agents' risk assessment about leaving the home to either work or go to school. On the other hand, terrorism may decrease the future returns to education by, for instance, eroding institutions. In the model, we distinguish these two mechanisms. We estimate the model's structural parameters, which lets us evaluate the relative importance of different channels, and to obtain an estimate for parents' perceived risk of children becoming casualties of a terrorist attack. Contrasting this to the objective probability, we further can use the model to assess the reduction in school attendance that is due to the misperception itself.

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. Comparing the perceived probability of dying with the actual number of deaths, our results suggests that parents over-estimate this probability by a factor of 7.5, 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, which we find to amount to 1.6 times the average annual earnings of an adult without any schooling.

Our paper complements the literature on the consequences of violence 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) or explicitly model the physical impacts such as destruction of infrastructure (Akbulut-Yuksel, 2014) or the effect on education personnel (Monteiro and Rocha, 2017). A separate body of work, in turn, analyses the importance of subjective expectations for educational decisions (Dominitz and Manski, 1996; Jensen, 2010; Giustinelli and Pavoni, 2017; Boneva and Rauh, 2018; Attanasio 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 expectations. In addition, by integrating the reduced form evidence in a structurally estimated behavioural model, we can quantify the discrepancy between objective and subjective risk from terrorist attacks, and evaluate its impact on education choices. A recent paper by Shany (2018) emphasizes the negative effect of psychological distress on exam results of Israeli high school graduates during the Second Intifada. Our paper instead focuses on enrolment as a human capital investment decision that we find to respond to the salience of attacks—for instance by drawing on media data. As such, the mechanism we investigate is closer to the work by Abadie and Gardeazabal (2003, 2008), who document large negative effects of terrorism on economic growth via a reduction in foreign direct investment, showing that terrorism can have severe economic costs despite a limited direct physical impact.

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 economic conditions (Miguel et al., 2004), 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) and donations (Limodio, 2018), social insurance (Fetzer, 2014) and unobserved coalitions between factions (Trebbi and Weese, forthcoming).

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 milita. 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 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.

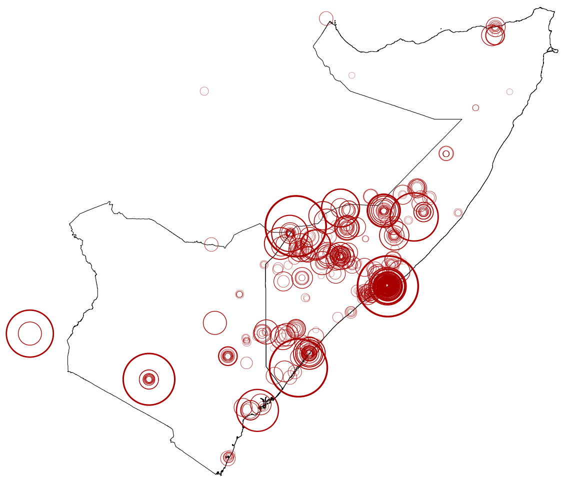
Figure 1 shows the geographical and temporal distributions of terrorist attacks carried out by al-Shabaab from the early 2000s onwards. The vast majority occur in Mogadishu and in the southwest of Somalia. A smaller number are carried out in other countries, mainly Kenya, but also Uganda. Attacks increase sharply from the late 2000s onwards.

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

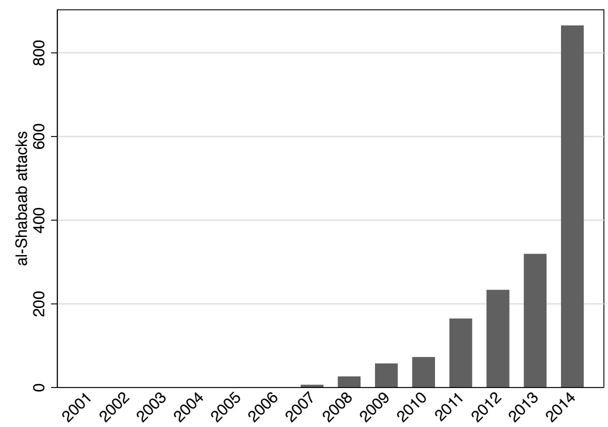
[3] See for instance Anderson and McKnight (2015) for an overview.

Figure 1: Attacks of al-Shabaab

(a) Casualties of al-Shabaab attacks



(b) Al-Shabaab attacks over time




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

Between the years 2001 and 2014, Kenya experienced 367 terrorist attacks (see panel A of table 1). Figure 2a 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 2b 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.

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 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.

[4]These are Mandera, Wajir and Garissa.

Table 1: Summary Statistics

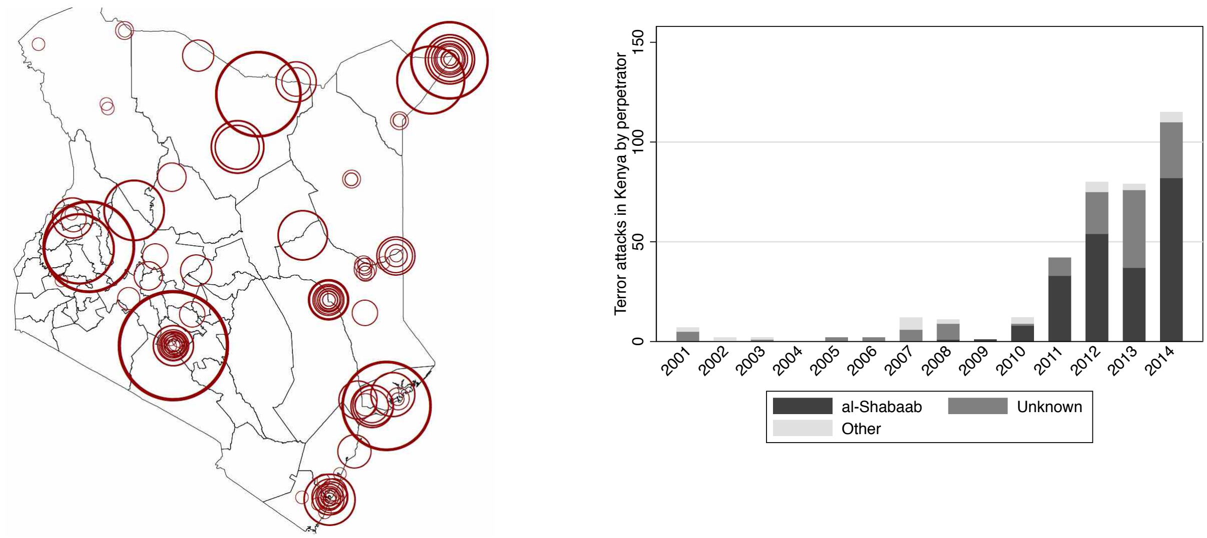
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | **Panel A:** Terrorist attacks in Kenya 2001-2014 | | | | | | |
| **Organisation** | All | al-Shabaab | un-known | other | | | |
| **Attacks** | 367 | 216 | 122 | 29 | | | |
| **Casualties** | 931 | 523 | 313 | 95 | | | |
| | **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 |
| | **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 | 7.0 | | | |

**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.

Figure 2: 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.

## 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

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

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:** Children enrol in primary school at age 6, and the school year runs from January to November. At the end of each year, children automatically advance to the next year. We use retrospective information on school enrolment contained in the DHS to construct a panel for Kenya's 47 counties as follows. 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 in school at age 6.[6] 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.[7]

For children turning 6 between 2010 and 2014, 79.2 percent enrolled by the age of 6. 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).[8]

**Summary statistics:** With 60.2 percent, enrolment in 2009 is considerable lower in the northeast than in Kenya as a whole, see panel C of table 1. Whilst for the whole country, gender gaps in enrolment are small, the northeastern regions show female disadvantages. Panel A of figure 3 plots the dependent variable over time for the northeastern counties and the rest of Kenya. The estimates show a clear parallel trends before 2008 and divergence afterwards, when terrorist attacks increase.

# 3 The effect of terrorism on schooling

Before examining in detail the role of expectations and individuals' perceptions in their response to terrorist threats, this section estimates the causal effect of terrorism on school enrolment. For this, we provide evidence from three completely different data sources described in the previous section. We employ a range of estimators including difference-in-differences, instrumental variables and household fixed effects estimations.

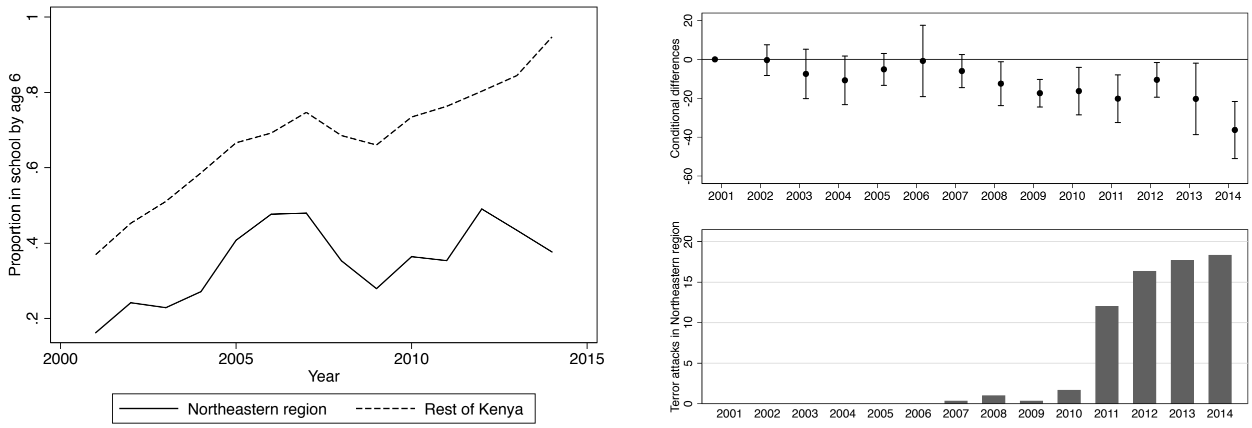
[6] We include children aged 7 at the time of interview since these children may have turned 7 between enrolling in school and being interviewed by the DHS.

[7] 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.

[8] 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.*

Figure 3: Terrorist attacks and schooling over time

(a) Unconditional means (b) Conditional differences




**Notes:** Panel a reports proportion of children enrolling in school by age 6 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 6 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.

## 3.1 Difference-in-differences and OLS estimations

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

$$enrolment_{ct} = \alpha \ post_t \times affected_c + \gamma_c + \tau_t + u_{ct}, \tag{1}$$

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 $t$. 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. We estimate equation (1) at the county level.

Table 2 reports the estimates for the difference-in-differences specifications. The data used are drawn from the DHS and the dependent variable is the percentage of children enrolling in school on time, i.e. by age 6. The estimated effect is economically and statistically significant, with a reduction in school enrolment of about 14 percentage points in regions experiencing terrorist attacks compared to those that do not. In column (5) we test for a difference in pre-trends and cannot reject that trends are indeed parallel.

Table 2: Effect of terrorism on school enrolment: difference-in-differences

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Dependent variable: percentage of children in school by age 6 | | | | |
| **Mean in pre-period** | 57.2 | 57.9 | 59.2 | 60.6 | 55.9 |
| | **Panel A:** $Affected = 1$ **for northeastern regions** | | | | |
| **Post × Affected** | $-14.72**$ | $-14.80**$ | $-14.03**$ | $-14.17***$ | |
| | (5.65) | (5.64) | (6.00) | (5.21) | |
| $c$ **and** $t$ **effects** | YES | YES | YES | YES | |
| **R squared** | 0.777 | 0.778 | 0.778 | 0.777 | |
| | **Panel B:** $Affected = 1$ **for northeastern regions+Nairobi+Mombasa** | | | | |
| **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 | |
| | **Panel C: Test for parallel trends in pre-period** ($\leq 2007$) | | | | |
| **Trend × Affected** | | | | | $-0.590$ |
| | | | | | (0.730) |
| $c$ **and** $t$ **effects** | | | | | YES |
| **R squared** | | | | | 0.781 |
| **Observations** | | | 658 | | 329 |
| **Post=1 for** | $\geq 2008$ | $\geq 2009$ | $\geq 2010$ | $\geq 2011$ | |

**Notes:** The 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 6; 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) in panel A and Nairobi, Mombasa, Mandera, Wajir and Garissa in panel B; data are drawn from 2009 and 2014 Kenyan DHS; panel C shows that parallel trends for the pre-period cannot be rejected; standard errors are clustered at the county level.

We also use this difference-in-differences framework to quantify and statistically test the effect suggested in panel A of figure 3. For this, we substitute the $post_t$ dummy in equation (1) with dummies for each year between 2002 and 2014. Panel B of figure 3 plots the yearly differences in enrolment rates between the northeastern regions and the rest of the country for each year. 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 2.

In order to quantify the effect of a single terrorist attack and to incorporate the fact that some counties not located in the northeast also experience terrorist attacks, albeit not many, we estimate a similar specification,

$$enrolment_{ct} = \delta \ attacks_{ct} + \kappa_c + \theta_t + v_{ct}, \tag{2}$$

where $attacks_{ct}$ denotes the number of terrorist attacks occurring in county $c$ in year $t$. We estimate equation (2) both at the county level, and using individual data that allow us to control for household and child characteristics. Results in both cases, reported in columns (1) and (3) of table 3, are very similar, and suggest that each attack decreases the share of children enrolling in time by 0.8-0.9 percentage points. This also lines up with the difference-in-differences estimates, as affected counties experience about 15 attacks per year. We also distinguish by gender of the child in columns (5) and (6), but find no significant differences.

## 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 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

Table 3: Effect of terrorism on school enrolment: OLS & IV

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent variable: percentage of children in school by age 6 | | | | | |
| | OLS | IV | OLS | IV | OLS | OLS |
| **Means** | 65.5 | | 69.6 | | 71.5 | 67.8 |
| **Terrorist attacks** | $-0.890^{***}$ | $-1.299^{***}$ | $-0.785^{***}$ | $-1.038^{***}$ | $-0.691^{***}$ | $-0.896^{***}$ |
| | (0.196) | (0.263) | (0.193) | (0.165) | (0.122) | (0.262) |
| **$c$ and $t$ effects** | YES | YES | YES | YES | YES | YES |
| **individual characteristics** | | | YES | YES | YES | YES |
| **F-statistic** | | 37.4 | | 16.3 | | |
| **R squared** | 0.780 | 0.779 | 0.229 | 0.229 | 0.255 | 0.211 |
| **Unit of observation** | county | | individual | | girls | boys |
| **Observations** | 658 | | 40,657 | | 20,168 | 20,489 |

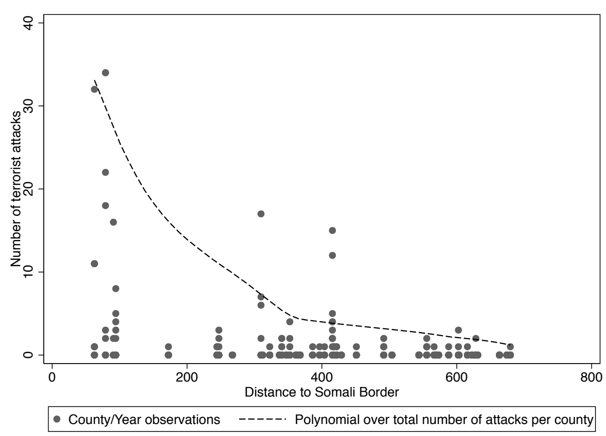
**Notes:** The table reports the effect of terrorist attacks on school enrolment; *Terrorist attacks* is the number of attacks classified as terrorist per county and year; Columns 1-2: dependent variable is the county average of children enrolled in school by age 6; data structure is a panel for the 47 counties for the years 2001-14; column 2 uses 3 instruments: interaction of 1/distance and attacks by AQAP, Yemen's exports of hydrocarbons in previous year and coal imports by United Arab Emirates in previous year; Columns 3-6: dependent variable takes value 100 if a child is enrolled in school by age 6; data structure is one observation per child; individual controls include indicators for gender, rural community, electricity at dwelling, radio in household, television in household; column 4 uses 3 instruments: interaction of 1/distance and attacks by AQAP, Yemen's exports of hydrocarbons in previous year and coal imports by United Arab Emirates in previous year; data are drawn from 2009 and 2014 Kenyan DHS; standard errors are clustered at the county level.

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 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 4 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 4: 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

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

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 carries out attacks mainly in Yemen and Saudi Arabia.

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 5a, 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).

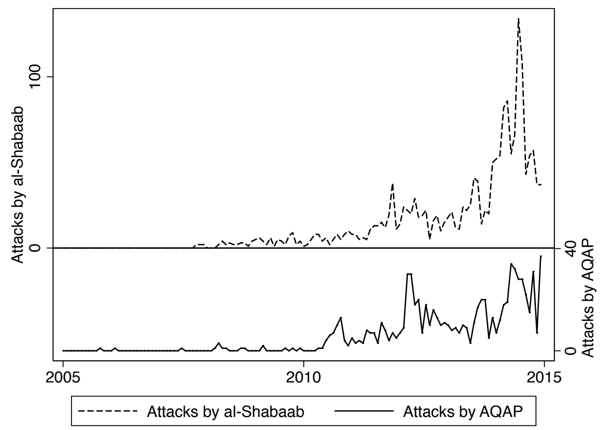
To investigate the correlations between attacks of both organisations further, we construct a weekly time series and regress the number of al-Shabaab attacks on attacks carried out by AQAP.[10] The latter operates in a completely different geographical region to al-Shabaab, almost exclusively in the Arabian peninsula, and never in Africa.[11] The parameter estimates in table 4 show strong correlations, which are robust to different fixed effects. Moreover, column (2) highlights that al-Shabaab attacks are correlated to AQAP attacks in the same

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

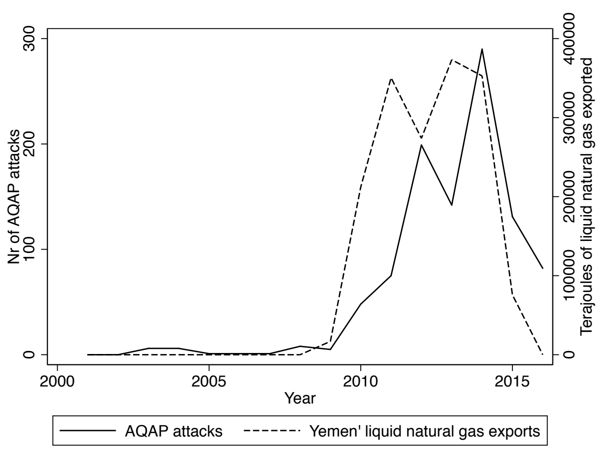
[11]The only terrorist incidences outside the Arabian peninsula attributed to AQAP were in the United Kingdom, the United States, and most recently the Charlie Hebdo attack in Paris 2015.

Figure 5: Natural gas, coal and terrorist attacks by AQAP and al-Shabaab

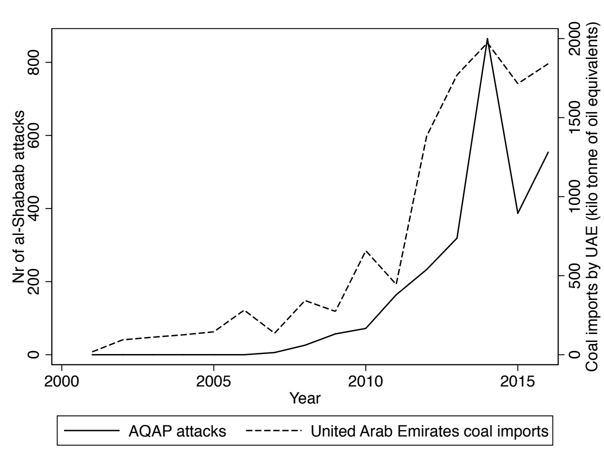
(a) Attacks by AQAP and al-Shabaab




(b) Yemen's gas exports and AQAP attacks




(c) UAE's coal imports and 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 attacks by al-Shabaab for each year and coal imports by United Arab Emirates in kilo tonne of oil equivalents; Sources: Global Terrorism Database and International Energy Agency, own calculations.

week but not in previous or successive weeks. Yet more strikingly, when we distinguish between private and public targets, we find that when AQAP attacks public (private) targets, so does al-Shabaab (columns 3 and 4).

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) |
| $c$ **and** $t$ **effects** | YES | YES | YES | YES |
| **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.

**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 5b 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, 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. We use exports in year $t-1$ to predict attacks in year $t$ to account for a lag in AQAP actually extracting funds from gas exports.

**Timing of attacks (III) — Coal 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). Gulf Countries are the main destination for Somali charcoal, with around 33 percent of Somali exports going the United Arab Emirates (UAE) as one of the largest importers.[13] 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).

We use imports of coal to the UAE as an exogenous shift in the demand for Somali coal and thus for al-Shabaab's finances. Figures from the United Nations Conference on Trade and Development (UNCTAD) show that between 2001 and 2012 Somalia accounted for around 75 percent of all coal imported to the UAE. Again, demand for coal in the UAE is arguably driven by factors exogenous to school enrolment choices by parents in Kenya. Figure 5c shows a very strong correlation between coal imports to the UAE and al-Shabaab attacks. The timing between the two figures further lends credence to a causal effect: coal imports to the UAE tend to increase a few months before al-Shabaab attacks also rise.

In columns (2) and (4) of table 3 we use all three instruments simultaneously. The slightly more negative 2SLS coefficients may point to the suspected upward bias in OLS estimates, 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. In appendix D we use all three instruments separately. The very similar estimates obtained using our three different instruments are reassuring.

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

[13] Made from acacia trees growing abundantly across the Horn of Africa, this charcoal is particularly prized for its long burning quality, which makes it ideally suited for smoking shisha.

### 3.3 Robustness

**Lags and an alternative measure of education:** In table 5 we scrutinize our specification in more detail. In column (1), we add the one year lag of attacks as an additional explanatory variable. The estimates suggest that lagged attacks are not important conditional on attacks in the same year. This supports our focus on contemporary attacks as the main explanatory variable. In columns (2) and (3) we re-estimate the effect of terrorism on education using an alternative data source. We digitised the total number of children in each county enrolled in primary school from reports by the Kenyan Ministry of Education. Column (2) shows that each attack decreases the number of pupils by 243 (controlling for the total population). Column (3) confirms that for this data source, the lag of attacks is not important either.

**Distinguishing between perpetrators and types of violence:** The GTD cannot attribute every attack unambiguously to an actor or organisation. As shown in figure 2, for some attacks the perpetrators are unknown. To illustrate the effect of attacks attributable to al-Shabaab only, we use only confirmed attacks. Column (4) of table 5 shows a negative effect, the magnitude of which exceeds the corresponding one for all attacks shown in column (1) of table 3 above. In column (5) 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 (6) 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.

**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 Appendix E). 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.

**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. First, since Kenya provides a contingent for the African Union Mission to Somalia (AMISOM), we analyse government

Table 5: Effect of terrorism - robustness

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent variables: | | | | | |
| | % of kids in school by age 6 | Nr of kids in school | | % of kids in school by age 6 | | |
| **Means** | 65.5 | 203,780 | | 65.5 | | |
| **Terrorist attacks** | $-0.808^{***}$ | $-243.37***$ | $-211.10***$ | | | |
| | (0.245) | (81.83) | (74.35) | | | |
| **Terrorist attacks (lag)** | $-0.061$ | | $-70.92$ | | | |
| | (0.176) | | (77.08) | | | |
| **Attacks by al-Shabaab** | | | | $-1.285^{***}$ | $-1.403^{***}$ | $-1.377^{***}$ |
| | | | | (0.253) | (0.246) | (0.248) |
| **Incidences of other violence** | | | | | | $-0.023$ |
| | | | | | | (0.082) |
| $c$ **and** $t$ **effects** | YES | YES | YES | YES | YES | YES |
| **county population** | | YES | YES | | | |
| **R squared** | 0.772 | 0.99 | 0.99 | 0.781 | 0.780 | 0.780 |
| **Source of education data** | DHS | MoE | MoE | DHS | DHS | DHS |
| **Source of violence data** | GTD | GTD | GTD | GTD | ACLED | ACLED |
| **Observations** | 611 | 282 | 282 | 658 | 658 | 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; *Terrorist attacks (lag)* is the number of attacks classified as terrorist per county in previous year; *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; Column 1: dependent variable is the percentage of children enrolled in school per county and year; data structure is one observation per county and per year; Columns 2 and 3: dependent variable is the total number of children in school per county and year; data structure is one observation per county and per year, data drawn from Ministry of Education (MoE); Columns 4 to 6: dependent variable is the percentage of children enrolled in school per county and year; data structure is one observation per county and per year.

expenditure on security. Second, we explore education expenditure. Including measures for both does not change our results. Moreover, we estimate specifications where we drop the two largest cities (Nairobi and Mombasa), use only the years 2009 to 2014 from the 2014 DHS, and include a separate time trend for the three northeastern counties. These results are reported in appendix E and show that the effect of terrorist attacks persists throughout.

### 3.4 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.

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 (2), 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 and the dependent variable takes the value 100 if the child is currently attending school. This dataset 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 table 6 show a significant negative impact of terrorism of a magnitude comparable to the DHS estimates in table 3. Columns (3) and (4) further show that the effect persists even conditional on household fixed effects. Before turning to the mechanisms explaining the observed negative effect of attacks on enrolment, we can use this household panel to investigate whether this coincides with an increased share of children working. The dataset lets us distinguish whether children go to school, stay at home or work outside, categories that we explicitly incorporate in the behavioural model of Section 5. Columns (5) to (8) of table 6 repeat the estimations for working as the outcome variable. In our definition "working" excludes unpaid domestic work. The effect is estimated equally precisely, though closer to zero. It suggests that rather than increasing the tendency to work for a wage outside the home, the lower school attendance

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

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Dependent variable = 100 if child is currently | | | | | | | |
| | Enrolled in school | | | | Working outside house | | | |
| **Means** | 61.3 | | | | 15.2 | | | |
| **Terrorist attacks** | −1.229*** | −1.215*** | −0.928 ** | −0.885 ** | 0.041 | 0.075 | −0.054 | −0.064 |
| | (0.333) | (0.321) | (0.325) | (0.326) | (0.242) | (0.236) | (0.203) | (0.197) |
| $c$ **and** $t$ **effects** | YES | YES | YES | YES | YES | YES | YES | YES |
| **R squared** | 0.016 | 0.092 | 0.021 | 0.094 | 0.000 | 0.061 | 0.000 | 0.064 |
| **Covariates** | no | yes | no | yes | no | yes | no | yes |
| **Cluster FE** | yes | yes | no | no | yes | yes | no | no |
| **Household FE** | no | no | yes | yes | no | no | yes | yes |
| **Observations** | 7,077 | | | | | | | |

**Notes:** The table reports the effect of terrorism on primary school attendance and child labour; terrorist attacks denote the number of terrorist attacks in the last 12 months wihtin a 25km radius of the municipality in which the child resides in; data are drawn from Hunger Safety Net Programme (HSNP) for counties Mandera and Wajir; columns 1-4: dependent variable takes 100 if child reports to be currently enrolled in school; columns 5-8: dependent variable takes 100 if child reports to be currently working outside the house; sample consists of children aged 6-14 at time of interview; all standard errors are clustered at municipality level.

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.

# 4 The importance of expectations and perceptions

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 affects expectations, 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 and returns associated with schooling. Nonetheless, 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.

In this section we provide three pieces of evidence which all point towards a crucial role of expectations in households' schooling decisions. First, we find that attacks occurring not in the immediate vicinity of Kenyan children's residence or on their way to school have a significant effect on school enrolment. For children in the border region, we document an effect even for attacks carried out in Somalia. Second, *threats* made by terrorist organisations and *media coverage* of terrorist attacks, which by themselves do not affect infrastructure or school personnel directly, are strongly and negatively associated with enrolment. Third, terrorism is found to affect self reported attitudes towards violence but has no impact on violence actually experienced.

## 4.1 Geographical location of attacks

In this section we first shed light on the importance of indirect factors by examining the proximity of attacks to respondents' homes and the way to the closest primary school. A second set of results rules out any direct effect by examining the effect of attacks on Somali soil on education outcomes in Kenya.

Both sets of estimations show the same pattern: Attacks in close proximity to individuals 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, even if they are located in a different administrative area. The latter shows that indirect channels, such as changes in expectations, have an effect that cannot be explained by direct physical impacts.

**Attacks in Kenya (I) - distance to respondents:** We begin by considering attacks within a given radius around the geographic coordinate of respondents' residence. This approach is similar to the one adopted in a recent study by Bertoni et al. (2018). The estimates in column (1) of table 7 show that terrorist attacks within 10km have a strong negative impact.

Crucially for our argument, however, column (2) shows a significant effect also of terrorist attacks that occur further away in the county (denoted as "Anywhere else in county"). The estimated effects are smaller than the ones for attacks within the 10km radius. This is to be expected, as the effect of attacks in the vicinity of children includes both *direct* and *indirect* effects of terrorism, and indirect effects plausibly increase with proximity. Nonetheless, the magnitude of attacks not located close to individuals is sizeable, around 0.6 percentage points per attack.

**Attacks in Kenya (II) - way to school:** To focus more closely on the effect on education, we isolate attacks occurring along and at a distance from each childs 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 on the *indirect* effects of terrorism differs from this and mandates that we focus on attacks without an immediate effect, and thus *not* on the way to school.

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.[14] 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. To account for possible detours on the way to school, we create a corridor of 5km around the shortest connecting line between each child and the closest school. This corridor includes a 5km radius around the school, and thus captures any attacks occurring in the vicinity of the school. As before, we add a variable counting the number of terrorist attacks occurring in the same administrative unit the child reside in but *not* on its way to school (denoted as "Anywhere else in county").

Column (3) of table 7 suggests that attacks occurring along the way to school have a

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

strong effect, with each attack decreasing the probability of a child enrolling by 1.1 percentage points. In column (4) we add the number of terrorist attacks in the same county but not falling between a child's residence and the closest primary school. As before, the coefficient estimate has a significant magnitude of around -0.7 percentage points. Columns (5) and (6) show that these effects are stronger for children living further than 2km from the nearest school. A possible explanation is that longer journeys to school make terrorist attacks a stronger concern. To allow for spatial dependence amongst children, we compute Conley standard errors (Conley, 1999). The results remain robust and are available upon request.

Table 7: Effect of terrorist attacks for different distances from child and on way to school

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent variable = 100 if child in school by age 6 | | | | | |
| **Mean** | 69.6 | | | | 75.5 | 45.1 |
| **Nr of terrorist attacks by location:** | | | | | | |
| $\leq$ 10km from child | −1.176∗∗∗ | −1.284∗∗∗ | | | | |
| | (0.181) | (0.116) | | | | |
| Between child and closest school | | | −1.116∗∗∗ | −1.222∗∗∗ | −1.082∗∗∗ | −1.836 ∗ ∗ |
| | | | (0.230) | (0.141) | (0.150) | (0.741) |
| Anywhere else in county | | −0.649∗∗∗ | | −0.695∗∗∗ | −0.539∗∗∗ | −0.853 ∗ ∗ |
| | | (0.234) | | (0.240) | (0.335) | (0.215) |
| **$c$ and $t$ effects** | YES | YES | YES | YES | YES | YES |
| **individual characteristics** | YES | YES | YES | YES | YES | YES |
| **Distance to closest school** | | | | | $<$ 2km | $\geq$ 2km |
| **R squared** | 0.228 | 0.230 | 0.228 | 0.230 | 0.187 | 0.187 |
| **Unit of observation** | Child | | | | | |
| **Observations** | 40,657 | | | | 32,727 | 7,930 |

**Notes:** The table reports the effect of terrorist attacks on school enrolment by precise geographical location of attacks; *Terrorist attacks ($\leq$ 10km)* is the number of attacks within 10km from each child per year; *Between child and closest school* is the number of attacks occurring between each child and the closest school per year; *Anywhere else in county* is the number of attacks per year that occur within the county of residence of the child but not within 10km (in column 2) and not between child and nearest school (in column 4); data are drawn from 2009 and 2014 round of DHS; all standard errors are clustered at county level.

**Attacks in Somalia (I) - Kenyan border counties:** The above results confirm that attacks do not have to occur on the way to school to affect education. It is strong evidence in favour of an indirect effect of terrorism. To further 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. An effect of terrorist attacks in Somalia on Kenyan infrastructure or education personnel is improbable. However, given the geographic proximity and shared ethnicity in the border region, Kenyans likely are well aware of violent events across the border.[15] We count the annual number of terrorist attacks in the two Somali provinces sharing a border with Kenya,[16] and interact this number with an indicator for the three Kenyan counties that share a border with Somalia.[17] By adding this interaction to the specification in equation (2), we can test whether the impact of terrorist attacks in Somalia on enrolment is larger in Kenyan border regions than in the rest of the country. The effect of Somali attacks on the whole of Kenya is absorbed by the time fixed effects. Column (1) of table 8 shows that each attack in the Somali border region decreases enrolment by 0.1 percentage points more in Kenyan border regions than the rest of the country. This holds despite the fact that we control for attacks carried out in each county. Column (2) considers Kenyan counties located in the east of the country only (highlighted in yellow in map (g) of Appendix A).[18] The estimates remain robust.

**Attacks in Somalia (II) - different distances from Kenyan children:** Finally, to estimate the direct, rather than the relative, effect of Somali terrorist attacks, we focus on individuals. Using respondents' geographic coordinates, we count, for each year, the number of attacks which occurred 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 (2).

Columns (3) and (4) of table 8 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 0.2 percentage points and 0.5 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 (5) and (6) select only children living in eastern Kenya; as before, highlighted in yellow in Appendix A. The estimates remain strong and significant for this sub-sample.[19]

[15] 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).

[16] These are Jubbada Hoose and Gedo.

[17] These are Mandera, Wajir and Garissa.

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

[19] 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

Table 8: Effect of terrorist attacks in *Somalia* on education in *Kenya*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent variables | | | | | |
| | % in school by age 6 | | Dummy for child in school by age 6 | | | |
| **Means** | 65.5 | 60.9 | 69.6 | 69.6 | 61.5 | 61.5 |
| **Attacks in Somalia × NE dummy** | −0.096*** | −0.098** | | | | |
| | (0.033) | (0.035) | | | | |
| **Attacks in Somalia ≤250km** | | | −0.190*** | | −0.190** | |
| | | | (0.068) | | (0.076) | |
| **Attacks in Somalia ≤100km** | | | | −0.479*** | | −0.481** |
| | | | | (0.130) | | (0.179) |
| **Attacks in same county** | −0.660*** | −0.507*** | −0.624*** | −0.746*** | −0.514*** | −0.631*** |
| | (0.203) | (0.156) | (0.114) | (0.169) | (0.105) | (0.161) |
| $c$ **and** $t$ **effects** | YES | YES | YES | YES | YES | YES |
| **R squared** | 0.781 | 0.784 | 0.230 | 0.229 | 0.229 | 0.231 |
| **Unit of observation** | county | | Child | | | |
| **Sample** | all | East | all | all | East | East |
| **Observations** | 658 | 238 | 40,657 | 40,657 | 15,204 | 15,204 |

**Notes:** The table reports the effect of terrorist attacks in Somalia on educational enrolment in Kenya; *Terrorist attacks* is the number of attacks classified as terrorist per county and year; *Attacks in Somalia* are total number of attacks in the two most western provinces of Somalia per year; *NE* dummy is an indicator taking the value 1 for the three northeastern Kenyan counties bordering Somalia (Mandera, Wajir and Garissa); *Attacks in Somalia* $\leq 250km$ are attacks on Somali soil occurring within 250km of child $i$ per year; *Attacks in Somalia* $\leq 100km$ are attacks on Somali soil occurring within 100km of child $i$ per year; East of Kenya consists of three regions: Eastern, Coast and Northeastern region; all standard errors are clustered at county level.

## 4.2 Threats of terrorism and media coverage of terrorist attacks

As a further corroboration of the importance of expectations, we analyse the role of two factors for which we can plausibly rule out any direct effect on infrastructure or the number of casualties. First, we consider *threats* made by terrorist organisations. A common strategy among these organisations is to issue threats of attacks or violence with reference to more or less precisely stated target locations. We find a strong relation between terrorist threats made about a particular area and primary school enrolment in that region. These persist even after we control for any terrorist incidences actually occurring in the region. Second, we estimate the role of *media coverage* of terrorist attacks. Again, we find a negative relation, which is robust to the inclusion of the number of attacks actually carried out.

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.[20] 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 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". Using this information, we sum all terrorist threats per region/year and include it to the OLS specification of equation (2). Figure 6 shows the evolution of terrorist threats and media coverage of terrorist attacks for Kenya and Somalia.

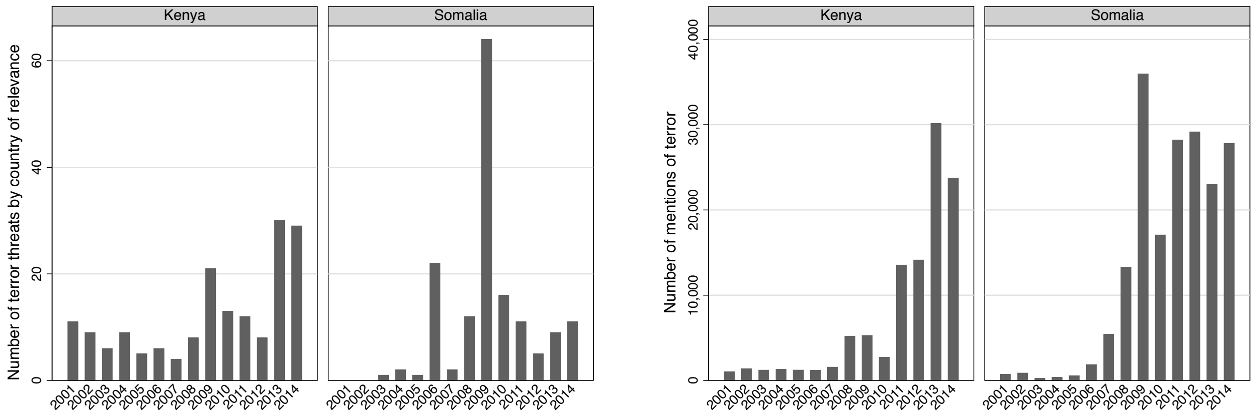
Panel A of table 9 shows the correlation between threats made to a particular area of Kenya and the number of actual attacks carried out in that area, net of time and county effects. The coefficient estimate is small and not statistically different from zero, suggesting a rather weak correlation between threats and actual occurrence of attacks. Panel B investigates the relationship between terrorist threats and educational enrolment. Column (1) shows a strong negative relationship between threats and the percentage of children in school by age 6. Column (2) highlights that this relation remains robust even after we control for attacks carried out in that particular region. This suggests an association of threats with educational outcomes above and beyond the number of attacks actually carried out in a given region. We also test whether terrorist threats made regarding Somalia affect behaviour in

the authors upon request.

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

Figure 6: Threat of terrorism and media coverage of terrorist attacks

(a) Number of terrorist threats (b) Number of mentions in international media




**Notes:** The figure shows yearly totals of terror threats in Kenya and Somalia (panel a) and yearly number of mentions in international media on terrorism in Kenya and Somalia (panel b); Source: Global Database of Events, Language, and Tone (GDELT).

the Kenyan border region. As before, we interact the Somalia specific variable with a dummy for the three Kenyan counties bordering Somalia. Column (3) shows a strong negative correlation. 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.

Next, we investigate media coverage of terrorist events. 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. Following practice suggested by GDELT, we then divide this sum by the total number of mentions regarding Kenya. Mentions of terrorist attacks are negatively related to school enrolment (column 4) even after we condition on the actual incidence of terrorist attacks (column 5). Column (6) further shows that mentions of terrorist attacks occurring in Somalia have a negative relation to education in Kenyan border regions. To investigate whether we are just picking up spurious correlations, we carry out two placebo treatments. Instead of mentions of terrorist attacks, we include mentions of "guns" (column 8) and "killings" (column 9). The coefficients on these two are

Table 9: Threats of terrorism, media coverage of attacks and school enrolment

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | **Panel A:** Effect of terrorism on threats and media coverage | | | | | | | | |
| **Dependent variables** | Terror threats | Media coverage | | | | | | | |
| **Means** | 0.77 | 2.55 | | | | | | | |
| **Terrorist attacks** | 0.009 | 0.370 ∗ ∗ | | | | | | | |
| | (0.028) | (0.178) | | | | | | | |
| **$c$ and $t$ effects** | YES | YES | | | | | | | |
| **R squared** | 0.491 | 0.602 | | | | | | | |
| | **Panel B:** Effect of terrorist threats and media coverage on education | | | | | | | | |
| **Dependent variable** | Percentage of children in school by age 6 | | | | | | | | |
| **Mean** | 65.5 | | | | | | | | |
| **Terrorist threats** | −0.697 ∗ ∗ | −0.666 ∗ ∗ | | | | | | | |
| | (0.299) | (0.284) | | | | | | | |
| **Threats for SOM × NE** | | | −0.199∗∗∗ | | | | | | |
| | | | (0.036) | | | | | | |
| **Media coverage of terrorism** | | | | −0.399∗∗∗ | −0.206∗ | | | | |
| | | | | (0.078) | (0.115) | | | | |
| **Media coverage for SOM × NE** | | | | | | −0.228∗ | | | |
| | | | | | | (0.130) | | | |
| **Media coverage of terrorism (z score)** | | | | | | | −0.943∗ | | |
| | | | | | | | (0.525) | | |
| **Media coverage of killings (z score)** | | | | | | | | −0.304 | |
| | | | | | | | | (0.306) | |
| **Media coverage of guns (z score)** | | | | | | | | | −0.455 |
| | | | | | | | | | (0.729) |
| **Terrorist attacks** | | −0.884∗∗∗ | −0.906∗∗∗ | | −0.814∗∗∗ | −0.780∗∗∗ | −0.814∗∗∗ | −0.881∗∗∗ | −0.842∗∗∗ |
| | | (0.193) | (0.193) | | (0.196) | (0.211) | (0.196) | (0.194) | (0.202) |
| **$c$ and $t$ effects** | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| **R squared** | 0.774 | 0.781 | 0.781 | 0.775 | 0.781 | 0.781 | 0.781 | 0.780 | 0.780 |
| **Unit of observation** | county | | | | | | | | |
| **Observations** | 658 | | | | | | | | |

**Notes:** The table reports relations between terrorist threats and media coverage of attacks and educational enrolment in Kenya; *Terrorist attacks* is the number of attacks classified as terrorist per county and year; *Terrorist threats* is the number of verbal threats issues by terrorist organisations for the respective region in Kenya; *Terrorist threats SOM* is the number of verbal threats issues by terrorist organisations for the whole of Somalia; *NE* dummy is an indicator taking the value 1 for the three northeastern Kenyan counties bordering Somalia (Mandera, Wajir and Garissa); *Media coverage of terrorism* is the proportion of mentions in international media on Kenya regions that cover terrorism; *Media coverage of terrorism SOM* is the proportion of mentions in international media on Somalia that cover terrorism; *Media coverage of killings* is the proportion of mentions in international media on Kenya regions that cover killed or murdered individuals; *Media coverage of guns* is the proportion of mentions in international media on Kenya regions that cover guns or gun crime; all standard errors are clustered at county level.

much smaller and statistically insignificant (we report z-scores for better comparability).

### 4.3 Attitudes

We also provide direct evidence on individuals' self-reported experiences of and attitudes towards violence. Our results suggest that terrorist attacks have no significant impact on self-reported experiences of violence. They do, however, have a large and statistically significant effect on fear of violence, life satisfaction and optimism regarding the future.

The data for this analysis are drawn from four rounds of the Afrobarometer for Kenya (carried out in 2005, 2008, 2011 and 2015). Afrobarometer surveys are conducted in more than 30 African countries and collect information on attitudes towards social, religious, political and economic topics as well as on experiences of crime and violence. We pool all four cross-sections and match respondents' county of residence to terrorist attacks in that location as reported by the GTD. We then estimate a specification as in equation (2), with the Afrobarometer responses as the dependent variable.

Attitudes are measured using three questions. The dependent variable in each case takes the value 1 if the respondent i) is often afraid of crime, ii) reports his or her living conditions to be "good" or "very good", and iii) expects the future economic conditions to be better than the present.[21] The parameter estimates in figure 7a show large and significant effects of terrorist attacks on all three measures of attitudes.

By contrast, when we analyse self-reported experiences of violence, we find no such relations. For self-reported experiences of violence, the dependent variable takes the value 1 if the respondent reports to have i) experienced an attack and ii) had anything stolen.[22] The results are reported in figure 7b and suggest no significant effect of terrorism on these two outcomes. The parameter estimates are small in size and not significantly different from zero.

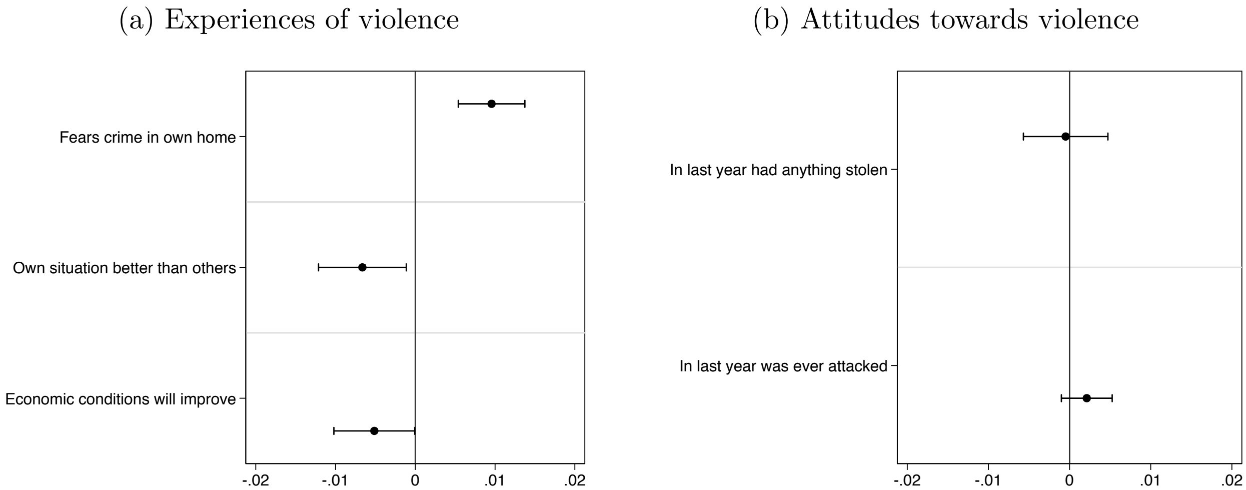
## 5 A model of expectations and enrolment choices

Having provided evidence supporting the importance of indirect effects in the previous section, we use this insight to formulate a model of activity choice for children that accounts

[21]The respective questions are i) "*Over the past year, how often (if ever) have you or anyone in your family: Feared crime in your own home?*", ii)"*In general, how do you rate: Your living conditions compared to those of other Kenyans?*", and iii) "*Looking ahead, do you expect the following to be better or worse: Economic conditions in this country in twelve months time?*"

[22]The questions are "*Over the past year, how often (if ever) have you or anyone in your family: Been physically attacked?*" and "*Over the past year, how often (if ever) have you or anyone in your family: Had something stolen from your house?*", respectively

Figure 7: Terrorist attacks and experiences of and attitudes towards violence




**Notes:** The figure shows coefficient estimates on terrorist attacks defined as the number of attacks classified as terrorist per county and year on attitudes towards violence (panel a) and experiences of violence (panel b); point estimates are shown as dots; 95% confidence intervals are indicated as horizontal lines; Source: Afrobarometer (2005-2015).

for parents' expectations about the costs and benefits of schooling relative to other activities in the presence of terrorism. Indirect effects include both a change in expectations about the danger of going to school, as well as expectations about the returns to schooling. We use the model to disentangle these two channels. The model's structural parameters are estimated using choices observed in the household panel described in Section 3.4. 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. We then first evaluate the degree of agents' misperception regarding the risk of dying in a terrorist attack. Second, we contrast the effect of this perceived risk to an expected decrease in the returns to schooling. Finally, we use the model to obtain an estimate of the longer-term welfare cost of terrorism.

## 5.1 Model

In line with the analysis in Section 3.4, 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 at the age of 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's home production may vary across locations, and is worth $\eta^{l_i}$. We denote these three activities with $S$(chool), $W$(ork) and $H$(ome). 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

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

where $\beta$ is an annual discount factor, and $T_c$ is the duration of childhood post age six.[23]

**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

$$V_{e_i}^{l_i} = \sum_{t=1}^{T_a} \beta^{T_c+t-1} w_{e_i}^{l_i},$$

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 $T_a$ denotes the duration of adult working life.[24]

**Payoffs under terrorism:** The presence of terrorist attacks affects the decision between the different activities via two distinct channels. First, if not staying at home, children face the risk of being caught in an attack. Thus, with probability $\pi$, households each period incur a utility loss $C$ associated with this event. Second, the rise in terrorist attacks may be seen as an indication of a longer-term deterioration of security and stability of the region, which would affect future returns to education. In the model, we thus allow parents to expect that with some probability $\psi$ future wages for educated and non-educated workers in the Kenyan locations affected by terrorist attacks fall to $\tilde{w}_E^T$ and $\tilde{w}_{NE}^T$, respectively.

[23]Primary school in Kenya covers ages 6 to 14, and so in the estimation, we set $T_c = 8$.

[24]In the estimatation, we set $T_a = 40$.

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, when terrorist attacks have started. The unconditional probability of dying in an attack in period $t$, while having survived so far is given by $\pi(1-\pi)^{t-1}$. Thus the payoffs for agents facing terrorist attacks in location $l_i = T$ in 2012 become:

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

during childhood, and

$$
V_{e_i}^{T,2012} = (1-\psi)\sum_{t=1}^{T_a} \beta^{t-1}(1-\pi)^t w_e^T + \psi \sum_{t=1}^{T_a} \beta^{t-1}(1-\pi)^t \tilde{w}_e^T + \beta^{t-1}\pi(1-\pi)^{t-1}C,
$$

during adult life.

Under the assumption that preference shocks $v^i$ are independent and extreme value distributed, the choice probabilities have a closed for solution.[25] 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 3.4, and a number of additional moments detailed below.

## 5.2 Identification and Estimation

In the Hunger Safety Net Programme evaluation data (see Section 3.4), we directly observe wages for adults with and without schooling, wages earned by children, as well as the cost of schooling. Table 10 lists the means of these variables, as we feed them into the structural model. Since here we focus on households in only two counties, the remaining regional differences largely reflect rural-urban gaps in wages and schooling costs. These, together with the different values of home production $\eta^{NT}$ and $\eta^T$ to be estimated can explain the enrolment difference across areas. As we demonstrate below, the model is able to replicate

[25] We allow for different standard deviations $\sigma_v^l$ of $v^i$ in the two locations. Additivity of $v$ in the utility function, independence and extreme value distribution imply that the location choice probabilities take a logistic form, with value functions in the home and host country as arguments (see e.g. Rust, 1987).

this difference very precisely.

Table 10: Data used in the structural estimation.

| | Mean | Std.dev. |
|---|---|---|
| adult wage, non-educated, non-terror region, $w_{NE}^{NT}$ | 784.57 | (508.06) |
| adult wage, educated, non-terror region, $w_{E}^{NT}$ | 1,290.65 | (775.71) |
| adult wage, non-educated, terror region, $w_{NE}^{T}$ | 908.10 | (649.07) |
| adult wage, educated, terror region, $w_{E}^{T}$ | 1,384.05 | (813.60) |
| child wage, non-terror region, $w_{c}^{NT}$ | 389.08 | (295.17) |
| child wage, terror region, $w_{c}^{T}$ | 373.51 | (262.06) |
| schooling costs, non-terror region, $c_{S}^{NT}$ | 39.20 | (98.13) |
| schooling costs, terror region, $c_{S}^{T}$ | 75.46 | (144.22) |

**Notes:** Terror regions include areas within a 25km radius of a terrorist attack. 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.

The parameters to be estimated are the values $\eta^{NT}$ and $\eta^{T}$ of home production in the two types of location, the spread parameters $\sigma_v^{NT}$ and $\sigma_v^{T}$ of the transitory preference shocks, and the subjective probabilities $\pi$ and $\psi$ perceived by parents that a child is hit in a terrorist attack and that economic conditions in Kenya deteriorate.[26] 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.

To identify the values of home production $\eta^{NT}$ and $\eta^{T}$, as well as the spread parameters $\sigma_v^{NT}$ and $\sigma_v^{T}$, we use the observed school attendance rates of children in different Kenyan regions, as well as the share of children who are working. Identification of the components determining payoffs in the presence of terrorist attacks requires additional information. In the model, the incentive to invest in children's education may be reduced for two reasons: the risk of children being hit in an attack, as well as an expected deterioration in the returns to education. To separately identify these mechanisms, 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 enrolment and on the propensity to work as moments for which the model predicts a direct counterpart. Using these reduced form effects, the model identifies the change in expected payoffs via which terrorism affects parental decisions: First, a negative effect on activities that require some traveling outside the home (work and school attendance) implies an expected utility cost of a child being hit in a terrorist attack. Second, a difference between the treatment effects on school attendance and the fraction of children working is informative about a change in the expected returns to schooling in regions affected by terrorist attacks in 2012 relative to

[26]The discount factor is set to $\beta = 0.95$.

non-terror locations.

Note that in both cases only the change in expected payoffs can be identified, which consist both of the respective probability of an event and the loss associated with it. That is, in the first case only a combination of $\pi$ and $C$ can be identified empirically, in the second case only a combination of $\psi$, $\tilde{w}_E^T$ and $\tilde{w}_{NE}^T$. In order to obtain interpretable magnitudes, we thus take values for $C$, $\tilde{w}_E^T$ and $\tilde{w}_{NE}^T$ from data and the literature, in order to then estimate $\pi$ and $\psi$ alongside the other parameters of the model. More specifically, we set $C = 577,000$ (PPP adjusted USD), corresponding to the value of a statistical life estimated in a recent paper by León and Miguel (2017) for Sierra Leone. This allows us to obtain an estimate of the perceived probability $\pi$ that we can contrast to the actually observed ratio of annual casualties to population size in the affected regions.

Wages $\tilde{w}_E^T$ and $\tilde{w}_{NE}^T$ are not readily observed, and we estimate $\psi$ under different assumptions. First, we consider the two extreme cases that returns to education drop to zero, or alternatively decrease by 10% only. As table 12 below shows, this yields a reasonably narrow range of estimates for $\psi$ between 0.4 and 1.2 percent. To narrow this down further, note that we observe a presumably close proxy which agents in the affected Kenyan regions are well-aware of: The counties Mandera and Wajir directly border southern Somalia, and the majority of the population in these counties are ethnic Somalis. In Section 4.1 we moreover have shown that even conditional on close-by attacks in Kenya, school enrolment in this region is affected by attacks that occur across the border in Somalia. Hence, we use the Somali High Frequency Survey (available for 2016) to compute mean wages for adults with and without schooling in Somalia, and use this information to fix $\tilde{w}_E^T$ and $\tilde{w}_{NE}^T$. This allows us to obtain a point estimate for $\psi$, which in this case represents the perceived probability that economic conditions in Kenya become like in its terror-ridden neighboring country, just across the border of the counties we consider.[27] An advantage of the additive separability of the payoff terms in our model is that other parameter estimates are unaffected by assumption about $C, \tilde{w}_E^T$ and $\tilde{w}_{NE}^T$. Table 11 lists the targeted moments and shows that our simple model is able to replicate these quantities exactly, and Appendix F provides further details on the estimation.

## 5.3 Results and Interpretation

**Structural estimates:** Table 12 lists the structural estimates of the model's parameters. The value of home production $\eta$ is higher in non-terror locations, which are more rural, with a presumably higher involvement of children in household work. The relatively high value

[27] Returns to schooling in Somalia are 48% of the corresponding magnitude in Kenya.

Table 11: Targeted moments and model fit.

| | Data | Std.err. | Model |
|---|---|---|---|
| Fraction enrolled in non-terror region | 48.69% | (0.014) | 48.69% |
| Fraction enrolled in terror region | 63.00% | (0.014) | 63.00% |
| Fraction of children working in non-terror region | 20.33% | (0.011) | 20.33% |
| Fraction of children working in terror region | 10.31% | (0.009) | 10.31% |
| DiD coefficient for enrolment | -8.17% | (0.043) | -8.17% |
| DiD coefficient for working | -1.15% | (0.025) | -1.15% |

**Notes:** Terror regions include areas within a 25km radius of a terrorist attack. 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. Source: Hunger Safety Net Programme evaluation data.

attributed to staying at home relative to other activity choices 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. The perceived probability $\pi$ of a child dying in a terrorist attack exceeds the objective probability $2 \cdot 10^{-5}$ by about a factor 7.5. This discrepancy is in line with directly elicited subjective expectations suggesting that individuals tend to strongly over-estimate mortality risk (see e.g. Fischhoff et al., 2000; Delavande et al., 2017). As explained above, we estimate the perceived probability $\psi$ that the returns to schooling deteriorate under different assumptions. Our preferred point estimate is obtained under the scenario that economic conditions including the returns to education in Kenya become similar to those in neighboring Somalia. We estimate that Kenyan parents attribute a small, though non-negligible probability of about 0.7 percent to this scenario.

**Counterfactual analysis:** With these estimates at hand, the model can be used for out-of-sample predictions and to examine different mechanisms. With an elasticity of school attendance with respect to a change in the perceived risk of leaving the house of -0.158, this channel clearly dominates the effect of an expected decrease in the returns to schooling (elasticity of -0.009). Figure 8 shows the response in school attendance for a range of subjective probabilities $\pi$ and $\psi$. Whereas we do not have an objective probability for the event that parts of Eastern Kenya descend into instability, we do observe the objective fraction of Kenyan children dying in a terrorist attack. Figure 8a illustrates that the degree to which agents overestimate the probability of a child dying in a terrorist attack causes a 7.0 percentage point reduction in school attendance.

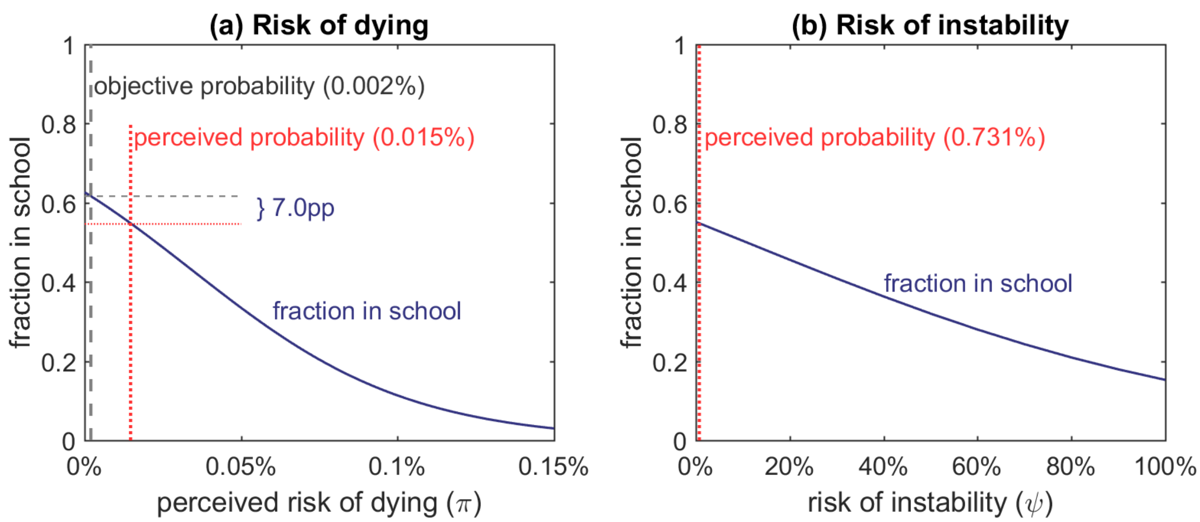
Finally, we use our simple model for a back of the envelope calculation of the welfare cost of terrorism over an individual's life course. At our estimated perceived probabilities, the discounted life-time loss amounts to 1,488 USD (purchasing power adjusted), corresponding

Table 12: Structural parameter estimates.

| Parameter | Point est. | Std. err. |
|---|---|---|
| perceived risk of dying, $\pi$ | 0.015% | ($< 10^{-5}$) |
| | | |
| perceived risk of decrease in returns to schooling, $\psi$ (different models): | | |
| (I) *10% drop in returns to schooling* | 1.206% | (0.004) |
| (II) *zero returns to schooling* | 0.351% | (0.001) |
| (III) *returns to schooling as in Somalia* | 0.731% | (0.002) |
| | | |
| value of home production in non-terror region, $\eta_{NT}$ | 601.863 | (0.371) |
| value of home production in terror region, $\eta_T$ | 567.281 | (0.190) |
| std. dev. of preferences in non-terror region, $\sigma_{NT}$ | 3399.583 | (2.729) |
| std. dev. of preferences in terror region, $\sigma_T$ | 1370.782 | (0.667) |

**Notes:** GMM estimates for the structural model parameters detailed in Section 5. The perceived risk of a decrease in the returns to schooling in regions affected by terrorist attacks, $\psi$, is estimated under different assumptions: (I) returns to schooling decrease by 10%, (II) returns to schooling fall to zero, and (III) returns to schooling fall to the Somali level (drop by 48%). Other parameter estimates remain unaffected by this assumption. Estimation based on HSNP (2010-2012) data. Asymptotic standard errors in parentheses.

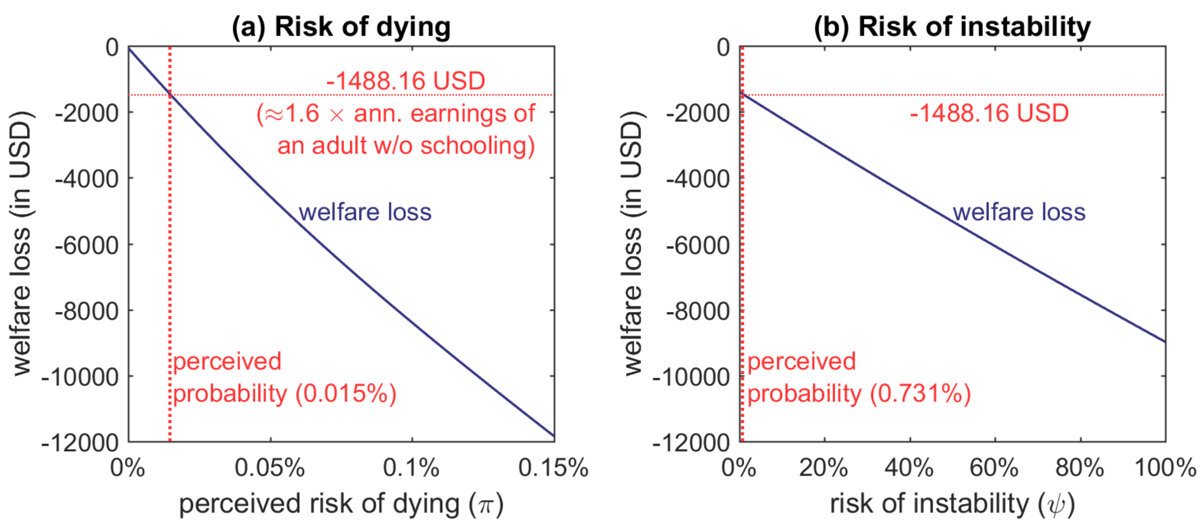
Figure 8: Perceived probabilities and school attendance




**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 perceived probabilities of dying in a terrorist attack, keeping the perceived risk of instability at its estimated value. Panel (b) shows school attendance for varying perceived probabilities of instability, keeping the perceived risk of dying in a terrorist attack at its estimated value.

to about 1.6 times the average annual earnings of an adult without any schooling in a location experiencing terrorist attacks. Figure 9 shows how this value varies for different probabilities. The right panel of the figure further shows that even if instability is no concern ($\psi = 0$), the welfare loss barely decreases, as agents are still concerned about the immediate danger of being killed in an attack. Instead, if the latter is eliminated ($\pi = 0$), the estimated perceived risk of instability ($\psi = 0.73\%$) alone only induces a relatively small expected (and discounted) welfare loss of 61 USD.

Figure 9: Perceived probabilities and welfare loss




**Notes:** Model simulations based on GMM estimates for the structural model parameters detailed in the text, using HSNP (2010-2012) data. Panel (a) shows the change in life-time utility for varying perceived probabilities of dying in a terrorist attack, keeping the perceived risk of instability at its estimated value. Panel (b) shows the change in life-time utility for varying perceived probabilities of instability, keeping the perceived risk of dying in a terrorist attack at its estimated value.

# 6 Conclusion

Besides a potential direct physical impact on school infrastructure or personnel that terrorist attacks share with other forms of violence, we show that indirect mechanisms like changes in expectations contribute significantly to the reduction in primary school enrolment of Kenyan children. In particular, terrorist attacks not occurring on a child's way to school, and even in a separate administrative area, have an effect, conditional on attacks occurring closer to the child. For these attacks, we can rule out any direct physical impact. Similarly, the salience of terrorism, as measured by threats and media reporting, reduces school enrolment above and beyond the effect of attacks carried out. Whereas we do not observe any correlation of attacks with self-reported experiences of violence, the correlation with concerns about violence is large. Based on this evidence, we structurally estimate a behavioural model in which terrorist attacks may alter agents' expectations about the costs and benefits of schooling. Our estimation suggests that the perceived risk of dying in a terrorist attack substantially exceeds the objective rate, resulting in an inefficiently low level of school attendance. Our back of the envelope calculations, furthermore, suggest that exposure to terrorism results in significant lifetime losses in welfare.

# References


**Abadie, Alberto and Javier Gardeazabal**, "The Economic Costs of Conflict: A Case Study of the Basque Country," *American Economic Review*, 2003, *93* (1), 113–132.

_ **and** _ , "Terrorism and the World Economy," *European Economic Review*, 2008, *52* (1), 1–27.

**Akbulut-Yuksel, Mevlude**, "Children of War: The Long-Run Effects of Large-Scale Physical Destruction and Warfare on Children," *Journal of Human Resources*, 2014, *49* (3), 634–662.

**Amodio, Francesco and Giorgio Chiovelli**, "Ethnicity and Violence During Democratic Transitions: Evidence from South Africa," *Journal of the European Economic Association*, 11 2017, *16* (4), 1234–1280.

**Anderson, David M. and Jacob McKnight**, "Understanding al-Shabaab: clan, Islam and insurgency in Kenya," *Journal of Eastern African Studies*, 2015, *9* (3), 536–557.

**Attanasio, Orazio, Teodora Boneva, and Christopher Rauh**, "Parental Beliefs about Returns to Different Types of Investments in School Children," *NBER Working Paper 25513*, 2019.

**Bazzi, Samuel and Christopher Blattman**, "Economic Shocks and Conflict: Evidence from Commodity Prices," *American Economic Journal: Macroeconomics*, 2014, *6* (4), 1–38.

**Becker, Gary S. and Kevin M. Murphy**, "Prosperity Will Rise Out of the Ashes," *Wall Street Journal, 29 October*, 2001.

**Berman, Nicolas, Mathieu Couttenier, Dominic Rohner, and Mathias Thoenig**, "This Mine Is Mine! How Minerals Fuel Conflicts in Africa," *American Economic Review*, June 2017, *107* (6), 1564–1610.

**Bertoni, Eleonora, Michele Di Maio, Vasco Molini, and Roberto Nisticò**, "Education is forbidden: The effect of the Boko Haram conflict on education in North-East Nigeria," *Journal of Development Economics*, 2018.

**Boneva, Teodora and Christopher Rauh**, "Parental Beliefs about Returns to Educational Investments—The Later the Better?," *Journal of the European Economic Association*, 2018, *16* (6), 1669–1711.

**Brück, Tilman, Michele Di Maio, and Sami H. Miaari**, "Learning The Hard Way: The Effect of Violent Conflict on Student Academic Achievement," *Journal of the European Economic Association*, forthcoming.

**Brückner, Markus and Antonio Ciccone**, "International Commodity Prices, Growth and the Outbreak of Civil War in Sub-Saharan Africa," *Economic Journal*, 2010, *120* (544), 519–534.

**Ciccone, Antonio**, "International Commodity Prices and Civil War Outbreak: New Evidence for Sub-Saharan Africa and Beyond," 2018.

**Conley, T.G.**, "GMM estimation with cross sectional dependence," *Journal of Econometrics*, 1999, *92* (1), 1 – 45.

**Delavande, Adeline and Basit Zafar**, "University Choice: The Role of Expected Earnings, Non-pecuniary Outcomes, and Financial Constraints," *Journal of Political Economy*, forthcoming.

**_ , Jinkook Lee, and Seetha Menon**, "Eliciting Survival Expectations of the Elderly in Low-Income Countries: Evidence From India," *Demography*, 2017, *54* (2), 673–699.

**Dominitz, Jeff and Charles F. Manski**, "Eliciting Student Expectations of the Returns to Schooling," *Journal of Human Resources*, 1996, *31* (1), 1–26.

**Dube, Oeindrila and Juan F. Vargas**, "Commodity Price Shocks and Civil Conflict: Evidence from Colombia," *Review of Economic Studies*, 03 2013, *80* (4), 1384–1421.

**Fanusie, Yaya J. and Alex Entz**, "Al Qaeda in the Arabian Peninsula: Financial assessment," *Terror Finance Briefing Book - Center of Sanctions and Illicit Finance*, 2017.

**_ and _** , "Al-Shabaab: Financial assessment," *Terror Finance Briefing Book - Center of Sanctions and Illicit Finance*, 2017.

**Fetzer, Thiemo R.**, "Social Insurance and Conflict: Evidence from India," 2014.

**Fischhoff, Baruch, Aandrew M. Parker, Wändi Bruine de Bruin, Julie Downs, Claire Palmgren, Robyn Dawes, and Charles F. Manski**, "Teen Expectations for Significant Life Events," *The Public Opinion Quarterly*, 2000, *64* (2), 189–205.

**Giustinelli, Pamela and Charles F Manski**, "Survey Measures of Family Decision Processes for Econometric Analysis of Schooling Decisions," *Economic Inquiry*, 2018, *56* (1), 81–99.

_ **and Nicola Pavoni**, "The evolution of awareness and belief ambiguity in the process of high school track choice," *Review of Economic Dynamics*, 2017, *25*, 93–120.

**Hansen, Stig Jarle**, *Al-Shabaab in Somalia*, Hurst and Company, London, 2013.

**Hartog, Joop and Luis Diaz-Serrano**, "Schooling as a Risky Investment: A Survey of Theory and Evidence," *Foundations and Trends in Microeconomics*, 2014, *9* (3-4), 159–331.

**Jensen, Robert**, "The (Perceived) Returns to Education and the Demand for Schooling," *Quarterly Journal of Economics*, 2010, *125* (2), 515–548.

**Justino, Patricia, Marinella Leone, and Paola Salardi**, "Short- and Long-Term Impact of Violence on Education: The Case of Timor Leste," *The World Bank Economic Review*, 2013, *28* (2), 320–353.

**Keatinge, Tom**, "The role of finance in defeating Al Shabaab," *Whitehall Report - Royal United Services Institute*, 2014, *2-14.*

**Kenya National Bureau of Statistics**, *Kenya Demographic and Health Survey*, P.O. Box 30266-00100 GPO Nairobi, Kenya, 2009.

_ , *Kenya Demographic and Health Survey*, P.O. Box 30266-00100 GPO Nairobi, Kenya, 2014.

**Khan, Sarah and Andrew J. Seltzer**, "The Impact of Fundamentalist Terrorism on School Enrolment: Evidence from North-Western Pakistan, 2004-09," *IZA Working Paper No 10168*, 2016.

**Koppensteiner, Martin Foureaux and Lívia Menezes**, "Afraid to Go to School? Estimating the Effect of Violence on Schooling Outcomes," 2018.

**Krueger, Alan B. and Jitka Maleckova**, "Education, Poverty and Terrorism: Is There a Causal Connection?," *Journal of Economic Perspectives*, December 2003, *17* (4), 119–144.

**Lahoud, Nelly**, "The Merger of al-Shabab and Qa'idat al-Jihad," *CTC Sentinel*, 2012, *5* (2), 1–5.

**León, Gianmarco and Edward Miguel**, "Risky Transportation Choices and the Value of a Statistical Life," *American Economic Journal: Applied Economics*, 2017, *9* (1), 202–228.

**Limodio, Nicola**, "Terrorism Financing, Recruitment and Attacks: Evidence from a Natural Experiment in Pakistan," 2018.

**Michalopoulos, Stelios and Elias Papaioannou**, "The Long-Run Effects of the Scramble for Africa," *American Economic Review*, July 2016, *106* (7), 1802–48.

**Miguel, Edward, Shanker Satyanath, and Ernest Sergenti**, "Economic Shocks and Civil Conflict: An Instrumental Variables Approach," *Journal of Political Economy*, 2004, *112* (4), 725 – 753.

**Monteiro, Joana and Rudi Rocha**, "Drug Battles and School Achievement: Evidence from Rio de Janeiro's Favelas," *Review of Economics and Statistics*, 2017, *99* (2), 213–228.

**Rehman, Faiz Ur and Paolo Vanin**, "Terrorism risk and democratic preferences in Pakistan," *Journal of Development Economics*, 2017, *124*, 95 – 106.

**Rollins, John**, "Al Qaeda and Affiliates: Historical Perspective, Global Presence, and Implications for U.S. Policy," *Congressional Research Service Report for Congress*, 2011.

**Rust, John**, "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher," *Econometrica*, 1987, *55* (5), 999–1033.

**Shany, Adi**, "Too Scared for School? The Effects of Terrorism on Student Achievement," 2018.

**Singh, Prakash and Olga N. Shemyakina**, "Gender-differential effects of terrorism on education: The case of the 1981-1993 Punjab insurgency," *Economics of Education Review*, 2016, *54*, 185 – 210.

**Trebbi, Francesco and Eric Weese**, "Insurgency and Small Wars: Estimaton of Unobserved Coalition Structures," *Econometrica*, forthcoming.

**United Nations Security Council**, "Resolution 2036, 22 February 2012," 2012.

_ , "Resolution 2444, 14 November 2018," 2018.

**Weidmann, Nils B., Jan K. Rod, and Lars-Erik Cederman**, "Representing ethnic groups in space: A new dataset," *Journal of Peace Research*, 2010, *47*, 491 – 499.

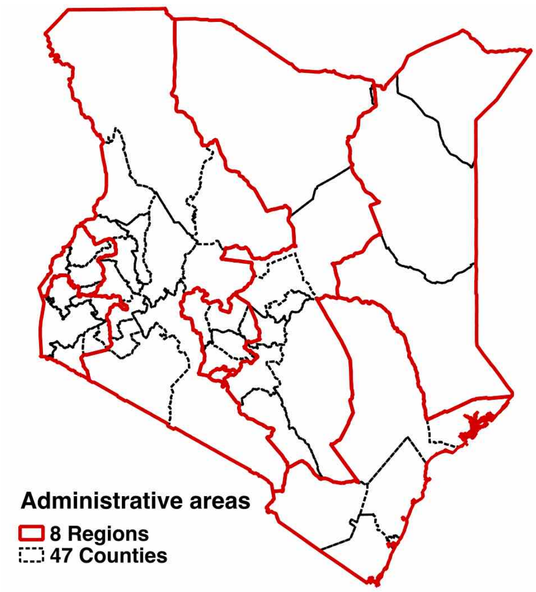
**Zarif, Maseh**, "Terror Partnership: AQAP and Shabaab," *Critical Threats Network report*, 2011.

**Zimmermann, Katherine**, "The Al Qaeda network: a new framework for defining the enemy," *Critical Threats Network report*, 2013.

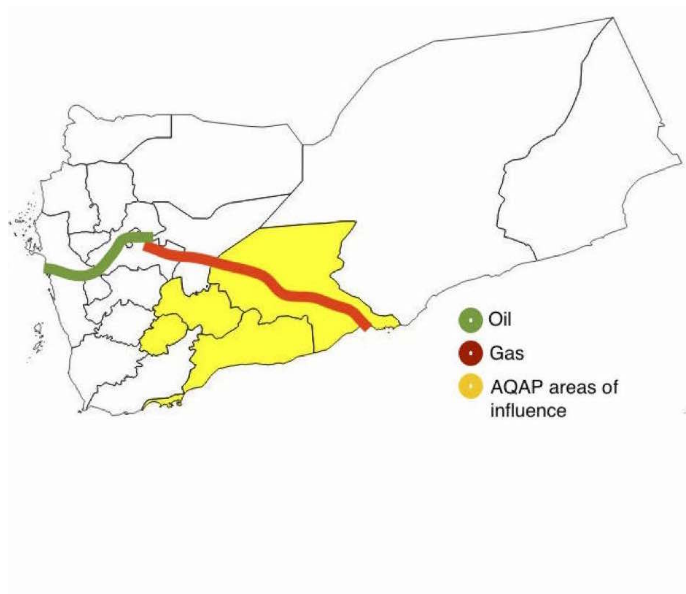
# Appendices - for online publication

## A Additional maps

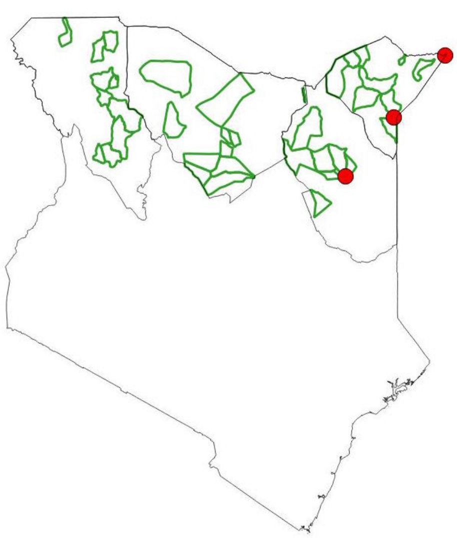
(a) Kenya's administrative areas



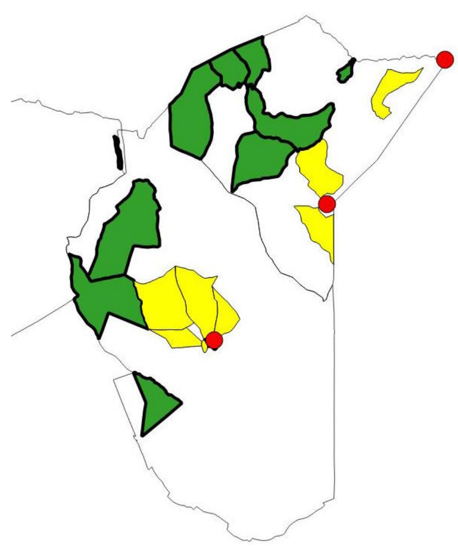

(b) Yemen - Natural gas and terrorism



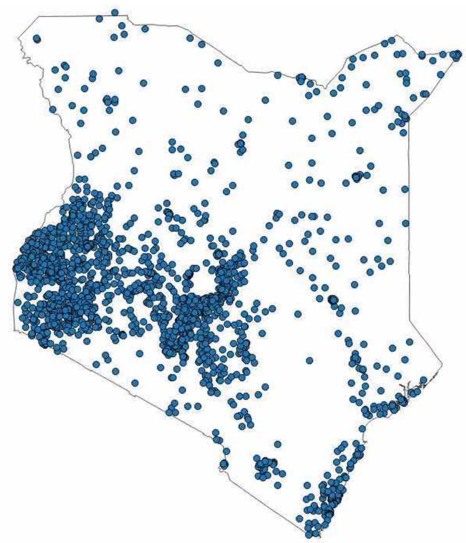

(c) HSNP clusters and terrorist attacks



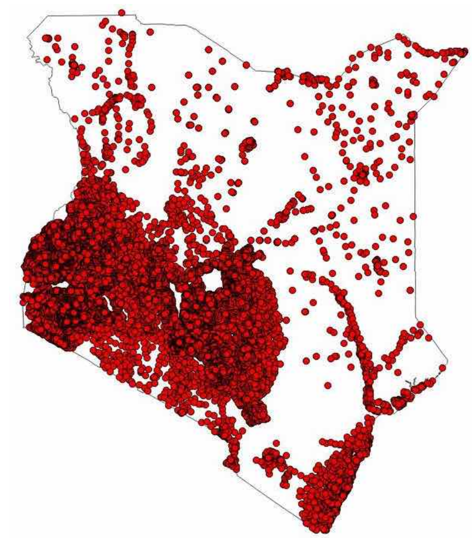
(d) HSNP - Treated and control clusters



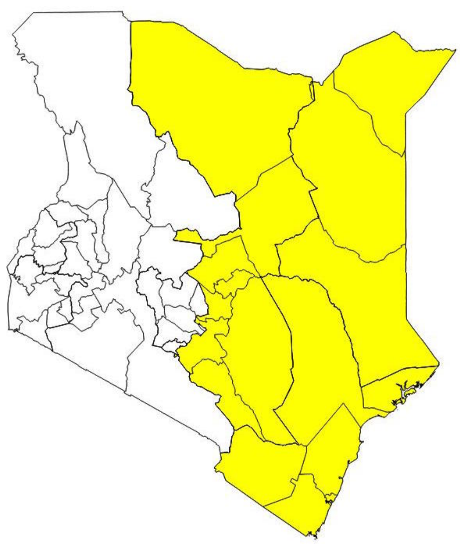
(e) DHS respondents



(f) Primary schools in Kenya

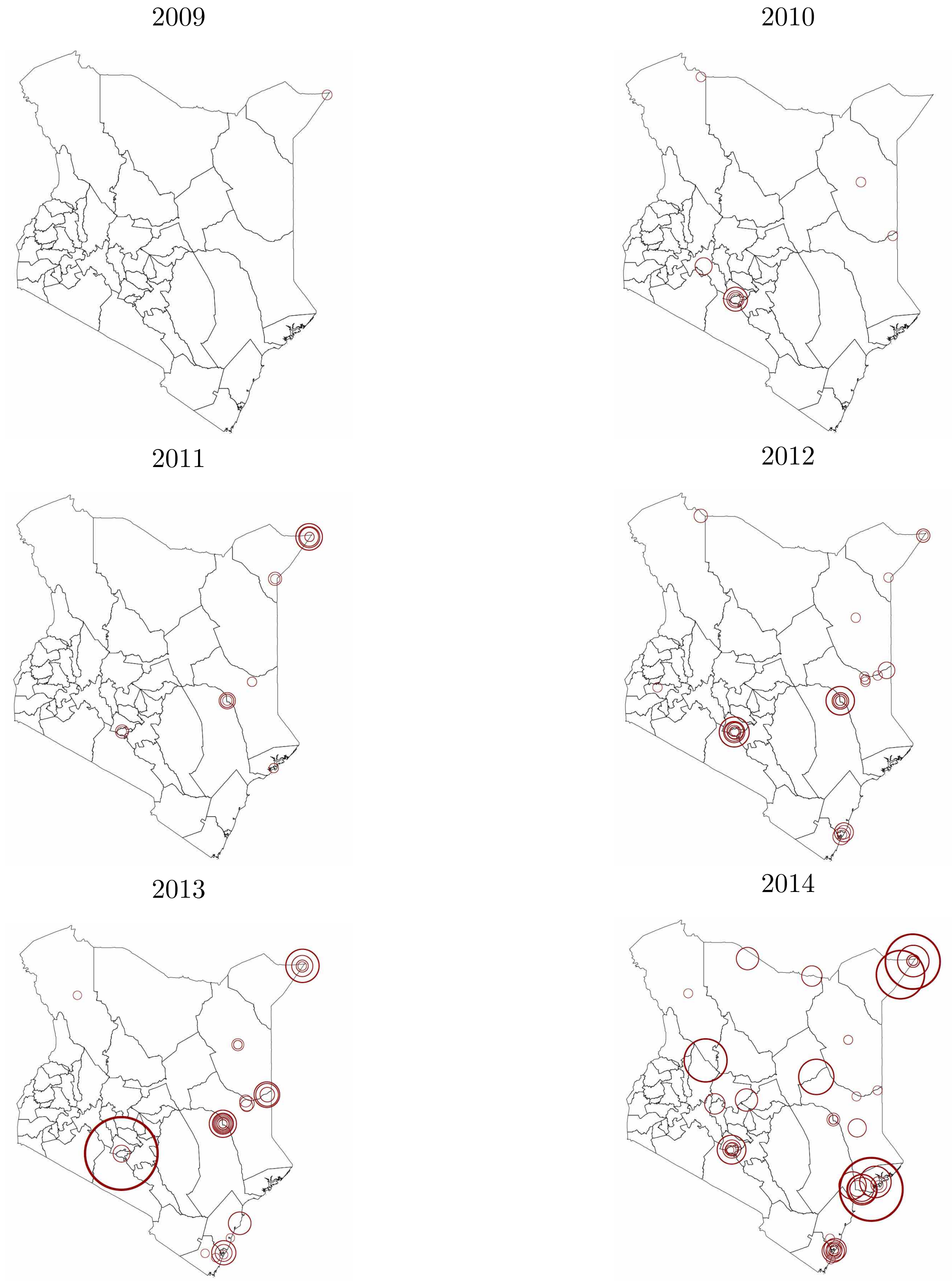


(g) East of Kenya



**Notes:** Map a: shows Kenya's 8 regions and 47 counties, Map b: show's Yemen's gas and petrol pipelines and AQAP controlled areas, Map c: shows municipalities interviewed under HSNP, Map d: shows municipalities interviewed under HSNP by terror status (red=attacks, yellow=experienced terror, green=did not experience terror), Map e: shows the geographical coordinates of respondents for the DHS 2009 and 2014, Map f: shows the geographical coordinates all 31,231 primary schools in Kenya, Map g: shows 3 most eastern regions of Kenya (East of Kenya).

# B Temporal and geographical variation




**Notes:** Maps show location of terrorist attacks in Kenya between 2009 and 2014, radii indicate number of casualties, red circles denote attacks by al-Shabaab, blue circles attacks that cannot be attributed to a particular perpetrator.

# 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: Separate IV estimates

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Dependent variable: percentage of children in school by age 6 | | | | | | | |
| **Means** | 65.5 | | | | 69.6 | | | |
| **Terrorist attacks** | −1.299*** | −1.318*** | −1.213*** | −1.529*** | −1.038*** | −1.050*** | −0.947*** | −1.271*** |
| | (0.263) | (0.254) | (0.266) | (0.245) | (0.165) | (0.158) | (0.161) | (0.176) |
| **$c$ and $t$ effects** | YES | YES | YES | YES | YES | YES | YES | YES |
| **indiv. charact.** | | | | | YES | YES | YES | YES |
| **F-statistic** | 37.4 | 21.3 | 13.3 | 28.6 | 16.3 | 42.3 | 47.6 | 34.0 |
| **Instrument** | All | AQAP | Gas | Coal | All | AQAP | Gas | Coal |
| **R squared** | 0.779 | 0.779 | 0.779 | 0.776 | 0.229 | 0.229 | 0.229 | 0.228 |
| **Unit of observation** | county | | | | individual | | | |
| **Observations** | 658 | | | | 40,657 | | | |

**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; Columns 1-4: dependent variable is the county average of children enrolled in school by age 6; data structure is a panel for the 47 counties for the years 2001-14; column 1 uses 3 instruments: interaction of 1/distance and attacks by AQAP, Yemen's exports of hydrocarbons in previous year and coal imports by United Arab Emirates in previous year; column 2 uses interaction of 1/distance and attacks by AQAP as instrument; column 3 uses interaction of 1/distance and Yemen's exports of hydrocarbons in previous year as instrument; column 4 uses interaction of 1/distance and coal imports by United Arab Emirates in previous year; Columns 5-8: dependent variable takes value 100 if a child is enrolled in school by age 6; data structure is one observation per child; individual controls include indicators for gender, rural community, electricity at dwelling, radio in household, television in household; column 5 uses 3 instruments: interaction of 1/distance and attacks by AQAP, Yemen's exports of hydrocarbons in previous year and coal imports by United Arab Emirates in previous year; column 6 uses interaction of 1/distance and attacks by AQAP as instrument; column 7 uses interaction of 1/distance and Yemen's exports of hydrocarbons in previous year as instrument; column 8 uses interaction of 1/distance and coal imports by United Arab Emirates in previous year; data are drawn from 2009 and 2014 Kenyan DHS; standard errors are clustered at the county level.

# E Effect of terrorism on school enrolment: Robustness

This appendix addresses the concern that terrorist attacks lead the government to change its expenditure patterns. It could be, 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 (2). Column (1) 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 main result in column (1) of table 3. We also control for education expenditure having a disproportionate effect in the northeast the same way 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.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Dependent variables: | | | | |
| | % of children in school by age 6 | | | % of women migrating | Total population |
| **Means** | | 65.5 | | 3.44 | 785.68 |
| **Terrorist attacks** | $-0.866^{***}$ | $-0.824^{***}$ | $-0.761^{***}$ | 0.0176 | 1.689 |
| | (0.200) | (0.199) | (0.208) | (0.0570) | (6.359) |
| **$c$ and $t$ effects** | YES | YES | YES | YES | YES |
| **R squared** | 0.780 | 0.780 | 0.781 | 0.016 | 0.974 |
| **Safety spening $\times$ NE** | YES | | YES | | |
| **Education spening $\times$ NE** | | YES | YES | | |
| **Observations** | | 658 | | 14,731 | 658 |

**Notes:** The table reports the effect of terrorist attacks on migration and school enrolment; *Terrorist attacks* 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; dependent variable is the county average of children enrolled in school by age 6; 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); all standard errors are clustered at county level.

To examine the robustness of the estimates provided in Table 3, in this appendix we also show OLS and IV estimates for different sub-samples. 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).

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent variable: percentage of children in school by age 6 | | | | | |
| | OLS | IV | OLS | IV | OLS | IV |
| **Means** | 64.5 | | 76.6 | | 65.5 | |
| **Terrorist attacks** | −0.813*** | −1.318*** | −0.388 | −0.615*** | −0.640 ** | −1.142*** |
| | (0.190) | (0.260) | (0.238) | (0.217) | (0.245) | (0.421) |
| $c$ **and** $t$ **effects** | YES | YES | YES | YES | YES | YES |
| **F-statistic** | | 38.6 | | 34.7 | | 10.5 |
| **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 6; 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 coal 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 Identification in the structural model

We estimate the structural parameter vector $\theta = (\pi, \psi, \eta_{NT}, \eta_T, \sigma_{NT}, \sigma_T)'$ 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.

To illustrate the informativeness of the moments we use for the parameters that we seek to identify, Figure 10 plots the criterion against different values of the structural parameters. For each parameter, the criterion obtains a clear local minimum.

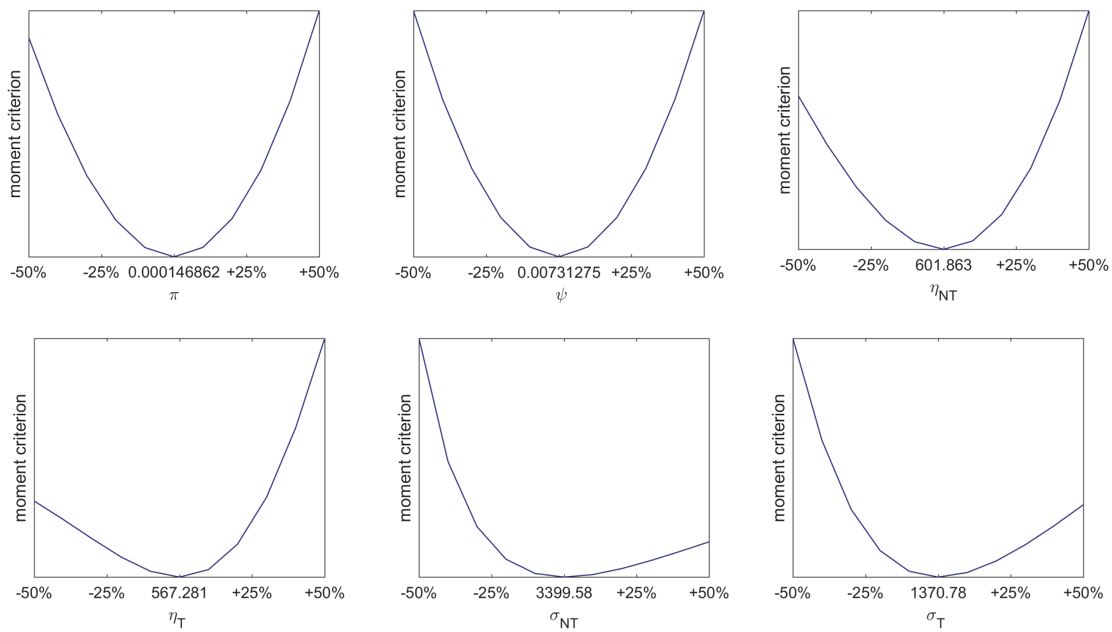



Figure 10: Local minima of the criterion with respect to values of structural parameters.