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ABSTRACT

Terrorism, Media Coverage and Education: Evidence from Al-Shabaab Attacks in Kenya*

We examine how terrorism alters the demand for education through perceived risks and returns by relating terrorist attacks to media signal coverage and schooling in Kenya. Exploiting geographical and temporal variation in wireless signal coverage and attacks, we establish that media access reinforces negative effects of terrorism on schooling. These effects are confirmed when we instrument both media signal and the incidence of attacks. For households with media access, we also find a significant relation between media content and schooling and a significant effect of attacks on self-reported fears and concerns. Based on these insights, we estimate a simple structural model where heterogeneous households experiencing terrorism form beliefs about risks and returns to education. We exploit the same quasi-experimental variation as in the reduced form analysis to identify how media change subjective expectations. The results show that households with media access significantly over-estimate fatality risks.

JEL Classification: D74, L82, F52, I21

Keywords: terrorism, media, expectations, education

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1 Introduction

Terrorists use violence strategically to spread fear and disruption beyond the violent act itself (Krueger and Malečková, 2003). The media, with their wide reach and powerful effect on many different outcomes (see DellaVigna and La Ferrara, 2015; for an overview), are the ideal vehicle to disseminate this disruption. In fact, terrorist organisations are aware of the crucial role of media: al-Qaeda leader Ayman al-Zawahiri, for instance, stated that "more than half of this battle is taking place in the battlefield of the media" (ICCT, 2021b). As a result of the interplay between terrorism and media, terrorists can affect core pillars of economic development such as education not only thorough infrastructure destruction or harm to personnel. Rather, terrorism can also affect the *demand* for schooling by changing the real and perceived risks associated with school attendance, or by altering expected returns to education. Along similar lines, Abadie and Gardeazabal (2003, 2008) argue that terrorism affects the economy not through its physical destruction but by diverting foreign direct investment as expected returns change. Yet, when analysing the effect of violence on other types of investments, such as in human capital, the role of information access and subjective risk assessment has remained largely unexplored.

This paper estimates how incidences of terrorism together with access to mass media affect human capital formation by changing the perceived risks and rewards associated with education. The setting for our analysis is Kenya, parts of which from the late 2000s have experienced a stark increase in terrorist activity by al-Shabaab, a Somali terrorist group with strong links to al-Qaeda. To explore the role of *perceptions*, we estimate whether the effect of attacks is amplified by access to mass media. As a UNESCO report puts it, "[a]ccusations of being the megaphone of terrorism to attract audiences weigh constantly on media, who are often operating on over-drive" (UNESCO, 2017, p 9). We measure exposure to media via wireless signal coverage for three separate and independent media sources: radio, mobile phones, and television, and complement this analysis with information on media content. Following a detailed reduced form analysis, we estimate a structural model of education and child labour choices for children in the face of terrorist attacks, where households form beliefs about risks and returns to education, and beliefs depend on media access. The model allows us to evaluate the effect of media exposure on subjective assessments of both fatality risks and returns to education, and to quantify longer-term costs of terrorism arising from education decisions.

We show that the well-documented negative effect of violent incidences on schooling is magnified by exposure to mass media. Our analysis exploits several margins of variation, the exogeneity of which we scrutinize in much detail (more on this below). First, we use geo-coded data on wireless signal strength for radio and television and the staggered rollout of mobile phone coverage as topographical and temporal variations in exposure to mass media. Second, we exploit the geographical concentration of terrorist attacks using information on their precise geographical location drawn from the Global Terrorism Database (GTD). Third, temporal variation in attacks over a long time period not only provides identifying variation, but also allows an examination of pre-trends in school enrolment. In addition, we instrument both the incidence of terrorist attacks and media signal coverage.

To examine the role of media, we overlay the geographical coordinates of individuals' residences with geo-coded data on radio signal coverage from `fmscan.org`, the location of governmental TV broadcasting antennae, and with mobile network data collected by the Global System for Mobile Communications (GSM) Association. Using Demographic Health Survey (DHS) data we find that for households without media access each attack suppresses school enrolment by 0.4-0.7 percentage points. For households with wireless signal coverage for radio, GSM telephone or television, the effect is a statistically significant 0.5-1.0 percentage points stronger. Whereas the effect of terrorism decays with distance for households outside the reach of wireless signal, it barely does so for households with signal coverage, for whom media can bridge the geographical distance to attacks. Data from the Hunger Safety Net Program also suggest that decreases in schooling are almost completely offset by increases in children staying at home rather than working.[1]

To investigate the link to media more closely, we complement the analysis with detailed information on media content drawn from the Global Database of Events, Language and Tone (GDELT). For households with access to media, we find a negative relation between the number of media items referring to terrorism in a specific Kenyan region and school enrolment in that very region, conditional on attacks actually carried out. For households without wireless signal, the association is zero.

Our study explores the role of attitudes further using Afrobarometer data and finds that attacks increase self-reported safety concerns and fear of crime. This effect is, again, amplified by media access. By contrast, we show that the effects on schooling are not driven by teacher absences and school closures (highlighted as an important issue in Kenya Glewwe et al., 2010; Duflo et al., 2012; Bold et al., 2017). Together with the fact that al-Shabaab barely targeted education facilities during the period we study, these results suggest that the effect is demand driven, and that awareness and the subjective risks associated with terrorism may be important. The amplification of effects through media may either be a response to better information or, alternatively, reflect an exacerbation of fears, leading to a sub-optimal over-response. We show that the latter dominates in our context.

We investigate whether the estimates are biased by omitted variables or reverse causality in several ways. First, we instrument both incidences of terrorist attacks and also media coverage. To predict attacks, we use three sources of variation arising from al-Shabaab's revenue streams and position in the al-Qaeda network: al-Shabaab's links to al-Qaeda in the Arabian Peninsula, al-Qaeda's revenues from Yemen's exports of hydrocarbons and al-Shabaab's revenues from charcoal export. To instrument media access, we use the fact that wireless transmission decreases with three factors: lightning strikes, terrain ruggedness and wind speed. Second, we exploit the marked increase in terrorist activity in the northeastern parts of Kenya to scrutinize pre-trends. Before the stark increase in attacks, we find

[1] Working here includes activities like herding the household's own life stock.

parallel trends. Thereafter, enrolment rates in affected areas decrease significantly more for households with than for those without media access. Third, we divide Kenya into a grid of 25km×25km cells and predict whether areas with better media access or higher school density are also more severely hit by terrorist attacks. We find—conditional on observable controls—no significant relation. Fourth, we use longitudinal data from some of the hardest hit areas to estimate our effects whilst controlling for household fixed effects. Finally, we carry out a number of robustness checks, including: accounting for a number of confounding factors such as economic conditions (highlighted by Bazzi and Blattman, 2014 and Crost and Felter, 2019; for instance), investigating labour market and migration outcomes, and controlling for the potential endogeneity of media further by allowing the effect of attacks to vary by education of the household head, population density and broader region.

Based on the findings of the reduced form analysis, we formulate and estimate a model of educational and labour supply choices for children. In our model, terrorist attacks change both the risk associated with children's activities outside the house (such as attending school or working) and the returns to education. Crucially, individuals form expectations regarding both fatality risks and returns to education, which we estimate separately for households with and without media access. By inferring perceived risks and expected returns from observed choices, our model sheds light on subjective expectations, about which surveys rarely inquire directly. The importance of distinguishing perceptions of violence and of economic conditions has been documented by Fair et al. (2018), who investigate support for insurgents in Pakistan. By estimating perceived probabilities under uncertainty, our model also speaks to the growing literature analysing risk preferences and perceptions within a structural framework (see Delavande and Zafar, 2019; Patnaik et al., forthcoming; for instance). We maintain a close link with the reduced form estimation by exploiting the same quasi-experimental variation in attacks, objective fatality risk and media access for identification in the structural estimation. In the data we use for the estimation of our model, no attack targets schools.[2] Rather, the majority is aimed at security forces, private individuals and businesses. We show, indeed, that school density is not a good predictor of terrorist attacks. Yet, activities outside the home expose children to the risk of violence. To disentangle different mechanisms, we note that any decrease in outside activities (i.e. school or work) indicates perceived fatality concerns, whereas a shift to non-schooling activities (i.e. work or staying at home) is informative about perceived educational returns. Our model allows for heterogeneity in the effect of attacks, both with media coverage and unobserved factors.

Our structural estimates show that the expected fatality risk for households without media coverage is very close to and for the median household statistically indistinguishable from the observed fatality rate. By contrast, the median household with media access over-estimates fatality risks by a factor of 11.8. Taken together, these two estimates suggest that media distort beliefs and exacerbate fears rather than providing more information on objective fatality risks. This tallies with recommendations laid out in a recent UNESCO 2017 report. Moreover, we find a negligible effect on expected returns to schooling for the median household. Our estimates imply that 72% of the estimated loss in adult life-time earnings that arise from the negative effect of terrorism on schooling can be attributed to the amplifying effect of media coverage alone. We also estimate a model in which terrorist attacks change agents' risk aversion rather than their misperception of risk. While this is a valid alternative channel through which media amplify the effects of terrorism, we favor the more staight forward interpretation of the risk perception channel.

Our structural estimates suggest that radio access and terrorist attacks jointly decrease school enrolment by about 8.5%. This effect size tallies with estimates from previous studies such as DellaVigna and Kaplan (2007), who find that Fox News increased Republican votes by 3.4%-28.3%, and DellaVigna et al. (2014), who find effects of 4.3% for radio reception on Croatian voting. Our model also relates to Besley et al. (2021)'s study on terrorist attacks,

[2] Kenya-wide, only 1.4% of attacks targeted schools between 2001 and 2014.

media, and credit card spending.[3]

This is the first study documenting how media can amplify terrorism's effect on child outcomes such as, for instance, schooling. As such, our paper complements the literature on the importance of media (see DellaVigna and La Ferrara, 2015, for a survey and Gentzkow et al., 2011; Bassi and Rasul, 2017; Qian and Yanagizawa-Drott, 2017; Mastrorocco and Minale, 2018; Besley et al., 2021; Enikolopov et al., 2020; Sequiera and Nardotto, 2021; for examples). Media itself has been shown to be a powerful influence on education (Jensen and Oster, 2009; Keefer and Khemani, 2014), violence, unrest and resistance (Bhuller et al., 2013; Yanagizawa-Drott, 2014; Adena et al., 2015; Shapiro and Weidmann, 2015; Brodeur, 2018; Boleslavsky et al., 2020; Gagliarducci et al., 2020; Manacorda and Tesei, 2020), but also reconciliation (Paluck and Green, 2009; Armand et al., 2020b). However, little is known about how media can function as a propagation mechanism for the effect of other social phenomena such as terrorism, which exploits fears and perceptions, on human capital investment. Different from the previous literature, our analysis thus demonstrates the complementary effect of media and violence. Moreover, we provide evidence on media's so far scarcely documented effect on perceived fatality risk from terrorism by embedding the reduced form evidence in an estimable behavioural model of the effects of terrorism. Becker and Rubinstein (2011) examine the use of services that are exposed to heightened risk of being targeted, like buses or cafés, in a model which however is not estimated. We use their insights, but go substantially beyond their analysis as we structurally estimate model parameters directly, which allows us to put numbers on crucial quantities and to simulate counterfactual predictions. Our analysis also relates to the growing body of work on the economic effects of terrorism and mass shootings, which finds negative effects of exposure to violence on schooling achievements (Ang, 2020; Bharadwaj et al., 2021). Furthermore, Brodeur and Yousaf (2019) draw a line between the economic impact of mass shooting and media.

In particular, we estimate—for the first time—how perceived death probabilities are

[3]Whilst this and other papers account for observable (typically spatial) heterogeneity, we believe that our model is the first in this literature to also allow for unobserved heterogeneity across agents.

affected by exposure to media. By highlighting how media perpetuates effects of terrorism on the demand for schooling, our study documents a thus far unexplored mechanism, and also contributes to the broader literature on the consequences of violence for education (León, 2012; Justino et al., 2013; Lekfuangfu, 2016; Brown and Velásquez, 2017; Bertoni et al., 2018; Fransen et al., 2018; Brück et al., 2019; Foureaux Koppensteiner and Menezes, 2021).

Finally, our analysis also speaks to studies relating life expectancy to human capital investment, for instance using variation in disease exposure (Oster et al., 2013; Burlando, 2015; Fortson, 2011) or by evaluating the impact of increased maternal life expectancy in India on girls' schooling (Jayachandran and Lleras-Muney, 2009). Hazan (2012) and Cervellati and Sunde (2013) use data over several decades to analyze the relation between life expectancy at different ages and educational attainment. Closer to our setting, Lekfuangfu (2016) investigates the impact of fatality risk from landmines in Cambodia and documents a negative effect on both schooling and health investments. We advance this literature by estimating whether these perceptions are affected by access to media.

After first describing the context and data sources used, we estimate in Section 3 how the effect of terrorist attacks on school enrolment is reinforced by media access and explore the role of media content. Section 4 presents the model together with its structural estimates and counterfactual analysis. Finally, Section 5 concludes.

2 Background and data

The setting for our analysis is Kenya, which experienced a sharp increase in terrorist activity from the late 2000s onwards. The majority of attacks were carried out 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*.[4] For each incident recorded, the GTD collects information on, among other things, the geographic coordinate, number of casualties and group responsible. The GTD singling out terrorist attacks serves our purpose,[5] see also the discussion on the value of information provided by different related datasets in Trebbi and Weese (2019).

Between the years 2001 and 2014, Kenya experienced a total of 367 terrorist attacks, 96% of which were carried out from 2007 onwards (see panel A of table 1). Most attacks are attributed to al-Shabaab, an Islamist terror organisation based in Somalia and founded in the early 2000s with the aim of overthrowing governments in the Horn of Africa region and to install Islamic rule.[6] As figure 1a shows, most attacks are concentrated in the three northeastern counties Mandera, Wajir and Garissa, which border Somalia. The two largest towns, Nairobi and Mombasa also experience a considerable number of attacks. Figure 1b shows the marked increase in terrorist activity after the mid-2000s (see appendix B for the geo-temporal variation).

During the period of our analysis, al-Shabaab rarely targeted schools (see panel B of table 1). The most common targets instead were security forces (96 attacks against police, 22 against military targets), as well as private individuals and businesses. Between 2001 and 2014, education institutions were targeted only 5 times, corresponding to 1.4% of all attacks.[7]

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

[5] Other sources like the Armed Conflict Location & Event Data (ACLED) allow a classification of incidences as terrorist attacks only through the definition of perpetrators as terrorist organisations.

[6] See for instance Anderson and McKnight (2015) for further background, and appendix A for the geographical distribution of attacks across Kenya and Somalia attributed to al-Shabaab.

[7] The most prominent attack on an educational institution was the 2015 assault on the University of Garissa. Our time frame is dictated by waves of the Demographic Health Surveys (DHS) and does not include this incident.

Table 1: Descriptives

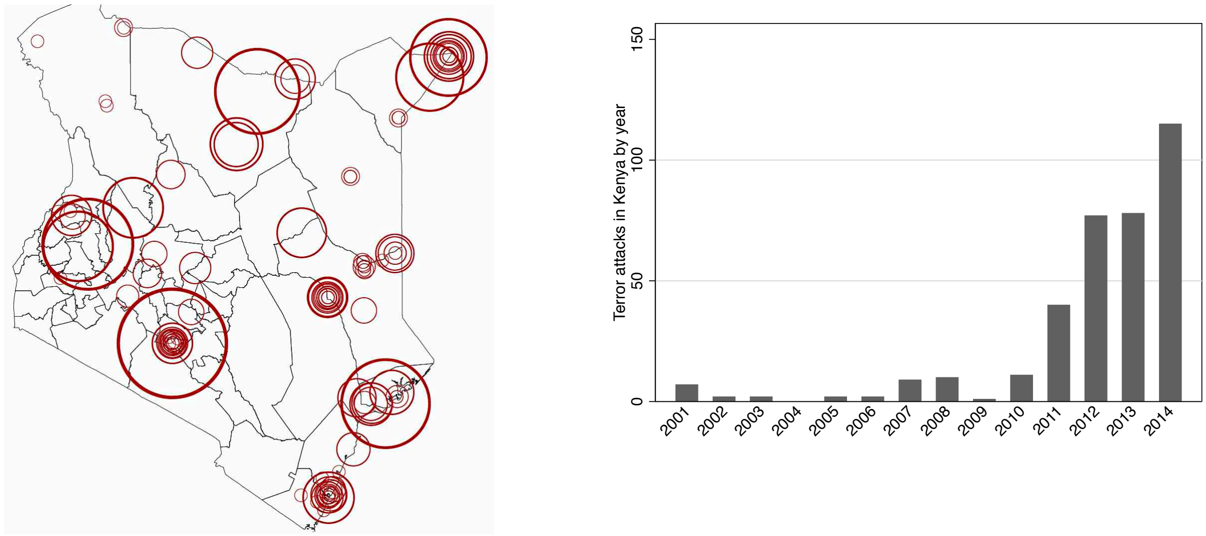
	Panel A: Terrorist attacks in Kenya 2001-2014						
Organisation	All	al-Shabaab		2001 - 2006		2007 - 2014	
Attacks	367	216		15		352	
Casualties	931	523		106		825	
	Panel B: Terrorist attacks in Kenya 2001-2014 by target						
Target	All	Police	Citizens	Business	Military	Education	Other
Attacks	367	96	74	53	22	5	117
Casualties	931	165	292	154	29	51	240
	Panel C: Characteristics of individuals in Kenya						
Data source	DHS	DHS		DHS		HSNP	
Sample	All	North-east		HSNP counties			
Year	2009	2009		2009		2010	
Children (6-14) currently at school	93.1	62.2		53.4		55.8	
Girls (6-14) currently at school	93.4	58.2		51.4		52.4	
Boys (6-14) currently at school	92.9	65.6		55.1		58.7	
Members per household	4.3	5.4		5.6		5.8	

Notes: Panel A: reports the total number and casualties of terrorist attacks by organisation and year in Kenya during 2001-2014; Source: Global Terrorism Database. Panel B: reports the total number of terrorist attacks by target of attack in Kenya during 2001-2014; Source: Global Terrorism Database. Panel C: reports the shares of children in school; first column is drawn from the 2009 DHS for the whole of Kenya; second column is drawn from the 2009 DHS for the northeast of Kenya (Mandera, Wajir and Garissa) only; third column is drawn from the 2009 DHS for counties Mandera, Marsabit, Turkana, and Wajir only; fourth column is drawn from the 2010 HSNP baseline survey for counties Mandera, Marsabit, Turkana, and Wajir.

Figure 1: Terrorist attacks in Kenya

(a) Terrorist attacks across space

(b) Terrorist attacks over time



Notes: The figure reports the number of casualties and attacks in Kenya. Panel a shows the geographic distribution of attacks occurring during the years 2001-2014, with radii indicating the number of casualties per attack; panel b shows the increase in the number of attacks over time; Source: Global Terrorism Database; own calculations.

2.2 Education in Kenya

Data on education in Kenya: We measure school enrolment in different ways using two distinct and independent data sources. First, we use individual level data drawn from two rounds of the Kenyan DHS, 2009 and 2014.[8] These are nationally representative and 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 a panel dataset collected to evaluate the Hunger Safety Net Programme (HSNP) to examine children's alternative activities, and also to condition on household fixed effects. 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. Although the HSNP was not designed as a representative sample of the counties it surveyed, the characteristics

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

of its respondents are similar to the overall populations in those counties (see panel C of table 1). This dataset records children's major activity, and thus allows us to assess how other activities are affected by the presence of terrorist attacks. We also use information on teacher absenteeism and school closures from this dataset.

The educational situation in Kenya: Primary school covers eight years, and the school year runs from January to October. Children automatically advance to the next year.

As our main dependent variable, we use enrolment and define an indicator for each child taking the value one if they enrolled in school by the age of 7. The school entry age set by the government is 6. We include children aged 7 at the time of interview since these children may have turned 7 between enrolling in school and being interviewed.[9]

The advantage of this variable is that it provides us with a longitudinal dimension reaching back in time (since children reach school entry age in different years), which allows us to examine trends in educational outcomes before the stark increase in terrorist attacks. Although we also estimate effects on current school attendance, our overall focus on enrolment better reflects parents' choice, and is unlikely to be affected by, for instance, teacher absenteeism, a channel that we examine in Section 3.5 in more detail. For the years 2010 to 2014, 81.2% enrolled by the age of 7, which tallies with World Bank net primary school enrolment rate of 80% in 2012 (the last year available).[10]

2.3 Access to media: radio, mobile phones and television

With over 100 radio stations and more than 20 television channels broadcasting in many local languages, there is a large and diverse media landscape in Kenya. The 2010 constitution guarantees freedom of speech and of the press. Whilst there have been reports of pressure applied to some media outlets, Kenya ranks relatively highly in terms of press freedom when

[9]We consider children who at the time of the interview were below 14 years old. For each child, we use information on the number of years in school to construct this indicator. 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.

[10]Source: `https://data.worldbank.org/`; accessed October 2019. 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.*

compared to other African countries. In 2014 for instance, Kenya scores 11 out of 16 on the 'Freedom of Expression and Belief' index by Freedom House, which makes it the 13^{th} highest ranked country in Africa (out of 54).[11]

We measure exposure to mass media via access to three types of wireless signal coverage: radio, mobile phone and television. Overlaying geo-coded information from three separate and independent sources, we classify an individual to be exposed to mass media if her residence falls within an area covered by wireless signal. We complement these data with information on media content in Section 3.2. An advantage of focusing on media *access* rather than the consumption of particular channels is that we are less concerned about selection issues (Durante and Knight, 2012).

Radio: Radio is a medium that has recently received increased attention as a significant factor for armed conflict in different historical settings (Yanagizawa-Drott, 2014; Armand et al., 2020b; Gagliarducci et al., 2020). According to the DHS (2009; 2014) around two thirds of households report to own a radio. We use information on areas with signal reception provided by `fmscan.org`, which supplies worldwide radio frequencies and transmitter maps, likely being the most complete worldwide database on radio signal coverage. `fmscan.org` identifies areas with radio signal coverage by estimating radio signal strength at thousands of different geographical points around a radio transmitter. The algorithm combines the transmission strength and height of the antenna with information on the terrain surface area, similar to measurements used for instance in Olken (2009) or Yanagizawa-Drott (2014). We distinguish areas at signal level 45 $dB\mu V$, which is generally regarded as providing good reception in and outside of buildings for different types of terrain, see figure 2a.[12]

To corroborate our results, we also use self-reported information on wireless receiver ownership provided by the DHS to distinguish households with and without a radio. While this last variable is likely endogenous, it provides variation across households beyond mere

[11] `https://freedomhouse.org/sites/default/files/2020-02/Freedom_in_the_World_2014_complete_book.pdf` Accessed July 2021.

[12] See `https://www.aerialsandtv.com/knowledge/decibels`, for instance (accessed January 2021).

geographical variation.

Wireless telephone: A common way to keep up with news in Kenya is via short messaging services (SMS). Most providers, such as for instance Safaricom, offer SMS services where news are sent via text message as part of their tariffs. We obtained data on mobile phone coverage from the GSM Association (GSMA). Digital maps are provided by Collins Bartholomew, who use submissions from mobile operators throughout the world to construct maps of GSM networks, which as the dominant standard in Africa has a near 100% market share. The fine geographical disaggregation of the data allows us to overlay these maps with the geographical coordinates of survey respondents to determine exactly which respondents are covered by GSM signal. Moreover, the staggered rollout of GSM coverage provides temporal variation in access to media. The Collins Bartholomew data are described in figure 2b.

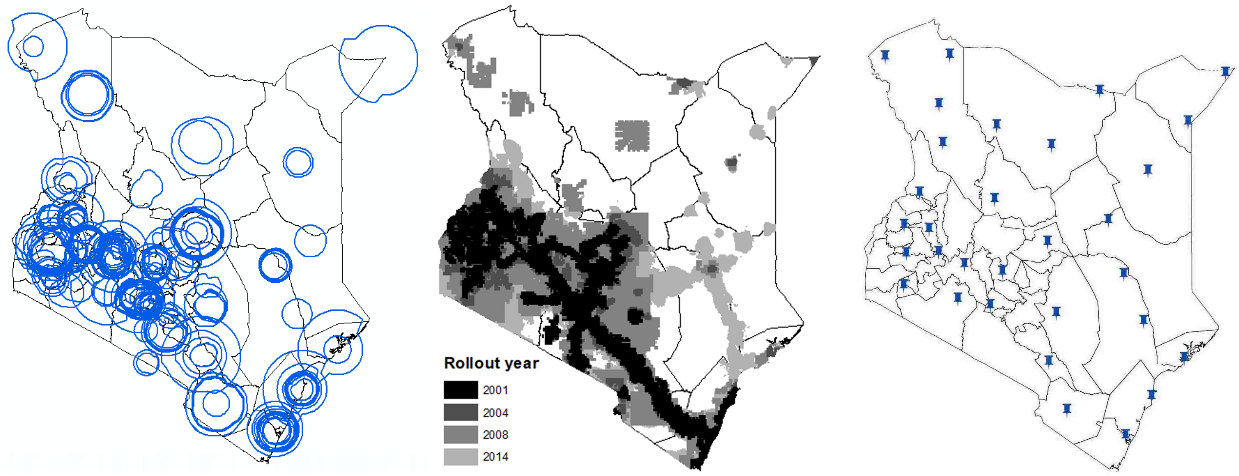
Television: To capture access to television, we employ information on the geographical location of governmental television broadcasting antennae from the Communication Authority of Kenya and calculate the distance between each household and the closest antenna, see figure 2c. The average reach of antennae in Kenya is around 45km, which we use as a cut-off. Results are robust to a variety of similar values.

Schooling and media access over time: To illustrate the relationship between attacks and school enrolment, we plot the proportion of children enrolling in school by age 7 for two regions of Kenya: the northeast—where most terrorist attacks occur—and the remainder of the country. As figure 3a shows, enrolment rates before the beginning of terrorist activity exhibit very parallel trends, with statistically indistinguishable slopes across both areas (p-value of 0.42). Note that these trends are parallel even unconditionally, so that the critique by Callaway and Sant'Anna (2021) does not apply. After terrorist activity starts in the Northeast, the trends begin to diverge.[13]

[13] Also in 2007, parts of Kenya experienced turmoil following the presidential elections. This crisis, however, was concentrated in Western Kenya (cf Dupas and Robinson, 2010), included in the solid line in Figure 3a, and thus cannot explain the divergence of enrolment trends.

Figure 2: Radio signal coverage, mobile network rollout and governmental TV antennae

(a) Radio signal coverage (b) GSM rollout (c) Broadcasting antennae



Notes: Map (a) shows radio signal coverage across Kenya (source: `fmscan.org`); map (b) shows the rollout of GSM mobile phone signal (source: Collins Bartholomew); map (c) shows the geographical distribution of governmental television antennae (source: Communication Authority of Kenya).

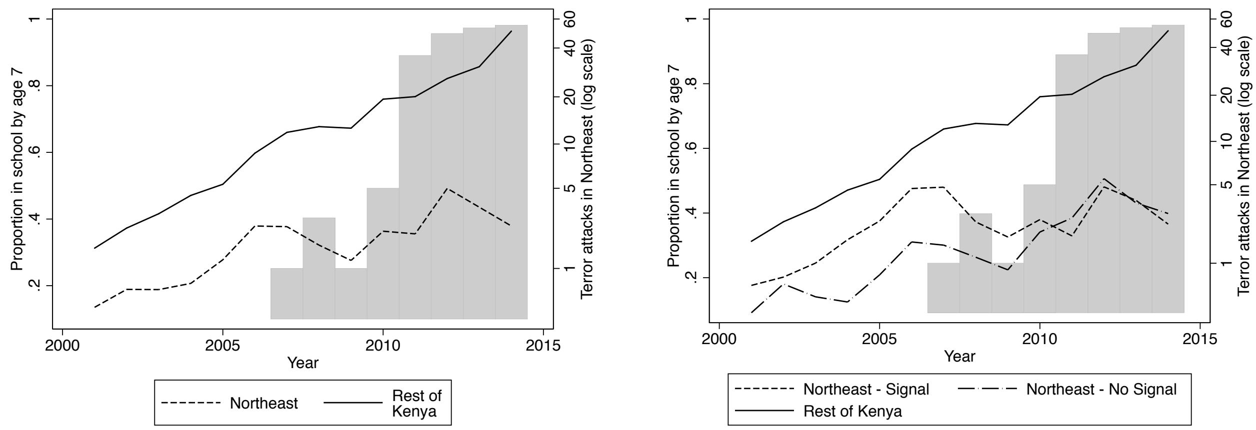
To explore the role of media access, we use information on radio signal coverage, GSM rollout and governmental television antennae to divide households in regions most affected by terrorism (the northeastern counties) into two groups: households with and without access to any of these three media sources. Figure 3b suggests that within northeastern Kenya the divergence in enrolment is driven by and more stark in areas covered by wireless signal. Again, this sub-region exhibits a very parallel pre-trend to other Kenyan regions.

3 The importance of media access and content

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

Figure 3: Terrorist attacks and schooling over time by access to media

(a) Means within regions (b) Means by signal coverage



Notes: Panel a reports the proportion of children enrolling in school by age 7 for northeastern Kenya (Mandera, Wajir and Garissa) and the rest of the country by year; Panel b reports the proportion of children enrolling in school by age 7 for northeastern Kenya (Mandera, Wajir and Garissa) with and without wireless signal and the rest of the country by year; bars in both panels denote attacks in northeast in logarithmic scale; sources: Demographic Health Surveys, `fmscan.org`, Collins Bartholomew, Communication Authority of Kenya and Global Terrorism Database.

may lower foreign direct investment and hamper economic growth. We extend this logic to human capital investment and explore the effects of awareness about terrorism on households' schooling decisions by considering access to media. We deepen this analysis further by using information on media content as well as on self-reported fears and concerns. In Section 4 we use a structural model to disentangle the effect of media exposure on risk perception from that on expected returns to schooling.

3.1 The effect of terrorist attacks and signal coverage

The negative impact of violent incidences on schooling is well-established in the literature (see e.g. León, 2012; Justino et al., 2013; Bertoni et al., 2018; Foureaux Koppensteiner and Menezes, 2021). In Alfano and Görlach (2021), we use various measures for schooling and exposure to conflict to show that terrorism is no exception.

As suggested in figure3b, we estimate whether access to mass media amplifies the effect of attacks on enrolment as follows

$$school_{it} = \alpha\ attacks_{it} + \beta\ attacks_{it} \times signal_{it} + \gamma\ signal_{it} + \boldsymbol{x}'_{it}\boldsymbol{\delta} + \kappa_{c_i} + \tau_t + u_{it}, \qquad (1)$$

where $school_{it}$ refers to enrolment of school entry aged child i in year t and $attacks_{it}$ to the number of terrorist attacks occurring in year t in the county child i resides in (out of 47 in Kenya). Further, $signal_{it}$ refers to wireless signal access using our four measures laid out in Section 2.3: radio signal coverage based on the `fmscan.org` data, GSM mobile network based on GSMA data, residence within 45km of a governmental television antenna, or ownership of a radio.[14] The coefficient β on the interaction term $attacks_{it} \times signal_{it}$ denotes how the effect of attacks on schooling varies between households with and without wireless signal coverage. We also condition on household characteristics $\boldsymbol{x}_{it}$, including the child's gender, an indicator for living in a rural location, for the household having electricity, radio and television, and for whether the household head has secondary education, as well as distance to the closest primary school, geographic latitude and longitude of the household; c_i and τ_t are county and year fixed effects respectively. Throughout, we report standard errors clustered at the county level. In appendix C, we also report spatial heteroscedastic and autocorrelation consistent Conley (1999) standard errors with 50km radius and one year lag. Parameter estimates are statistically significant for both sets of standard errors. We choose county level clustering for our estimates since it appears somewhat more conservative.

We address various identification concerns in Section 3.4. Among other things, we instrument both incidences of terrorist attacks and also media coverage, focus on the most affected regions using detailed longitudinal data along with household fixed effects, and also examine whether media coverage or school density predict terrorist attacks.

Panel A of table 2 confirms the pattern of figure 3b. For all four measures for wireless access, the effect of terrorist attacks is about twice as strong for households with signal

[14]Whereas for GSM mobile phone coverage and radio ownership, *signal* varies across individuals and over time, radio and television coverage vary across individuals only.

coverage than for those without, and more so for the three more exogenous measures in columns (1)-(3).[15] An advantage of the household-level variation in radio ownership instead is that it can provide insight into the importance of spillovers between households within the same location. Appendix E provides suggestive evidence for the presence of such local spillovers.

To illustrate how media access can perpetuate the effect of terrorist attacks across space, we document how the distance to attacks increases enrolment rates differentially for households with and without wireless signal, using our preferred measure, radio signal.[16] Households plausibly can learn about close-by attacks without resorting to mass media. The role of the latter increases, however, for further away incidences. Overlaying the geo-graphical coordinates of households and terrorist attacks, we calculate—for each year—the distance between each child and the closest terrorist attack occurring in each of the years 2001-2014. We then estimate how enrolment rates change with distance to attacks semi-parametrically by regressing school enrolment in a given year on 4 dummies dividing the distance to the closest attack into four bins: 0 to 24km (the base category), 25 to 49km, 50km to 99km and 100km or more. The triangles in figure 4a show how for households without radio signal school enrolment for children living further away from the closest attack increases drastically with distance. For households with radio signal, by contrast, school enrolment does not increase with distance to the closest attack (squares in figure 4a). For more than 100km distance, the difference between the effects for households with and without radio signal is statistically significant.

3.2 Media content relating to terrorist attacks

After having shown that the effect of terrorist attacks varies with access to media, here we use data on *media content* to further tie down the crucial role of media. We find a

[15] If determinants of radio ownership which correlate with enrolment are not fully accounted for by our control variables, we would expect a positive bias in the estimate in column (4).

[16] Radio signal coverage is our preferred measure, as radio is cheap and widely available in Kenya—more than two thirds of households own a radio (DHS 2009; 2014).

Table 2: Media exposure, media coverage of terrorism, and school enrolment

	(1)	(2)	(3)	(4)
Dependent variable	=100 if child in school by age 7 (mean: 67.5)			
	Panel A: Actual terrorist attacks			
# terrorist attacks	−0.417	−0.444	−0.358	−0.570
	(0.301)	(0.303)	(0.184)	(0.155)
# terrorist attacks	−0.545	−0.525	−0.634	−0.402
× **Media Access**	(0.174)	(0.197)	(0.101)	(0.138)
c **and** t **effects and covariates**	YES	YES	YES	YES
	Panel B: Reporting on terrorism			
Mentions of terrorism (in 100s)	0.176	0.219	0.133	−0.041
	(0.317)	(0.284)	(0.276)	(0.197)
Mentions of terrorism (in 100s)	−0.517	−0.584	−0.539	−0.396
× **Media Access**	(0.296)	(0.268)	(0.287)	(0.137)
c **and** t **effects and covariates**	YES	YES	YES	YES
# terrorist attacks	YES	YES	YES	YES
Type of Media Access	Radio Signal	GSM Signal	Close to Antenna	Owns Radio
Observations	40,724	40,724	40,724	40,724

Notes: The table reports the relation between media access, media items on attacks and education enrolment in Kenya; dependent variable in all regressions takes value 100 if child enrolled in school by age 7; data are drawn from 2009 and 2014 rounds of DHS, and GTD; *# terrorist attacks* is the number of attacks classified as terrorist per county and year; *Mentions of terrorism (in 100s)* is the number of media mentions for each Kenyan region and year that cover terrorism, adjusted by the total number of media items referring to that particular region; *Media Access=1* if household has media access through i) radio signal (at least 45 $dB\mu V$ according to `fmscan.org`); ii) GSM mobile phone signal (source: GSM Association); iii) television (within 45km of a governmental broadcasting antenna; source: Communication Authority of Kenya); iv) radio ownership (source: DHS); covariates include a child's gender, rural location, distance to closest primary school, latitude and longitude of the location, household having electricity, radio and TV and for whether household head has secondary education; regressions in panel B further control for the number of actual attacks carried out per county and year; standard errors are clustered at the county level and reported in parentheses.

negative relation between media content on terrorism and school enrolment, which is robust to the inclusion of the number of attacks actually carried out. Importantly, we find large and significant correlations only for households with access to media, as measured by signal coverage.

The data for this analysis are drawn from the Global Database of Events, Language, and Tone (GDELT) project, which monitors media outlets such as print, broadcast and web news worldwide, and provides information on organisations, people, themes, quotes, and images in almost real time. GDELT data have recently been used for instance by Armand et al. (2020a) in a study of the effects of natural resource discoveries in Mozambique or by Manacorda and Tesei (2020) when analysing protests in Africa.[17] For Kenya, the GDELT records to which of the country's eight regions an event refers (see map b in appendix A). 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). For each region and year, we sum media mentions across all of GDELT's source documents.[18] Figure A5 in appendix F shows the evolution of media mentions relating to terrorism over time.

To examine the relation between media mentions and educational enrolment empirically, we match the region/year panel of media mentions to the enrolment information and data on terrorist attacks in the 47 counties used so far, which are sub-strata of the eight regions. Since we expect the effects of media items on terrorism to increase with individuals' media access, we interact our four measures for media access with the total number of terrorism related media items in each region. We then regress education on media mentions whilst controlling for attacks carried out per county and year. The parameter estimates in panel B of table 2 show a negative correlation of terrorist mentions with enrolment only for households with likely better access to media. The estimation suggests a significant relation between

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

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

media items about terrorism and educational outcomes while conditioning on the number of attacks actually carried out in a given region, much in line with effects on tourism spending documented by Besley et al. (2021).

3.3 Effect of terrorist attacks on concerns and fears

Given the nature of terrorism, fear in a broader sense likely is an important factor in explaining the observed effects much of the literature has investigated (such as Becker and Rubinstein, 2011; Manelici, 2017; Bertoni et al., 2018; Brodeur, 2018). In fact, media are routinely suspected of "contributing to the amplification of the terrorist impact, and even its exaggeration." (UNESCO, 2017, p 49).

To illustrate the link between media, terrorism and attitudes, we estimate the effect of terrorist attacks on self-reported safety concerns and on fear of crime. We pool four rounds of the Afrobarometer surveys (2005, 2008, 2011 and 2014) and overlay the geographical coordinates of respondents with radio signal coverage to distinguish individuals with and without access to media. Subsequently we re-estimate equation (1) for two dependent variables: i) whether the respondent is concerned about safety, and ii) whether the respondent is afraid of crime.[19] The results in figure 4b show not only that exposure to terrorist attacks increases self-reported concerns and fears but that this effect is significantly larger if respondents have access to radio signal coverage.

The reinforcement of the effects of terrorism through media coverage shown in Sections 3.1 and 3.2 may arise due to two mechanisms. On the one hand, any effect of media access or media content may be a rational response to better information. On the other hand, differing responses to attacks may reflect an exacerbation of fears, and lead to a sub-optimal over-response in important decisions like school attendance. In Section 4 we use a more structural framework to pin down alternative channels, and find evidence for the second interpretation. This lines up both with our own finding of strong emotional responses due to media access,

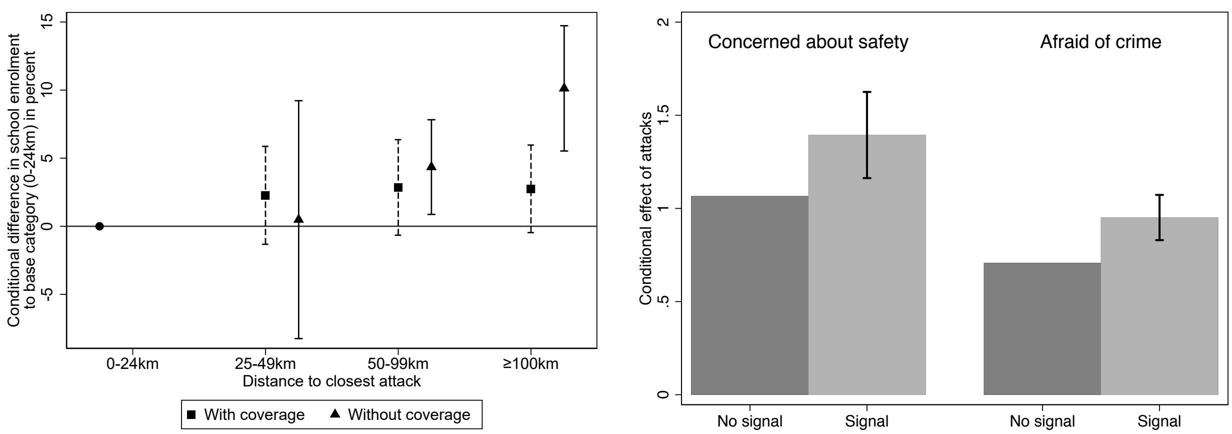
[19] Since the Afrobarometer samples per county are smaller, we report Conley standard errors with 50km radius.

and with the common argument in policy analyses, such as the assessment by UNESCO that we cite above. The exacerbation of fears we document in this paper is a consequence of increasing media penetration. Previous studies have pointed out that countries actively manipulate media content (Yanagizawa-Drott, 2014; for instance). Our findings show that even without active intervention, media can magnify violence's effect on education. This constitutes an ethical dilemma for journalists, who, while providing an information service, may inadvertently amplify terrorists' messages (ICCT, 2021a).

Figure 4: Distance from attacks, radio signal coverage, and safety concerns

(a) Distance to attack and schooling by radio signal coverage

(b) Attacks and concerns by radio signal coverage



Notes: The figure shows the effect of attacks on enrolment rates, safety concerns and on fear of crime. Panel a shows how enrolment rates change with distance to attacks for households with radio signal (triangles) and those without (squares), on intervals of 0-24km, 25-49km, 50-99km and ≥100km of distance; triangles and squares denote point estimates from regressions of school enrolment on distance to closest attack in each year, conditional on a child's gender, rural location, household having electricity, radio and TV, household head having secondary education and latitude and longitude of the respondent's residence; estimates are normalized to the base category (0-24km); sources: Demographic Health Surveys 2009 and 2014, Global Terrorism Database and `fmscan.org`. Panel b shows coefficient estimates for the effect of terrorist attacks on concerns regarding safety and fear of crime by signal coverage; dependent variable for left bars takes value 100 if respondent answers question *In your opinion, what are the most important problems facing this country that government should address?* with either *Crime and security*, *Political violence* or *Civil War* (out of 3 options); dependent variable for right bars takes value 100 if respondent answers question *Over the past year, how often, if ever, have you or anyone in your family: Feared crime in your own home?* with *many times* or *always*; radio signal coverage is defined as having at least 45 $dB\mu V$ by `fmscan.org`; estimation conditions on age, dummies for respondent being female, having no education, living in rural area, being Muslim, latitude, longitude, year and county indicators; sources: 2005, 2008, 2011 and 2014 rounds of the Kenyan Afrobarometer, Global Terrorism Database and `fmscan.org`.

3.4 Identification and robustness

In this section, we address a number of identification and robustness concerns. Specifically, we instrument both the occurrence of terrorist attacks and media access. We also zoom into the most heavily affected region of Kenya, condition on household fixed effects, and examine whether areas with signal coverage or higher school density attract terrorist attacks.

3.4.1 Instrumenting both terrorist attacks and media coverage

In figure 3 we do not find evidence for a violation of the parallel trend assumption. Nevertheless, our estimators would be biased if either al-Shabaab targeted areas that experience shocks (which are correlated with enrolment) or if families with media access differ in unobserved, time varying characteristics. In other contexts, for instance economic or natural disaster shocks have been argued to affect terrorist activity (Montalvo and Reynal-Querol, 2019), and likely correlate with school enrolment. We address these two concerns by instrumenting both terrorist attacks and media access. Either way, we estimate very similar effects.

Instrumenting terrorist attacks. We predict terrorist attacks by leveraging plausibly exogenous variation arising from al-Shabaab's revenue streams and links to the al-Qaeda network. See Alfano and Görlach (2021) for a detailed discussion and appendix G.1 for more details. To predict the *timing* of attacks, we use three margins of variation. First, we note that al-Shabaab receives support and strategic guidance from the Yemeni branch of al-Qaeda, al-Qaeda in the Arabian Peninsula (AQAP). In Alfano and Görlach (2021) we document not only that al-Shabaab closely follows AQAP in its timing of attacks, but also that it chooses similar targets. Second, we exploit the fact that revenue streams for al-Qaeda derived from Yemen's exports of hydrocarbons increase the intensity of attacks by both AQAP and al-Shabaab. Finally, we look at al-Shabaab's main source of income directly: the export of charcoal.[20] A major trading partner for Somalia's charcoal are the United Arab Emirates where it is mainly used to smoke water pipe. Accordingly, we use tobacco imports into the UAE as a third exogenous shifter of its demand for charcoal and thus al-Shabaab's revenues.

We interact these time varying determinants of terrorist activity with distance to the Somali border, a strong predictor for the *location* of attacks. Estimation then uses only the interaction between predictors for the timing and for the location as an instrument for terrorist attacks, and separately controls for time and location effects. Aggregate developments, such as changes in international fuel prices, as well as fixed location characteristics are thus accounted for.

Instrumenting media access. We predict media access using three climatic and topographical variations, which affect wireless signal transmission. We focus on our preferred measure, radio, and use the pre-period to evaluate the validity of our instruments.

First, following Manacorda and Tesei (2020) we instrument media access using lightning strikes. These electronic discharges decrease the supply of wireless signal by causing electrical blackouts and also by damaging infrastructure, such as antennae. These interferences may also discourage radio adoption, thus decreasing demand for the medium. We use NASA Global Hydrology Resource Center data (Blakeslee, 2010). See map f in appendix A.

Second, following previous studies (e.g. Yanagizawa-Drott, 2014) we use terrain surface as an additional instrument. Unequal terrain blocks radio waves, thus worsening radio reception. We measure terrain surface via the ruggedness index as used by Nunn and Puga (2012); see map g in appendix A.

Third, we use wind speed as an instrument. Wind causes structural and electrical damage to transmitting antennae and also refracts radio waves thus decreasing the quality of radio signal reception. We measure wind at 100 metres altitudes, where most of radio transmission

[20] See UN Security Council Resolutions 2036 and 2444 (United Nations Security Council, 2012, 2018).

occurs using data from the Wind Atlas.[21] See map h in appendix A, and appendix G.2 for further details.

Results. We start by instrumenting terrorist attacks only. As column (1) of table 3 shows, the IV estimates are slightly larger (in absolute size) yet similar to the OLS estimates. In column (2), we instrument both terrorist attacks and media access and again find very similar results. Given the similarity between our OLS and IV estimates, we use terminology implying causality also for our non-instrumented estimates in this section. See appendix G for further details and for first stage estimations.

How credible is the exclusion restriction for media? One concern regarding the three instruments for wireless signal coverage is that lightning strikes, terrain surface and wind can have a direct effect on schooling rather than operating through coverage. It is possible, for instance, that lightning strikes discourage children to leave the house thus decreasing school enrolment. To address this concern, we exploit the fact that terrorist attacks increase markedly from around 2010 onwards. If our three instruments had a direct effect on enrolment, we would expect differences in enrolment before the stark increase in attacks. In figure 5, we compare enrolment rates for children with high and low predicted probabilities of wireless signal coverage.[22] The fact that we do not find any differences before 2010 suggests that our three instruments do not have a direct impact on schooling.

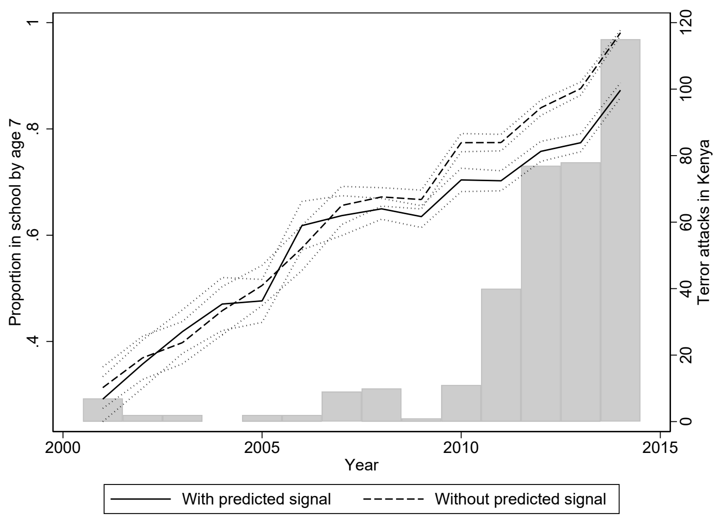
3.4.2 Does unobserved heterogeneity cause a bias?

Another possible concern is that unobserved household heterogeneity within counties is related to both enrolment and the exposure to attacks. For instance, it is possible that ethnic cleavages lingering from the Shifta War back in the 1960s or the colonial division of Somali

[21] Data are freely available under `https://globalwindatlas.info/`.

[22] Since we have multiple instruments, we create the first principal component, and distinguish households in locations above and below the mean.

Figure 5: Predicted media coverage and schooling over time



Notes: Figure reports the proportion of children enrolling in school by age 7 for households with high predicted probabilities of radio signal coverage (where the first principal component of lightning strikes, ruggedness and wind at 100 metres is below the mean) as solid line, and households with low predicted radio signal coverage (where the first principal component of lightning strikes, ruggedness and wind at 100 metres is above the mean) as dashed line; 95% confidence intervals are indicated by dotted lines; bars denote total number of terrorist attacks in Kenya per year; sources: Demographic Health Surveys, NASA, Nunn and Puga (2012), Global Wind Atlas and Global Terrorism Database.

Table 3: Instrumental variable estimates and mechanisms.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	=100 if child school by age 7		Enrolled in school	=100 if child is currently Working	Staying at home	Enr. in school (13-14 y.o.)	=100 if Adult works	=100 if child is currently enrolled in school		=100 if child in school by 7
Mean	67.5		59.0	18.3	22.8	59.4	54.5	59.0		67.5
	Instrumental variables									
Instruments for attacks	YES	YES								
Instruments for media coverage		YES								
# terrorist attacks	−0.705	−0.692	0.060	0.195	−0.255	0.118	0.170	0.060	0.199	−0.326
	(0.248)	(0.267)	(0.350)	(0.231)	(0.422)	(0.623)	(0.215)	(0.351)	(0.286)	(0.292)
# terrorist attacks	−0.871	−0.969	−0.962	−0.055	1.017	−1.108	−0.219	−0.952	−0.867	−0.648
× Media Access	(0.253)	(0.484)	(0.262)	(0.217)	(0.375)	(0.611)	(0.246)	(0.261)	(0.237)	(0.192)
Kleibergen-Paap F-Statistic	33.4	40.0								
Type of Media Access					Radio Signal					
Data source	DHS	DHS	HSNP	HSNP	HSNP	HSNP	HSNP	HSNP	HSNP	DHS
t effects and covariates	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
c effects	YES	YES								YES
Household effects			YES	YES	YES	YES	YES	YES	YES	
Dropping if								Teacher absent	School closed	School closed
Observations	40,724	40,276	12,603	12,603	12,603	2,687	19,056	12,590	12,417	38,495

Notes: The table instruments both terrorist attacks and media coverage, and examines mechanism; *# terrorist attacks* is the number of attacks classified as terrorist per county and year; *Media Access=1* if household has media access through radio signal (at least 45 $dB\mu V$ according to `fmscan.org`); dependent variable takes value 100 if child enrolled in school by age 7 based on DHS data (columns 1, 2, and 10); if child is currently attending school (columns 3, 6, 8, and 9), working outside of the house (column 4) or staying at home (column 5); if adults are in work (column 7) based on HSNP data. column 1 instruments terrorist attacks using three instruments: attacks by AQAP, Yemen's exports of natural gas or tobacco imports by the UAE, each divided by distance to the Somali border (see appendix G.1); column 2 instruments terrorist attacks and also media coverage using lightning strikes, terrain surface and wind (see appendix G.2); column 8 drops any children not attending school due to teacher absence (based on HSNP); column 9 drops any children not attending school due to school closure (based on HSNP); column 10 drops any children whose closest school is closed (based on DHS); covariates include a child's gender, rural location, distance to closest primary school, latitude and longitude of the location, household having electricity, radio and TV and for whether household head has secondary education; standard errors are clustered at county level and reported in parentheses.

homelands might still influence both terrorist attacks and school enrolment.[23] Whilst this concern is partly addressed by the parallel trends shown in figure 3 and by our instrumental variables estimates, we provide further evidence against it here.

Specifically, we re-estimate the effect of terrorist attacks using a household panel dataset covering the most affected regions. The Hunger Safety Net Programme (HSNP) household panel was implemented in four counties in the northern part of the country (Mandera, Marsabit, Turkana, and Wajir). Two of these counties are among the hardest hit by terrorist attacks (Mandera and Wajir). These estimations allow a comparison of children within a more homogeneous environment whilst controlling for household fixed effects. For the sake of consistency, we use the same definition of attacks, i.e. attacks occurring per county and year.[24] Map d in appendix A shows the location of sampling clusters. Column (3) of table 3 confirms that the negative effect of terrorist attacks on school attendance is driven by areas with radio coverage.

We use the same data to examine whether the stronger effects for households with media coverage can be explained by heterogeneous responses which are, in turn, correlated with households' income. In appendix H, we exploit the longitudinal dimension of the HSNP data to construct a household-level measure of responses to terrorist attacks. We show that the change in a household's share of children going to school per change in attacks in the household's county is uncorrelated with household income. Thus, stronger responses to terrorist attacks of households with media access are unlikely to be driven by differential responses to attacks by income. We explore the possible confounding role of household income further in section 3.4.4.

[23]For a recent survey on historical legacies and African development, see Michalopoulos and Papaioannou (2020).

[24]We have also estimated the effect of attacks within a narrow radius around respondents' residency, and find similar effects; results are available upon request.

3.4.3 Do terrorists target areas with media coverage or schools?

To address the concern that unobserved heterogeneity may bias the results by simultaneously affecting media coverage and terrorist attacks, or that areas with better signal coverage or more schools attract more severe attacks, we examine the predictive power of media coverage and school density for incidences and severity of attacks. For this, we divide the whole of Kenya into 856 squares of 25km×25km size—see map e in appendix A. For each cell, we record the total number of attacks as well as the fatalities resulting from these attacks and regress these two dependent variables on our three wireless signals: the percentage of each cell covered by radio signal or by GSM mobile network, and the distance of the cell's centroid to the closest government antenna. Due to the temporal variation provided by the staggered rollout of GSM telephone coverage, we measure attacks and fatalities per cell and year. For the other two measures, we sum all attacks and fatalities between 2001 and 2014. Columns (1) and (4) of table 4 show that GSM rollout is not a good predictor for attacks and fatalities. The same holds for radio signal coverage in columns (2) and (5) and distance to governmental television broadcasting antennae in columns (3) and (6). Moreover, all three measures of media access only make up a small percentage of the R-squared once we condition on cell and year or alternatively on county effects.

We repeat this exercise using school density as a predictor. To this end, we use data from the universe of Kenyan primary schools, count the number of schools within each cell and divide it by population. As columns (4) and (8) show, the resulting measure is not a good predictor of attacks or fatalities.

3.4.4 Other robustness checks

In table 5 we carry out additional robustness checks. We do not find any effect of terrorist attacks on migration of mothers. Using migration histories reported in the DHS, we create a panel for each respondent for the years 2001 to 2014 and define an indicator variable for whether the respondent migrated in a given year. Column (1) of table 5 shows a parameter estimate close to zero yet precisely estimated.

In columns (2) to (4) we re-estimate how the effect of attacks on schooling varies with radio signal coverage controlling for additional, potentially important factors. Across the board, the results remain very stable.[25] First, we include the distance between each child and the closest terrorist attack. If the larger response to attacks in areas with signal is due to terrorists targeting these areas, the mechanism should be picked up by this additional covariate. Second, we control for public safety spending[26] interacted with a northeastern dummy. We also add the interaction between GDP per capita and the northeastern dummy to account for unequal growth in those areas experiencing high terror incidences.

In columns (5) to (7) we address the potential endogeneity of media coverage further. Since more densely populated areas are more likely to have signal coverage, we interact the number of attacks with the average population density in the respondent's 25km cell. This specification allows for the effect of attacks to vary by population density. Similarly, we also allow for attacks to have a different effect if the head of household is highly educated (column 6), and if the household is located more than 0.5 km from the closest school (column 7). Throughout, the estimates remain unchanged.

A further concern is that wealthier households are both more likely to have access to media and also react stronger to attacks. Note that our IV estimates address this problem at the locational level. Here we provide further household-level evidence against this concern. In columns (8) and (9) of table 5 we interact $attacks_{it}$ in equation (1) with two proxies for household wealth: whether the family's dwelling has more than one room for sleeping and a household wealth indicator created by the DHS, respectively. These specifications allow for attacks to affect poor and rich households differently, thus absorbing confounding variation based on differing responses. Our estimates remain stable to these changes. This finding

[25]For the sake of conciseness, we present results for radio signal coverage, which is our preferred measure, only. Estimates for GSM and television are similar and available upon request.

[26]In 2011/12, for instance, Kenyan forces entered southern Somalia (operation Linda Nchi), and following this also provided a contingent for the African Union Mission to Somalia (AMISOM) fighting al-Shabaab in Somalia.

tallies with two others we have already presented: the results in column (6), since more educated households are likely to be wealthier, and the results on heterogeneity by income presented in appendix H.

Table 4: Attacks, media coverage, and school density

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables	# terrorist attacks				# fatalities of terrorist attacks			
Percentage of cell with GSM signal	0.0009				0.0013			
	(0.0006)				(0.0011)			
Percentage of cell with Radio signal		0.0050				0.0008		
		(0.0057)				(0.0091)		
Distance to closest antenna			−0.0013				0.0023	
			(0.0072)				(0.0152)	
Schools per 1,000 inhabitants				−0.0003				0.0086
				(0.0083)				(0.0236)
% R^2 explained by predictor	0.7%	2.6%	1.2%	0.6%	0.7%	1.3%	1.2%	0.1%
Total R^2	0.318	0.291	0.289	0.060	0.191	0.395	0.395	0.087
cell **effects**	YES				YES			
c **effects**		YES	YES	YES		YES	YES	YES
t **effects**	YES				YES			
Cell controls		YES	YES	YES		YES	YES	YES
Observations	9,845	856	856	856	9,845	856	856	856

Notes: The table shows the predictive power of wireless signal coverage for the number and scale of terrorist attacks. For a grid of 856 squares of 25km×25km size, column 1 shows the correlation between annual number of attacks and the percentage of the cell with GSM coverage; column 2 shows the correlation between total number of attacks during 2001-2014 and the percentage of the cell with radio signal; column 3 shows the correlation with distance between each cell's centroid and the closest antenna; column 4 shows the correlation between annual number of attacks and the total number of primary schools per 1,000 inhabitants; 5-8 show the corresponding correlations with the number of fatalities from terrorist attacks; columns 1 and 5 control for cell and year effects, columns 2, 3, 6 and 7 control for average population density, latitude, longitude, distance to Somali border and county effects; columns 4 and 8 control for latitude, longitude, distance to Somali border and county effects; *Total* R^2 is the R^2 of all regressors, *%* R^2 *explained by predictor* is the percentage of total R^2 explained by each predictor alone; spatial HAC Conley (1999) standard errors with 70km radius in parentheses (70km allows for correlation between one cell and its eight neighbouring cells).

3.5 Children's activity and schooling provision

To provide more evidence on the mechanisms through which terrorist attacks affect enrolment, we use detailed information on children's activity and schooling provision from the HSNP. We also will use this data source for the structural estimation in Section 4.

Table 5: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variables	=100 if migrated	=100 if child in school by age 7							
# terrorist attacks	0.018	−0.402	−0.358	0.014	−0.399	−0.400	−0.647	−0.369	−0.414
	(0.057)	(0.300)	(0.313)	(0.383)	(0.301)	(0.309)	(0.109)	(0.305)	(0.301)
# terrorist attacks × Radio signal		−0.508	−0.556	−0.651	−0.478	−0.504	−0.490	−0.517	−0.409
		(0.187)	(0.177)	(0.197)	(0.163)	(0.158)	(0.119)	(0.167)	(0.168)
c **and** t **effects**	YES	YES	YES	YES	YES	YES	YES	YES	YES
Distance to closest attack		YES							
Security spending × NE			YES						
GDP per capita × NE				YES					
attacks × population density					YES				
attacks × educated hhh						YES			
attacks × far from school							YES		
attacks × many rooms								YES	
attacks × rich									YES
Data Source					DHS				
Observations	206,234	40,724	40,724	40,724	40,724	40,724	40,724	40,724	40,724

Notes: The dependent variable in column 1 takes value 100 if respondent has migrated in a given year (from DHS); columns 2 to 9 show the specification in equation (1), but controlling for distance to the closest attack (column 2), an interaction of an indicator for the northeast with Kenyan security expenditure (column 3) or GDP per capita (column 4), or controlling for an interaction of attacks with population density in the same 25km×25km cell as the respondent (column 5), for the interaction between attacks and a dummy for the household head having primary education (column 6), for the interaction between attacks and a dummy for the closest school being further than 0.5km (column 7), for the interaction between attacks and a dummy for the residence containing more than 1 room for sleeping (column 8), for the interaction between attacks and a dummy for the household belonging to the highest wealth quintile (column 9); covariates include a child's gender, rural location, latitude and longitude of the location, household having electricity, radio and TV and for whether household head has secondary education; standard errors are clustered at the county level and reported in parentheses; data are drawn from the DHS and GTD.

Children's time allocation: In addition to the schooling information mentioned in Section 3.4.2, the HSNP records the major activities of household members. We use this information to classify the activities of children aged 6 to 14 into three groups: i) currently attending school, ii) working outside the house and iii) staying at home.[27] In Section 4, we explicitly model how the choice between these alternatives varies with exposure to terrorist attacks and media coverage.

We find that the decrease in school attendance described in Section 3.4.2 is not accompanied by an increase in child labour, see column (4) of table 3. Rather, we observe an almost identical increase in the likelihood of children staying at home (column 5). To investigate potential long term effects of attacks on education, we re-estimate our effects for children about to enter secondary school (i.e. aged between 13 and 14). The fact that in column (6) we find similar effects for this sub-sample suggests that our effects have the potential of being long lasting. We also test whether terrorist attacks affect the adult labour market in column (7) and find no effect on the probability that adults are working.

Supply of education: Two sets of results show that the *supply* of education is not a significant mechanism of impact. First, we use information on school closures and teacher absences contained in the HSNP. When collecting information in 2010 and 2012 about the reasons for children not attending school, the survey asks about teacher absenteeism and school closures. Columns (8) and (9) of table 3 re-estimate the effect of attacks on schooling whilst dropping children, who did not attend school due to teacher absences or school closures, respectively. In both cases, the results remain robust. Second, we repeat this exercise using Kenya-wide DHS data. To this end, we overlay the geo-spatial coordinates of children in the DHS with the location of all primary schools in Kenya (taken from the Kenyan Ministry for Education and shown in map i of appendix A) and match each child to its clos-

[27]We include activities related to household income generation, such as herding and helping on the family's farm, in the category 'working outside house'.

est primary school.[28] Thereafter, we re-estimate the effect of terrorist attacks on schooling whilst dropping any children whose closest primary school is closed. Column (10) shows that the results remain robust to this change as well. In appendix D, we also re-estimate the same specification using the three other media access measures (GSM, television, and self-reported radio ownership) and find very similar results.

4 A model of expectations and school attendance

Building on the evidence for the importance of media access from the previous section, we estimate a structural model in which parents choose an activity for their children subject to their perceived risk and expected returns to schooling in the presence of terrorism. In our model, children can either attend school, work or stay at home. The presence of terrorist attacks affects the fatality risk of any activity that involves leaving the house (i.e. attending school or working) as well as future returns to having attended school. Subjective expectations of both risks and returns, in turn, are a function of media exposure. To keep the structural estimation both credible and close to the reduced form estimates above, we exploit some of the same identifying variation as before.

Our model has three main purposes. First, by estimating the perceived risk of dying in a terrorist attack separately for individuals with and without media coverage, our model sheds light on the question whether agents with media access over-estimate fatality risk. Our finding that agents without media coverage accurately estimate fatality risks from terrorist attacks whereas agents with coverage significantly over-estimate these suggests that media access magnifies fears rather than providing information. We also compare this to an alternative model that allows media exposure to change agents' risk aversion. Second, the model allows us to simulate outcomes under different counterfactual degrees of fatality

[28]We use the universe of Kenyan primary schools provided by the Information and Communication Technology Authority to identify for each DHS respondent the closest primary school. `http://www.opendata.go.ke/`.

risk, and to obtain an estimate of the longer-term cost of terrorism.[29] Finally, the model is informative about the importance of different mechanisms. In particular, we compare the effect of perceived fatality risk and of risk aversion to an expected decrease in the future returns to schooling.

4.1 Model

In line with the analysis in Section 3.5, we distinguish choices made by parents of child i in the four counties covered by the HSNP data, within which we distinguish locations with and without radio signal coverage $l_i \in \{C, NC\}$. Two of these counties (Mandera and Wajir) have seen a substantial increase in terrorist attacks since 2010. Besides county-coverage-specific effects which ensure that our results are not driven by regional heterogeneity, the model also allows for unobserved heterogeneity in the responses to terrorism.

Childhood: When children are of age six, parents decide whether to enroll them in school. If children do attend school, households face a location-specific monetary cost $cost_{l_i,t}$. If not in school, children either work to earn a wage $w^{child}_{l_i,t}$ or stay at home. We label the three activities as S(chool), W(ork) and H(ome). Household income net of a child's earnings is $y_{l_i,t}$, and the household derives utility $u(x_i) = (x_i)^\phi/\phi$, where $1-\phi$, with $\phi \leq 1$, measures risk aversion. The function's argument x_i denotes total disposable household income (including child wages and net of school costs) divided by the number of household members. In addition to the monetary payoffs associated with each activity, parents are heterogeneous in terms of their preference v^i_S, v^i_W and v^i_H for each choice.

In the presence of terrorist attacks, children are exposed to an objective fatality risk $\tilde{p}_{c_i,t}$ in county c_i and year t if not staying at home. Given that in the data we use for our model (Mandera, Marsabit, Turkana and Wajir in the years 2010 to 2012) no attacks were targeted at schools and that school density does not predict attacks, we assume that

[29] For a survey on measuring the cost of terrorism, see Gardeazabal (2012).

fatality risks outside the house are independent of children's activity.[30] While we observe objective fatality rates, factors like media reporting may affect the risk *perceived* by parents. To explore this possibility, our model allows the fatality risk $p_{i,t}$ as perceived by agents to vary from its objective value by a factor π_i, which multiplies observed fatality risk as $p_{i,t} = \pi_i \cdot \tilde{p}_{c_i,t}$. We estimate the distribution of π_i, which may vary for households with and without media coverage. Moreover, the model allows π_i to differ across households *within* the same locations to account for heterogeneity in responses to terror. In Section 4.4, we consider an alternative model, in which observed changes in activity choices reflect an effect of terrorism and media exposure on risk aversion. For now, we treat risk aversion $(1-\phi)$ as an invariant "deep" parameter.

In a household of size n, the payoffs associated with the three options during childhood are given by

$$\begin{aligned} U_{i,t}^{S} &= \sum_{a=1}^{T_c} \beta^{a-1}(1-p_{i,t})^a u((y_{l_i,t} - cost_{l_i,t})/n_{l_i,t}) + \kappa_{c_i,l_i}^{S} + \tau_t^{S} + \upsilon_i^{S} && \text{if in school} \\ U_{i,t}^{W} &= \sum_{a=1}^{T_c} \beta^{a-1}(1-p_{i,t})^a u((y_{l_i,t} + w_{l_i,t}^{child})/n_{l_i,t}) + \kappa_{c_i,l_i}^{W} + \tau_t^{W} + \upsilon_i^{W} && \text{if working} \\ U_{i,t}^{H} &= \sum_{a=1}^{T_c} \beta^{a-1} u(y_{l_i,t}/n_{l_i,t}) + \upsilon_i^{H} && \text{if staying home,} \end{aligned} \tag{2}$$

where β is an annual discount factor, and T_c is the duration of childhood post age six. To ensure that our results are not driven by regional heterogeneity or aggregate trends, these payoff functions include county-by-coverage specific effects κ_{c_i,l_i}^{S} and κ_{c_i,l_i}^{W} that determine the values of schooling and work relative to staying at home, as well as year effects τ_t^{S} and τ_t^{W}, all of which we estimate jointly with the structural parameters of interest.

[30] Even for the whole sample, as shown in table 1, only 1.4% of attacks are targeted at schools directly, while the majority is directed towards security forces, private individuals and businesses. Columns 4 and 8 of table 4 show that school density neither predicts the number nor the severity of terrorist attacks in our context.

Adult life: Positive returns to education imply that the schooling decision during childhood determines expected continuation values during adult life. Besides affecting agents' risk perception, the rise in terrorist attacks may be seen as an indication of a longer-term deterioration of security and stability of the region, and parents may expect a decline in the future returns to education. On the other hand, a decrease in the supply of educated workers could raise the returns to schooling. The overall effect via this channel thus is theoretically ambiguous. As with perceived fatality risk, our model allows for heterogeneity also in parents' optimism or pessimism regarding returns to education. Specifically, each attack changes the future expected wage for an educated adult by a factor ρ_i.

For an individual with school education, the continuation value hence is given by

$$V_{i,t}^{E} = \sum_{a=1}^{T_a} \beta^{T_c+a-1}(1-p_{i,t})^{T_c}\mathrm{E}[u\left((1+\rho_i)^{attacks_{c_i,t}} w_{i,t}^{E}/n_{l_i,t}\right)], \tag{3}$$

whereas without schooling it is

$$V_{i,t}^{NE} = \sum_{a=1}^{T_a} \beta^{T_c+a-1}(1-p_{i,t})^{T_c}\mathrm{E}_w[u\left(w_{i,t}^{NE}/n_{l_i,t}\right)]. \tag{4}$$

In these expressions, T_a denotes the duration of adult working life and $attacks_{c_i,t}$ is the number attacks in county c_i and year t. The expectations $\mathrm{E}_w[\cdot]$ is over the distributions of wages for adults with and with education, $w_{i,t}^{E}$ and $w_{i,t}^{NE}$, and accounts for the fact that adult outcomes are realized several years into the future.

Taken together, an agent's maximized expected welfare is given by

$$W = \mathrm{E}\max\left\{U_{i,t}^{S} + V_{i,t}^{E}, U_{i,t}^{W} + V_{i,t}^{NE}, U_{i,t}^{H} + V_{i,t}^{NE}\right\}. \tag{5}$$

Under the assumption that preference shocks v_i are independent and extreme value distributed with distribution function $F(v) = \exp(-\exp(-v))$, choice probabilities take a logistic form and are given by

$$\begin{aligned}
\text{Prob}[S] &= \frac{\exp(U^S_{i,t} + V^E_{i,t})}{\exp(U^S_{i,t} + V^E_{i,t}) + \exp(U^W_{i,t} + V^{NE}_{i,t}) + \exp(U^H_{i,t} + V^{NE}_{i,t})}, \\
\text{Prob}[W] &= \frac{\exp(U^W_{i,t} + V^{NE}_{i,t})}{\exp(U^S_{i,t} + V^E_{i,t}) + \exp(U^W_{i,t} + V^{NE}_{i,t}) + \exp(U^H_{i,t} + V^{NE}_{i,t})}, \\
\text{Prob}[H] &= \frac{\exp(U^H_{i,t} + V^{NE}_{i,t})}{\exp(U^S_{i,t} + V^E_{i,t}) + \exp(U^W_{i,t} + V^{NE}_{i,t}) + \exp(U^H_{i,t} + V^{NE}_{i,t})}. \qquad (6)
\end{aligned}$$

To estimate the model's parameters, we draw both on the estimates reported in table 3, and a number of additional moments detailed below.

4.2 Identification and estimation

We estimate the model using data from the Hunger Safety Net Programme evaluation (see Sections 2.2 and 3.5). In these data we directly observe household sizes, wages for adults with and without schooling, wages earned by children, as well as the cost of schooling, which includes fees and expenses for supplies, transport and uniform (see table A6 in appendix I). The level of these costs is similar to that reported by Haushofer and Shapiro (2016) for the control group of their cash transfer intervention in Kenya. Regional differences within the subset of counties largely reflect rural-urban gaps in wages, schooling costs and household sizes, all of which are modeled explicitly. To absorb any other spatial differences in factors that determine activity choices for children before the ascent of terrorist attacks, we include full sets of county-coverage-specific ($\kappa^S_{c_i,l_i}$ and $\kappa^W_{c_i,l_i}$), as well as year (τ^S_t and τ^W_t) effects in the payoff functions specified in equations (2). These parameters are estimated jointly with all other parameters. They shift the payoff for schooling and work relative to staying at home, which serves as a base category. In addition, we allow for a differential impact of terrorist attacks by media access through perceived fatality risk ($p_{i,t}$) and expected returns to schooling (ρ_i).[31] Perceived fatality risk $p_{i,t} = \pi_i \cdot \tilde{p}_{c_i,t}$ is a function of the heterogeneous

[31]We focus here on our preferred medium, radio, for which we identify signal coverage using the same data from `fmscan.org` as in the previous sections.

parameter π_i. We call the last term the *fear factor*. Moreover, our model accounts for heterogeneity in these channels across individuals, conditional on media coverage.[32] We implement this through a finite mixture with ten unobserved types, five of which with and five without media access. We estimate all parameters using a minimum distance estimator, exploiting for identification amongst others the variation induced by radio signal and terrorist attacks across space and time, and the effects on school attendance and child labour. The model is over-identified, and—as we show below—able to replicate the differential impact very well.

To identify $\kappa^S_{c_i,l_i}$, $\kappa^W_{c_i,l_i}$, τ^S_t and τ^W_t, we target the fractions of children in school and the fractions of children working by county and year, as reported in the HSNP data. We further do this separately for children who live in locations (within county) with radio signal coverage and for those without. In the model, the incentive to invest in children's education may be reduced for two reasons following terrorist attacks: the risk of children being hit in an attack and an expected deterioration in the returns to education. To separately identify these two channels (model parameters π_i and ρ_i), we draw on the estimation in Section 3.5, where we have established that terrorist attacks have a negative effect on school enrollment in Kenya, that this effect is reinforced for households with media access, and that children in affected locations more often stay at home rather that work outside the home. We use the coefficient estimates of columns (3) and (4) of table 3 as moments for which the model predicts direct counterparts. Recall that in our data schools are not directly targeted by terrorists but that any activity outside the home exposes children to the risk. Hence, if we observe a negative effect on activities that require some traveling outside the home (work

[32] Primary school in Kenya covers ages 6 to 14, and so in the estimation, we set $T_c = 8$. Life expectancy in Kenya in the middle of our sample period for the HSNP (2011) was 64 years. Correspondingly, we set $T_a = 64 - 14 = 50$. We take risk aversion from experiment-based estimates by Gandelman and Hernández-Murillo (2015). While they do not provide estimates for Kenya, they estimate relative risk aversion to be respectively 0.67 and 1.26 for the neighbouring countries Uganda and Tanzania. We thus set risk aversion $(1-\phi) = 0.965$ as the mid-point between these two numbers. In Section 4.4 we consider an alternative model in which we estimate risk aversion directly. The discount factor is set to $\beta = 0.9$. Finally, using population and fatality numbers from our Kenyan datasets, we calculate annual probabilities $\tilde{p}_{c_i,t}$ of dying in a terrorist attack ranging between 0 and 0.0057%.

and school attendance), it implies that fatality risk is a major concern. A shift towards non-school activities (work and staying at home), on the other hand, would be informative about a decrease in the expected returns to schooling in regions affected by terrorist attacks.

By targeting heterogeneity in the effects of terrorist attacks, we can identify the distributions of the fear factor π_i, as well as that of expected changes ρ_i in the returns to schooling. We furthermore can distinguish these distributions for households in locations with radio signal coverage ($l_i = C$) in those without ($l_i = NC$). We implement this heterogeneity in parameters through a finite mixture of types of households, each of which is characterized by a combination (π_i, ρ_i). To identify heterogeneity in (π_i, ρ_i), we use the same proxy for household-level responses to attacks as referred to in Section 3.4.2. Appendix H describes a measure for the response q_i^S in the fraction of household i's share of children going to school, as well as for responses q_i^W in the share of children working outside the house. Our estimation then targets quantiles of q_i^S and q_i^W.[33] Appendix figure A8 shows the model's fit to these distributions. The correlation between π_i and ρ_i is pinned down by the joint density function of crossed quantiles of q_i^S and q_i^W. Panel (d) of figure A7 visualizes this joint density. Appendix I provides further details on the estimation, including the fit for all remaining moments in figure A9. In particular, it provides the exact estimation criterion, and, to indicate for each parameter which moments contribute to its identification, figure A10 displays the gradient matrix of moments with respect to the parameters.

4.3 Results and interpretation

Parameter estimates: The distributions of the scaling factor are reported in figure 6, where dots indicate the estimated π_i for each of the 10 unobserved types, 5 in locations with (red) and 5 in locations without (blue) coverage. The vertical lines denote bootstrapped

[33] We approximate unobserved heterogeneity via 10 types of households, 5 in locations with and 5 in locations without signal coverage. Accordingly, we target the mid-points in quintiles of q_i^S and q_i^W in non-coverage and coverage locations.

99% confidence intervals.[34] For four fifths of households in non-coverage locations (in blue), π_i hovers around 1. The one fifth of households denoted by the left-most point, by contrast, barely responds to variation in attacks in their county. This finding implies that the activity choices for children for the vast majority of households without media access align with a model in which these households estimate the fatality risk correctly.

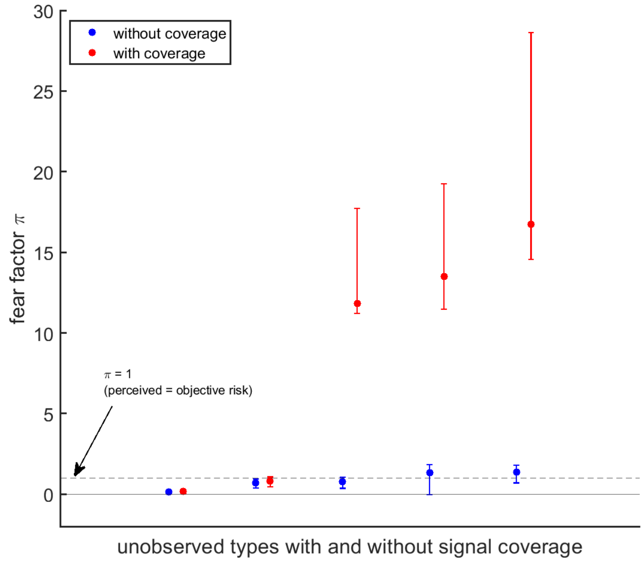
By contrast, the estimates of π_i for the majority of households with media access (in red) exceed 1 by a large factor with a median of $\pi_{med,C} = 11.8$. The finding that π_i exceeds 1 for households with radio coverage, whereas it does not for households without, suggests that media access leads to an over-estimation of fatality risks from terrorist attacks. Similar to households without radio coverage, one fifth barely react to terrorist attacks. The estimates show a strong heterogeneity in risk perception conditional on observables. Note that our model flexibly controls county-by-coverage and time level differences through $\kappa^S_{c_i,l_i}$, $\kappa^W_{c_i,l_i}$, τ^S_t and τ^W_t in equation (2).

Our findings for media's magnifying effect on perceived fatality risks tallies with the anecdotal evidence provided in the policy reports cited earlier, and is related to other studies on media and beliefs. Becker and Rubinstein (2011) argue that fear and media coverage exacerbate subjective beliefs. Yet, the authors do not estimate their model and consequently cannot put a number on this factor. In a different context Besley et al. (2021) formulate a model of belief formation and estimate a media multiplier of 2.5 for the effect of terrorist violence on tourists' credit card spending. DellaVigna and Kaplan (2007) examine the persuasion effect of Fox News on Republican votes and depending on the specification and data source estimate that the programme convinced between 3.4% and 28.3% of its audience who were not already voting Republican to do so. Using a similar model, DellaVigna et al. (2014) estimate a persuasion effect of 4.3% of Serbian radio reception on Croatian nationalist votes. For comparison, at a mean of 5 attacks per county and year in the most affected areas, our estimate for the fear factor rationalizes that radio access and terrorist attacks jointly

[34]These are based on 1,000 bootstrap replications. Note that asymptotic standard errors are not meaningful in this context, since parameters are defined only on $\mathbb{R}^+_0$, and confidence intervals are thus asymmetric.

decrease school enrolment by $(5 \times 1.0)/59.0 \approx 8.5\%$ (see column 3 of table 3).

Figure 6: Estimates of the fear factor



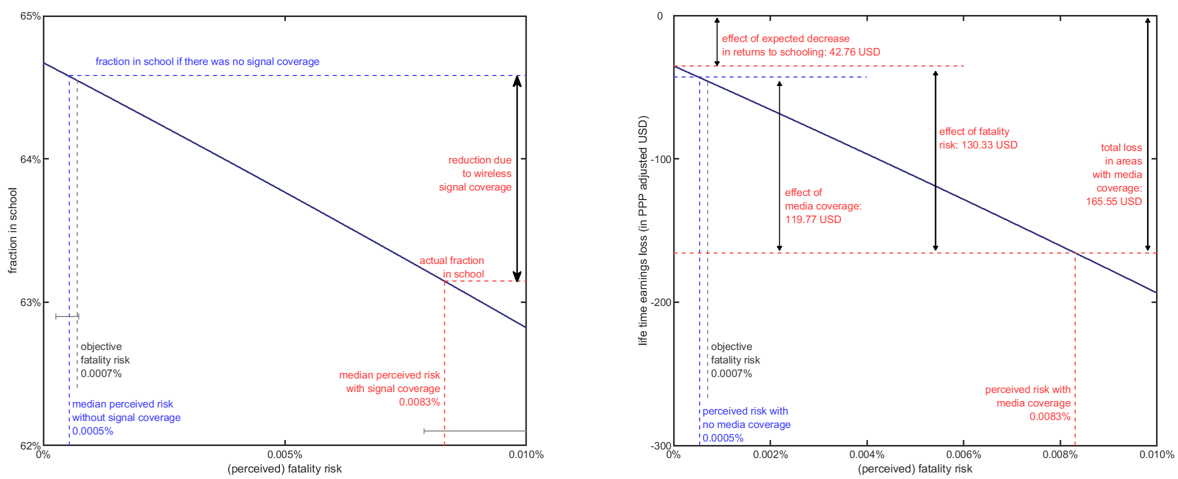
Notes: The figure shows estimates of the heterogeneous fear factor π_i. Specifically, blue dots indicate the points of support for π_i for the finite mixture used to approximate unobserved heterogeneity in locations without signal coverage, red dots in locations with signal coverage. Whiskers show the 99% confidence intervals obtained from 1,000 bootstrap replications.

In our model, terrorist attacks further affect agents' expectation about future returns to schooling. Appendix Table A7 shows that the median household in non-coverage and in coverage locations respectively expects each attack in its county to decrease the wages for schooled adults by $\rho_{med,NC} = 1.5\%$ and $\rho_{med,C} = 1.1\%$.

The fear factor: With these estimates at hand, the model can be used for out-of-sample predictions and to quantify the importance of radio signal coverage for individuals' risk perceptions. Figure 7a shows the effect of fatality risk by plotting the fraction of children attending school as a function of the risk as perceived by agents. The objective risk of dying in a terrorist attack in the northern counties covered by the HSNP during the years 2010-2012 ranges between 0 and 0.0057%, with an average of 0.0007%. Figure 7a contrasts this to the risk perceived by the median type of households, each within locations without signal coverage (in blue) and among those with coverage (in red). Fatality risk perception in areas without wireless signal coverage (blue line) is indistinguishable from the objective fatality risk (grey line). By contrast, the median household in locations with radio signal perceives a fatality risk which exceeds these small objective probabilities by a factor $\pi_{med,C} = 11.8$.

Figure 7: Counterfactual simulations

(a) Fatality risk and school attendance (b) Terrorism and lifetime earnings



Notes: Simulations based on minimum distance estimates for the model parameters detailed in Section 4.1, using HSNP (2010-2012) data. Panel (a) shows counterfactual school attendance in locations with signal coverage for varying fatality risks, indicating perceptions by the median household with and without coverage. Panel (b) shows the implied loss in adults' life-time earnings.

The costs of terrorism: The threat of terrorism complemented with media coverage induces a sizable reduction in school attendance, as Section 3.1 has shown—with lasting consequences for individuals' earnings potential. The estimated model can be used for a back of the envelope calculation of the longer-term cost of terrorism in terms of earnings forgone. Figure 7b shows how the expected discounted loss in earnings during an individual's adult lifetime varies for different levels of (real or perceived) fatality risk. Expected decreases in the returns to education by individuals with radio signal lower school enrolment leading to an earnings loss of about 43 USD (PPP adjusted), even with zero expected fatality risk. Perceived fatality risk raises this loss to 166 USD, corresponding to about one quarter of a year's average earnings of an adult who has not attended school. The largest part, 72%, of this decrease, corresponding to 120 USD, can be attributed to the higher perceived fatality risk by households living within radio signal coverage compared to those without coverage.

4.4 An alternative model: Change in risk aversion

The above model (henceforth "Model A") rationalizes the stronger effect of terrorist attacks on school attendance in areas with wireless signal via agents' perception of fatality risk and expected returns to schooling. In doing so, it treats risk aversion as an invariant "deep" structural parameter. Following the studies by Callen et al. (2014) and Jakiela and Ozier (2019), we also consider an alternative model ("Model B") in which agents in all areas assess fatality risk correctly, but in which the exposure to media coverage changes risk aversion. In this model we set $\pi = 1$ and instead allow terrorist attacks together with media access to affect the curvature of the utility function as $u(x_i) = (x_i)^{\phi_i}/\phi_i$. As in model A, we allow for heterogenous effects, this time on the utility function's curvature.

We maintain the same data moments, and the only difference between the two models relates to the source of heterogeneity and hence the channel through which signal coverage may affect choices. Yet, whereas π_i in Model A enters only the choices of going to school and going to work, the curvature ϕ_i enters utility derived for any choice made by households. It follows, that other parameter estimates may be affected by this change. In line with the studies cited above, Model B predicts a slightly higher risk aversion for agents in locations with signal coverage. Specifically, we estimate a median risk aversion $1 - \phi_{med,NC} = 0.92$ for households in non-coverage locations, and $1 - \phi_{med,C} = 0.95$ in locations with signal coverage (see appendix table A8). Other estimates are only mildly affected.

These are two behavioural models rationalizing the differential effect of terrorist attacks on children's school attendance by media access, and the choice ultimately is with the researcher. In Model A, matching observed activity choices implies an increase in fatality risk by 0.0076 percentage points; in Model B an increase in risk aversion by 0.03. In weighing between the two models, we note that Model B follows the spirit of the excellent research by Callen et al. (2014) and Jakiela and Ozier (2019). On the other hand, we believe that Model A is aligned more closely with the reading of anecdotal evidence, such as the UNESCO report cited in the introduction, as well as with studies documenting the difficulty of assessing low probability events with a high impact (Fischhoff et al., 2000). Finally, we also appreciate the ease of interpretation of the parameter π_i scaling fatality risk to its subjective level.

5 Conclusion

The findings presented in this paper show that media exacerbate the widely documented negative effect of conflict on schooling. Media reporting on terrorist acts, in particular, reduces school enrolment even after controlling for attacks carried out, a relation that is observed only for households with access to this information. Media exposure further heightens self-reported fears and safety concerns; media also prevents the effects of terrorism from decaying with distance from an attack. For the specific case of education choices, this is a channel that may well have lasting effects on longer-term economic development (Rocha et al., 2017). Based on the evidence for the importance of media, we estimate a model in which media access alters the effect of terrorist attacks on expected risks and returns of schooling. Our estimation results suggest that media may substantially raise agents' perceived fatality risk, resulting in an inefficiently low level of school attendance. Besides a potential direct physical impact on school infrastructure or personnel that terrorism shares with other forms of violence, our results hence show that due to indirect mechanisms like fear, terrorism has a quantitatively important negative impact on the *demand* for education and hence the life-time earnings potential of Kenyan children. Taken together, our results show that the ever-increasing interconnectedness through media can lead to inefficient over-responses, which, in turn, decrease educational attainments. As such, our results can be considered as a caution against sensationalism and in favour of moderate and facts-oriented reporting of terrorist events.

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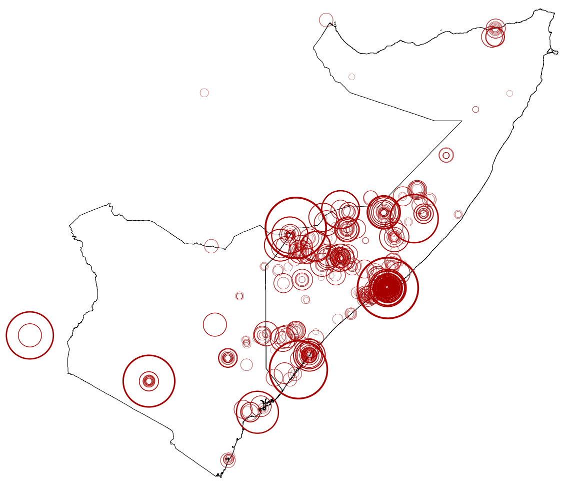
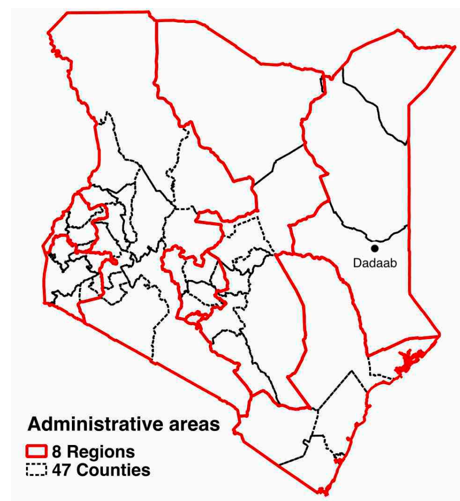
Online Appendix

A Additional maps

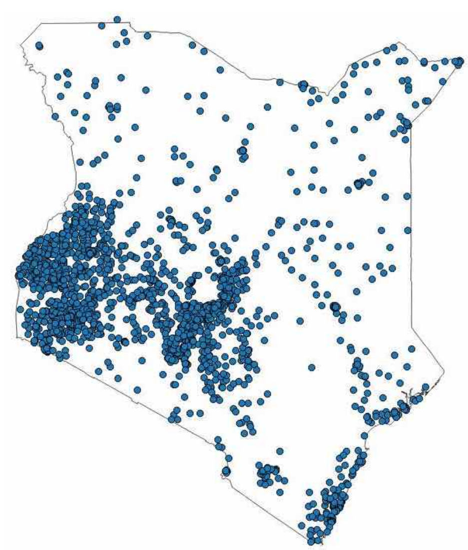
(a) Casualties of al-Shabaab attacks



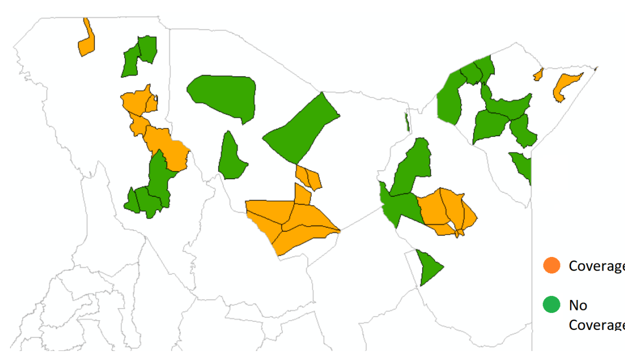
(b) Kenya's administrative areas



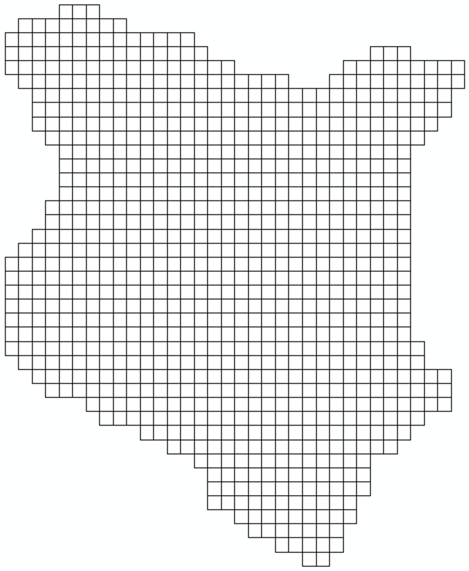
(c) DHS respondents



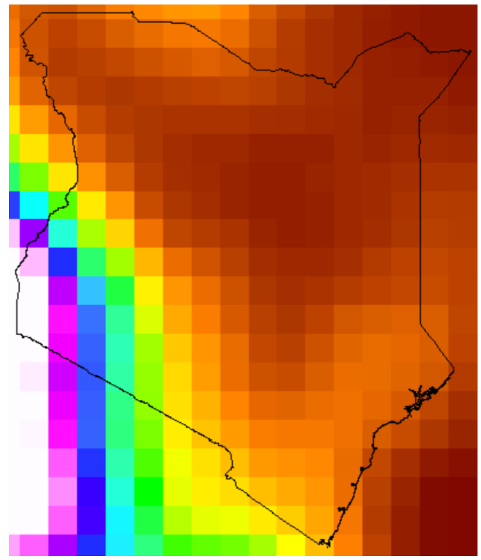
(d) HSNP clusters and wireless coverage



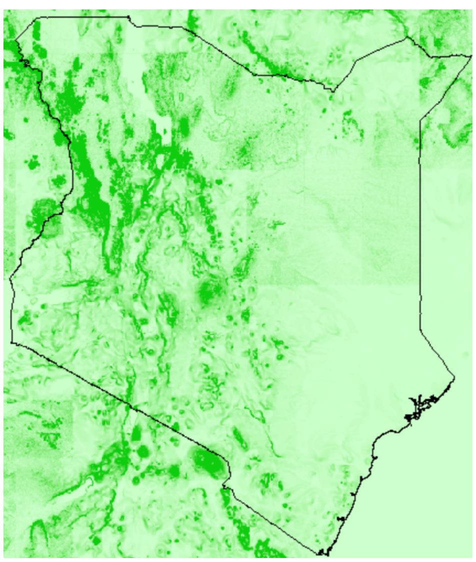
(e) Kenya 25km×25km raster



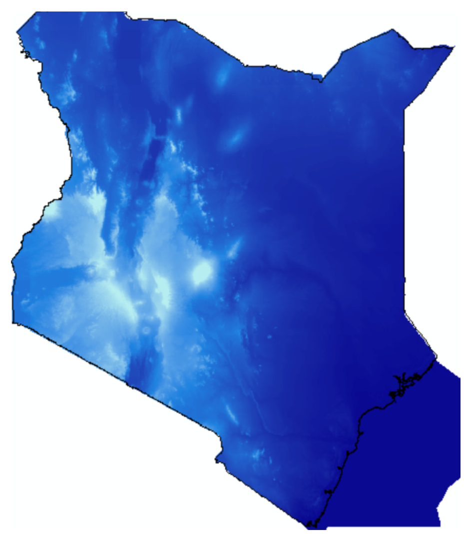
(f) Kenya lightning strikes



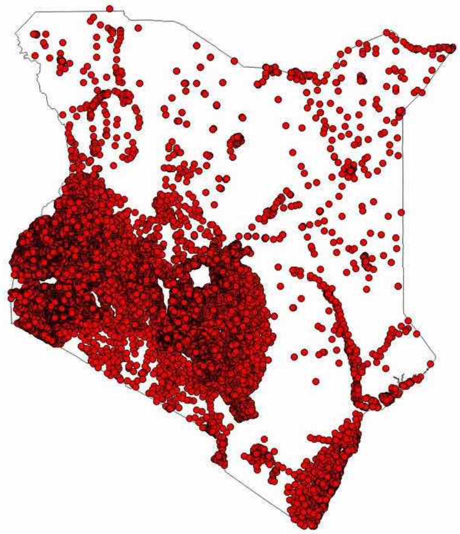
(g) Kenya ruggedness



(h) Kenya wind

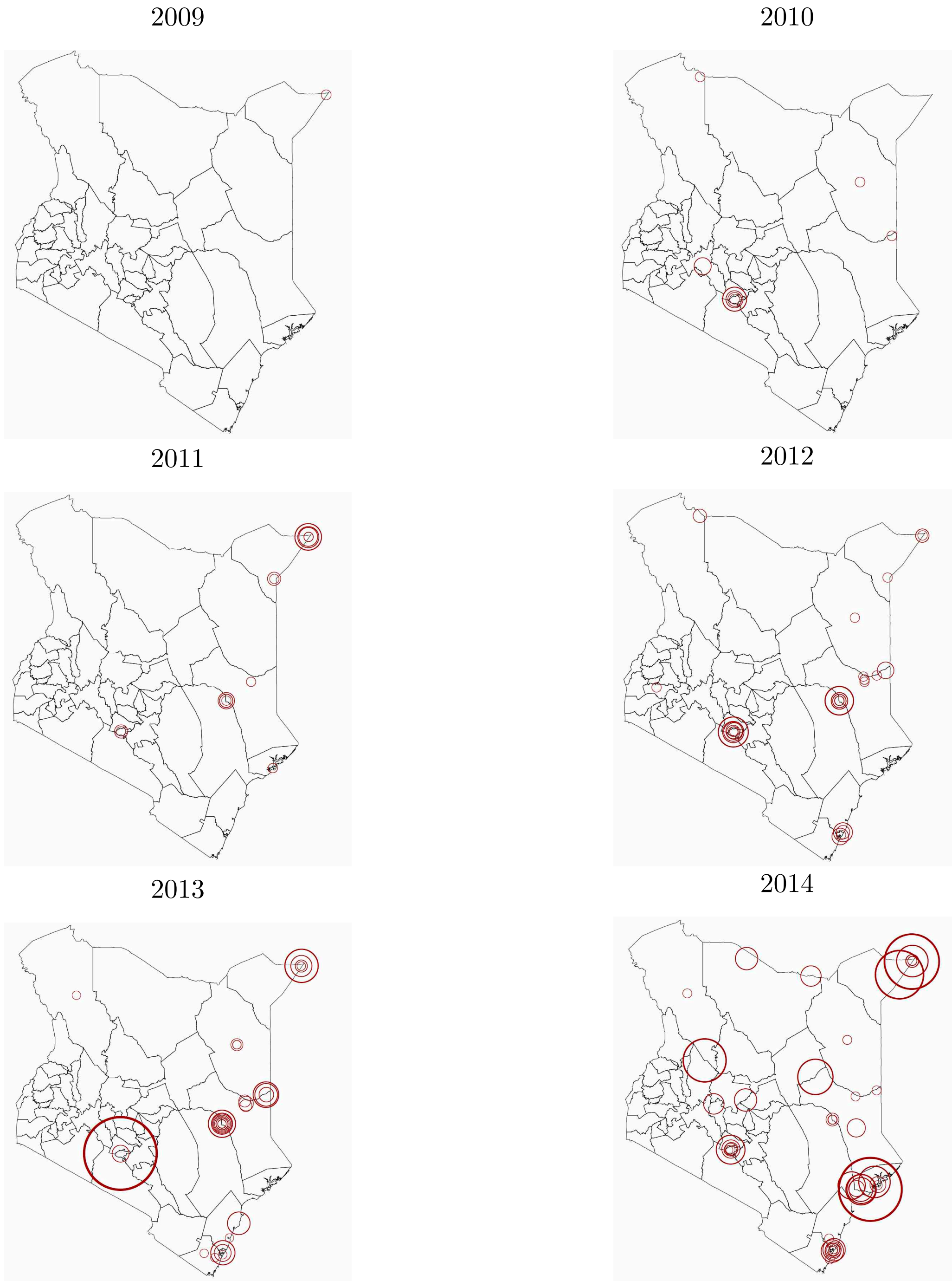


(i) Primary schools in Kenya



Notes: Map a: shows attacks by al-Shabaab, including in Somalia; Map b: shows Kenya's 8 regions and 47 counties; Map c: shows the geographical coordinates of respondents for the DHS 2009 and 2014; Map d: shows municipalities interviewed under HSNP by wireless signal coverage; Map e: shows Kenya divided into a raster of 856 squares, each of size 25km×25km; Map f: shows frequency of lightning strikes, source: NASA Global Hydrology Resource Center (Blakeslee, 2010); Map g: shows ruggedness, source: Nunn and Puga (2012); Map h: shows air density at 100 metres, source: Global Wind Atlas (`https://globalwindatlas.info/`); Map i: shows the geographical coordinates of all 31,231 primary schools in Kenya.

B Temporal and geographical variation in attacks



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

C Conley standard errors

Table A1: Main estimates with spatial HAC Conley (1999) standard errors

	(1)	(2)	(3)	(4)
Dependent variable	=100 if child in school by age 7 (mean: 67.5)			
	Panel A: Actual terrorist attacks			
# terrorist attacks	−0.417	−0.444	−0.358	−0.570
Standard errors clustered at county	(0.301)	(0.303)	(0.184)	(0.155)
Conley standard errors	[0.181]	[0.159]	[0.158]	[0.114]
# terrorist attacks × Media Access	−0.545	−0.525	−0.634	−0.402
Standard errors clustered at county	(0.174)	(0.197)	(0.101)	(0.138)
Conley standard errors	[0.210]	[0.161]	[0.180]	[0.142]
c **and** *t* **effects and covariates**	YES	YES	YES	YES
	Panel B: Reporting on terrorism			
Mentions of terrorism (in 100s)	0.176	0.219	0.133	−0.041
Standard errors clustered at county	(0.317)	(0.284)	(0.276)	(0.197)
Conley standard errors	[0.238]	[0.251]	[0.222]	[0.112]
Mentions of terrorism (in 100s) × Media Access	−0.517	−0.584	−0.539	−0.396
Standard errors clustered at county	(0.296)	(0.268)	(0.287)	(0.137)
Conley standard errors	[0.227]	[0.231]	[0.196]	[0.139]
c **and** *t* **effects and covariates**	YES	YES	YES	YES
# terrorist attacks	YES	YES	YES	YES
Type of Media Access	Radio Signal	GSM Signal	Close to Antenna	Owns Radio
Observations	40,724	40,724	40,724	40,724

Notes: The table reports the relation between media access, media items on attacks and education enrolment in Kenya with two types of clustering for standard errors; standard errors in parentheses are clustered at county level (there are 47 counties in Kenya); standard errors in brackets are spatial HAC Conley (1999) standard errors with 50km radius and one year lag; all other notes are identical to table 2.

D Dropping children whose closest school is closed

Table A2: Main estimates without school closures

	(1)	(2)	(3)	(4)
Dependent variable	=100 if child in school by age 7 (mean: 67.5)			
# terrorist attacks	−0.326	−0.368	−0.284	−0.575
	(0.292)	(0.303)	(0.133)	(0.150)
# terrorist attacks	−0.648	−0.594	−0.705	−0.316
× Media Access	(0.192)	(0.219)	(0.123)	(0.142)
c **and** t **effects and covariates**	YES	YES	YES	YES
	Panel B: Reporting on terrorism			
Mentions of terrorism (in 100s)	0.172	0.196	0.132	−0.094
	(0.309)	(0.311)	(0.244)	(0.182)
Mentions of terrorism (in 100s)	−0.523	−0.569	−0.556	−0.328
× Media Access	(0.312)	(0.316)	(0.273)	(0.117)
c **and** t **effects and covariates**	YES	YES	YES	YES
# terrorist attacks	YES	YES	YES	YES
Dropping if school closed	YES	YES	YES	YES
Type of Media Access	Radio Signal	GSM Signal	Close to Antenna	Owns Radio
Observations	38,495	38,495	38,495	38,495

Notes: The table reports the relation between media access and education enrolment in Kenya for children whose school was not closed; dependent variable in all regressions takes value 100 if child enrolled in school by age 7; data are drawn from 2009 and 2014 rounds of DHS and GTD; # terrorist attacks is the number of attacks classified as terrorist per county and year; Mentions of terrorism (in 100s) is the number of media mentions for each Kenyan region and year that cover terrorism, adjusted by the total number of media items referring to that particular region; Media Access=1 if household has media access through i) radio signal (at least 45 dBμV according to `fmscan.org`); ii) GSM mobile phone signal (source: GSM Association); iii) television (within 45km of a governmental broadcasting antenna; source: Communication Authority of Kenya); iv) radio ownership (source: DHS); covariates include a child's gender, rural location, distance to closest primary school, latitude and longitude of the location, household having electricity, radio and TV and for whether household head has secondary education; regressions in panel B further control for the number of actual attacks carried out per county and year; standard errors are clustered at the county level and reported in parentheses.

E Possible spillover effects

Although radio ownership potentially is more endogenous than our three main measures of media access (radio signal coverage, vicinity to TV antennae and GSM rollout), its household-level variation relative to the spatial variation of the other measures can give insight into the presence of spillovers. We regress school enrolment on attacks and their interaction with radio ownership, distinguishing areas with high and low radio ownership density. In areas where only few households own radio receivers, information spillovers are unlikely (since not many have access to media). Consequently, households with radio receivers should react disproportionately to terrorist attacks. By contrast, when a high proportion of households own radio receivers, media content can be communicated across households and radio ownership should not affect the impact of terrorist attacks. Table A3 shows exactly this pattern.

Table A3: Spillovers across households within the same location

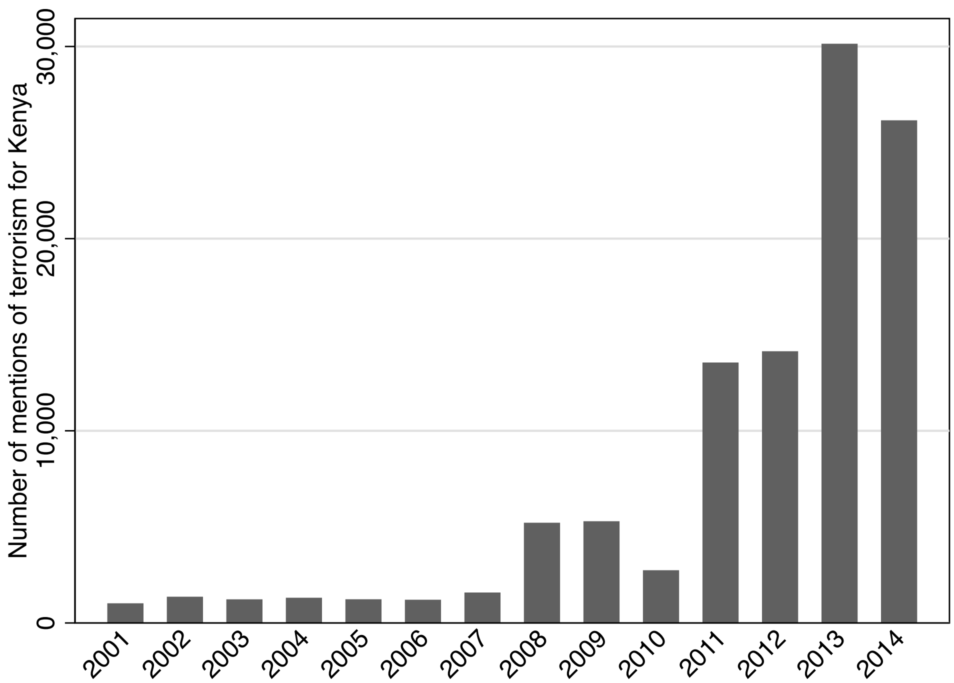
	(1)	(2)	(3)	(4)
Dependent variable	=100 if child in school by age 7 (mean: 67.5)			
# terrorist attacks	−0.570	−0.434	−0.522	−0.353
	(0.155)	(0.111)	(0.138)	(0.351)
# terrorist attacks × Radio Ownership	−0.402	−0.555	−0.693	−0.171
	(0.138)	(0.127)	(0.231)	(0.208)
c **and** t **effects and covariates**	YES	YES	YES	YES
Sample	All	Coverage	Coverage & low radio density	Coverage & high radio density
Observations	40,724	33,664	16,705	16,959

Notes: The table reports the effect of attacks on school enrolment by radio signal coverage and radio ownership; dependent variable in all regressions takes value 100 if child enrolled in school by age 7; data are drawn from 2009 and 2014 rounds of DHS and GTD; *# terrorist attacks* is the number of attacks classified as terrorist per county and year; *Radio Ownership* takes the value 1 if household reports to own a radio; samples are as follows: whole Kenya (column 1), only households with radio signal coverage (at least 45 dBμV according to `fmscan.org`, column 2), only households with radio signal coverage <u>and</u> living in clusters where proportion of households that own a radio is below median (column 3); only households with radio signal coverage <u>and</u> living in clusters where proportion of households that own a radio is above median (column 4); covariates include a child's gender, rural location, distance to closest primary school, latitude and longitude of the location, household having electricity, radio and TV and for whether household head has secondary education; standard errors are clustered at the county level and reported in parentheses.

F Distribution of media items on terrorism over time

Figure A5 shows the evolution of media items on terrorism in Kenya, as reported by the Global Database of Events, Language, and Tone (GDELT). 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).

Figure A5: Media items on terrorism



Notes: The figure shows the yearly number of mentions in international media on terrorism in Kenya; see text for definitions. Source: Global Database of Events, Language, and Tone (GDELT).

G Instrumenting terrorist attacks and media access

Although we do not find evidence for a violation of the parallel trend assumption, our panel estimations would be biased if al-Shabaab targeted areas that experience shocks which are correlated with enrolment decisions or if households with media access differ in unobserved, time varying characteristics. To address this, we instrument both terrorist attacks and media access. This appendix provides more details on the estimates reported in columns (1) and (2) of table 3.

G.1 Instrumenting terrorist attacks

We instrument both the timing and location of attacks by interacting three plausibly exogenous predictors for the timing of attacks with a determinant for the geographic location of attacks. Throughout, we only use the *interaction* between predictors for the timing and for the location as our instrument for terrorist attacks, and separately control for time and location effects. We summarise the main points of these predictors below.

To predict the *timing* of attacks, we use three sources of variation related to revenue streams of al-Shabaab and its position in the al-Qaeda network.

i) Al-Shabaab affiliation to al-Qaeda: First, we note that al-Shabaab receives support and strategic guidance from the Yemeni branch of al-Qaeda, al-Qaeda in the Arabian Peninsula (AQAP). Whilst there is no systematic data on financial or material support between members of the al-Qaeda network, in Alfano and Görlach (2021) we document data patterns that are highly consistent with a strong degree of coordination between the two organisations. To illustrate this, we construct in table A4 a weekly time series of al-Shabaab attacks. We then regress the number of al-Shabaab attacks per week on the number of attacks in the same week attributed to AQAP. Column 3 reveals a strong correlation of attacks carried out by the two groups in the exact same week. Moreover, as columns 4 and 5 show, when AQAP strikes public (private) targets, so does al-Shabaab and vice versa. In what follows, we denote the number of attacks carried about by AQAP in year t with $AQAP_t$.

ii) Importance of Yemen's exports of hydrocarbons for al-Qaeda's revenues: 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. Figure A6a illustrates a strong correlation between attacks by AQAP and liquid natural gas exports. In Alfano and Görlach (2021) we show that in 2014, less than 0.01% of Yemen's natural gas was exported to Africa, so that we can rule out a direct link with outcomes in Kenya. Moreover, in Alfano and Görlach (2021) we also correlate the Kenyan trade share of fuel with Yemeni gas exports and find no correlation between the two. We denote the level of natural gas exports from Yemen in year t with gas_t.

iii) Importance of Somalia's coal exports for al-Shabaab's revenues: Finally, we look at al-Shabaab's main source of income directly: the export of charcoal, the importance of which is highlighted in United Nations Security Council (2012) Resolution 2036.[35] A

[35] 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

major trading partner for Somalia's charcoal are the United Arab Emirates (UAE) where it is mainly used to smoke water pipe. Figure A6b shows a strong correlation between the UAE's tobacco imports from the United Arab Emirates Federal Competitiveness and Statistics Authority and the country's coal imports as reported by the International Energy Agency. The UAE's tobacco imports, in turn, map very closely with al-Shabaab activity thus confirming UN Resolution 2036—see figure A6c. In Alfano and Görlach (2021), moreover, we provide evidence that charcoal related employment in Kenya is uncorrelated with our instruments and does not track the UAE's tobacco imports. Accordingly, we use tobacco imports into the UAE as a third exogenous shifter of its demand for charcoal and thus al-Shabaab's revenues. We call this variable $tobacco_t$.

We interact these time varying determinants of terrorist activity with distance to the Somali border, a strong predictor for the *location* of attacks. Carrying out terrorist attacks is expensive, and this cost increases with the distance to the area in which the terrorist organisation is based. Figure A6d illustrates the strong relationship between distance to the Somali border and the number of attacks carried out. We denote this variable $location_i$. The resulting three instruments $AQAP_t/location_i$, $gas_t/location_i$ and $tobacco_t/location_i$ make for a strongly over-identified model, and the implied exclusion restrictions are not rejected. Please refer to Alfano and Görlach (2021) for further details.

We use these three measures (and their interaction with $signal_i$ or its instruments, see appendix G.2) to instrument the endogenous variables $attacks_{it}$ and $attacks_{it} \times signal_i$. Note that, since we instrument radio signal coverage, there is no temporal variation in $signal_i$ and thus we omit the t subscript. The first stage equations corresponding to column 1 of table 3 are the following:

$$\begin{aligned} attacks_{it} &= \lambda_1 \frac{AQAP_t}{location_i} + \lambda_2 \frac{gas_t}{location_i} + \lambda_3 \frac{tobacco_t}{location_i} \\ &+ \lambda_4 \frac{AQAP_t}{location_i} \times signal_i + \lambda_5 \frac{gas_t}{location_i} \times signal_i + \lambda_6 \frac{tobacco_t}{location_i} \times signal_i \\ &+ \boldsymbol{x}'_{it}\boldsymbol{\delta} + \kappa_{c_i} + \tau_t + u_{it}, \end{aligned}$$

$$\begin{aligned} attacks_{it} \times signal_i &= \pi_1 \frac{AQAP_t}{location_i} + \pi_2 \frac{gas_t}{location_i} + \pi_3 \frac{tobacco_t}{location_i} \\ &+ \pi_4 \frac{AQAP_t}{location_i} \times signal_i + \pi_5 \frac{gas_t}{location_i} \times signal_i + \pi_6 \frac{tobacco_t}{location_i} \times signal_i \\ &+ \boldsymbol{x}'_{it}\boldsymbol{\delta} + \kappa_{c_i} + \tau_t + u_{it}, \end{aligned}$$

In table A5, we display the first stage results for the instrumented estimates reported in table 3 in the main text. Note that we instrument both the number of attacks and their interaction with the different measures for media access. In table A5 we report the F-statistics for each regression separately whereas we provide the joint test in table 3.

Council, 2018).

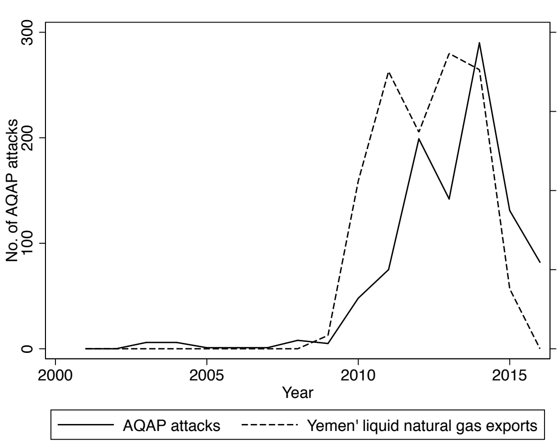
Table A4: Attacks by AQAP and al-Shabaab

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Number of weekly al-Shabaab attacks by target				
Target	Any	Any	Any	Public	Private
Means	2.39	2.39	2.39	1.60	0.80
AQAP attacks	0.158	0.184	0.212		
	(0.075)	(0.074)	(0.079)		
AQAP attacks 1 week before			0.070		
			(0.077)		
AQAP attacks 2 weeks before			0.046		
			(0.077)		
AQAP attacks 1 week after			0.077		
			(0.077)		
AQAP attacks 2 week safter			0.002		
			(0.076)		
AQAP attacks on "public" targets				0.295	−0.037
				(0.072)	(0.037)
AQAP attacks on "private" targets				−0.191	0.157
				(0.135)	(0.070)
R squared	0.732	0.740	0.753	0.707	0.593
Observations	728	728	726	728	728
Timetrend (squared and cubed)	NO	YES	YES	YES	YES

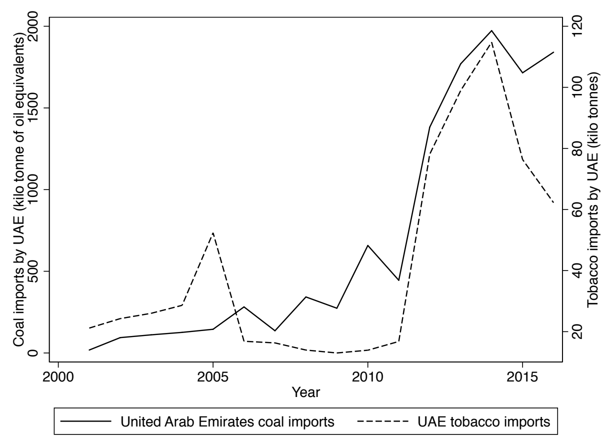
Notes: This table shows correlations in the weekly number of attacks carried out by al-Shabaab and al-Qaeda in the Arabian Peninsula (AQAP); public targets are police, military, governments and educational institutions; private targets are civilians, religious leaders and businesses. Data are drawn from Global Terrorism Database; see Alfano and Görlach (2021) for further details.

Figure A6: Natural gas, tobacco, coal and terrorist attacks by AQAP and al-Shabaab

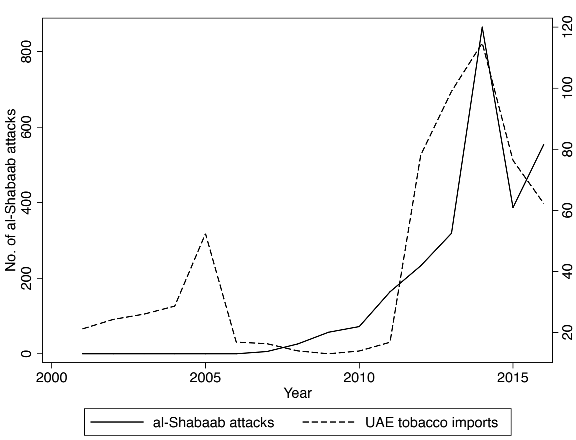
(a) Yemen's gas exports and AQAP attacks



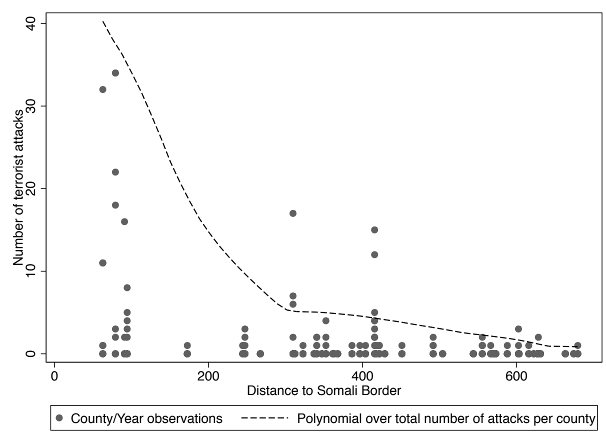
(b) UAE's tobacco and coal imports



(c) UAE tobacco imports and al-Shabaab attacks



(d) Attacks and distance to Somali border



Notes: Panel (a) shows attacks by AQAP for each year and terajoules of natural liquid gas exported by Yemen; Panel (b) shows coal imports by the UAE in kilo tonne of oil equivalents and tobacco imports in kilo tonnes; Panel (c) shows attacks by al-Shabaab for each year and tobacco imports by the UAE in kilo tonnes; Panel (d) shows the number of annual attacks occurring in each Kenyan county between 2001 and 2014 by distance between the county's centroid and the Kenyan/Somali border; Sources: Global Terrorism Database, International Energy Agency, and UAE Federal Competitiveness and Statistics Authority; see Alfano and Görlach (2021) for further details.

G.2 Instrumenting media access

Based on previous findings, we instrument media access using three climatic and topographical variables.

i) Lightning strikes: We instrument media access using the frequency of lightning strikes, which decrease radio reception (see Manacorda and Tesei, 2020). For this we use lightning strike information drawn from the NASA Global Hydrology Resource Center, which records mean annual total lightning flash rates on a 0.5 degree grid from November 1997 to April 2015. We overlay the NASA map with the geographical coordinates of DHS respondents to calculate lightning strikes at the exact geographical location of households. Given the non-linear relationship between lightning strikes, infrastructural damage, and radio signal, we define the variable $light_i = \frac{1e-6}{strikes_i^2}$, where $strikes_i$ denotes the mean annual total lightning flash rate.[36]

ii) Terrain surface: Uneven terrain worsens radio reception. In fact, terrain surface is one major components of the ITM/Longley-Rice algorithm commonly used for calculating radio reception (see Yanagizawa-Drott, 2014). We measure terrain surface via the Terrain Ruggedness Index, which denotes changes in elevations and has been used by Nunn and Puga (2012). Given the non-linear relationship between terrain surface and radio signal reception, we define the variable $rugged_i = \frac{1e6}{ruggedness_i^2}$, where $ruggedness_i$ is the Terrain Ruggedness Index.

iii) Wind speed: Wind speed decreases both radio signal transmission and its reception. Wind can damage infrastructure, such as antennae, and can also cause electrical problems thus decreasing radio transmission. Moreover, wind can refract radio waves and hence decrease radio reception. We measure wind as air density at 100 metres altitude, which corresponds roughly to the height of antennae. Given the non-linear relationship between wind speed and radio signal reception, we define the variable $wind_i = exp(airdensity_i)/1e6$, where $airdensity_i$ denotes air density at 100 metres altitude.

Using these three measurements combined with the three instruments for terrorist attacks outlined above, we instrument the three endogenous variables $attacks_{it}$, $signal_i$ and $attacks_{it} \times signal_i$. Note that, since we instrument radio signal coverage, there is no temporal variation in $signal_i$ and thus we omit the t subscript. The first stages corresponding to column 2 of table 3 are as follows:

[36] Since the exogeneity of our instruments does not depend on transformations, we choose functional forms which yield a strong first stage.

$$
\begin{aligned}
attacks_{it} \;=\;& \psi_1 \frac{AQAP_t}{location_i} + \psi_2 \frac{gas_t}{location_i} + \psi_3 \frac{tobacco_t}{location_i} \\
&+\psi_4 \frac{AQAP_t}{location_i} \times light_i + \psi_5 \frac{gas_t}{location_i} \times light_i + \psi_6 \frac{tobacco_t}{location_i} \times light_i \\
&+\psi_7 \frac{AQAP_t}{location_i} \times rugged_i + \psi_8 \frac{gas_t}{location_i} \times rugged_i + \psi_9 \frac{tobacco_t}{location_i} \times rugged_i \\
&+\psi_{10} \frac{AQAP_t}{location_i} \times wind_i + \psi_{11} \frac{gas_t}{location_i} \times wind_i + \psi_{12} \frac{tobacco_t}{location_i} \times wind_i \\
&+\psi_{13} light_i + \psi_{14} rugged_i + \psi_{15} wind_i + \boldsymbol{x}'_{it}\boldsymbol{\delta} + \kappa_{c_i} + \tau_t + u_{it},
\end{aligned}
$$

$$
\begin{aligned}
attacks_{it} \times signal_i \;=\;& \phi_1 \frac{AQAP_t}{location_i} + \phi_2 \frac{gas_t}{location_i} + \phi_3 \frac{tobacco_t}{location_i} \\
&+\phi_4 \frac{AQAP_t}{location_i} \times light_i + \phi_5 \frac{gas_t}{location_i} \times light_i + \phi_6 \frac{tobacco_t}{location_i} \times light_i \\
&+\phi_7 \frac{AQAP_t}{location_i} \times rugged_i + \phi_8 \frac{gas_t}{location_i} \times rugged_i + \phi_9 \frac{tobacco_t}{location_i} \times rugged_i \\
&+\phi_{10} \frac{AQAP_t}{location_i} \times wind_i + \phi_{11} \frac{gas_t}{location_i} \times wind_i + \phi_{12} \frac{tobacco_t}{location_i} \times wind_i \\
&+\phi_{13} light_i + \phi_{14} rugged_i + \phi_{15} wind_i + \boldsymbol{x}'_{it}\boldsymbol{\delta} + \kappa_{c_i} + \tau_t + u_{it},
\end{aligned}
$$

$$
\begin{aligned}
signal_i \;=\;& \xi_1 \frac{AQAP_t}{location_i} + \xi_2 \frac{gas_t}{location_i} + \xi_3 \frac{tobacco_t}{location_i} \\
&+\xi_4 \frac{AQAP_t}{location_i} \times light_i + \xi_5 \frac{gas_t}{location_i} \times light_i + \xi_6 \frac{tobacco_t}{location_i} \times light_i \\
&+\xi_7 \frac{AQAP_t}{location_i} \times rugged_i + \xi_8 \frac{gas_t}{location_i} \times rugged_i + \xi_9 \frac{tobacco_t}{location_i} \times rugged_i \\
&+\xi_{10} \frac{AQAP_t}{location_i} \times wind_i + \xi_{11} \frac{gas_t}{location_i} \times wind_i + \xi_{12} \frac{tobacco_t}{location_i} \times wind_i \\
&+\xi_{13} light_i + \xi_{14} rugged_i + \xi_{15} wind_i + \boldsymbol{x}'_{it}\boldsymbol{\delta} + \kappa_{c_i} + \tau_t + u_{it},
\end{aligned}
$$

Table A5: IV First Stages

	(1)	(2)	(3)	(4)	(5)
	Instumenting attacks		Instumenting signal and attacks		
Dependent variable:	# terrorist attacks	# terrorist attacks × Signal	Signal Coverage	# terrorist attacks	# terrorist attacks × Signal
AQAP/Distance	3.708	0.662	0.383	2.736	−5.185
	(3.112)	(0.565)	(0.088)	(5.481)	(2.848)
Gas/Distance	1.494	0.142	−0.151175	1.525884	−0.298902
	(1.330)	(0.272)	(0.056)	(1.840)	(0.657)
Tobacco/Distance	1.493	−0.375	−0.972	1.164	−1.877
	(4.269)	(1.053)	(0.176)	(6.413)	(3.345)
(AQAP/Distance)× Signal	−0.099	1.994			
	(1.056)	(1.841)			
(Gas/Distance)× Signal	0.049	1.452			
	(0.457)	(1.055)			
(Tobacco/Distance)× Signal	−0.018	3.494			
	(1.349)	(2.622)			
(AQAP/Distance)× Lightning			−0.269	11.020	9.313
			(0.105)	(3.926)	(2.977)
(Gas/Distance)× Lightning			0.172	−4.250	−1.810
			(0.076)	(2.386)	(1.575)
(Tobacco/Distance)× Lightning			0.640	−12.576	−5.296
			(0.246)	(6.312)	(4.420)
(AQAP/Distance)× Ruggedness			0.071	5.877	5.741
			(0.099)	(1.479)	(1.400)
(Gas/Distance)× Ruggedness			−0.062	−2.649	−2.623
			(0.049)	(0.729)	(1.095)
(Tobacco/Distance)× Ruggedness			−0.226	−7.013	−8.328
			(0.259)	(2.398)	(3.104)
(AQAP/Distance)× Wind			−3.987	−35.058	44.461
			(0.728)	(51.856)	(37.166)
(Gas/Distance)× Wind			1.409	18.519	21.545
			(0.487)	(24.829)	(18.265)
(Tobacco/Distance)× Wind			10.537	58.463	69.164
			(1.590)	(64.292)	(58.252)
Lightning			0.349	4.039	0.349
			(0.877)	(4.554)	(1.848)
Ruggedness			0.026	1.617	1.261
			(0.114)	(1.002)	(0.961)
Wind			−5.987	−18.313	−20.106
			(2.655)	(19.610)	(12.947)
Kleinbergen-Paap F-Statistic	83.1	35.5	31.0	917.2	1662.2
***c* and *t* effects and covariates**	YES	YES	YES	YES	YES
R squared	0.737	0.637	0.494	0.756	0.492
Observations	40,724	40,724	40,276	40,276	40,276

Notes: The table reports the first stage results for the replication of our main estimates in table 3; variables are defined in appendix G; standard errors are clustered at county level.

H Heterogeneous responses

We use the longitudinal dimension of the HSNP data for an additional check on whether the response to terrorist attacks is correlated with income. The same heterogeneity in the response will also be used for identification of unobserved heterogeneity in expectations in the structural model.

Specifically, we compute a proxy for household-level responses

$$q_i^S \equiv (res_{it}^S - res_{it-1}^S)/(res_{c_i,t}^{attacks} - res_{c_i,t-1}^{attacks})$$

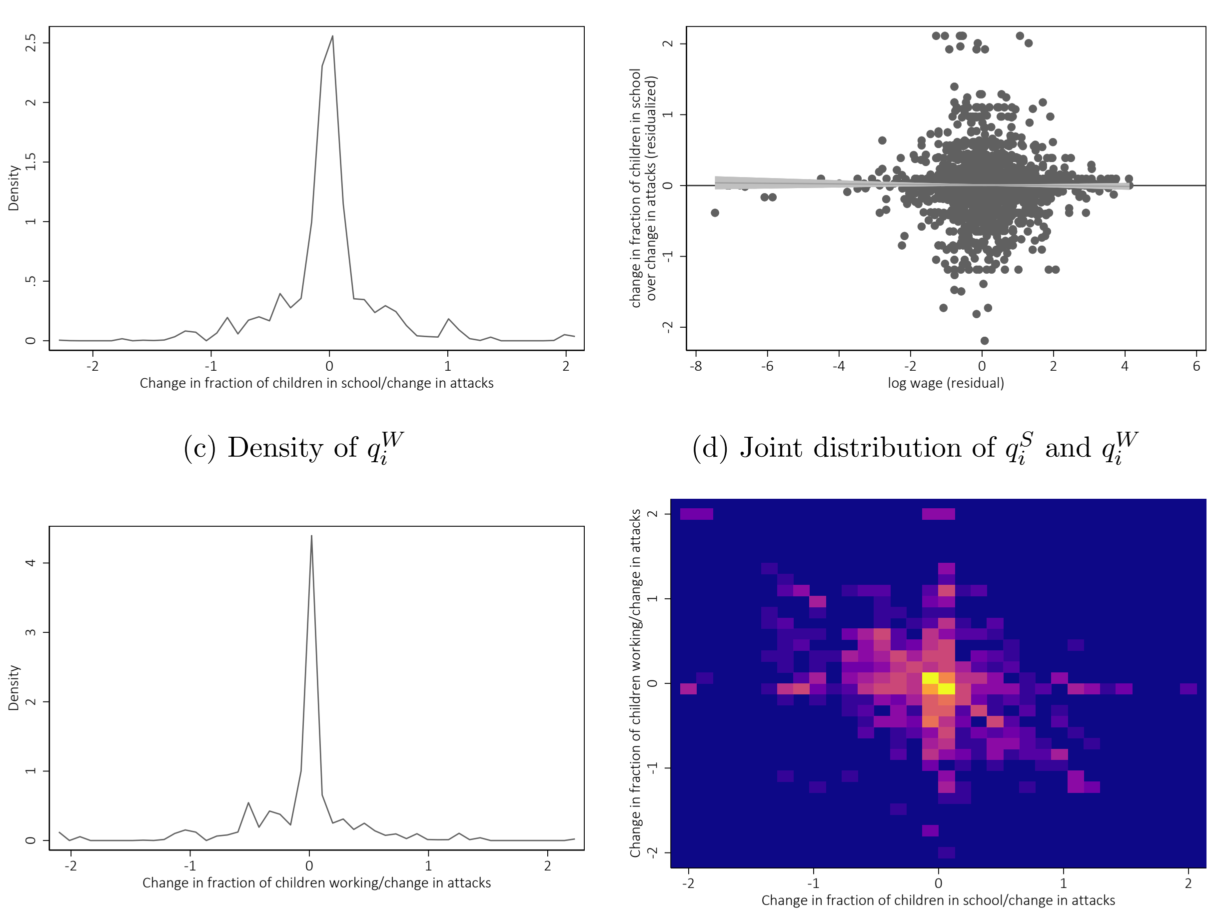
in the share of children enrolled in school to a change in attacks, where res_{it}^S and $res_{c_i,t}^{attacks}$ denote respectively residuals from regressions of household i's share of children going to school and of the number of attacks in the household's county c_i on county and year effects. This measure indicates, for each household, how the fraction of children in school changes relative to the change in attacks in the household's county. Panel (a) of figure A7 displays the distribution of q_i^S. To examine whether the response to attacks is driven by high- or low-income households, we plot q_i^S against (log) household income reported in the first wave of the HSNP, prior to the steep increase in attacks. Panel (b) of figure A7 displays the correlation between the two variables conditional on county effects, and reveals no significant relation.

We construct a similar measure for the household-level responses

$$q_i^W \equiv (res_{it}^W - res_{it-1}^W)/(res_{c_i,t}^{attacks} - res_{c_i,t-1}^{attacks})$$

in the share of children working to a change in attacks, where now res_{it}^W is the residual from a regression of household i's share of children working on county a year effects. Panel (c) of figure A7 displays the distribution of q_i^W, whereas panel (d) shows the density of the joint distribution of q_i^S and q_i^W. Our structural estimation of the model presented in Section 4 targets this joint density to identify the different dimensions of unobserved heterogeneity in the model.

Figure A7: Income and the response to terrorist attacks



(a) Density of q_i^S

(b) Correaltion with household income

(c) Density of q_i^W

(d) Joint distribution of q_i^S and q_i^W

Notes: The figure shows (a) the density of household's response intensity q_i^S in the fraction of children in school relative to attacks as described in the text; (b) the correlation of q_i^S with log household income, conditional on county effects; (c) the density of household's response intensity q_i^W in the fraction of children in work; and (d) the density of the joint distribution of q_i^S and q_i^W as a heat map. Source: Hunger Safety Net Program evaluation data 2010-2012.

I Details on data, identification and calculations in the structural model

Data: Most components of the model presented in Section 4.1 are observed directly in the survey data from the Hunger Safety Net Program. Table A6 lists the means of these variables as they are fed into the model.

Estimation: We estimate the structural parameter vector $\boldsymbol{\theta} = \{\boldsymbol{\pi}, \boldsymbol{\rho}, \boldsymbol{\kappa}^S, \boldsymbol{\kappa}^W, \boldsymbol{\tau}^S, \boldsymbol{\tau}^W\}$ of the model in Section 4.1, which comprises a total of 40 parameters, by minimizing the distance between theoretical moments $\boldsymbol{m}_m$ implied by the model and the corresponding data

Table A6: Model variables observed in the HSNP data

	Locations without signal coverage		Locations with signal coverage	
	Mean	Std.err.	Mean	Std.err.
Household income, y	907.95	(27.36)	1,155.87	(31.57)
Adult wage, non-educated, $w(e_i = NE)$	584.50	(16.35)	655.98	(15.29)
Adult wage, educated, $w(e_i = E)$	1,226.62	(112.17)	1,499.91	(87.98)
Child wage, w_c	188.88	(8.87)	232.86	(13.39)
Schooling costs, c_S	61.58	(12.07)	77.30	(3.37)
Household size, n	5.79	(0.05)	5.99	(0.06)

Notes: Signal coverage refers to radio signal coverage as indicated by data from `fmscan.org`. Source: Hunger Safety Net Programme evaluation data.

moments $\boldsymbol{m}_d$ from the HSNP sample. We use three groups of moments. First, we target the fractions of children in school and the fractions of children working by county and year, as reported in the HSNP data. We further do this separately for children who live in locations (within county) with radio signal coverage and for those without. This yields a first set of 2 activities x 4 counties x 3 years x 2 coverage states = 48 moments. Second, we target the regression coefficients reported in columns (3 and 4) of Table 3 (4 moments). Among the estimates that are based on the HSNP, these are our main reduced-form estimates of the effect of terrorist attacks on school enrolment and working by radio signal coverage. Third, we target heterogeneity in the response to terrorism. Specifically, we first construct the household-level proxy for changes in the fraction of children in school or working per change in attacks, q_i^S and q_i^W, which we describe in appendix H. We then target the mid-point of each quintile of these distributions, again separately for households with and without radio signal coverage (2 activities x 2 coverage states x 5 quintiles = 20 moments). Finally, we also target the joint density of crossed quintiles in these response measures by radio signal coverage (2 coverage states x 5 schooling response quintiles x 5 working response quintiles = 50 moments). Overall, this amounts to 122 moments used in the estimation. Our estimation minimizes the estimation criterion

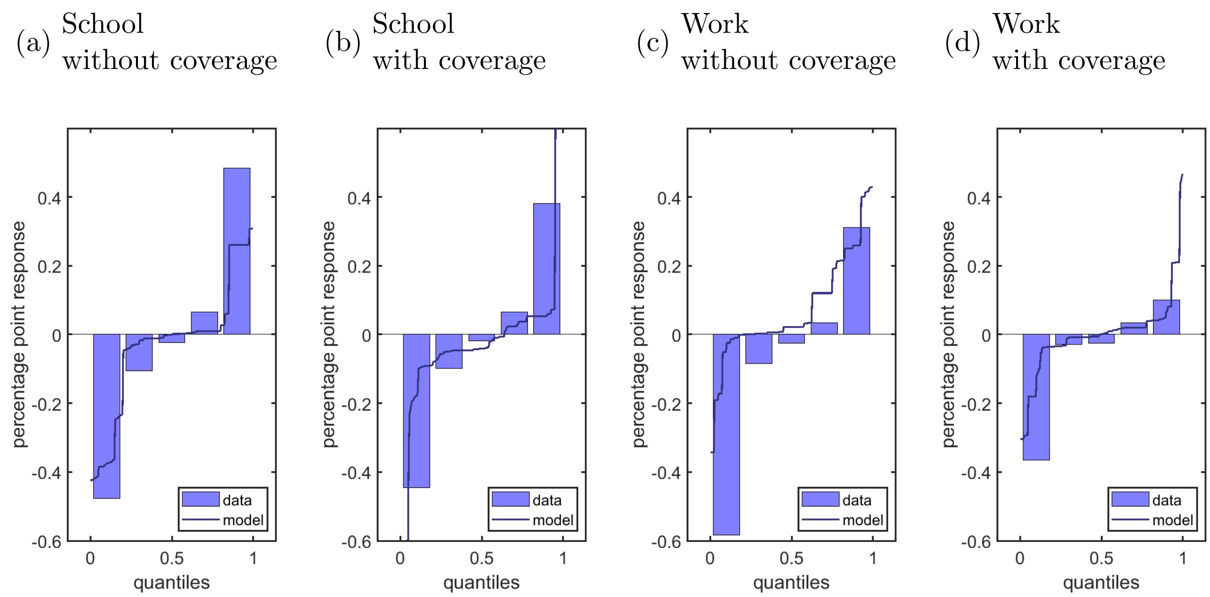
$$crit(\boldsymbol{\theta}) = \left(\boldsymbol{m}_d - \boldsymbol{m}_m(\boldsymbol{\theta})\right)' \left(\boldsymbol{m}_d - \boldsymbol{m}_m(\boldsymbol{\theta})\right),$$

The moments targeted and the model's fit are summarized in figures A8 and A9.

Identification: We describe the intuition for the identification of different sets of parameters in Section 4.2. To further support local identification of the model parameters through our set of moments, figure A10 visualizes the gradient matrix of moments with respect to parameters, $\frac{\partial \boldsymbol{m}_m'}{\partial \boldsymbol{\theta}}$. Identification requires that none of the parameters has a zero gradient vector (which would imply a blank row in figure A10), and that gradient vectors are linearly independent. In our gradient matrix this is the case, so that our set of moments point identifies the parameters under the model.

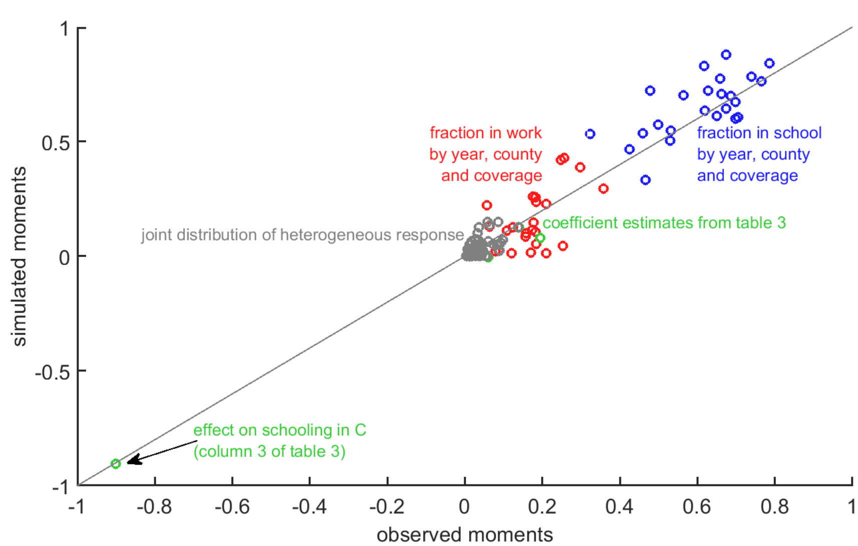
Alternative model: Data and targeted moments used in the estimation of the alternative model ("Model B") in Section 4.4 are the same as above. The resulting structural parameters are presented in table A8

Figure A8: Model fit I—Marginals of heterogeneous responses q_i^S and q_i^W



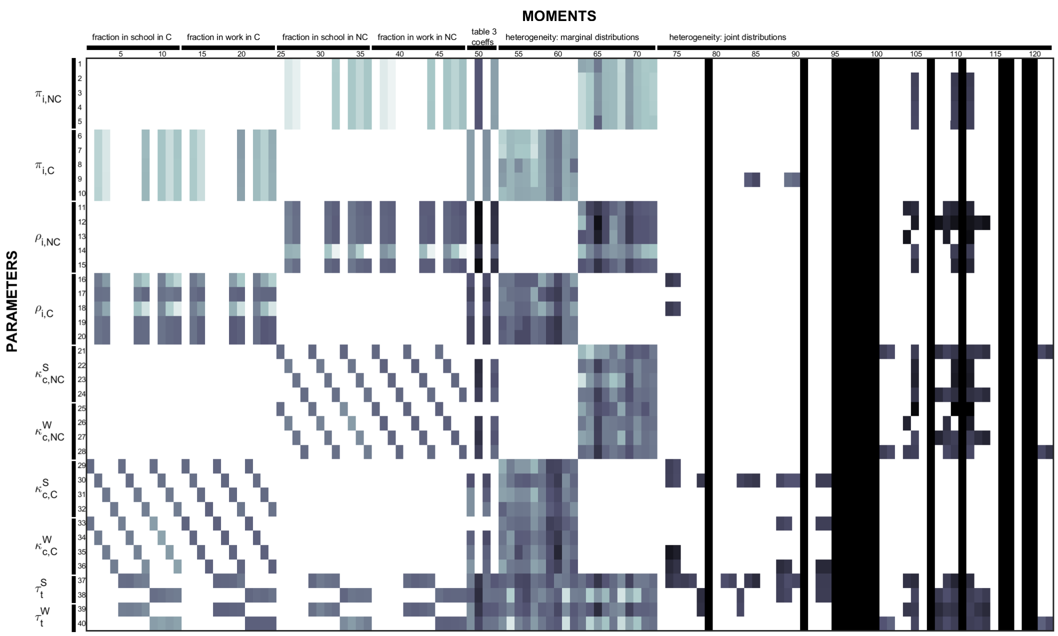
Notes: The figure shows the model fit with respect to the heterogeneous responses in school enrolment and working to terrorist attacks, separately for areas with and without radio signal coverage. Source: Hunger Safety Net Program evaluation data 2010-2012.

Figure A9: Model fit II—Other moments



Notes: Data and model moments that are not shown in figure A8. Coefficient estimates refer to the numbers in columns (3) and (4) of table 3. Source: Hunger Safety Net Programme evaluation data 2010-2012.

Figure A10: Gradient matrix



Notes: This figure visualizes the gradient matrix of moments (columns) with respect to parameters (rows). Darker shades indicate larger absolute gradients.

Table A7: Parameter estimates

	Fear factor (π_i)		**Returns to schooling** (ρ_i)	
Without signal coverage:				
Type	Point est.	99% CI	Point est.	99% CI
1	0.132	[0.058 ; 0.190]	-0.093	[-0.124 ; -0.071]
2	0.695	[0.369 ; 0.926]	-0.015	[-0.020 ; -0.008]
3	0.770	[0.361 ; 1.039]	-0.009	[-0.012 ; -0.006]
4	1.313	[0.000 ; 1.830]	0.967	[0.768 ; 1.476]
5	1.367	[0.698 ; 1.780]	-0.102	[-0.130 ; -0.067]
With signal coverage:				
Type	Point est.	99% CI	Point est.	99% CI
6	0.164	[0.065 ; 0.223]	0.578	[0.511 ; 0.767]
7	0.792	[0.454 ; 1.070]	-0.011	[-0.015 ; -0.006]
8	11.818	[11.219 ; 17.718]	0.746	[0.552 ; 0.909]
9	13.488	[11.469 ; 19.257]	-0.298	[-0.322 ; -0.259]
10	16.733	[14.558 ; 28.639]	-0.292	[-0.316 ; -0.254]
County $\times$ coverage and year effects included				

Notes: Estimates for the model parameters detailed in Section 4.1, based on HSNP (2010-2012) data. Bootstrapped 99% confidence intervals (1,000 replications) in brackets.

Table A8: Parameter estimates for alternative model

	Risk aversion (γ_i)		**Returns to schooling (ρ_i)**	
Without signal coverage:				
Type	Point est.	99% CI	Point est.	99% CI
1	0.787	[0.689 ; 0.792]	-0.139	[-0.154 ; -0.104]
2	0.916	[0.911 ; 0.966]	-0.008	[-0.010 ; -0.007]
3	0.921	[0.913 ; 0.947]	-0.018	[-0.022 ; -0.014]
4	0.967	[0.962 ; 0.975]	-0.108	[-0.120 ; -0.086]
5	0.990	[0.988 ; 0.992]	0.822	[0.649 ; 1.013]
With signal coverage:				
Type	Point est.	99% CI	Point est.	99% CI
6	0.933	[0.925 ; 0.961]	-0.370	[-0.463 ; -0.346]
7	0.939	[0.933 ; 0.965]	-0.271	[-0.302 ; -0.252]
8	0.948	[0.942 ; 0.968]	0.892	[0.786 ; 1.143]
9	0.985	[0.982 ; 0.990]	0.690	[0.630 ; 0.913]
10	0.991	[0.991 ; 0.995]	-0.015	[-0.018 ; -0.011]
County × coverage and year effects included				

Notes: Estimates for the parameters of the alternative model ("Model B") detailed in Section 4.4, based on HSNP (2010-2012) data. Bootstrapped 99% confidence intervals (1,000 replications) in brackets.