Received: 2 February 2023 | Revised: 10 January 2024 | Accepted: 22 January 2024

DOI: 10.1002/jae.3058

WILEY Journal of APPLIED ECONOMETRICS

RESEARCH ARTICLE

Terrorism and education: Evidence from instrumental variables estimators

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Summary

This paper estimates the effect of exposure to terrorist violence on education. Since terrorists may choose targets endogenously, we construct a set of novel instruments. To that end, we leverage exogenous variation from a local terrorist group's revenues and its affiliation with al-Qaeda. Across several Kenyan datasets, we find that attacks suppress school enrolment more than predicted by difference-in-differences-type estimators. This indicates that terrorists target areas experiencing unobserved, positive shocks. Evidence suggests fears and concerns as mechanisms of impact, rather than educational supply.

KEYWORDS

education, instrumental variables, terrorism

1 | INTRODUCTION

The threat of terrorism has risen high on the global policy agenda. Between 2000 and 2015, the number of terrorist attacks per year has increased from less than 2,000 to more than 16,000.[1] Contrary to war, civil conflict, organised crime and other forms of violence, the effect of terrorism on human capital investment has received relatively little attention. Yet, the analysis of terrorism entails unique empirical challenges and thus warrants its own distinct considerations, since terrorists may chose their targets strategically to maximise impact (Brandt & Sandler, 2010; Krueger & Maleckova, 2003; Kydd & Walter, 2006; Santifort et al., 2013).

This paper estimates the effect of terrorist attacks on education using a novel set of instruments to explicitly account for a bias arising from terrorists' target choices. The focus of our analysis is on terrorist attacks in Kenya by al-Shabaab, a terrorist organisation belonging to the al-Qaeda network. Terrorists may select targets based on time and location varying factors, which may not be observable to the researcher. If these unobserved factors also correlate with schooling, difference-in-differences (DiD) type estimators will be biassed. Our analysis first provides a theoretical framework for such a bias to occur. Thereafter, the paper addresses the possible endogeneity of terrorist attacks by estimating their effect on schooling using three different instruments, which leverage the group's position in the al-Qaeda network and its revenue sources.

We instrument both the timing and location of attacks using unique features of the Kenyan context. To predict the *timing* of attacks, we use three sources of variation related to revenue streams of al-Shabaab as well as its position in the al-Qaeda network. 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). We document not only that al-Shabaab closely follows AQAP in

[1]Global Terrorism Database, https://www.start.umd.edu/gtd/search/Results.aspx?search=&sa.x=54&sa.y=3, accessed March 2022.

its timing of attacks but also that it chooses similar targets. Second, we exploit the fact that revenue streams for al-Qaeda derived from Yemen's exports of hydrocarbons increase the intensity of attacks by both AQAP and al-Shabaab. Finally, we look at al-Shabaab's main source of income directly: the export of charcoal. A major trading partner for Somalia's charcoal is the United Arab Emirates (UAE) 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.[2] Throughout our specifications, 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. Our estimation hence allows for unobserved heterogeneity particular to a location or country wide variation over time to both correlate with terrorist exposure and affect school enrolment. The resulting three instruments make for a strongly overidentified model, and the implied exclusion restrictions are not rejected.

Based on enrolment data digitised from reports by the ministry of education, we find that each attack keeps 711 children out of school. We complement this analysis with nationally representative Demographic Health Survey data, which allow us to construct enrolment rates back to 2001, before terrorist attacks had started. For the years before the stark increase in terrorist attacks, we find parallel trends between areas affected and unaffected by attacks. Our results show that enrolment at school entry age decreases by around 1.0 percentage points per attack. At an average number of 13.4 attacks per county in the most affected regions[3] after 2010, this translates into a sizeable negative effect on school enrolment. The 2SLS estimate of −1.0 percentage points per attack is a statistically significant 0.31 percentage points more negative than the corresponding panel estimate. In other words, the true effect of terrorism is $(1.00–0.69)/0.69 \approx 45\%$ stronger than suggested by the DiD estimator. This positive bias in conventional panel estimators suggests that terrorist groups do not strike at random. Instead, our results indicate that terrorists target areas that experience positive shocks.

Information on alternative activities by children and on the reasons for not attending school shows that many children stay at home rather than substituting work with school in response to terrorist attacks near by. Moreover, we find no effect of terrorist attacks on teacher absences as a reason for school absences by children, suggesting that rather than supply side factors, parents' fear is the driving force behind the reduction in schooling. We corroborate this by using data on self-reported fears and concerns from four rounds of the Afrobarometer, a representative attitudinal survey. The results show that attacks increase fear of crime and decrease optimism about future economic conditions. Again, effects are stronger for IV than for DiD estimates. These additional results are suggestive of broader mental health effects (Kim & Albert Kim, 2018; Metcalfe et al., 2011; Whalley & Brewin, 2007). Other potential mechanisms include effects on risk aversion for which the literature provides some evidence (Brown et al., 2019).

We also explore the importance of geographically disaggregated data and show that the discrepancy between the DiD and IV estimators disappears when we use more finely geocoded measures of individuals' exposure to attacks. Specifically, we consider attacks within a 2.5 km radius around children's dwellings, 2.5 km around the closest primary school or 2.5 km around the way to school. Our results suggest that spatially disaggregated measurements of individuals' exposure to terrorist attacks can mitigate the estimation bias when it arises on a broader geographic level. Using the exact geographical coordinates of attacks, individuals and schools allows the researcher to compare children who are more or less directly affected by terrorist attacks, while holding constant any shock that might be occurring to the region as a whole.

We provide numerous pieces of evidence supporting the validity of the exclusion restriction and the robustness of our results. Since we use solely the interaction between timing and location variations as an instrument, the only factors that can violate the exclusion restriction must vary over time and simultaneously by geographical location. Thus, any global event affecting the whole of Kenya, such as oil prices, for instance, is absorbed by the fixed effects. One possibility is that UAE tobacco imports increase the profitability of charcoal production thus directly affecting the opportunity costs of children's schooling. Using detailed information on children's and adults' activities drawn from a longitudinal survey, we show that charcoal producing activities and also charcoal expenditure are uncorrelated with our instruments. We also address the concern that global economic trends drive both Yemeni gas exports and schooling in Kenya by showing that Kenya's fuel trade share is uncorrelated with gas exports from Yemen. Moreover, we do not find evidence of households closer to the Somali border having higher news consumption that could explain a direct response to AQAP activity abroad rather than to locally carried out terrorist attacks. We also find no effects on children moving away nor do we observe

[2]Past research has pointed out that physical distance presents a significant obstacle to terrorism (Krueger, 2007). In the Kenyan case, this corresponds to distance from the Somali border. As a robustness check, we consider the distance of respondents to the Dadaab refugee complex located in the northeastern county of Garissa.

[3]The northeastern counties Garissa, Mandera and Wajir.

trends in the emigration rate from Kenya that would mirror the rise in terrorist events. Results remain robust when we absorb the possible confounding effect of public expenditures and GDP by using specifications that allow these to have a disproportionate effect in regions most affected by terrorism. We further submit our estimates to a battery of robustness checks, dropping, for instance, certain areas and time periods from our sample, and find no significant changes in our estimates. We find no heterogeneity with respect to the specific targets of attacks.

Our paper directly complements the literature estimating the impact of violence on educational outcomes (Bertoni et al., 2019; Brown & Velásquez, 2017; Brück et al., 2019; Cabral et al., 2021; Di Maio & Nisticò, 2019; Foureaux Koppensteiner & Menezes, 2021; Guariso & Verpoorten, 2019; Justino et al., 2013; Lekfuangfu, 2022; León, 2012; Monteiro & Rocha, 2017) but addresses the identification challenges idiosyncratic to terrorist attacks directly using instrumental variables estimators.

Our first stage estimations also contribute to the knowledge base on the workings of terrorist networks, which have received considerable attention in the quantitative social sciences during the last two decades (Abadie & Gardeazabal, 2003; Abadie, 2006; Ashworth et al., 2008; Berman & Laitin, 2008; Shapiro & Siegel, 2007). Our analysis on al-Shabaab's revenues and its position within the al-Qaeda network provides the first quantitative evidence on the strong relation between al-Shabaab on the one hand and its revenues and attacks carried out by AQAP on the other, links which thus far have been analysed from a qualitative point of view (e.g., in Zimmermann, 2013).

After describing the context and data sources used, we discuss our instrumental variables in Section 3. Thereafter, Section 4 discusses the results, addresses identification concerns and provides robustness checks. Finally, Section 5 concludes.

2 | CONTEXT AND DATA

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 geographical coordinate, number of casualties and group responsible.

Most attacks in Kenya are carried out by al-Shabaab, an Islamist terror organisation founded in the early 2000s in Somalia with the aim of overthrowing governments in the Horn of Africa region and to install Islamic rule. During the last two decades, al-Shabaab has been present in large parts of Somalia.[5]

Al-Shabaab is an affiliate of al-Qaeda with particularly strong ties to AQAP. Al-Qaeda operates in a network structure with al-Qaeda core, led directly by the 'emir', at its centre along with sets of associated groups. Closest to the core are the regional affiliates, such as al-Qaeda in Iraq, al-Qaeda in the Islamic Maghreb and AQAP. Next are groups subscribing to al-Qaeda's ideology and influence and which are officially recognised by al-Qaeda core. These organisations have pledged allegiance to the 'emir', and al-Shabaab is one of them. Furthest away are associates that have not been publicly recognised as al-Qaeda but are close in terms of ideology. These include, for instance, Boko Haram in Nigeria. See Zimmermann (2013) for more details and supporting information Appendix A for the geographical distribution of attacks across Kenya and Somalia attributed to al-Shabaab.

We focus on the years 2001 to 2014, during which Kenya experienced 367 terrorist attacks aimed mainly at civilians and businesses (122 attacks) and police and military forces (118); see Table A1 in Appendix C in the supporting information. Figure 1a illustrates their geographical distribution across the country (circle sizes are proportional to the number of fatalities of terrorist attacks). Most attacks are concentrated in the three northeastern counties Mandera, Wajir and Garissa, which border Somalia, as well as in the two largest towns, Nairobi and Mombasa. The bars in Figure 1b show the temporal variation in terrorist attacks, with a sharp increase in the intensity of attacks from the late 2000s onwards. Maps in the supporting information Appendix B show the geo-temporal variation of terrorist attacks. Figure A4 in Appendix C in the supporting information further illustrates the vicinity between children and terrorist attacks in two different ways. Figure C4a displays the proportion of attacks occurring in the vicinity of schools and shows that between 2011 and 2014, about 80% of attacks occurred within 5 km of a school. Figure C4b calculates the percentage of

[4] The data are available online (https://www.start.umd.edu/gtd/about/).

[5] See, for instance, Anderson and McKnight (2015) for further background.

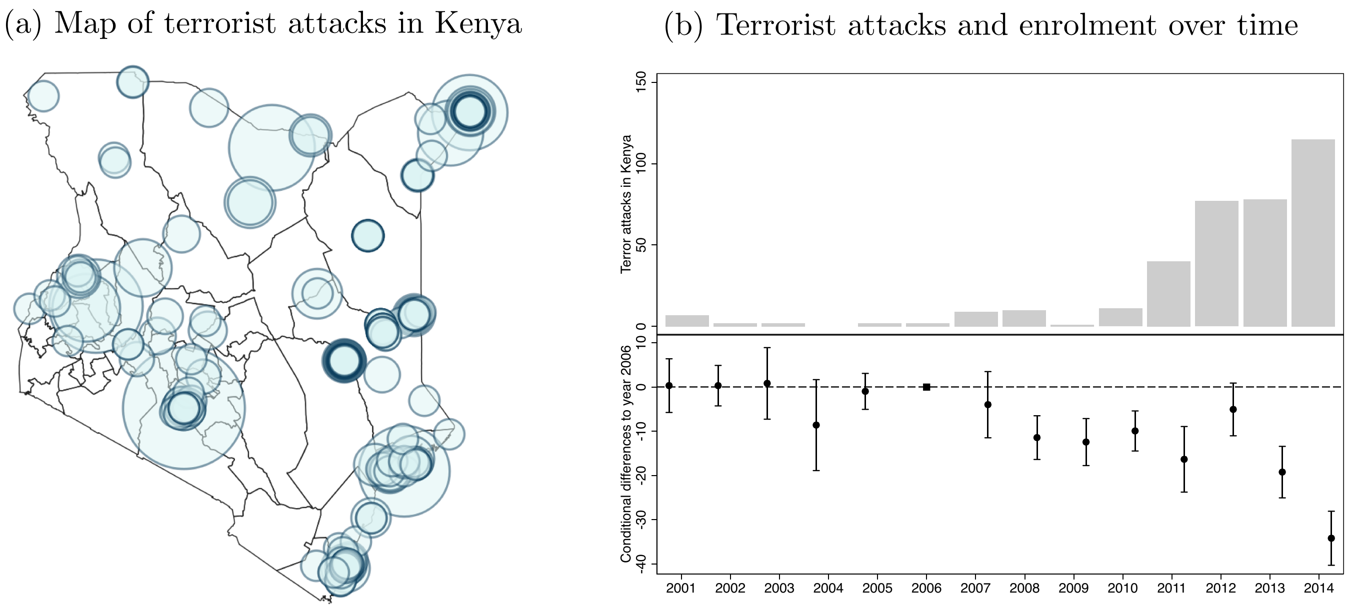

FIGURE 1 Terrorist attacks in Kenya—spatial and temporal variation. *Notes*: The Figure shows (a) the spatial variation in terrorist attacks during the years 2001-2014; circle radii are proportional to number of fatalities in an attacks; panel (b) reports the total number of attacks over time (bars) and yearly differences in children enrolling in school by age 7 between northeastern Kenya (Mandera, Wajir and Garissa) and the rest of the country conditional on covariates, county and time effects; the coefficient for 2006 has been normalised; Sources: Global Terrorism Database and Demographic Health Surveys.

children for whom a terrorist attacks occurs on the way to school. For the whole of Kenya (thus including areas with no terrorist attacks), almost 5% of primary school children experienced an attack within 2.5 km around the line connecting their residence to the closest primary school. This share increases to around 30% in the most exposed areas of the Northeast.

2.2 | Measurement of terrorist attacks

Following the approaches taken by previous studies, we use three different measurements for children's exposure to attacks. As our most basic measure, we count the number of terrorist attacks per county. As an alternative, we consider attacks within a given radius (2.5 km) around the geographic coordinate of respondents' residence. This definition of treated areas is similar to the one adopted in a recent study by Bertoni et al. (2019). Following the detailed analysis by Foureaux Koppensteiner and Menezes (2021), we sharpen our measure further by linking children to primary schools in two ways. First, we identify the closest primary school to each child and measure attacks 2.5 km around it. Second, we identify attacks occurring within a corridor around the line connecting a child's residence with the closest primary school (see maps (c) and (d) in the supporting information Appendix A).

2.3 | Data on education in Kenya

Kenyan primary education covers 8 years, and the school year runs from January to October. At the end of each year, children automatically advance to the next year. Determinants of education outcomes in Kenya have been investigated, for instance, by Duflo et al. (2011), Lucas and Mbiti (2012), Lucas and Mbiti (2014) and Bold et al. (2018). We measure school enrolment in different ways using three distinct and independent panel data sources. First, we use official information on the total number of children enrolled in primary school for each county, which we digitised from printed reports by the Ministry of Education (Kenya National Bureau of Statistics, 2004).

We complement this county panel with individual level data drawn from two rounds of the Kenyan Demographic Health Surveys (DHS), 2009 and 2014.[6] These two rounds of the Kenyan DHS are nationally representative and interviewed

[6] Demographic Health Survey data are publicly available online (dhsprogram.com).

9057 and 36,430 households, respectively.[7] The questionnaires collect extensive information on educational enrolment and years spent in school for all household members. We combine information on the current age of each child with the number of completed school years to calculate school entry age.[8] We then define a dummy variable taking the value 1 if children of school entry age indeed enrol in school.[9] The advantage of this measure is that it provides us with a longitudinal dimension reaching back in time as children reach school entry age in different years and thus allows us to examine educational time trends before the stark increase in terrorist activity.

To investigate changes in enrolment rates over time, we regress the dummy for whether children enrol at the age mandated by the government on the interaction of year dummies and an indicator variable for the child residing in one of the strongly affected northeastern counties.[10] The bottom part of Figure 1b shows the resulting coefficients, with 2006 as the base period.[11] Enrolment before the sharp increase in terrorist activity exhibits very parallel trends, with statistically indistinguishable slopes across both areas (p-value of 0.21). As attacks increase, enrolment in the affected areas decreases.

Third, we use household data collected to evaluate the Hunger Safety Net Programme (HSNP) in four counties of Kenya: Mandera, Marsabit, Turkana and Wajir (see map (f) in supporting information Appendix A). Mandera and Wajir are among the counties experiencing the highest number of terrorist attacks, and the detailed information on reasons for not attending school, including teacher absence and alternative time use by children, provides insights into likely mechanisms behind the estimated effects. See supporting information Appendix C for more detail.

3 | ESTIMATION

Before estimating the effect of terrorist attacks on education using our instruments, we recreate the approach taken by much of the previous literature, which relates various enrolment measures, $school_{it}$, for an individual i in year t to violent (and in our case terrorist) incidences in the individual's vicinity, $attacks_{it}$, as

$$school_{it} = \alpha \, attacks_{it} + \boldsymbol{X}'_{it}\boldsymbol{\beta} + \gamma_{c_i} + \tau_t + u_{it}, \tag{1}$$

where we control for unobserved factors γ_{c_i} determining the level of enrolment in the county c_i where individual i resides, as well as for country wide variation in aggregate conditions over time through year indicators τ_t. In addition, we control for a number of household and location specific characteristics $\boldsymbol{X}_{it}$, including the child's gender, an indicator for living in a rural location, for the household having electricity, radio and TV, for whether the household head has secondary education as well as rainfall (for the whole year and growing-season specific) and latitude and longitude of the child's residence.

3.1 | Endogeneity of terrorist attacks

3.1.1 | Strategic target choice by terrorists

Terrorism is different from other types of violence in as much as terrorists are interested in the societal effect of their actions beyond the violent events themselves. As a consequence, terrorists are likely to select their targets to maximise the psychological impact of the attacks. This strategic target choice, in turn, throws up identification challenges, which may not apply to other types of violence. For instance, when analysing shootings in cities such as São Paulo (Foureaux Koppensteiner & Menezes, 2021), incidences of violence may be plausibly (conditionally) quasi-random. By contrast, it

[7] The Kenyan DHS strongly expanded across the two waves, with each cross-section being nationally representative.

[8] We consider children who at the time of the interview were below 14 years old. We drop the small percentage (6%) of children in school 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.

[9] The school entry age set by the government is 6. We include children aged 7 since these children may have turned 7 between enrolling in school and the time the DHS was collected. Our measure tallies with aggregate enrolment data for similar years. The World Bank, for instance, reports a net primary school enrolment rate of 80% in 2012 (the last year available on the World Bank Open Data homepage https://data.worldbank.org/, accessed October 2019. In our data, the fraction of children enrolled by the age of 7 is 81.2% for the years 2010 to 2014.

[10] The counties Garissa, Mandera and Wajir bordering Somalia together suffered almost 12 times more terrorist attack per capita than the rest of in Kenya.

[11] The 2007 presidential elections were followed by sever turmoil and may have slightly affected enrolment rates. This crisis, however, was concentrated in Western Kenya, included in the control group, and thus cannot explain the divergence of enrolment trends.

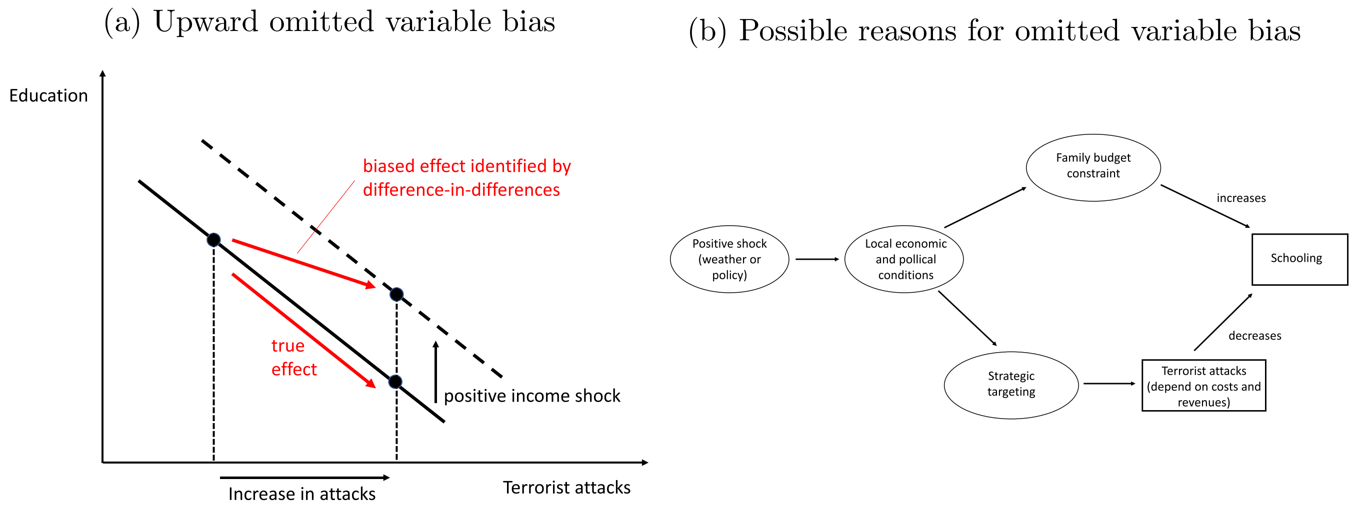

FIGURE 2 Theory—graphical illustration. *Notes*: Panel a) illustrates the bias in DiD estimators if terrorists target areas experiencing positive shocks. Panel b) illustrates one possibility through which this bias can arise.

might be al-Shabaab's strategy to target areas experiencing positive development shocks, possibly in order to maximise impact and social distress.[12] In the supporting information Appendix D, we provide some suggestive evidence for strategic targetting by terrorist groups. The table shows the correlation between predicted levels of education (using information from the period before terrorist attacks started) and terrorist attacks. Columns (1) and (3) show a positive (albeit insignificant) positive association. This correlation suggests that terrorists target areas that are predicted to fare better in terms of education.

3.1.2 | Omitted variable bias

If terrorists' strategic choices correlate with both the treatment and the outcome variable (and cannot perfectly be controlled for by the researcher), it will lead to an *omitted variable bias*. If terrorist targets areas experiencing positive shocks, the regression estimates of the effect of terrorism on school enrolment are biassed *upward* despite no obvious violation of the parallel trends assumption before the sharp increase in terrorist activity shown in Figure 1b. Crucially, it is not possible to address this concern using DiD estimators.

Unobserved shocks that vary over time and by location can arise from a number of sources. Weather shocks, for instance, have been documented to affect both economic conditions and conflict (Bazzi & Blattman, 2014; Buonanno et al., 2015; Burke et al., 2015; Chassang & Padró i Miquel, 2009; Gehring et al., 2023; Harari & La Ferrara, 2018; Miguel et al., 2004). Another example is the staggered rollout of development projects. The World Bank, for instance, has invested 1.1 billion from 2010 onwards to increase electricity capacity[13] and USD 44 million from 2004 to 2008 to boost agricultural productivity.[14]

Figure 2a illustrates the bias that would arise in standard estimators if terrorists target areas experiencing positive income shocks (as highlighted by Berman et al., 2017). In this case, the estimated effect would be weaker (i.e. less negative) than the real effect, since income shocks and the increase in attacks (the two black arrows in Figure 2a) correlate positively. Figure 2b provides an example of how unobserved shocks can both increase (by increasing budget available to families) and decrease (through attracting more attacks) schooling.

[12]Even absent strategic considerations, income shocks can either increase or decrease violent incidences (Dube & Vargas, 2013). An increase in income will translate into higher opportunity costs of violence thus decreasing its incidence. Alternatively, a rise in income can translate into more funds for armed groups and hence increase violence (Berman et al., 2017; for instance). Previous work has highlighted the latter income channel to be particularly relevant for terrorist groups (Koehler-Derrick & Milton, 2017; Limodio, 2022), which generally lack access to financial markets.

[13]https://projects.worldbank.org/en/projects-operations/project-detail/P103037 accessed December 2023.

[14]https://projects.worldbank.org/en/projects-operations/project-detail/P082396 accessed Dec 2023.

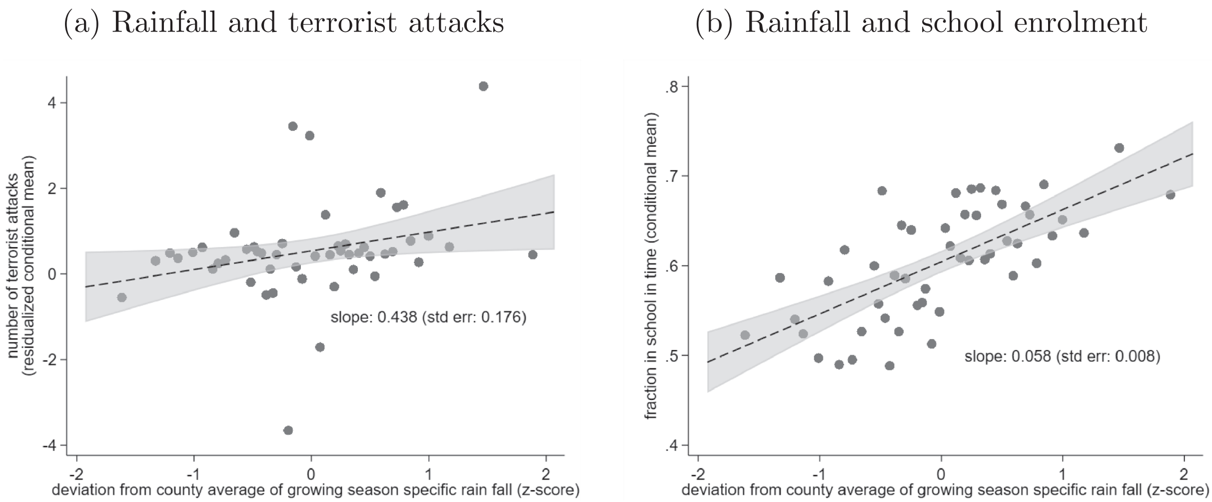

FIGURE 3 Rainfall as an illustration of income shocks correlated with both terrorist attacks and school enrolment. *Notes*: The Figure shows the correlation between rainfall during region specific growing seasons (as deviation from the county average) and (a) the number of attacks in each county during the years 2007-2014; and (b) the share of children aged 7 enrolled in school in each county during the years 2007-2014; both are net of county effects. The graph indicates both the conditional means of variables on the vertical axis within 50 equally sized bins for rainfall (as dots), and fitted regression lines with 95% confidence intervals. Sources: Global Terrorism Database, World Food Program, and Demographic Health Surveys.

3.1.3 | Illustration of omitted variable bias

We illustrate the identification problem faced by DiD estimators by showing how income shocks can cause an omitted variable bias. We focus on rainfall—a common source of exogenous income variation in Africa—and document how it affects both schooling and attacks, respectively, the dependent and explanatory variables in our main regressions. Figure 3 shows a significant and positive relation between average rainfall during the county specific growing season and both the number of terrorist attacks (panel a) and average school enrolment (panel b) in the same county. These two positive associations imply a positive omitted variable bias. While we can (and do) control for rainfall in our main estimations, Figure 3 highlights a broader problem, as similar economic shocks can arise from a large array of sources, some of which will inevitably remain unobserved to the researcher.

3.2 | Predicting terrorist attacks

After having laid out the conventional DiD estimator, we address the identification challenges particular to terrorism by re-estimating the effect of terrorist attacks on schooling using our instruments. In doing so, we exploit several unique features of the context al-Shabaab operates to predict both the timing and location of their attacks. Specifically, we use three distinct factors that influence the *timing* of attacks but are plausibly exogenous to the Kenyan context and which derive from al-Shabaab's affiliation to al-Qaeda, and revenue streams arising from hydrocarbon and coal exports, both known to be major sources of revenues for these terrorist organisations (more on this below). We combine each of these with the insight that the probability of attacks decreases with distance to the Somali border. Note that the parallel pre-trends between the most affected counties and the rest of the country documented in Figure 1b support the construction of instruments based on separate cross-sectional and time variation. With the resulting three instruments, we have overidentification and can test instrument validity.

3.2.1 | Timing (I)—Al-Shabaab's affiliation to al-Qaeda:

We use al-Shabaab's link to the al-Qaeda network to obtain exogenous variation in the timing of terrorist attacks carried out by al-Shabaab in Kenya. Al-Shabaab is an affiliate of al-Qaeda with particularly strong ties to AQAP. With encouragement of al-Qaeda core, AQAP established and maintained close links with al-Shabaab (Rollins, 2011; Zarif, 2011). In practice, AQAP supports al-Shabaab in several ways. AQAP has provided al-Shabaab with financial help, and it is believed

TABLE 1 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 (0.075)	0.184 (0.074)	0.212 (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 weeks after			0.002 (0.076)		
AQAP attacks on ‘public’ targets				0.295 (0.072)	−0.037 (0.037)
AQAP attacks on ‘private’ targets				−0.191 (0.135)	0.157 (0.070)
R squared	0.732	0.740	0.753	0.707	0.593
Observations	728	728	726	728	728
Year and week fixed effects	Yes	Yes	Yes	Yes	Yes
Timetrend (squared and cubed)	No	Yes	Yes	Yes	Yes

Note: 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; all estimations control for week and year fixed effects; data are drawn from Global Terrorism Database (2000 to 2014).

that access to al-Qaeda's resources was one of the reasons for al-Shabaab's loyalty pledge (Keatinge, 2014). Furthermore, AQAP has provided al-Shabaab directly with weapons, supporting personnel and military training (Hansen, 2013; Zimmermann, 2013). AQAP itself operates in a different geographical region to al-Shabaab, almost exclusively in the Arabian peninsula and no recorded attack in Africa.[15] Given its global standing, the hierarchy plausibly puts AQAP above al-Shabaab in this relation (see also Lahoud, 2012; Zimmermann, 2013).

Unsurprisingly, there are no systematic data on the documented financial, material and training support between terrorist organisations. Nonetheless, we do observe data patterns that are highly consistent with the qualitative evidence provided in the literature. The strong degree of coordination between the two organisations is supported by the high correlation in the timing of attacks that we highlight in Table 1. We construct a weekly time series and regress the number of al-Shabaab attacks on attacks carried out by AQAP conditioning on week and year fixed effects.[16] The parameter estimates show strong and robust correlations in the timing of attacks (columns 1 and 2) by the two organisations. Moreover, attacks by AQAP in the 2 weeks before or after do not appear to bear any correlation with al-Shabaab's attacks (column 3). Furthermore, when AQAP strikes public (private) targets, so does al-Shabaab (columns 4 and 5).[17]

3.2.2 | Timing (II)—Natural gas exports from Yemen

Our second source of exogenous variation in the timing of terrorist attacks carried out by al-Shabaab in Kenya is the volume of Yemen's exports of liquid natural gas. Besides ransom and extortions, AQAP derives a large part of its income from those exports (Fanusie & Entz, 2017a). Since, as mentioned before, AQAP provides financial assistance to al-Shabaab, part of these gas revenues may indirectly be channelled to al-Shabaab. This financial resource channel is particularly important since terrorist organisations cannot easily save or borrow over time (Limodio, 2022). The pipeline to Balhaf

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

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

[17]In Section 4.2, we explore whether households in Kenya react to AQAP activity directly.

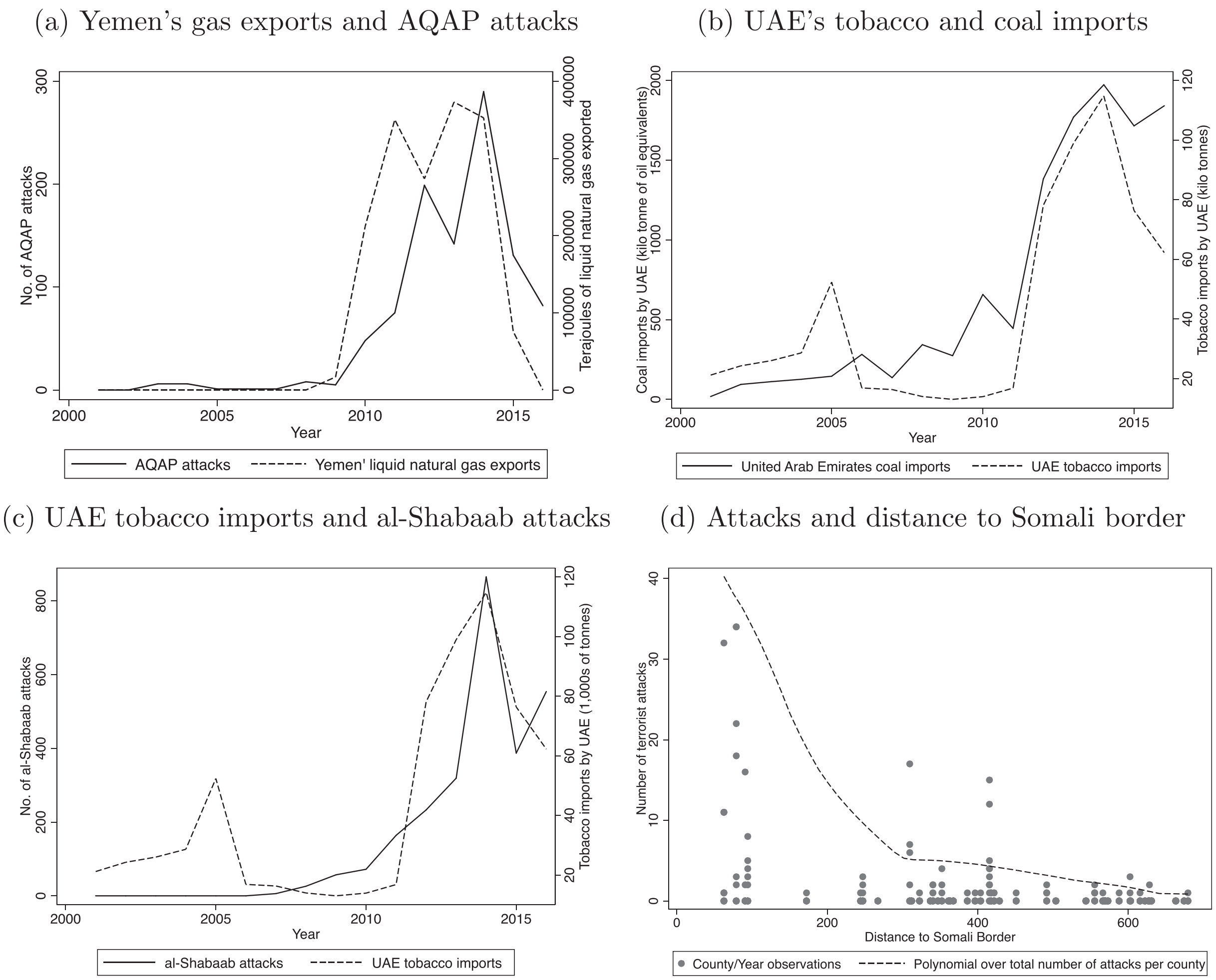

FIGURE 4 Natural gas, tobacco, coal and terrorist attacks by al-Qaeda in the Arabian Peninsula (AQAP) and al-Shabaab. *Notes*: Panel (a) shows attacks by AQAP for each year and terajoules of natural liquid gas exported by Yemen; panel (b) shows coal imports by the UAE in kilo tonne of oil equivalents 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.

from where natural gas from Yemen is exported in fact falls within territory controlled by AQAP; see map (e) in the supporting information Appendix A.[18]

Figure 4a illustrates the strong correlation between attacks by AQAP and liquid natural gas exports. In 2014, less than 0.01% of Yemen's natural gas was exported to Africa, so that we can rule out any direct link with outcomes in Kenya.[19] When scrutinizing the validity of our exclusion restriction in Section 4.2, we also show that the Kenyan trade share of fuel does not correlate with Yemeni gas exports. Our second instrument thus predicts the timing of attacks by using Yemen's exports of natural gas in hepta tons.

3.2.3 | Timing (III)—Tobacco imports by the United Arab Emirates

Exporting and trading charcoal is one of the largest sources of funding for al-Shabaab, which generated an estimated USD 83 million per annum between 2012 and 2014 (Fanusie & Entz, 2017b). Due to the close link between coal exports and al-Shabaab's revenues, the United Nations Security Council (2012) Resolution 2036 banned coal exports from Somalia

[18]https://worldview.stratfor.com/article/areas-aqap-control-yemen. Accessed October 2023.

[19]Trade data reported in this section are retrieved from the United Nations Conference on Trade and Development webpage, https://unctadstat.unctad.org, accessed April 2019.

in 2012. Despite this resolution, however, Somali coal exports continue illicitly and remain a major source of income for al-Shabaab (United Nations Security Council, 2018). Gulf countries are the main destination for Somali charcoal, with around 33% of Somalia's 2001–2012 coal exports going the UAE alone.

Made from acacia trees growing abundantly across the Horn of Africa, this charcoal is particularly prized for its long burning quality, which makes it well suited for smoking water pipe. We thus use imports of tobacco to the UAE as an exogenous shifter in the demand for Somali charcoal and hence for al-Shabaab's finances. We collect the UAE's tobacco imports from the United Arab Emirates Federal Competitiveness and Statistics Authority[20] and plot these against the country's coal imports as reported by the International Energy Agency. Figure 4b shows a strong correlation. Tobacco imports, moreover, map closely to al-Shabaab's activity—see Figure 4c. In Section 4.2, we show that charcoal-related employment in Kenya, in contrast, is uncorrelated with our instruments and does not track the UAE's tobacco imports. Thus, demand for tobacco in the UAE is plausibly exogenous to school enrolment choices by parents in Kenya. In fact, UCTAD figures show that coal from the Horn of Africa makes up only 6% of the UAE's coal imports for the most recent years for which data are publicly available (2010 to 2012).

3.2.4 | Location

To obtain three time and space varying instruments, we interact each of these sources of time variation with cross-sectional variation in distance to the Somali border. The rationale for our choice of cross-sectional variation is simple: Carrying out terrorist attacks is expensive,[21] and this costs increases with distance from the area controlled by the organisation in question. In the Kenyan case, this corresponds to distance from the Somali border. An additional factor decreasing the costs of attacks close to the border in our setting derives from the population in the border region being primarily of Somali ethnicity, implying a lower cost for maintaining network structures and carrying out attacks. In cross-sectional estimations, distance to border has been used as an instrument for terrorist attacks (Rehman & Vanin, 2017).[22]

Figure 4d illustrates the predictive power of distance to the border by plotting the total number of terrorist attacks each county experienced between 2001 and 2014 against the distance between that county's centroid and the Somali border. The graph shows a clear negative correlation of hyperbolic shape. We provide further evidence on the importance of distance to the border controlling for other county characteristics in Appendix E in the supporting information, confirming that distance to border is by far the strongest predictor for the location of terrorist attacks.

Combining the different sources of variation suggests a first-stage equation of the form:

$$attacks_{it} = \phi\, timing_t / distance_i + \boldsymbol{X}'_{it}\boldsymbol{\delta} + \kappa_{c_i} + \theta_t + w_{it}, \tag{2}$$

where $distance_i$ is the aerial distance between individual i's location of residence and the closest point on the Somali border. Since we condition on a full set of both county and year effects as well as on latitude and longitude of child i's residence (included in $\boldsymbol{X}_{it}$), the identifying variation derives purely from the interaction of the distance measures and the time variation we use. In columns (2) and (4) of Appendix D in the supporting information, we estimate the correlation between attacks as predicted by our three instruments and (predicted) future education. Compared with realised attacks (columns 1 and 3), the correlation is markedly weaker pointing towards the validity of our instruments.

4 | RESULTS

Our main measurement for $attacks_{it}$ is the annual number of terrorist attacks in child i's county of residence. In Section 4.3, we further consider attacks within a 2.5 km radius around a child's residence, 2.5 km around the closest primary school and attacks 2.5 km around the way to school (see Section 2.2).

[20] Available on https://fcsa.gov.ae/; accessed April 2019.

[21] See, for instance, Council on Foreign Relations, https://www.cfr.org/backgrounder/tracking-down-terrorist-financing, accessed December 2018.

[22] In a robustness test, we alternatively consider the distance from respondents to the Dadaab refugee complex located in the northeastern county of Garissa (see map (b) in Appendix A in the supporting information), which hosts over 200,000 Somali refugees in Kenya. See the Office of the United Nations High Commissioner for Refugees, https://www.unhcr.org/ke/dadaab-refugee-complex, accessed October 2019. The Kenyan government has repeatedly threatened to close Dadaab, which it suspects to offer a safe haven to al-Shabaab. When we use distance to Dadaab as an alternative cross-sectional variation, column (7) of Table 4 shows very similar estimates as in our main results described below.

TABLE 2 Effect of terrorism on school enrolment.

Estimator	(1) DiD	(2) IV	(3) IV	(4) IV	(5) IV
	A: Dependent variable = number of children in primary school (MoE)				
# terrorist attacks	−243.4	−663.2	−817.4	−665.9	−711.0
	(81.8)	(245.1)	(339.3)	(251.2)	(268.4)
Kleibergen–Paap F-statistic	-	37.3	13.9	31.3	57.3
DWH test (p-value)	-	0.005	0.002	0.006	0.002
Observations	282				
	B: Dependent variable = 100 if child enrols in school by age 7 (DHS)				
# terrorist attacks	−0.690	−1.005	−1.083	−0.950	−1.029
	(0.106)	(0.149)	(0.152)	(0.168)	(0.135)
Kleibergen–Paap F-statistic	-	219.6	174.2	118.8	144.6
DWH test (p-value)	-	0.001	0.001	0.046	0.001
Observations	40,486				
c, t effects & covariates	Yes	Yes	Yes	Yes	Yes
Instrument	-	AQAP	Gas	Tobacco	All 3

Note: # terrorist attacks is the number of terrorist attacks per county and year; column 1 reports DiD estimates; columns (2)–(4) instrument attacks, respectively, with attacks by al-Qaeda in the Arabian Peninsula (AQAP), Yemen's exports of natural gas or tobacco imports by the UAE, each divided by distance to the Somali border; column (5) uses all three instruments simultaneously; F-statistic and p-value of Durbin–Wu–Hausman (DWH) test reported for each estimate; first stages in Appendix F in the supporting information; panel A: dependent variable is total number of children in school, drawn from official reports by Kenyan Ministry of Education (2009–2014); controls include county and year effects and county population in each year; standard errors are clustered at the county level and reported in parentheses; panel B: dependent variable takes value 100 if child enrolled in school by age 7; controls include county and year effects, a child's gender, rural location, household having electricity, radio and TV, whether household head has secondary education, and latitude/longitude of the residence as well as growing season specific rainfall; spatial HAC Conley (1999) standard errors with 50 km radius and 1 year lag are reported in parentheses.

4.1 | Main estimates

Table 2 compares estimates derived from conventional panel estimators (in column 1) to 2SLS estimates based on our instruments (columns 2 to 5). Panel A shows the effect of the number attacks on the total number of children enrolled in primary school in each county taken from the administrative enrolment records. Three aspects are worth highlighting. First, our preferred estimate, which uses all three instruments jointly (column 5), predicts that each attack keeps over 700 primary school aged children out of school. Second, for all three instruments, the estimates are remarkably similar, supporting their validity. Third, all IV estimates are considerably larger in absolute magnitude than the DiD estimates reported in column (1), suggesting an estimation bias when the endogeneity of attacks is not accounted for. A Durbin–Wu–Hausman test performed for each instrument confirms this statistically. The upward bias (toward zero) supports the suspicion that al-Shabaab may target areas when they are on an upward trend.

For panel B, we use retrospective information on school enrolment contained in the DHS to define an indicator for whether each child enrolled on time (see Section 2.3 and Appendix C in the supporting information for a detailed description). To account for both time and spatial correlation, we report spatial HAC Conley (1999) standard errors.[23] Panel B uses the same definition of $attacks_{it}$ as panel A, that is, the total number of attacks in the child's county of residence in the same year. The estimates show a decline in enrolment rates by about 1.0 percentage points per attack. These figures suggest that a one standard deviation increase in the number of attacks decreases school enrolment by between 3 and 4 percentage points, which is remarkably similar to estimates analysing the impact of the Boko Haram insurgency (Bertoni et al., 2019). The very similar magnitude of estimates obtained for different instruments again lets them pass the overidentification test (p-value of 0.88). The less negative coefficient estimated by DiD and the DWH test indicate an endogeneity of attacks also with respect to this alternative measure for school enrolment. We report the first stage results in Appendix

[23]We allow for correlation within a 50 km radius and 1 year lag. The estimated standard errors are similar for different cut-offs. We use the Stata command *acreg* by Colella et al. (2019).

TABLE 3 Effect of terrorism on outcomes observed in the HSNP evaluation data.

	(1)	(2)	(3)	(4)	(5)	(6)
			=100 if			
Dependent variable	**Child is currently attending school**	**Child is currently working**	**Child is currently staying home**	**Teacher is absent**	**Person's main activity is collecting wood**	
Estimator	**IV**	**IV**	**IV**	**IV**	**IV**	**IV**
# terrorist attacks	−0.548	0.095	0.454	−0.018	−0.002	0.011
	(0.265)	(0.091)	(0.280)	(0.018)	(0.009)	(0.156)
Kleibergen–Paap F-statistic	304.9	304.9	304.9	357.6	304.9	260.3
Observations	12,603	12,603	12,603	8,536	12,603	15,406
Ages	6–14	6–14	6–14	6–14	6–14	18–60
HH and year fixed effect	Yes	Yes	Yes	Yes	Yes	yes
Data source	HSNP					

Note: # terrorist attacks is the number of terrorist attacks within 50 km per year; dependent variable in column (1) takes value 100 if child is currently attending school; dependent variable in column (2) takes value 100 if child is currently working; dependent variable in column (3) takes value 100 if child is currently staying at home; dependent variable in column (4) takes value 100 if teacher absence is reason for child not attending school; dependent variable in columns (5) and (6) takes value 100 if person's main activity involves collecting bush products for sale; all regressions are based on Hunger Safety Net Programme (HSNP) data; covariates include number of rooms and individuals living in the household, number of adult females with primary education in household, and indicators for gender and age of child; all regressions include household and year fixed effects and use three instruments (attacks by AQAP, Yemen's exports of natural gas and tobacco imports by the UAE, each divided by distance to Somalia) simultaneously. Spatial HAC Conley (1999) standard errors with 50 km radius and 3 years lag are reported in parentheses.

F in the supporting information.[24] Apart from one instance in which the use of a single instrument leads to an F-statistic close to 10, our instruments make for strong first stages throughout. For robustness, we re-estimate Equation (1) dropping different subsamples. As Appendix G in the supporting information shows, the results remain robust. We also re-estimate our main regressions using an alternative dependent variable (defining age 6 as a cut-off rather than age 7) in columns (13) and (14). The estimates are very similar. In Section 4.3, we use the same individual level indicator for school enrolment to evaluate the effects for different measurements for the exposure to terrorist attacks.

4.2 | How credible is the exclusion restriction?

Our 2SLS estimator uses only the interaction between the exogenous time-varying shifters—AQAP activity, Yemeni gas exports and UAE tobacco imports—and proximity to the Somali border as instruments. Thus, any factors that affect the whole of Kenya in any given year (such as global economic conditions) or any unobserved heterogeneity (such as educational infrastructure or cultural environment) particular to a location that affect school enrolment and terrorist attacks simultaneously is accounted for by the year and location controls included in the estimations. A violation of the exclusion restriction hence can only arise as a result of factors that vary both over time and across regions *simultaneously*. This section addresses such concerns.

4.2.1 | Do UAE tobacco imports affect education via the demand for charcoal?

A first concern is that our instruments affect schooling not through the frequency of attacks but through labour market opportunities in Kenya (either for children or their parents). The rationale for exploiting variation in tobacco imports into the UAE is the financing of al-Shabaab through charcoal exports from *Somalia*. Yet, it is possible that the same tobacco imports by the UAE increase the profitability of producing charcoal also in *Kenya*. Demand for tobacco could thus affects the opportunity costs of schooling.

[24]Although one could exploit our continuous instruments to evaluate effect heterogeneity, this is complicated by the fact that treatment intensity varies continuously. Given the similarity of our estimates across different instruments, however, we are less concerned about identifying some nonrepresentative local effect.

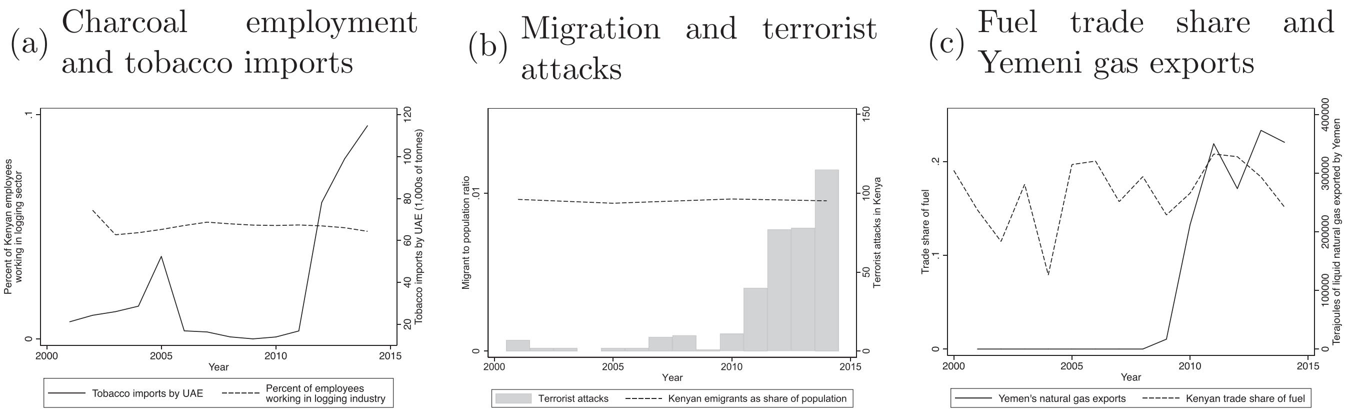

FIGURE 5 Charcoal employment, tobacco imports, fuel trading and migration. *Notes*: The Figure shows (a) the percentage of all employees who work in charcoal burning or wood logging and the time series of tobacco imports by the UAE; (b) the number of Kenyans living abroad over the Kenyan population and total number of terrorist attacks; and (c) the Kenyan trade share of fuel (the sum of fuel exports and imports over the sum of total exports and imports) together with natural gas exports from Yemen. Sources: Kenya Bureau of Statistics, UAE Federal Competitiveness and Statistics Authority, UNCTAD, International Energy Agency, UN Population Division.

We address this concern in two ways. First, we use detailed information on employment activities to show that our instruments are uncorrelated with charcoal producing activities of children and adults. We use longitudinal data collected as part of the Hunger Safety Network Programme (HSNP) administered in Turkana, Marsabit, Mandera and Wajir, where the latter two are among the hardest hit counties. The HSNP records the main activity of all household members, which allows us to estimate correlations between our instruments and activities related to charcoal production. Before doing so, however, we reproduce our main estimates for the HSNP data, using *current* attendance of children aged 6 to 14 as the dependent variable.[25] Column (1) of Table 3 confirms the negative effect on current school attendance also conditional on household fixed effects. In order to estimate a correlation between our instrument and charcoal production activities, we define an indicator variable taking value 100 if the person's main activity consists of wood collection and manufacture.[26] If demand for charcoal were to have a direct effect on schooling via the production of charcoal, one would expect to find a significant correlation between attacks and activities related to charcoal manufacture. Column (5) of Table 3, however, shows a rather precisely estimated null-effect of attacks on children working in that sector[27] and also no statistically significant effect for adults (column 6).

To address this concern in a second and different way, we juxtapose Kenya wide employment rates in charcoal producing industries with our instrument. Using data provided by the Kenya Bureau of Statistics, we calculate the percentage of all employees who work in charcoal producing industries (i.e. charcoal burning and wood logging). Figure 5a plots this percentage over time and shows two noteworthy patterns. First, the percentage of employees working in the charcoal producing sector in Kenya is low, less than 0.1% of all employees. Second, the share of charcoal employees barely varies over time and does not track tobacco imports by the UAE.

4.2.2 | Does migration drive the results?

A further possibility is that the presence of terrorist attacks induces some individuals to migrate. We address this concern in three ways. First, using data from the United Nations Population Division,[28] we plot the number of Kenyans living abroad as a share of the Kenyan population against the number of terrorist attacks. As Figure 5b shows, the proportion of emigrants is very low throughout, around 1% and does not correlate with attacks. Second, we estimate whether attacks

[25]Using information on location of residence, we define the number of attacks as all terror incidence occurring within a radius of 50 km during the last 12 months. This radius creates geographical areas just slightly smaller than an average Kenyan county and thus makes estimates comparable across datasets. Map (f) in Appendix A in the supporting information shows the location of sampling clusters. To focus on *current* attendance, we consider children aged 6 to 14 (i.e. primary school age).

[26]The HSNP classifies this activity as "collecting bush products for sale".

[27]We also find no effect on the overall share of children working instead of going to school (shown in column 2 and discussed below).

[28]United Nations database, POP/DB/MIG/Stock/Rev.2015; available online at https://www.un.org/en/development/desa/population/migration/data/estimates2/estimates15.asp, accessed April 2021.

TABLE 4 Effect of terrorism on school enrolment: Identification concerns and robustness.

Dependent variable	(1) Number of children living away from home	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Log of expen-ditures
		=100 if child in school by age 7							
# terrorist attacks	−0.006	−0.778	−1.011	−0.717	−0.762	−0.704	−0.777	−1.087	0.013
	(0.004)	(0.172)	(0.128)	(0.203)	(0.243)	(0.191)	(0.131)	(0.180)	(0.013)
Kleibergen–Paap *F*-statistic	27.9	109.2	139.4	125.1	27.5	57.5	377.6	154.9	94.6
Mothers only	Yes								
Excluding migrants		Yes							
Security spending × NE			Yes						
Education spending × NE				Yes					
GDP × NE					Yes				
Time trend × NE						Yes			
Alt. IV: distance to Dadaab							Yes		
Rural sample only								Yes	
c and *t* effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Data source	DHS	DHS	DHS	DHS	DHS	DHS	DHS	DHS	MoE
Observations	29,225	40,724	40,724	40,724	40,724	40,724	40,724	30,128	226

Note: # terrorist attacks is the number of terrorist attacks per county and year; dependent variable in column (1) is the number of a mother's children who live away from home, controls include indicators for mother's age, primary education, rural location, ownership of radio and electricity; dependent variable in columns (2) to (8) takes value 100 if child enrolled in school by age 7; controls include county and year effects, a child's gender, rural location, household having electricity, radio and TV, whether household head has secondary education, and latitude/longitude of the residence as well as growing season specific rainfall; column (2) excludes children who moved to their current residence after turning 7; columns (3) to (6), respectively, interact trends for national public expenditure on security or education, GDP and a time trend with an indicator for northeastern Kenya; column (7) uses distance to the Dadaab refugee complex instead of distance to the border for all three instruments; column (8) only uses rural respondents, dependent variable in column (9) is the log of county government expenditures; controls include county and year effects, and county's population; all regressions use three instruments (attacks by AQAP, Yemen's exports of natural gas or tobacco imports by the UAE, each divided by distance to Somalia; except column (7), which divides by distance to Dadaab) simultaneously, and control for county and year effects; spatial HAC Conley (1999) standard errors with 50 km radius and 1 year lag are reported in parentheses.Abbreviation: DHS, Demographic Health Surveys.

increase the number of children residing away from home.[29] As column (1) of Table 4 shows, attacks have no significant effect on the migration of children. Third, we use migration histories of respondents in the 2014 DHS and drop any children that migrated to their current place of residence after the year in which they turned 7. Column (2) of Table 4 shows that omitting migrants does not significantly alter the effect of terrorist attacks. The estimates are robust to different definitions of migrants.

4.2.3 | Do public policies drive the results?

Another concern regarding the exclusion restriction is that al-Shabaab's revenues and activities elicit responses by the Kenyan government, which in turn can have a direct effect on schooling in Kenya. In particular, the Kenyan government could adjust public expenditure on security, which might have a particularly strong impact on those parts of Kenya most exposed to terrorist attacks, that is, the northeastern counties (Mandera, Wajir and Garissa). Kenya, for instance, provides a contingent for the African Union Mission to Somalia (AMISOM) fighting al-Shabaab in Somalia. To account for the possibility that these expenditures have a differential effect in the northeastern regions, we digitised information on government expenditure on "Public Order and Safety" from government reports published by the Kenyan Bureau of National Statistics and include its interaction with a northeastern dummy as a covariate. The inclusion of this variable will absorb any disproportional effect of security expenditures on education in those areas hit particularly hard by terrorist attacks. We repeat this exercise for "Educational expenditures". Columns (3) and (4) of Table 4 show that the effect of attacks is robust to the inclusion of these controls. Moreover, in column (9), we digitised county level expenditures on all services for 34 of the 47 counties, which is available for the years 2009 to 2014. Using this as a dependent variable shows that terrorist attacks have no effect on county level (log) expenditures. The coefficients are small in size yet precisely estimated.

[29]For this exercise, we can only use the two DHS cross-sections in the years 2009 and 2014. We drop any women without children.

4.2.4 | Do global economic conditions simultaneously affect Yemeni gas exports or UAE tobacco imports and Kenyan economic growth?

A more general concern is that global economic conditions may affect trade volumes, economic growth and simultaneously also influence school enrolment in Kenya. Recall that any effect of global conditions on Kenya as a whole is absorbed by the year fixed effects. Thus, for global economic conditions to violate the exclusion restriction, such conditions would have to affect schooling disproportionately in areas that experience more terrorist attacks. We explicitly investigate this possibility in two ways. First, we include Kenya's annual GDP interacted with a dummy for the northeastern counties as an additional covariate, thus absorbing any differential effect of economic conditions in those areas with high incidences of terrorist attacks. Column (5) of Table 4 shows that our estimate remain robust. Column (6) further shows that allowing for a separate time trend for the strongly affected counties Mandera, Wajir and Garissa does not alter the estimated effect. Second, we compare Kenya's fuel imports to Yemen's exports of hydrocarbons over time. If both were driven by global economic conditions, one would expect the two outcomes to track each other. However, Figure 5c shows that this is not the case.

4.2.5 | Alternative geographical variation and rural sample

In column (7), we re-estimate our model using the distance to the Dadaab refugee complex rather than the distance to the Somali border to predict the location of attacks in Equation (2) (see footnote 22). Moreover, in column (8), we estimate whether our effects still hold for the sample of rural households. In both cases, the results remain robust.

TABLE 5 Effect of terrorism on school enrolment with disaggregated measurement.

Estimator	(1) DiD	(2) IV	(3) IV	(4) IV	(5) IV
	A: Dependent variable = 100 if child enrols in school by age 7				
# terrorist attacks within 2.5 km of residence	−1.283	−1.380	−2.043	−1.471	−1.336
	(0.246)	(0.589)	(0.790)	(0.618)	(0.576)
Kleibergen–Paap F-statistic	-	48.1	11.5	13.4	166.0
DWH test (p-value)	-	0.822	0.084	0.665	0.898
Observations	40,724				
	B: Dependent variable = 100 if child enrols in school by age 7				
# terrorist attacks within 2.5 km of closest school	−1.133	−1.377	−2.042	−1.471	−1.329
	(0.225)	(0.590)	(0.793)	(0.623)	(0.575)
Kleibergen–Paap F-statistic	-	46.0	11.2	12.9	156.8
DWH test (p-value)	-	0.561	0.026	0.402	0.637
Observations	40,724				
	C: Dependent variable = 100 if child enrols in school by age 7				
# terrorist attacks within 2.5 km of way to school	−1.305	−1.357	−2.014	−1.455	−1.306
	(0.254)	(0.584)	(0.790)	(0.622)	(0.568)
Kleibergen–Paap F-statistic	-	43.2	10.8	12.3	146.2
DWH test (p-value)	-	0.902	0.105	0.734	0.992
Observations	40,724				
c, t effects & covariates	Yes	Yes	Yes	Yes	Yes
Instrument	-	AQAP	Gas	Tobacco	All 3

Note: # terrorist attacks within 2.5 km of residence is the annual number of terrorist attacks within 2.5 km a child's residence; # terrorist attacks within 2.5 km of closest school is the annual number of terrorist attacks within 2.5 km of child's closest primary school; # terrorist attacks within 2.5 km of way to school is the annual number of terrorist attacks within 2.5 km along the way from a child's residence to the closest primary school; column (1) reports DiD estimates; columns (2)–(4) instrument attacks, respectively, with attacks by al-Qaeda in the Arabian Peninsula (AQAP), Yemen's exports of natural gas or tobacco imports by the UAE, each divided by distance to the Somali border; column (5) uses all three instruments simultaneously; F-statistic and p-value of Durbin–Wu–Hausman (DWH) test reported for each estimate; first stages in Appendix F in the supporting information; dependent variable takes value 100 if child enrolled in school by age 7; controls include county and year effects, a child's gender, rural location, household having electricity, radio and TV, whether household head has secondary education, and latitude/longitude of the residence as well as growing season specific rainfall; spatial HAC Conley (1999) standard errors with 50 km radius and 1 year lag are reported in parentheses. Source: Kenyan DHS 2009, 2014.

4.2.6 | Do Kenyan households react to AQAP activity directly?

A possibility is that households in Kenya are aware of AQAP activity abroad and react by keeping their children out of school independently of attacks actually carried out in their area. Recall that this would only pose a problem if parents reacted to AQAP attacks *differentially* by distance to the Somali border, that is, households closer to the border should react stronger to AQAP attacks. Figure A5 in Appendix H in the supporting information suggests that this is not the case. The two panels report radio and television use by distance to the Somali border and show no significant differences (media use if anything decreases closer to the Somali border).

4.3 | Spatial disaggregation

Our main estimates in Table 2 measure a child's exposure to terrorism using the number of attacks in the child's county of residence. In this section, we sharpen the exposure measure. Panel A of Table 5 shows the impact of attacks occurring within 2.5 km of a respondent's home. As expected, these on average geographically closer attacks have a larger effect on enrolment than the county level treatments. Importantly, the DiD point estimate for this more narrow measure increases by more (in absolute terms) than the instrumented estimates, so that the estimated effects are no longer statistically distinguishable. In panel B, we use spatial information by the Kenyan Ministry for Education to identify terrorist attacks occurring 2.5 km around the closest primary school.[30] Overlaying the geographical coordinates of children's residences with the topographical location of all Kenyan primary schools, we identify the closest primary school, draw a 2.5 km radius around it and count all terrorist attacks occurring within the resulting area. In panel C, we draw a straight line between a child's residence and its closest primary school as an approximation to the way to school.[31] To account for possible detours, we draw a 2.5 km radius around this line and count all terrorist attacks occurring within the resulting corridor. The patterns remain unchanged. We report the first stage results together with those for Table 2 in Appendix F in the supporting information.

The disappearance of the bias in Table 5 suggests that the endogeneity arising from terrorists targeting areas when these are on an upward trend can, in fact, be mitigated by using finely geocoded data. Using the exact geographical coordinates of attacks, individuals and schools makes it possible to distinguish—within larger areas experiencing positive shocks—children affected and unaffected by terrorist attacks. By comparing these two sets of individuals over time, one can difference out the confounding variation arising from unobserved shocks. The finer spatial disaggregation allows us to also control for region-specific time trends. We show the estimates from this tighter specification in columns (10)–(12) in Appendix G in the supporting information. The negative effect of terrorist attacks in the vicinity of a child's residence, school or their way to school prevails.

4.4 | Mechanisms and impact

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. The HSNP records whether children of school age stay at home or work rather than attending school. We use this information to estimate the effect of terrorist attacks on children's alternative activity. Columns (2) and (3) in Table 3 show that most of the lower school attendance due to terrorist attacks is driven by an increase in the number of children staying home rather than an effect on child labour.

4.4.1 | No effect on teacher absence

The 2010 and 2012 rounds of the HSNP data further allow us to evaluate whether effects are driven by teachers' absence from school. Defining a dependent variable taking value 100 if the child is not attending school and teacher absence is given as the primary reason, we find no effect of attacks on this outcome—see column (4) of Table 3.

4.4.2 | Heterogeneity

We find little heterogeneity when distinguishing different targets of terrorist attacks in columns (1)–(7) of Table 6. Given very different frequencies of attacks across targets, we denote the number of attacks in standard deviations within each

[30]Information and Communication Technology Authority, https://www.opendata.go.ke/, accessed May 2019.

[31]The mean distance to the closest primary school for primary school aged children in the DHS data is 1.98 km.

TABLE 6 Effect of terrorism on school enrolment: Heterogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable = 100 if child enrols in school by age 7 (DHS)									
Model	**IV**	**IV**	**IV**	**IV**	**IV**	**IV**	**IV**	**IV**	**IV**	**IV**
# of attacks	−4.314	−4.776	−3.854	−4.210	−3.923	−6.836	−5.707			
(standardised by target type)	(0.955)	(1.430)	(1.019)	(0.547)	(0.976)	(6.871)	(2.481)			
# of attacks								−1.286	−0.739	−1.029
								(0.182)	(0.168)	(0.419)
Lagged # attacks										0.084
										(0.534)
Type of target	All	Police	Citizens	Businesses	Military	Education	Other	All	All	All
Child's gender	All	All	All	All	All	All	All	Male	Female	All
c, *t* effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
K-P *F*-statistic	57.3	10.8	4.7	11.8	5.3	0.8	3.3	132.4	140.7	43.2
Observations	40,724	40,724	40,724	40,724	40,724	40,724	40,724	20,553	20,171	39,746

Note: Dependent variable takes value 100 if child enrolled in school by age 7; # terrorist attacks is the number of terrorist attacks per county and year; columns (1)–(7) estimate effects by target type and measure the number of attacks in standard deviations within each type of target; columns (8) and (9) estimate effect for boys and girls respectively; column (10) includes the lag of attacks per county and year (lagged # attacks), using lagged instruments; all regressions use three instruments (attacks by al-Qaeda in the Arabian Peninsula (AQAP), Yemen's exports of natural gas or tobacco imports by the UAE, each divided by distance to Somalia simultaneously, and control for county and year effects; other controls include county and year effects, a child's gender, rural location, household having electricity, radio and TV, whether household head has secondary education, and latitude/longitude of the residence as well as growing season specific rainfall; spatial HAC Conley (1999) standard errors with 50 km radius and 1 year lag are reported in parentheses.

target type. Columns (8) and (9) of Table 6 estimate the effect of terrorist attacks separately for boys and girls. We estimate a stronger effect for boys, both in absolute terms and relative to enrolment rates, which for girls and boys, respectively, average 69.3% and 65.7% across counties. We include lagged attacks in column (10), and the results show that the effects are driven by contemporaneous attacks, potentially pointing towards agents' immediate fear rather than longer-term considerations. In the section below, we explore the role of attitudes in more detail by looking at fears directly.

4.4.3 | Large effect on fears and concerns

The above findings suggest that effects are demand driven rather than through an impact on the supply of education. To substantiate this, we use data from four rounds of the Afrobarometer on self-reported fears and concerns. The Afrobarometer is a representative attitudinal survey with geocoded information on respondents' location of residence. We regress indicators for whether a respondent reports (i) to be afraid of crime and (ii) to believe future economic conditions will be better than at present on the number of attacks in the respondent's county, which we instrument using all three instruments jointly. Table 7 shows that each attack raises the fear of crime by 1.2 percentage points (over a mean of 14.0). Exposure to terrorism further reduces optimism about future economic conditions by 0.9 percentage points (over a mean of 36.8).

Plausibly, these concerns contribute to parents' decision to keep their children out of school. If mothers are core in this decision, this channel is further supported by effects being concentrated among women. In particular, concerns regarding future economic conditions decrease by a full 3 percentage points among women in response to a terrorist attack (column 8 of Table 7), whereas we find no effect for men. We should note, however, that the Kenyan sample of the Afrobarometer has a smaller number of observations than the sources we use for our main estimations, and the *F*-statistics here are closer to 10. The results in Table 7 thus are to be treated with more caution.

4.4.4 | Approximation of longer-term impact

Our main estimates indicate that each attack reduces the number of children enroling in school on time by 1.0 percentage points. An estimation using the more detailed data from the HSNP for Kenya's northern counties confirms this magnitude also for school attendance by children at the end of primary school. For children aged 13–14, we find a negative effect of similar magnitude (−0.920, standard error 0.403) to the whole sample, suggesting that the effect of terrorist attacks may further affect the likelihood of transitioning to secondary school. For a back-of-the-envelope estimation of the possible

TABLE 7 Effect of terrorism on attitudes.

Estimator	(1) DiD	(2) IV	(3) DiD	(4) IV	(5) IV	(6) IV	(7) IV	(8) IV
Dependent variable				=100 if respondent is				
	Afraid of crime		Optimistic about future econ cond.		Afraid of crime		Optimistic about future econ cond.	
Mean	14.0		36.8		15.3	13.0	35.5	37.8
# terrorist attacks	1.022	1.231	−0.480	−0.877	1.088	1.171	0.153	−3.113
	(0.159)	(0.273)	(0.226)	(0.452)	(0.246)	(0.594)	(0.644)	(1.113)
Kleibergen–Paap *F*-statistic		13.9		13.9	10.2	24.6	10.2	24.6
Gender	All	All	All	All	Men	Women	Men	Women
Observations	7178	7178	7178	7178	4088	3090	4088	3090

Note: # terrorist attacks is the number of terrorist attacks per county and year; dependent variable in columns (1), (2), (5) and (6) takes value 100 if respondent reports to be afraid of crime in their own home; dependent variable in columns (3), (4), (7) and (8) takes value 100 if respondent reports to believe future economic conditions will be better than present; all IV estimates use three instruments (attacks by al-Qaeda in the Arabian Peninsula (AQAP), Yemen's exports of natural gas or tobacco imports by the UAE, each divided by distance to Somalia) simultaneously; covariates include respondent age, and dummies for respondent being muslim, respondent being female, respondent not having primary education and respondent living in rural area; all regressions account for year and county fixed effects; source 2005, 2008, 2011 and 2014 rounds of Afrobarometer; spatial HAC Conley (1999) standard errors with 50 km radius are reported in parentheses.

longer-term economic effects in terms of individual earnings, we use the first round of the HSNP data to estimate a simple Mincer-type equation that regresses annual earnings of adults aged 18–60 on their years of schooling, controlling for a full set of age indicators, gender and municipality of residence. This estimation suggests that each year in education augments earnings by 219 purchasing power adjusted USD per year. Among the counties covered by the HSNP, Mandera county has seen the largest number of terrorist attacks, amounting to 11 attacks in each 2011 and 2012. We assume that children dropping out of school re-enrol the following year lose 1 year of education. With 40 years of work of the life cycle, a rough approximation suggests a loss in life time earnings of $40 \cdot 11 \cdot 0.01 \cdot 219 \approx 964$ USD PPP, which amounts to about 70% of the average household's annual income (1380 USD PPP). Since not all children, who dropped out of school, re-enrol the year after, this estimate in fact is a lower bound, while the true cost is likely to be substantially higher.

5 | CONCLUSION

Terrorism, like other forms of violence, has the potential to suppress education. Unlike with other types of conflict, however, the analysis of terrorist attacks' effect raises its own unique identification concerns. The possibility of terrorists choosing the location and timing of attacks strategically to maximise impact, for instance, introduces a potential omitted variable bias. To address this concern, our paper instruments terrorist attacks in Kenya using the main perpetrator's position in the al-Qaeda network and its revenue streams. A comparison of different estimators shows a positive bias in standard DiD estimators, suggesting that areas are particularly prone to experience terrorist attacks when they experience positive shocks; a finding with policy relevant implications. In doing so, we document not only that the activity of terrorist organisations strongly depends on their revenues but also that independent branches of the same terrorist network appear to coordinate their activity, often striking similar targets in the same week. As such, our findings highlight the high degree of coordination and planning that underlies violent incidences, as well as the importance of targeting revenue streams of terrorist organisations. These patterns resonate with a recent overview article (Verwimp et al., 2019), where the authors argue against the myth that violent behaviour is irrational. We also show, however, that finely disaggregated data, as used, for instance, in recent papers by Bertoni et al. (2019) and Foureaux Koppensteiner and Menezes (2021), can help mitigate such a bias.

OPEN RESEARCH BADGES

This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at https://doi.org/10.15456/jae.2024086.1716710187.

DATA AVAILABILITY STATEMENT

The data, instructions, and Stata do-files used in this paper are available at the Journal of Applied Econometrics Data Archive.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of the article.

How to cite this article: Alfano, M., & Görlach, J.-S. (2024). Terrorism and education: Evidence from instrumental variables estimators. *Journal of Applied Econometrics*, *39*(5), 906–925. https://doi.org/10.1002/jae.3058