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Abstract

Contrary to the extant literature, this paper shows that the impact of terrorism on economic growth is insignificant in five regional samples. These surprising results follow when Nickell bias and cross-sectional dependence are taken into account. Previous studies have not properly adjusted for these biases. Our provocative findings are robust to alternative measures of terrorism (i.e., domestic, transnational, and total) and to alternative specifications of terrorism (e.g., level, first differenced, and attacks per capita). These findings are also robust to the inclusion of investment and population growth. Moreover, we find that the various forms of terrorism do not affect consumption, investment, and government expenditures. Our results have important policy implications.

Keywords: Economic growth, Terrorism, Dynamic panel, Nickell bias, Cross-sectional dependence

JEL codes: O40, C52, D74

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1. Introduction

Terrorists engage in acts of intimidating violence as a means of pressuring a targeted government into granting political or social concessions. Although terrorists' bombs and bullets are aimed at specific victims, their real target of intimidation is a wider audience who can apply pressures on a government to concede to terrorists' political demands. A besieged government may be willing to grant political concessions if the anticipated costs of future terrorist attacks are greater than the consequences of concessions, taking into account losses to the government's reputation (Lapan and Sandler, 1988). Terrorists can raise these anticipated costs from their attacks through higher body counts or greater economic losses. There are many instances where terrorists have sought to cause economic consequences (e.g., WorldNetDaily, 2003). The crashing of two planes on September 11, 2001 (henceforth, 9/11) into the two towers of the World Trade Center is the most successful single terrorist blow against an economy, with direct and indirect economic losses estimated at $80-90 billion (Kunreuther, Michel-Kerjan, and Porter, 2003). These losses were about 0.8% of total US annual output in 2001. The attacks on 9/11 also temporarily impacted world stock exchanges for 30-40 days; previous large-scale terrorist attacks impacted world stock markets for just days, if at all (Chen and Siems, 2004). Euskadi ta Askatasuna (ETA) engaged in attacks during the 1980s against tourist hotels and resorts with the intent to cause economic hardships to Spain (Mickolus, Sandler, and Murdock, 1989). Busea et al. (2007) calculated the costs of the March 11, 2004 terrorist attack against commuter trains in Madrid (henceforth, 3/11) at 211.5 million euros or 0.03% of Spanish GDP in 2004.

Can terrorist attacks truly affect a country's economic growth? There are considerations that both support and deny the possibility that a terrorist attack can reduce economic growth. Terrorist attacks may adversely affect growth through a number of channels. First, a significant

terrorist threat increases uncertainty, which, in turn, may reduce investors' confidence (Abadie and Gardeazabal, 2008; Enders, Sachida, and Sandler, 2006; Enders and Sandler, 1996). Second, a sustained terrorist campaign raises the costs of doing business in terms of wages, security, and insurance premiums, which may reduce profit margins causing some impacted firms to fold. Third, increased government counterterrorism spending can crowd out private and public investment (Blomberg, Hess, and Orphanides, 2004; Gaibulloev and Sandler, 2008, 2009). Fourth, well-aimed terrorist attacks can destroy critical infrastructure, supply lines, and social overhead capital. Fifth, terrorist attacks can harm specific industries such as tourism (see e.g., Drakos and Kutan, 2003; Enders, Sandler, and Parise, 1992). Sixth, for developing countries, a sustained terrorist campaign may reduce foreign assistance and curtail foreign direct investment (FDI), an important source of saving.

On the contrary, there are compelling factors that may greatly limit the ability of terrorist attacks, even large-scale ones such as 9/11 and 3/11, from curtailing growth. The losses from such spectacular terrorist attacks are a relatively small proportion of GDP, which is illustrated by the 3/11 losses. Countries that experience a limited number of terrorist incidents are anticipated to display localized losses, analogous to those of crime. This is particularly true when one realizes that transnational terrorist attacks kill on average a single person and injure two persons (Enders and Sandler, 2012). Obviously, a greater economic growth effect is anticipated for a small country, plagued by terrorism at a given time (Eckstein and Tsiddon, 2004). Rich, diversified economies are likely able to escape significant growth effects as economic activities shift from terrorism-prone sectors to nonimpacted sectors (Gaibulloev and Sandler, 2009). Moreover, rich economies are better equipped to deploy monetary and fiscal policies to recover from large terrorist attacks, as the United States did following 9/11 (Enders and Sandler, 2012, 294–298). The crowding-out effect of increased counterterrorism spending for many terrorism-

impacted countries may be limited unless the country is experiencing many attacks (e.g., the United Kingdom during the Irish troubles) or is considered to be a prime-target country. Even some developing countries may actually receive foreign assistance to address their terrorism problem if the donor country's interests are at risk (Bandyopadhyay, Sandler, and Younas, 2011; Fleck and Kilby, 2010).

The real impact of terrorism on growth is open to debate owing to these opposing considerations. The primary purpose of this paper is to reevaluate the empirical relationship between terrorism and economic growth by applying some new insights and methods from dynamic panel analysis. We assume an agnostic view of past cross-sectional and panel studies of terrorism and growth that provide an average picture for a large number of countries. However, we have no complaints with country-specific studies of terrorism and economic growth (e.g., Abadie and Gardeazabal, 2003). For our dynamic panel analysis, we divide the sample by regions to limit the number of countries, *N*, in relation to the number of time periods, *T*, and investigate the relationship between terrorism and growth. In so doing, we distinguish between domestic (homegrown and home-directed) and transnational terrorism. The latter involves venue, perpetrators, or victims from at least two different countries. For completeness, we examine myriad specifications that allow for lagged terrorist attacks and a host of control variables. Moreover, we study the impact of terrorism on per capita gross domestic product (GDP) growth and on the growth of various GDP components (e.g., consumption and investment). We also account for cross-country correlations,[1] which have been recently shown

[1] Given that terrorists share common grievances and ideologies, terrorist attacks in one country may be influenced by attacks in other countries, thereby giving rise to cross-country correlations of such attacks. Demonstration effects associated with terrorist innovations (i.e., new modes of attack such as suicide car bombings) and counterterrorism innovations (e.g., stun grenades to end hostage incidents) are anticipated to create cross-country correlations of terrorist events. These cross-country correlations may also stem from a shock that affects terrorism in many countries (e.g., the US retaliatory raid on Libya in April 1986 or the Abu Ghraib prison revelations in April 2004). Because terrorists often receive training in a few countries, this may also give rise to cross-country correlations as

to be an important consideration for transnational terrorism (Gaibulloev, Sandler, and Sul, 2013). Our findings indicate that there is no statistically significant impact of terrorism (domestic, transnational, or aggregate) on economic growth when appropriate dynamic panel methods are applied. This surprising finding holds across all specifications and casts doubt on many previous analyses (see Section 2) that found a significant, but modest, impact of terrorism on economic growth. Our findings also hold for alternative regional subsamples. As a secondary purpose, we indicate why some previous studies are misspecified. A tertiary purpose involves drawing some policy conclusions.

An understanding of the impact of terrorism on growth is essential for a number of reasons. Quantifying this impact informs governments, in part, on how much to allocate to counterterrorism because economic losses are an important negative consequence stemming from terrorism. Obviously, body counts, fear, and political backlash are other adverse consequences. If, for example, terrorism has little influence on growth, then governments may want to assign fewer resources to defensive and proactive counterterrorism measures. Moreover, knowledge of the impact of terrorism on economic growth can assist policymakers to determine their expansionary fiscal and monetary policy following large-scale attacks or sustained terrorist campaigns. In terms of foreign assistance, knowledge of this impact assists nations to determine how much aid to give to a developing country following its terrorist attacks. In addition, gauging the impact of terrorism on the economy can allow economists to compare and contrast this effect with those from greater violence in the form of civil and external wars.

The remainder of the paper has five sections. In Section 2, we review past studies of

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terrorists respond in a similar fashion to events. The presence of terrorist networks across countries also fosters such correlations. Cross-sectional correlations of terrorist attacks may also arise from target countries having assets at home and abroad.

terrorism and growth, and investigate why previous studies are misspecified. The data is briefly described in Section 3. Section 4 provides our empirical methodology for addressing Nickell bias and cross-sectional dependence. This section also contains our empirical estimates, followed by robustness checks in Section 5. The final section draws conclusions.

2. Issues associated with previous empirical studies on terrorism and growth

Recently, there has been a strong interest in investigating terrorism as a potential determinant of economic growth. Empirical studies on terrorism and growth have adopted the econometric specification used in the standard growth literature, which has evolved from cross-sectional to dynamic panel regressions. However, the econometric issues that have plagued standard growth models were overlooked by past studies of terrorism's impact on growth. We believe that this has led to an erroneous belief that terrorism has a significant negative effect on growth even in countries not beset by large-scale terrorist campaigns.

[Table 1 near here]

Table 1 provides a brief summary of the recent empirical studies of the impact of terrorism on per capita income growth. In Table 1, the left-most column indicates the study; the second column displays the terrorist data source; the third column denotes the sample; the fourth column depicts the studies' time period; the fifth column indicates the type of analysis; the sixth column lists some key (select) controls other than a measure of terrorism; and the right-most column highlights the influence of various measures of terrorism on per capita income growth. Two studies – Blomberg, Hess, and Orphanides (2004) and Tavares (2004) – used a world sample. The other studies, including the latter half of Blomberg, Hess, and Orphanides (2004), analyzed regional samples. All previous studies utilized panel data; three of these studies performed additional cross-sectional analysis. Blomberg, Hess, and Orphanides (2004) and

Blomberg, Broussard, and Hess (2011) found a significant negative impact of terrorism on per capita income growth in their cross-sectional estimates for the world and an African sample, respectively. For their panel estimates, Blomberg, Hess, and Orphanides (2004) found mixed results for their regional samples – e.g., terrorism did not have a significant negative impact on growth in the Middle East (see their Tables 4 and 5). Some studies distinguished between transnational (Trans) and domestic (Dom) terrorism, while others (i.e., Tavares, 2004; Meierrieks and Gries, 2012) did not. Studies that relied on terrorism data drawn from *International Terrorism: Attributes of Terrorist Events* (ITERATE) used just transnational terrorist events, since this data set does not include domestic incidents. Most of the previous studies found that one or more measures of terrorism had a negative and significant impact on per capita income growth regardless of the choice of empirical specifications, regions, and types of terrorism. Gaibulloev and Sandler (2008) found insignificant results with their cross-sectional regression and their panel regression with domestic terrorism, but uncovered a negative and significant impact of total and transnational terrorism on Western European per capita income growth. We challenge the past significant empirical findings, and discuss how and why previous empirical results are invalid econometrically.

Except for Meierrieks and Gries (2012), all previous empirical studies primarily relied on either cross-sectional or panel regression models of terrorism and growth, based on the following augmented Solow growth regression models:

$$\Delta \ln y_i = a + \psi \ln y_{0i} + \beta \tau_i + z_i \gamma + u_i, \tag{1}$$

$$\Delta \ln y_{it} = a_i + \psi \ln y_{it-1} + \beta \tau_{it} + z_{it} \gamma + u_{it}, \tag{2}$$

where $\Delta \ln y_i$ is the *i*th country's per capita real GDP growth rate; $\ln y_{0i}$ is the log of the initial value of per capita GDP for country *i;* τ_i denotes the *i*th country's transnational terrorist events;

z_i represents a vector of control variables for country *i*; and u_i is an error term. Similarly, $\Delta \ln y_{it}$ indicates the *i*th country's per capita real GDP growth rate at time *t*; $\ln y_{it-1}$ is log of lagged per capita income for country *i*; τ_{it} denotes the *i*th country's transnational terrorist events at time *t*; z_{it} is a vector of control variables for country *i* at time *t*; and u_{it} is an error term. In Eq. (1), *a* is an intercept, ψ and β are coefficients for initial per capita income and for terrorism, respectively, in country *i*, and γ is a vector of parameters for the control variable. Similarly, in Eq. (2), a_i is a country-specific intercept, ψ and β are coefficients for log of lagged per capita income and for terrorism, respectively, and γ is a vector of parameters for the control variable.

Levine and Renelt (1992) indicated that an augmented Solow or a cross-sectional growth regression is not capable of capturing the causal relationship between economic growth and explanatory variables. For example, economic growth rates in rich countries are usually lower than fast-developing countries. If, therefore, terrorists target slow-growing rich countries, then the cross-sectional relationship between economic growth and terrorism may appear to be negative when it is not the case. At the same time, some fast-growing poor countries may suffer reduced growth from terrorism, but still display relatively high growth. Therefore, it is not clear whether or not terrorism lowers economic growth for a cross-section of rich and poor countries that grow at different rates.

In order to avoid such issues, recent empirical studies on economic growth have used dynamic panel regressions (see Levine, 2005, for the detailed survey on this issue). However, the panel studies suffer from two serious econometric issues, which are inconsistency and invalid statistical inference. To highlight inconsistency, we rewrite Eq. (2) as

$$\ln y_{it} = a_i + \rho \ln y_{it-1} + \beta \tau_{it} + z_{it}' \gamma + u_{it}, \tag{3}$$

where $\rho = 1 + \psi$. Note that $\hat{\beta}$ associated with Eq. (3) is exactly the same as $\hat{\beta}$ associated with Eq. (2). It is well known that the fixed-effects estimator in Eqs. (2) and (3) are inconsistent as $N \to \infty$ for any fixed *T*. To establish this inconsistency, we rewrite Eq. (3) in the following matrix form:

$$\ln y = a + \rho \ln y_{-1} + Xb + u, \tag{4}$$

where $a = (a_1, a_2, \ldots, a_N)'$, $X = (\tau, z)$, $b = (\beta, \gamma)'$, $\ln y = (\ln y_1, \ln y_2, \ldots, \ln y_N)'$, and $\ln y_i = (\ln y_{i1}, \ln y_{i2}, \ldots, \ln y_{iT})'$. Other variables are defined similarly. Nickell (1981) indicated that the exact bias for the within group (WG) estimator of b is given by

$$\text{plim}_{N\to\infty}\left(\hat{b} - b\right) = -\text{plim}_{N\to\infty}\left[\left(X'X\right)^{-1} X' \ln y_{-1}\right] \text{plim}_{N\to\infty}\left(\hat{\rho} - \rho\right), \tag{5}$$

where $\text{plim}_{N\to\infty}\left(\hat{\rho} - \rho\right) < 0$. If, therefore, current terrorism is negatively correlated with past income (in other words, bad economic conditions in past years cause terrorist attacks in the current year), then the WG estimate for β becomes negative even when the true β is zero.

The second issue arises because the statistical inference of $\hat{\beta}$ – in other words, its t-statistics – becomes invalid owing to the impact of Nickell bias on the limiting distribution and to cross-sectional dependence. We begin with the problem of Nickell bias on the limiting distribution. As long as $N/T \to c$ as $N, T \to \infty$, Alvarez and Arellano (2003) showed that the limiting distribution of $\hat{b}$ is given by

$$\sqrt{NT}\left(\hat{b} - b\right) \to^{d} N\left(c, \sigma_b^2\right), \tag{6}$$

where c is a function of many nuisance parameters, including the N/T ratio. In other words, a typical t-statistic becomes either positive or negative infinity as $N, T \to \infty$. As Table 1 shows, except for Gaibulloev and Sandler (2008) and Meierrieks and Gries (2012), all other studies

considered larger *N* than *T*. The size of *T* is around 30 to 40, but the size of *N* is around 42 to 51 in the regional studies. In the case of the world samples, the size of *N*, which is 177 countries for Blomberg, Hess, and Orphanides (2004), is much larger than *T*. Therefore, we question the findings in previous empirical results.

Furthermore, the cross-sectional dependence directly hampers the estimation of the covariance and the variance of $\hat{b}$. Typically, the time fixed effects are introduced in the panel regression in Eq. (2) to control for the cross-sectional dependence, but recent econometric studies showed that time fixed effects cannot effectively control for cross-sectional dependence – see Section 4 for further details.

3. Data

Terrorism comes in two forms. Transnational terrorism occurs when an incident in one country involves perpetrators, victims, institutions, governments, *or* citizens of another country. If, for example, a foreigner is kidnapped for political purposes, then the incident is an instance of transnational terrorism. The data on transnational terrorist events come from ITERATE (Mickolus et al., 2011). Among other variables, ITERATE records the incident's date and its country location, which we use for the number of incidents for each country during 1970–2009.

For domestic terrorist events, the perpetrators, victims, and audience are all from the host or venue country. Domestic terrorist incidents are far more common than transnational terrorist attacks. We draw our data on domestic terrorism from the *Global Terrorism Database* (GTD), maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START). GTD data and variables are described in START (2009) and are available at START (2011). We draw the number of domestic terrorist incidents for 1970–2009 applying a breakdown procedure of GTD incidents into transnational and domestic attacks, devised by

Enders, Sandler, and Gaibulloev (2011). Because we have more confidence in ITERATE's tally of transnational terrorist event, we rely on ITERATE for these attacks. We also use the total number of terrorist incidents, which is the sum of transnational and domestic terrorist incidents obtained from GTD.

Macroeconomic data come from two sources. We obtain PPP-converted real GDP per capita at 2005 constant prices, consumption share of per capita real GDP (PPP converted at 2005 constant prices), government consumption share of per capita real GDP, investment share of per capita real GDP, and population from *Penn World Table Version 7.0* (Heston, Summers, and Aten, 2011). Information on gross domestic savings as a percentage of GDP is obtained from World Bank (2011). GDP components and savings, which are in percentages, are converted into 2005 international dollars using per capita real GDP. Based on this information, we construct our economic variables, which are discussed in the estimation section.

Our world sample covers 99 countries during 1970–2009. Using World Bank definitions, we construct five regional balanced panel datasets. Appendix Table A1 presents the list of sample countries by regions. The important consideration for choosing a particular country for our sample was data availability. Our main econometric method – the feasible interactive fixed-effects estimator – requires a balanced panel dataset. Therefore, we do not include countries with missing information over the sample period. We focus at the regional level to ensure that the number of years is sufficiently larger than the number of countries, essential for a proper econometric specification.

We believe that using regional balanced panel data does not drive the differences between our results and those in the literature. First, six of the seven studies, listed in Table 1, performed regional investigations of the impact of terrorism on economic growth. Each of these six articles emphasized the importance of regional analysis in isolating terrorism's impact on

growth because, in part, each region had unique and essential considerations. The regional partitioning is, thus, necessary for the validity of our exercise and is unlikely to drive our findings. Moreover, we perform alternative data partitioning in the robustness analysis to illustrate that our results are not sensitive to a particular grouping. Second, we include 99 countries that are representative of the world. Most countries that are not in our sample experienced few terrorist attacks during much of our sample period. For example, Oceania and Caribbean countries had little or no terrorism. Similarly, the former Soviet Union and most Eastern European countries reported little or no terrorism until the 1990s owing to limited press freedom (Sandler 1995). Thus, if anything, exclusion of these countries should make it easier to find an impact of terrorism on growth, thereby making our argument even stronger. Third, we compare the conventional method and our method using the same regional samples to show that the results still differ and that this difference is driven by methodology, not by the data. Fourth, in the robustness analysis, we replicate a study from the literature to further demonstrate the sensitivity of previous results to econometric specifications.

4. Empirical methodology adjusting for Nickell bias and cross-sectional dependence

In this section, we modify the conventional dynamic panel approach to avoid Nickell bias and appropriately account for the cross-sectional dependence. We first deal with Nickell bias (Section 4.1) and then we address cross-sectional dependence (Sections 4.2 and 4.3).

4.1. *Impact of Nickell bias on point estimates*

The inconsistency of $\hat{\beta}$ associated with Eqs. (2) and (3) is dependent on the true value of ρ and the correlation between the lagged dependent variable and the explanatory variables [see Eq.

(5)]. As ρ approaches unity, the inconsistency becomes more serious. A typical solution for Nickell bias is to use GMM/IV estimation with valid instrumental variables as long as ρ is not near unity. When, however, ρ is near unity, the GMM/IV methods fail due to weak instruments. Christopoulos and Tsionas (2004) found that the log of per capita GDP follows an I(1) process; hence, we are not able to utilize the GMM/IV approaches to correct for Nickell bias.

When the dependent and independent variables are I(1), the cointegration approach has been used (e.g., Christopoulos and Tsionas, 2004). However, Enders and Sandler (2005) and Enders, Sandler, and Gaibulloev (2011) found that the number of terrorists attack is stationary, so that cointegration analysis is not germane for the study of the impact of terrorism on growth. Instead, we impose a nonstationary restriction of $\rho = 1$ on Eqs. (3) and (4), and use the first difference of the log of per capita GDP, (i.e., economic growth) as the dependent variable. By imposing the unit root restriction, we avoid Nickell bias indicated in Eq. (5).[2] Our specification is

$$\Delta \ln y_{it} = a_i + \beta \tau_{it} + \theta_t + u_{it}, \tag{7}$$

where θ_t is the time fixed effects.

[Table 2 near here]

Table 2 shows the empirical results based on Eqs. (2) and (7). We also control for time fixed effects in Eq. (2) – see conventional specification in Table 2. We consider two measures of terrorism – the total number of terrorist attacks divided either by 1,000 or by population – and perform separate regressions for total (domestic and transnational), domestic, and transnational

[2]. The log of per capita GDP has an upward deterministic trend, whereas the terrorism data do not. Therefore Eq. (3) becomes unbalanced. By imposing the unit root restriction, we can also avoid the unbalanced regression problem.

terrorism. We report estimates for the whole sample and for the regional subsamples. After the column for the samples, the first three columns of Table 2 report the point estimates of β in Eq. (2). The boldface coefficients indicate that they are significantly different from zero at the 5% level. Consistent with previous empirical studies (see Table 1),[3] the point estimates are generally negative, including for the regional subsamples. When per capita terrorism data are used, the t-statistics become larger in absolute value. The second three columns show the point estimates of β in Eq. (7) and the last three columns display the difference between the estimates of β in Eqs. (2) and (7). Since Eq. (7) is free of Nickell bias, the difference between the β coefficients in Eqs. (2) and (7) represents the Nickell bias in Eq. (2). Evidently, the unit root restriction usually produces smaller point estimates of β in absolute value so that the bias is positive in absolute terms. Moreover, the absolute values of the t-statistic also become generally smaller; hence, there are many fewer statistically significant cases with the unit root restriction in Eq. (7) than in Eq. (2).

Interestingly, imposing the unit root restriction does not always reduce the point estimates, because the inclusion of common time effects or time fixed effects does not properly control for cross-sectional dependence. With cross-sectional dependence, Phillips and Sul (2007) showed that Nickell bias becomes random even when N is very large. If the time fixed effects properly controlled for cross-sectional dependence, the point estimate in Eq. (7) would have always been smaller than that in Eq. (2). More important, we are not able to judge whether the conventional critical value for the t-statistics is valid. Under cross-sectional dependence, the

[3] For the conventional equation, our findings for transnational terrorism does, however, differ from those of Blomberg, Hess, and Orphanides (2004), whose β was negative and significant for a larger sample and a different sample period ending in 2000. These sample differences are likely behind these differences in findings. These authors do not examine domestic terrorist incidents, which far outnumber transnational terrorist incidents. Moreover, their regional results for alternative transnational terrorism measures are not robust in keeping with our findings.

limiting distribution of the t-statistic becomes unknown, so that the use of the conventional critical value, such as –1.96 for the 5% level, is invalid.

4.2. *Bootstrap approach*

As an initial remedy, we use the bootstrap approach to control for cross-sectional dependence. Before discussing this approach, we address further specification issues. First, per capita income growth rates are possibly serially correlated. To account for serial correlation, we include the lagged dependent variable, $\Delta \ln y_{it-1}$, as an extra regressor, so that

$$\Delta \ln y_{it} = a_i + \alpha \Delta \ln y_{it-1} + \beta \tau_{it} + u_{it}, \tag{8}$$

where α stands for the autocorrelation between the GDP growth rates, which is different from ψ in Eq. (2). The regression model in Eq. (8) has been widely used in the empirical literature; however, this specification does not reveal the true causal relationship between past terrorism and current economic growth (e.g., see Section 3.2.3 in Levine, 2005, for further details). In other words, the empirical evidence of $\beta \neq 0$ does not imply that $E\left(\tau_{it} \Delta \ln y_{it+k}\right) \neq 0$ for any $k \geq 1$. To appreciate this insight, without loss of generality, consider the following VAR(1) model:

$$\begin{aligned} \Delta \ln y_{it} &= a_{i1} + \alpha_{11} \Delta \ln y_{it-1} + \alpha_{12} \tau_{it-1} + u_{it}, \\ \tau_{it} &= a_{i2} + \alpha_{21} \Delta \ln y_{it-1} + \alpha_{22} \tau_{it-1} + v_{it}, \end{aligned} \tag{9}$$

where we assume that the innovation of economic growth, u_{it}, is contemporaneously correlated with the innovation of terrorism, v_{it}; that is,

$$u_{it} = \delta v_{it} + \varepsilon_{it}.$$

Let us assume that $\alpha_{12} = \alpha_{21} = 0,$ so that there is no causal relationship between terrorism and economic growth. Furthermore, for simplicity, let $\alpha_{22} = 0$. Economic growth can then be re-written as:

$$\Delta \ln y_{it} = \left(a_{i1} - \delta a_{i2}\right) + \alpha_{11} \Delta \ln y_{it-1} + \delta \tau_{it} + \varepsilon_{it}. \tag{10}$$

Based on Eqs. (8)-(10), $\beta = \delta$ when $\alpha_{12} = \alpha_{21} = \alpha_{22} = 0.$ Hence, even in the absence of any causal relationship, economic growth can still be correlated with current terrorism as long as $\delta \neq 0$. This is why recent empirical studies (e.g., Chambers and Guo, 2011; Cieślik and Tarsalewska, 2011; Meierrieks and Gries, 2012) considered dynamic panel regressions with lagged explanatory variables. Therefore, our final specification becomes

$$\Delta \ln y_{it} = a_i + \alpha \Delta \ln y_{it-1} + \beta \tau_{it-1} + u_{it}. \tag{11}$$

Estimating β and testing the null hypothesis of $\beta = 0$ in Eq. (11) is not straightforward. First, the fixed-effects estimator in Eq. (11) becomes inconsistent if $N > T$ due to Nickell bias. Alvarez and Arellano (2003) showed that such inconsistency, however, goes away as long as $T > N$. In this case, the WG estimator becomes consistent. Hence, we use only regional panel data sets to avoid this N/T ratio issue. In our regional panels, the biggest *N* is 24 while *T* is 40; hence, *T* is always greater than *N* for our regional panel estimates. Alternatively, we could have applied the GMM/IV estimator to the world panel data set; however, we decided to use the regional panel data to avoid Nickell bias. Second, Phillips and Sul (2003, 2007) showed that under cross-sectional dependence the typical co-variance estimator becomes inconsistent. Ignoring cross-sectional dependence usually leads to larger t-ratios, which then result in overrejection of the null hypothesis even when $\beta = 0$.[4.] To overcome this concern, we apply a

[4] Gaibulloev and Sandler (2011) used standard errors that are robust to cross-sectional dependence. Other terrorism and growth studies do not account for cross-sectional dependence.

sieve nonparametric bootstrapping method to compute the t-statistics. If, however, $N > T$, the limiting distribution of the resulting estimator is not pivotal, so that the bootstrapping method does not work asymptotically. Because we are only using regional panel data sets where $T > N$, we are then free from this statistical concern.

The sieve bootstrapping procedure takes the following steps:

1. Estimate Eq. (9) with fixed effects and obtain all estimates and residuals. Also, we run Eq. (11) to get the fixed-effects estimates and their t-statistics.
2. For each time *t*, randomly draw *N* observations with replacement from among *N* values of $\hat{u}_{it}$ and $\hat{v}_{it}$ jointly. By so doing, we keep the cross-sectional dependence in the residuals. We, then, re-center pseudo residuals. Finally, we generate $T + K$ pseudo variables $\Delta \ln y_{it}^{*}$, and τ_{it}^{*} from Eq. (9) and delete the first *K* observations to avoid the initial value effect, where we impose zero restrictions on τ_{it}^{*} if $\tau_{it}^{*} < 0$.
3. Estimate $\Delta \ln y_{it}^{*} = a_i^{*} + \alpha^{*} \Delta \ln y_{it-1}^{*} + \beta^{*} \tau_{it-1}^{*} + \varepsilon_{it}^{*}$ and compute the bootstrap t-value as

$$t_{\alpha}^{*} = \frac{\hat{\alpha}^{*} - \hat{\alpha}}{SE\left(\hat{\alpha}^{*}\right)} \quad \text{and} \quad t_{\beta}^{*} = \frac{\hat{\beta}^{*} - \hat{\beta}}{SE\left(\hat{\beta}^{*}\right)}.$$

4. Steps 2 and 3 are repeated 2,000 times to obtain the empirical distributions of the t-statistics. We then calculate the bootstrap critical values of the t-statistics – to compare with the actual t-ratios – and *p*-values (probability that a bootstrap t-ratio is larger than the actual t-ratio).

[Table 3 near here]

Table 3 presents the nonparametric sieve bootstrap results. Separate analysis is performed for total (domestic and transnational), domestic, and transnational terrorism. Furthermore, terrorism is measured as the number of terrorist incidents divided by 1,000 and,

alternatively, as the number of terrorist incidents divided by population. We report empirical results with both level and first differenced terrorism. The boldface and italic numbers indicate the rejection of the null hypothesis that the parameter of interest is zero at the 5% and 10% level of significance, respectively. When the lagged level of terrorism divided by 1,000 is used as a regressor, three cases become significantly different from zero at the 5% level of significance: total and domestic terrorism in America and transnational terrorism in sub-Saharan Africa for first differenced terrorism. If lagged terrorism per capita is used, five cases are significantly different from zero: total and domestic terrorism in America at the 10% level of significance, transnational terrorism in America at the 5% level of significance, and lagged and differenced transnational terrorism in sub-Saharan Africa at the 5% level of significance. The rest of the terrorism coefficients are not statistically significant. Surprisingly, the point estimates on lagged economic growth rates do not vary much with the choice of terrorism. For example, for sub-Saharan Africa with lagged terrorism per capita data, the point estimates on the lagged economic growth rates are around 0.06 regardless of the choice of terrorism as an additional regressor. When total and domestic terrorism data (per capita level) are used for sub-Saharan Africa, the associated point estimates are not significantly different from zero. In contrast, transnational terrorism is generally negative and significant for sub-Saharan Africa in Table 3. Another peculiar finding is that the significant cases are somewhat different compared to Table 2. The sole exception is America when per capita level terrorism is used for the conventional specification. Such non-robust results may arise due to possible correlation between regressors and common factors in the regression errors. In the next subsection, we thus control for cross-sectional dependence by using the factor augmented panel regression.

4.3. *Factor augmented approach*

The bootstrapping method assumes that the common factors of the error term and those of the explanatory variables are not correlated. Failure of this assumption leads to endogeneity bias. Therefore, we next refer to the recently developed interactive fixed-effects or factor augmented panel model to accommodate cross-sectional dependence (Pesaran, 2006, Bai, 2009, Greenaway-McGrevy, Han, and Sul, 2012). Combining causal relationship with interactive fixed effects yields

$$\Delta \ln y_{it} = a_i + \alpha \Delta \ln y_{it-1} + \beta \tau_{it-1} + u_{it},\ u_{it} = \lambda_i^{'} F_t + \varepsilon_{it}, \tag{12}$$

where F_t is a column vector of common factors, and $\lambda_i^{'}$ is a row vector of corresponding coefficients. The interactive fixed-effects model allows for possible correlation between some of the common factors of the regressors and the common factors of the regression errors. That is, $E\left(\Delta \ln y_{it-1} F_t\right) \neq 0$ and $E\left(\tau_{it-1} F_t\right) \neq 0$.

Since the common factors are unknown, the feasible interactive fixed-effects estimator is applied, which requires estimation of F_t. Several estimation methods for common factors are available: Pesaran (2006) suggested using the cross-sectional means of the regressand and regressors, whereas Bai (2009) recommended using the principal component estimator of the regression residuals. Pesaran's estimation fails if the number of common factors is larger than the number of variables in the regression due to the lack of identification. Bai's method does not require such an assumption, but needs a consistent estimator. Finally, Greenaway-McGrevy, Han, and Sul (2012) proposed estimating the interactive fixed-effects model by using the common factors to the regressand and regressors as the proxy of F_t. They call this approach the first-stage estimator, which is consistent but inefficient. Greenaway-McGrevy, Han, and Sul (2012) suggested using the first-stage estimator as the initial estimator for Bai's estimator. Following Greenaway-McGrevy, Han, and Sul (2012) at the second stage, we estimate the

common factors from the first-stage residuals and then estimate Eq. (12). After obtaining the second-stage estimator, we re-estimate the common factors until the point estimates converge. The maximum number of common factors is set at five and an iteration criterion is 0.001. The estimated factor numbers are slightly different across different regions; for most of the cases, the estimated factor numbers are between one and two. We also note that we use Pesaran's common correlated estimation and find that our conclusion still holds (these estimates are available upon request).

[Table 4 near here]

Table 4 shows the factor augmented panel regressions results. As before, various measures of terrorism are used. Moreover, the total number of countries for each region differs – see Appendix Table A1. The domestic GTD sample for Western Europe does not include Iceland; whereas, the ITERATE sample does not include Macau (Asia), Morocco (Middle East and North Africa), and Finland (Western Europe). We excluded these countries because they have zero terrorist incidents over the sample period, which does not allow us to perform the factor augmented panel regression. In terms of magnitudes, the terrorism estimates in Table 4 are mostly smaller than the terrorism estimates from Eq. (2) in Table 2. Notably, there is no statistically significant impact of terrorism on economic growth, which holds across all cases. Even though we do not report their *p*-values, most of them are far from 0.5, so that the terrorism coefficients are not significant even at the 50% level. When, for example, terrorism is divided by 1000, total and domestic level terrorism in America are significantly different from zero in Table 3 with point estimates between –0.06 and –0.07. With factor augmented terms, these point estimates, however, drop to about –0.05 and, more important, are insignificant. Hence, we can conclude that the common factor in the regression error is correlated with domestic and total terrorism data. In our estimates, the common factor is explaining the variation of the dependent

variable in Eq. (12). In fact, under the presence of endogeneity between regressors and the regression errors, the bootstrap does not have any asymptotic justification, so that the bootstrapped critical values become invalid. Notice that the significant regional terrorism coefficients in Table 2 become insignificant when we account for cross-sectional dependence and Nickell bias in Table 4. This strongly suggests that the results from the previous literature are sensitive to model specifications.

5. Robustness checks

So far we did not include any control variables in the dynamic panel regressions. We check the sensitivity of our results to the inclusion of control variables by including the first difference of log investment $(\Delta \ln I)$ and population growth rates (Δn) as additional regressors in Eq. (12). The empirical results with alternative measures of terrorism are reported in Table 5. Evidently, the inclusion of other key growth variables in Eq. (12) does not impact our main conclusion. The point estimates on the terrorism coefficients vary in their magnitude and, sometimes, their sign, but there are no consistent patterns to these changes. For example, for Western Europe, the estimate of the level of transnational terrorism changes from 0.010 (in Table 4) to –0.014 (in Table 5), whereas the estimate of transnational terrorism per capita changes from –2.051 (in Table 4) to 0.068 (in Table 5). Most important, all terrorism estimates remain statistically insignificant. To conserve space, we do not report the point estimates on lagged economic growth and other control variables (some of which are significant) in Table 5; these results are available upon request.

[Table 5 near here]

We then decompose the growth regression (12) into each of its primary GDP components. The evidence in the literature suggests that terrorism reduces investment but

increases government spending (e.g., Blomberg, Hess, and Orphanides, 2004; Gaibulloev and Sandler, 2008). Hence, the negative impact of terrorism on investment may possibly offset the positive effect of terrorism on government spending, thereby resulting in a zero overall impact on growth. We investigate this possibility by estimating separate regressions for consumption, government spending, and investment.

[Table 6 near here]

Table 6 displays the results. We do not report the point estimates on the lagged growth rate for each GDP component in order to save space (these estimates are available upon request). Our main conclusion still holds: terrorism is not statistically significant across all regressions. Point estimates fluctuate around zero, and their signs do not show any consistent pattern. These results support that terrorism does not affect the growth rate of GDP components.[5]

Now, we examine alternative partitioning of the data based on per capita income in US dollars and on the number of terrorist attacks. In particular, we split our sample into three subsamples of countries with average per capita GDP of less than $3,000 (30 countries), between $3,000 and $15,000 (28 countries), and over $15,000 (23 countries), respectively. A few countries with relatively little terrorism are excluded to make sure that *N* is sufficiently less than *T* to avoid Nickell bias. Using factor augmented dynamic panel regression for each of the subsamples, we re-estimate Table 4 separately for total, domestic, and transnational terrorism. Both level and first differenced terrorist attacks are investigated. Terrorism is measured as the number of incidents per 1,000 persons and, alternatively, as the number of incidents per capita. For all estimates, terrorism is never a statistically significant determinant of growth. We also re-estimate Table 4 for the 30 most attacked sample countries for 1970–2009, based on the number

[5] The domestic GTD sample for Western Europe again excludes Iceland. Additionally, the ITERATE-drawn sample excludes Macau (Asia), Morocco (Middle East and North Africa), and Finland (Western Europe). In Table 5 and for the investment regressions in Table 6, we dropped Nicaragua and Sierra Leone because some investment values are reported as negative

of total, transnational, and domestic terrorist attacks, respectively. Additionally, we analyze a panel of the 30 most attacked sample countries (in terms of total terrorism) with average per capita GDP of less than $15,000, and a panel of the 30 most frequently attacked sample countries based on the number of years of at least one terrorist attack. For all factor augmented dynamic panels, terrorism is never a significant determinant of growth (available upon request).

Finally, we have chosen a data set used by Gaibulloev and Sandler (2008) to further show that econometric specification issues are behind the differences between our results and those of the previous literature. Their original data covered 18 Western European countries for 1971–2004 and satisfied the $N < T$ condition. We dropped Finland to perform the factor augmented panel regression, since Finland had no terrorism over the sample period. Gaibulloev and Sandler (2008) used trade openness and investment as control variables, and found that total and transnational terrorism reduced economic growth. We are able to replicate their results. However, when we revise their model specification and apply the factor augmented dynamic panel regression, the terrorism coefficients are no longer statistically significant (available upon request).

6. Concluding remarks

This paper reinvestigates the impact of various forms of terrorism on economic growth by providing estimates of dynamic panel regressions for five regional conglomerates. Even though the extant literature showed a negative and significant effect of terrorism on economic growth, our sequence of estimations does not find any such significant impact. Given that most countries experienced a rather modest amount of terrorism in most years, the results here indicate that our regional samples are insulated from the harmful economic ramifications of terrorism. This is not to imply that a country, plagued by terrorism, would escape detrimental economic effects.

Our findings identify two biases in the literature: Nickell bias and cross-sectional dependence. In Table 2, we show the possible impact of Nickell bias on conventional estimates. When lagged income per capita growth and lagged terrorism are included as regressors in Table 3, our bootstrapped dynamic panel estimates uncover few significant terrorism coefficients if Nickell bias and cross-sectional dependence are partially addressed. In Table 4, we address both Nickell bias and cross-sectional dependence, and find that terrorism in its various forms and specifications has no impact on economic growth at the regional level. Cross-sectional dependence is handled with the help of factor augmented dynamic panel regressions. The absence of an impact is robust to the inclusion of investment and population growth. Moreover, factor augmented dynamic panel regressions display no impact of terrorism on GDP components – i.e., consumption, government spending, and investment – in contradiction to the previous literature (e.g., Blomberg, Hess, and Orphanides, 2004; Gaibulloev and Sandler, 2008, 2009) that showed that terrorism reduced investment and increased government expenditures. When, therefore, appropriate dynamic panel methods are utilized, terrorism does not affect economic growth or the components of GDP. This finding holds for total, domestic, and transnational terrorism when expressed in levels or differenced.

This provocative result is of essential importance because it contradicts conventional wisdom, drawn from previous findings that did not adjust for key biases. In addition, our findings have much to say about the terrorists' expressed wish to damage targeted economies. Quite simply, their past efforts have not generally accomplished this goal. Our empirical insights also indicate that monetary and fiscal policies are seldom needed following terrorist attacks, except in the extremely rare instance of a catastrophic 9/11-like attack (Enders and Sandler, 2012). The results here also imply that only modest offsets in aid are typically required for developing countries to address harmful economic consequences of terrorism unless there is a

large terrorist campaign. Generally, terrorism has localized effects like crime on an economy, but terrorist incidents are far less frequent than crime. Economies may insulate themselves from any terrorism-induced economic harm through transference of economic activities away from terrorism-prone sectors (Enders and Sandler, 2012). The general absence of terrorism-induced economic harm also has something to say about counterterrorism expenditures, since this absence curbs somewhat the need for such countermeasures.

Appendix

Table A1. List of sample countries by regions

America	Asia	ME & NA	sub-Saharan Africa	W. Europe
Argentina	Afghanistan	Algeria	Angola	Austria
Bolivia	Bangladesh	Bahrain	Burundi	Belgium
Brazil	Cambodia	Cyprus	Chad	Denmark
Canada	China	Egypt	Congo (Brazzaville)	Finland
Chile	Hong Kong	Iran	Congo (Kinshasa)	France
Colombia	India	Iraq	Ethiopia	Germany
Costa Rica	Indonesia	Israel	Ivory Coast	Great Britain
Cuba	Japan	Jordan	Kenya	Greece
Dominican Republic	Laos	Lebanon	Lesotho	Iceland
Ecuador	Macau	Morocco	Mali	Ireland
El Salvador	Malaysia	Syria	Mozambique	Italy
Guatemala	Maldives	Tunisia	Namibia	Luxembourg
Haiti	Nepal	Turkey	Niger	Malta
Honduras	Pakistan		Nigeria	Netherlands
Mexico	Philippines		Rwanda	Norway
Nicaragua	Singapore		Senegal	Portugal
Panama	South Korea		Sierra Leone	Spain
Peru	Sri Lanka		Somalia	Sweden
Puerto Rico	Taiwan		South Africa	Switzerland
United States	Thailand		Sudan	
Uruguay	Vietnam		Togo	
Venezuela			Uganda	
			Zambia	
			Zimbabwe	

Note: ME & NA stands for Middle East and North Africa and W. Europe denotes Western Europe.

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Table 1. A summary of the past literature on the impact of terrorism on per capita income growth

Study	Data	Sample	Period	Type of analysis	Select controls	Findings
Blomberg, Hess, and Orphanides (2004)	ITERATE	World; World; Regions	1968–2000	Cross sectional Panel Data	$\ln y_{it-1}$ I/Y, open, conflict	(–)* (–)* mixed
Tavares (2004)	IPIC	World	1987–2001	Panel Data	Terrorism × political rights	(–)*
Gaibulloev and Sandler (2008)	ITERATE TWEED	18 Western European	1971–2004	Cross sectional Panel Data Total (Trans + Dom) Trans Dom	$\ln y_{it-1}$ I/Y, open	(–) (–)* (–)* (–)
Gaibulloev and Sandler (2009)	ITERATE	42 Asian	1970–2004	Panel Data	$\ln y_{it-1}$ I/Y, open, conflict	(–)*
Gaibulloev and Sandler (2011)	ITERATE GTD	51 African	1970–2007	Panel Data Trans Dom	$\ln y_{it-1}$ I/Y, open, conflict	 (–)* (–)
Blomberg, Broussard, and Hess (2011)	ITERATE	46 sub -Saharan African	1968–2004	Cross sectional Panel Data	$\ln y_{it-1}$ I/Y, open, conflict	(–)* (–)*
Meierrieks and Gries (2012)	GTD	18 Latin American	1970–2007	Panel Granger Causality	–	(+)

Note: ITERATE stands *for International Terrorism: Attributes of Terrorist Events* (Mickolus et al., 2011); IPIC indicates International Policy Institute for Counterterrorism; TWEED denotes *Terrorism in Western Europe*: *Event Data* (Engene, 2007); and GTD represents *Global Terrorism Database* (START, 2011). ITERATE contains just transnational terrorist incidents (Trans), while the other two data sets contain domestic (Dom) and transnational terrorist incidents. Enders, Sandler, and Gaibulloev (2011) partitioned GTD into domestic and transnational terrorist incidents. y_{it-1} is lagged per capita income for country *i*; *I*/*Y* is ratio of investment to GDP; open is a measure of trade openness; and conflict includes internal conflict and external wars. *denote the 5% level of significance.

Table 2. Impact of Nickell bias on point estimates on current level terrorism

	Conventional [Eq. (2)]			Unit Root Restriction [Eq. (7)]			Eq. (2) – Eq. (7)		
	Total	Dom	Trans	Total	Dom	Trans	Total	Dom	Trans
Terrorism is divided by 1000									
World (99)	–0.025	–0.034	0.274	–0.012	–0.021	0.304	–0.013	–0.013	–0.030
America (22)	–0.062	–0.072	**–0.612**	–0.052	–0.061	–0.551	–0.010	–0.011	–0.061
Asia (21)	–0.018	–0.025	0.355	0.042	0.034	0.517	–0.060	–0.059	–0.162
ME & NA (13)	–0.045	–0.072	**1.353**	0.061	0.044	**1.320**	–0.106	–0.116	0.033
S.S. Africa (24)	**–0.284**	**–0.207**	–1.232	**–0.239**	–0.164	–1.032	–0.045	–0.043	–0.200
W. Europe (19)	–0.010	–0.008	–0.012	–0.012	–0.008	–0.055	0.002	0.000	0.043
Terrorism is divided by population (in thousands)									
World (99)	**–1.055**	**–1.179**	1.905	**–1.057**	**–1.155**	1.520	0.002	–0.024	0.385
America (22)	**–1.054**	**–1.059**	**–12.84**	–1.036	–1.036	**–13.18**	–0.018	–0.023	0.338
Asia (21)	–1.670	–1.613	12.48	–1.011	–0.837	14.65	–0.659	–0.776	–2.168
ME & NA (13)	0.106	**–1.748**	**4.802**	0.371	–0.910	**3.747**	–0.265	–0.838	1.055
S.S. Africa (24)	–2.827	–1.791	–8.689	–2.475	–1.395	–7.518	–0.352	–0.396	–1.171
W. Europe (19)	**–1.370**	–0.779	**–5.945**	–1.231	–0.514	**–5.764**	–0.139	–0.265	–0.181

Conventional: $\Delta \ln y_{it} = a_i + \psi \ln y_{it-1} + \beta \tau_{it} + \theta_t + u_{it}$

Unit Root Restriction: $\Delta \ln y_{it} = a_i + \beta \tau_{it} + \theta_t + u_{it}$

Note: Boldface numbers are significantly different from zero at the 5% level. Panel robust standard errors are used. The numbers in parentheses stand for the number of countries.

Table 3. Dynamic panel regression with lagged economic growth and terrorism

Dependent: $\Delta \ln y_{it}$	Explanatory Variables					
	$\Delta \ln y_{it-1}$			τ_{it-1}		
Terrorism/1000	Total	Dom	Trans	Total	Dom	Trans
America	**0.220**	**0.219**	**0.229**	**−0.060**	**−0.068**	−0.074
Asia	**0.214**	**0.214**	**0.213**	0.028	0.024	0.445
ME & NA	−0.110	−0.110	−0.110	0.071	0.081	0.083
S.S. Africa	0.057	0.057	0.054	−0.053	−0.033	−1.361
W. Europe	**0.384**	**0.384**	**0.386**	−0.014	−0.010	0.076
Terrorism/population						
America	**0.215**	**0.215**	**0.213**	*−0.498*	*−0.574*	**−6.263**
Asia	**0.213**	**0.214**	**0.215**	−1.512	−1.204	−1.503
ME & NA	−0.110	−0.109	−0.108	−0.501	0.235	−0.654
S.S. Africa	0.055	0.056	0.052	−1.278	−1.264	**−11.863**
W. Europe	**0.384**	**0.385**	**0.395**	−0.023	0.878	3.439
Terrorism/1000	$\Delta \ln y_{it-1}$			$\Delta \tau_{it-1}$		
America	**0.230**	**0.230**	**0.233**	−0.006	−0.022	0.261
Asia	**0.214**	**0.214**	**0.214**	0.042	0.064	−0.012
ME & NA	−0.110	−0.110	−0.118	−0.018	−0.046	0.839
S.S. Africa	0.058	0.058	0.056	0.118	0.133	**−2.321**
W. Europe	**0.386**	**0.385**	**0.384**	−0.054	−0.035	−0.007
Terrorism/population						
America	**0.229**	**0.228**	**0.227**	−0.138	−0.271	−4.081
Asia	**0.215**	**0.214**	**0.215**	−0.149	0.223	−2.523
ME & NA	−0.110	−0.113	−0.119	−1.344	−2.894	3.307
S.S. Africa	0.057	0.057	0.057	−0.706	−0.654	**−12.751**
W. Europe	**0.384**	**0.385**	**0.392**	−0.024	0.650	2.293

Regression: $\Delta \ln y_{it} = a_i + \alpha \Delta \ln y_{it-1} + \beta \tau_{it-1} + u_{it}$ or $\Delta \ln y_{it} = a_i + \alpha \Delta \ln y_{it-1} + \beta \Delta \tau_{it-1} + u_{it}$

Note: Boldface and italic numbers imply that they are significantly different from zero at the 5% and 10% level, respectively. Standard errors are calculated from nonparametric sieve bootstrap procedures.

Table 4. Factor augmented dynamic panel regression

Dependent: $\Delta \ln y_{it}$	Explanatory Variables					
	$\Delta \ln y_{it-1}$			τ_{it-1}		
Terrorism/1000	Total	Dom	Trans	Total	Dom	Trans
America	0.233	0.233	0.235	−0.053	−0.054	−0.027
Asia	0.161	0.162	0.156	−0.078	−0.080	−0.012
ME & NA	−0.060	−0.060	0.023	0.034	0.046	0.186
S.S. Africa	0.113	0.113	0.111	−0.091	−0.065	−1.172
W. Europe	**0.446**	**0.366**	*0.270*	0.0001	−0.0002	0.0102
Terrorism/population						
America	0.227	0.228	0.222	−0.509	−0.497	−5.162
Asia	0.171	0.173	0.146	−1.802	−0.800	−27.70
ME & NA	−0.063	−0.064	0.018	0.658	1.099	1.224
S.S. Africa	0.113	0.114	0.107	−1.854	−1.769	−11.82
W. Europe	**0.447**	**0.376**	0.256	0.234	0.656	−2.051
Terrorism/1000	$\Delta \ln y_{it-1}$			$\Delta \tau_{it-1}$		
America	0.236	0.236	0.240	−0.004	−0.010	0.338
Asia	0.172	0.172	0.160	0.015	0.021	0.196
ME & NA	−0.043	−0.044	0.022	0.132	0.143	−0.010
S.S. Africa	0.113	0.113	0.115	−0.066	−0.006	−2.233
W. Europe	**0.445**	**0.360**	0.267	−0.048	−0.043	−0.033
Terrorism/population						
America	0.236	0.235	0.236	−0.314	−0.360	1.135
Asia	0.169	0.174	0.160	1.102	1.577	−14.36
ME & NA	−0.051	−0.054	0.020	1.394	1.346	1.646
S.S. Africa	0.113	0.114	0.116	−1.840	−1.540	−12.94
W. Europe	**0.447**	**0.373**	0.267	0.336	0.625	−0.748

Regression: $\Delta \ln y_{it} = a_i + \alpha \Delta \ln y_{it-1} + \beta \tau_{it-1} + \lambda_i^{'} F_t + \varepsilon_{it}$ or $\Delta \ln y_{it} = a_i + \alpha \Delta \ln y_{it-1} + \beta \Delta \tau_{it-1} + \lambda_i^{'} F_t + \varepsilon_{it}$

Note: Boldface and italic numbers are significantly different from zero at the 5% and 10% level, respectively.

Table 5. Factor augmented dynamic panel regression with control variables

	τ_{it-1}		
Terrorism/1000	Total	Dom	Trans
America	–0.056	–0.061	–0.084
Asia	–0.038	–0.035	0.142
ME & NA	–0.006	–0.009	0.402
S.S. Africa	–0.124	–0.107	–0.891
W. Europe	0.020	0.017	–0.014
Terrorism/population			
America	–0.503	–0.522	–3.628
Asia	–2.689	–2.268	–9.526
ME & NA	0.341	0.523	1.838
S.S. Africa	–1.950	–1.953	–12.696
W. Europe	–0.070	0.397	0.068
Terrorism/1000	$\Delta\tau_{it-1}$		
America	–0.030	–0.039	0.231
Asia	0.031	0.037	0.435
ME & NA	0.048	0.051	0.016
S.S. Africa	–0.090	–0.025	–2.413
W. Europe	–0.024	0.003	–0.031
Terrorism/population			
America	–0.489	–0.572	–0.161
Asia	–0.583	0.715	0.728
ME & NA	–0.152	0.233	0.979
S.S. Africa	–1.984	–1.590	–15.526
W. Europe	–0.152	0.819	0.068

Regression: $\Delta \ln y_{it} = a_i + \alpha \Delta \ln y_{it-1} + \beta \tau_{it-1} + \beta_1 \Delta \ln(I)_{it} + \beta_2 \Delta n_{it} + \lambda_i^{'} F_t + \varepsilon_{it}$

or $\Delta \ln y_{it} = a_i + \alpha \Delta \ln y_{it-1} + \beta \Delta \tau_{it-1} + \beta_1 \Delta \ln(I)_{it} + \beta_2 \Delta n_{it} + \lambda_i^{'} F_t + \varepsilon_{it}$

Note: Boldface and italic numbers imply that they are significantly different from zero at the 5% and 10% level, respectively.

Table 6. Factor augmented dynamic panel regression for GDP components

	Consumption			Government Spending			Investment		
	Total	Dom	Trans	Total	Dom	Trans	Total	Dom	Trans
Terrorism/1000					τ_{it-1}				
America	–0.051	–0.053	–0.326	–0.033	–0.039	–0.200	–0.099	–0.088	0.204
Asia	–0.068	–0.073	0.001	–0.027	–0.026	–0.601	–0.060	–0.083	0.421
ME & NA	–0.047	–0.054	0.769	–0.013	–0.010	0.380	0.405	0.493	–0.344
S.S. Africa	–0.460	–0.450	–1.350	0.153	0.099	0.640	0.465	0.552	–6.035
W. Europe	0.045	0.063	–0.028	0.011	–0.003	0.075	–0.075	–0.079	–0.033
Terrorism/Pop									
America	–0.466	–0.454	–8.627	–0.315	–0.376	–2.816	0.029	0.237	–9.808
Asia	–2.929	–3.536	–0.959	–1.642	–2.355	–16.418	–0.047	–0.814	8.346
ME & NA	–0.892	–0.673	1.237	–1.885	–2.289	–0.230	0.313	0.877	–1.347
S.S. Africa	–7.828	–9.070	–7.150	–0.497	0.670	5.253	3.887	4.430	–14.226
W. Europe	1.231	1.048	0.344	1.252	1.708	–0.309	5.914	7.745	6.495
Terrorism/1000					$\Delta\tau_{it-1}$				
America	0.019	0.013	0.284	–0.006	–0.014	–0.038	0.172	0.194	0.753
Asia	0.037	0.042	0.026	–0.123	–0.117	–0.429	–0.020	–0.035	–0.656
ME & NA	0.124	0.114	1.233	0.087	0.094	0.957	0.250	0.306	–1.991
S.S. Africa	–0.241	–0.203	–1.119	0.263	0.219	0.238	0.203	0.037	–3.036
W. Europe	0.017	0.023	–0.044	0.016	–0.007	0.010	–0.235	–0.226	–0.046
Terrorism/Pop									
America	–0.042	–0.044	–1.843	0.394	0.328	–0.841	1.752	1.913	13.983
Asia	0.094	–0.700	–1.646	–1.744	–4.106	–17.430	4.223	–2.159	12.232
ME & NA	0.950	0.980	3.557	–0.518	–0.222	–0.268	–2.447	–4.194	3.356
S.S. Africa	–5.407	–5.152	–7.278	0.813	1.577	4.217	0.821	–2.194	12.273
W. Europe	0.224	–0.238	1.613	0.233	0.232	–0.807	0.218	4.165	–2.014

Regression: $\Delta \ln z_{it} = a_i + \alpha \Delta \ln z_{it-1} + \beta \tau_{it-1} + \lambda_i^{'} F_t + \varepsilon_{it}$ or $\Delta \ln z_{it} = a_i + \alpha \Delta \ln z_{it-1} + \beta \Delta \tau_{it-1} + \lambda_i^{'} F_t + \varepsilon_{it}$, where z is the relevant GDP component.