



المجلة العراقية للعلوم الاقتصادية
Iraqi Journal For
Economic Sciences



PISSN : 1812-8742

EISSN : 2791-092X

Arcif : 0.375

The Influence of Some Economic and Non-Economic Factors on Terrorism in the Seven Most Affected Countries During the Years 2000–2021

تأثير بعض العوامل الاقتصادية وغير الاقتصادية على الإرهاب في الدول السبع الأكثر تضرراً خلال الفترة 2000-2021

م.د. زكي حسين قادر

Zaki Husein Qader

zaki.qader@su.edu.krd

م.د. سارة أحمد حسن جاوشين

Sarah Ahmed Cawsheen

Sarah.chawsheen@su.edu.krd

كلية الإدارة والاقتصاد / جامعة صلاح الدين - اربيل

المستخلص:

تهدف هذه الدراسة إلى فحص تأثير بعض العوامل الاقتصادية وغير الاقتصادية مثل العوامل السياسية والديموغرافية على الإرهاب في سبع دول هم: العراق، أفغانستان، جمهورية الكونغو الديمقراطية، نيجيريا، باكستان سوريا، واليمن خلال السنوات 2000-2021. تم استخدام تحليل البيانات اللوحة لإنشاء نوعين من النماذج: أحدهما بعوامل اقتصادية بحتة والآخر بخليط من العوامل الاقتصادية والسياسية والديموغرافية. أظهرت النتائج الأولية بأن نموذج التأثير العشوائي (REM) مناسبة للمتغيرات الاقتصادية ونموذج التأثير الثابت (FEM) للمتغيرات المختلطة. بعد تحديد مدى ملاءمة المتغير المعتمد على التأخر، تم تطوير نماذج ديناميكية ذات تأخر تلقائي مترجع موزع (ARDL). تكشف نتائج نموذج PMG المختارة عن وجود علاقة سلبية بين معدل نمو الناتج المحلي الإجمالي والإرهاب. في حين توجد علاقة إيجابية بين معدل التضخم والإرهاب. للعولمة الاقتصادية تأثير سلبي على الإرهاب في الأمد القريب. نموذج PMG للمتغيرات الاقتصادية يصحح اختلال التوازن في الفترة الماضية بمعدل 10.9٪ سنويًا، مما يؤدي إلى تأثير طويل الأمد على عواقب الإرهاب. في حين يصحح نموذج المتغيرات المختلطة اختلال التوازن بنسبة 25.6٪ سنويًا مما يؤدي إلى تأثير متوسط المدى على الإرهاب. أظهر اختبار سببية جرانجر DH لـ Dumitrescu and Hurlin (2012) أن نمو الناتج المحلي الإجمالي والاستقرار السياسي يسبب الإرهاب في بلدان مختارة. لذلك، نوصي السلطات في البلدان المختارة بالعمل على زيادة ناتجها المحلي الإجمالي وخفض معدلات التضخم، وتعزيز العولمة الاقتصادية من خلال التبادلات التجارية والتكنولوجية وتعزيز الاستقرار السياسي، وتخفيف الضغوطات الديموغرافية، وتعزيز العلاقات مع المنظمات والبلدان التي تشترك في المصالح المتبادلة.

الكلمات الرئيسية: الإرهاب، الاقتصاد الكلي، تحليل البيانات اللوحية

Abstract: The aim of this study to inspect the influence of some economic and non-economic factors such as political, demographic, on terrorism in seven countries; Iraq, Afghanistan, Democratic Republic of the Congo, Nigeria, Pakistan, Syria, and Yemen during the years 2000-2021. Panel data analysis is used to create two types of models: one with purely economic variables and another with a mix of economic, political, and demographic variables. The initial results showed that random effect models (REM) are suitable for economic regressors and fixed effect models (FEM) for the mixed. After determining the relevance of the lag-dependent variable, dynamic Auto Regressive Distributed Lag (ARDL) models are developed. The selected PMG models reveal existence of a negative relationship between growth rate of GDP and terrorism. While a positive relationship exists between inflation rate and terrorism. Economic Globalization has a negative impact on terrorism in the short-run. The economic PMG model corrects its past period disequilibrium at a rate of 10.9% annually, resulting in a long-term

impact on terrorism's consequences. While the model of mixed factors corrects disequilibrium at 25.6% annually, resulting in a medium-term impact on terrorism. The Dumitrescu and Hurlin(2012) DH test showed GDP growth and political stability Granger cause terrorism in selected countries. Therefore, we recommend the authorities in the selected countries to work on increasing their gross domestic product, decreasing inflation rates, enhancing economic globalization through trade and technological exchanges, fostering political stability, alleviating demographic pressures, and strengthening ties with organizations and countries that share mutual interests.

Keywords: Macroeconomic, Terrorism, panel data analyses, FEM REM ARDL PMG, Granger Causality

1. Introduction

Terrorist activities have increased in several countries during the last decade, resulting in substantial human and economic losses, as well as deep psychological traumas. While recent efforts have been made to better understand the origins and consequences of terrorism, but a thorough assessment of the issue remains lacking. Terrorism is frequently connected with political aims sought by some parties in order to attain specific goals, although it involves much more than just political violence. Scholars such as Okeke(2005) and Nacos(2006) contend that terrorism is ultimately motivated by political ambitions, independent of terrorists' short-term doctrines and beliefs. As a result, the literature has yet to achieve a clear and specific definition of, terrorism However in 2004, UN Resolution 1566 identified common ground on key aspects of the definition of terrorism. It classifies terrorists as members of certain religious or ethn groups, mostly non-state actors. Therefore, terrorism in the words of The UN is: Criminal acts, including against civilians, committed with the intent to cause death or serious bodily injury, or taking of hostages, with the purpose to provoke a state of terror in the general public or in a group of persons or particular persons, intimidate a population or compel a government or an international organization to do or to abstain from doing any act”(UN, Resolution 1566, 2004). Terrorist attacks are predicted to have the greatest impact on identical and low-level economies that are subject to ongoing operations. Terrorism causes immediate and indirect costs on impacted areas. The immediate consequences include unfathomable human losses, misery, and psychological anguish. Indirect costs, on the other hand, include costs for damaged buildings, equipment, inventory, property damage, and a reduction in return on investment(Enders and Sandler, 2011). Taking an example, the US Bureau of Labor Statistics(2003) asserted that around 145,000 workers were put off for about 30 days after the 9/11 attacks in New York in 2001. Furthermore, unemployment increased by a percentage point in the very first quarter following the occurrence, resulting in a total production loss of \$47 billion. Ito and Lee(2005) found that a brief surge in panic however transient, lowered demand for flights by more than 30%. However, factors such as heightened screening of passengers and security checks caused a permanent 7.4% drop in airline demand. During the prior decade, there were a median of 26,000 deaths each year, with substantial variance between years. The world's total mortality impact fluctuated between 8,200 in 2011 to 44,600 in 2014 before beginning to decline, with an expected 22,847 fatalities caused by terrorism in 2020(Herre 2023). Macroeconomic studies like Goldstein(2005) contends that unemployment employment has a substantial association with terrorism in 105 nations. According to Piazza(2006), the fundamental causes of terrorism in ninety-six states between 1986 and 2002 were poverty, inequality, and inadequate economic development. Richardson

(2011) discovered unemployment and a large population were highly associated with a rise in the number of terrorist attacks, but higher education had no meaningful link with terrorism levels. A study by Kis-Katos, Liebert, and Schulze(2011) discovered that fear stems not from economic need, but rather from failed nations and previous conflicts. The chance of terrorist occurrences rises with GDP per capita is higher in more democratic countries. Local and international terrorism have the same fundamental causes, with domestic strife, anarchy, and regime changes all contributing to the spread of terrorism. Overall, these variables contribute to an increase in terrorism. According to Chuku Abang, and Isip(2017) there is an inverse association among terrorism and economic development in Nigeria. As terrorism caused a shift in economic activity away from private investment and toward government spending resulting in a change in the spending structure. Nigeria's projected yearly GDP loss due to terrorism was 0.82%. The study also focused on the dynamic linkages between terrorism and economic causes. Social inequality, GDP, continuous military conflicts corruption, and political instability all led to the rise in terrorism(Bren, Zeman, and Urban, 2019). Also, Tejkal1, Odehnal, and Michálek(2020) discovered that opportunity costs and growth in the economy decrease incentive for aggressive action. Tahir(2020) highlights the significant impact of factors such as high literacy rates per capita GDP and political instability on terrorism. Increased physical and human capital reduces terrorism, while government consumption and inflation show positive links with terrorism. Military spending has a dual relationship with terrorism, with an inverse connection in Muslim countries and a direct one in non-Muslim ones. Corruption has minimal impact on terrorism, but a negative correlation exists when comparing Muslim and non-Muslim nations. Economic globalization is incorporated as a variable in the models estimated in this research. Rajput, Khoso, Sial, Dakhan, and Syed(2021) discovered a negative link between economic globalization and terrorism, whereas there was no notable correlation found between social and political globalization. If terrorism used as a predictive factor, it could influence a country's economic growth according to the findings of Ilyas, Mehmood and Aslam(2017). They noted that both poverty and terrorism play roles in causing economic stagnation in 22 African nations leading to a prolonged adverse impact on economic growth. Terrorist attacks not only have a negative impact on economic growth but also exert a significantly greater influence on low-income countries, as being three times more compared to their impact on high-income countries(Çinar, 2017).

1.1 Problem of the Study

Worldwide terrorism killed the greatest number of people in 2014, with 33,555 deaths and a \$US 111 billion economic effects. Terrorism-related deaths climbed by 353% between 2011 and 2014, while incidences grew by 190%. Between years 2003 and 2018, Iraq was the most impacted country by terrorism, with the September 11, 2001 tragedy, having the biggest economic effect at \$40.6 billion. Since 2000, terrorism has cost the global economy around \$855 billion(Bardwell and Iqbal,2020). Various perspectives on economic, political, and social elements have attempted to clarify the rise in terrorist occurrences throughout the world. Nonetheless, despite their many interpretations, there is a paucity in empirically confirmed studies which examine the key economic, political, and demographic drivers of terrorism in the most affected countries between 2000 and 2021.

1.2 Importance: This study might serve as a helpful guide for the investigated countries as they implement strategic economic, political, and demographic reforms, in order to provide more secure environment for their people, and hence a sustainable economic growth.

1.3 The objectives: This study attempts to expose the most significant economic, political, and demographic factors that trigger terrorism in the seven most impacted countries all over the world from 2000 to 2021. The selected countries include; Iraq, Afghanistan, Pakistan, Democratic Republic of the Congo, Syria, Nigeria, and Yemen.

1.4 The Methodologies: The research utilizes various approaches, including; the descriptive statistics, tests for cross-section dependence, assessments for data stationarity through unit root tests, examinations for cointegration in long-run regression models, and employs several panel data models including but not limited to: Pooled Ordinary Least Squares (POLS), Random Effect (RE), Fixed Effect (FE) Pool Mean Group (PMG), Mean Group (MG), and Dynamic Fixed Effect (DFE) models.

1.5 The Hypothesis: There are variations in the size and type of relationship between the independent variables studied, and the dependent variable (terrorism index) for both long, and short terms.

1.6 The Scope and the Sample of the Study:

This study examines yearly balanced panel data spanning the years 2000 to 2021 for seven selected countries. The nations under investigation are specified as: 1. Iraq. 2. Afghanistan. 3. Democratic Republic of the Congo. 4. Nigeria. 5. Pakistan. 6. Syria. 7. Yemen. Global Terrorism Index (GTI) data to identify countries with the highest terrorist scores each five consecutive years up till year 2021. The dependent variable is the yearly terrorism index. The independent variables include GDP growth rate, inflation rate, unemployment rate, and Economic Globalization Index. The second set includes six macroeconomic, political, and demographic determinants: the indices of Political Stability, Demographic Pressures, External Interventions, GDP Growth Rate, Inflation Rate, and Economic Globalization.

1.7 Data Sources : Table (1) summarizes the data sources, variables, measurements, and expected signs, with the Terrorism Index (TI) as the dependent variable and some economic political, and demographic indices serving as independent variables.

Table (1) Variables Measurements and the Data Sources

Acronym	Description	Measur-ement	Expected sign	Data Source
TI (dependent variable)	Terrorism Index	0 to 10	+ for TI lags	The Institute for Economics and Peace (IEP). Annual GTD reports, available via https://www.economicsandpeace.org/?s=terrorism
INF	Inflation rate	% Rate	+	World Bank, available via: https://data.worldbank.org
GDPG	Annual GDP growth	% Rate	-	World Bank, available via: https://data.worldbank.org
G	Economic Globalization Index	0 to 100	+ or -	"KOF Swiss Economic Institute", available via: https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html
UEMP	Unemployment	% Rate	+	World Bank, available via: https://data.worldbank.org
PS	Political Stability Index	-2.5 to 2.5	-	World Bank, available via: https://www.theglobaleconomy.com
DP	Demographic Pressures Index	0 to 10	+	The Fund for Peace FFP, available via: https://www.theglobaleconomy.com
EXI	External Interventions Index	0 to 10	+ or -	The Fund for Peace FFP, available via: https://www.theglobaleconomy.com

Source: Prepared by the researchers, 2023.

2. Theoretical Concepts Related to Terrorism

2.1 Definition of Terrorism:

The definition of terrorism is explained differently. Each group or scholar defines terrorism in accordance with his or her beliefs regarding the actions of the operation's perpetrators. Thus numerous literatures agree that terrorism is a difficult subject to describe. The Global Terrorism Database (GTD) uses La Free et al. (2009)'s definition of terrorism, which is: "Acts of violence by non-state actors, perpetrated against civilian populations, intended to cause

fear, in order to achieve a political objective.(Herre, 2023f). The definition presented by Enders and Sandler(2011) is as follows:“Terrorism is the premeditated use or threat to use violence by individuals or subnational groups to obtain a political or social objective through the intimidation of a large audience beyond that of the immediate victims.(Enders,2011). The United States Department of State defines terrorism as: “Terrorism means premeditated, politically motivated violence perpetrated against noncombatant targets by subnational groups or clandestine agents, usually intended to influence an audience.(22 U.S.Code § 2656f-Annual country reports on terrorism, no date).

2.2 Types of terrorism Enders and Sandler(2012) classify terrorism into two broad categories:

1- Domestic terrorism: This sort of terrorism originates within the country and primarily targets the host country. It includes attacks on the country's institutions, people, property, and government. Domestic terrorism involves offenders, victims, and citizens from the same nation. Domestic terrorism has implications that are limited to the originating country's boundaries.

2- Transnational terrorism: Terrorism that starts in one country and spreads to other countries. It refers to situations that span national borders and affect several countries. For example airline hijackings in nation X with the goal to reach country Y, or the burst of an explosive device that.The origins of the two forms of terrorism may stem from distinct sources, such as fluctuations in food costs, which drive domestic terrorism instead of international terrorism. In truth, the impact of terrorism on a country's GDP development varies. The potential impact of transnational terrorism on a country's GDP growth is likely to be more pronounced, given its influence on foreign direct investment, which is considered a significant driver of income growth(Gaibulloev and Sandler 2008).Our study, conducted at the national level, incorporated the growth rate of GDP and the globalization index as macroeconomic indicators. Internal terrorism is constraining and reducing financial returns, a consequence often attributed to political turmoil and local disturbances. Conversely, the negative repercussions on the financial system from transnational terrorism occurring outside the country are comparatively less severe(Kollias, Papadamou, and Arvanitis 2013).The dynamic characteristics of these two types of terrorism exhibit notable differences.As stated by Enders, Sandler, and Gaibulloev(2011),domestic terrorism contributes to global terrorism, but the reverse is not true.

2.3 Classification of Terrorism:

According to Noricks taken from Davis and Cragin(2009,53) terrorism could be categorized into: 1. criminal, 2. ethno-nationalist, 3. Religious, 4. generic secular, 5. right-wing(religious) 6. secular left wing, 7. secular right wing, 8. single issue, 9. personal/idiosyncratic,10.state-sponsored. Terrorism is classified into three types: criminal, ethno-nationalist, and 3. Religion, 4. general secular, 5. right-wing(religious), 6. secular left wing, 7. secular right wing, 8. particular issue, 9. personal/idiosyncratic10. government-sponsored(Noricks) taken from(Davis and Cragin 2009, p.53).

2.4 Factors Causing Terrorism: Ideological causes:

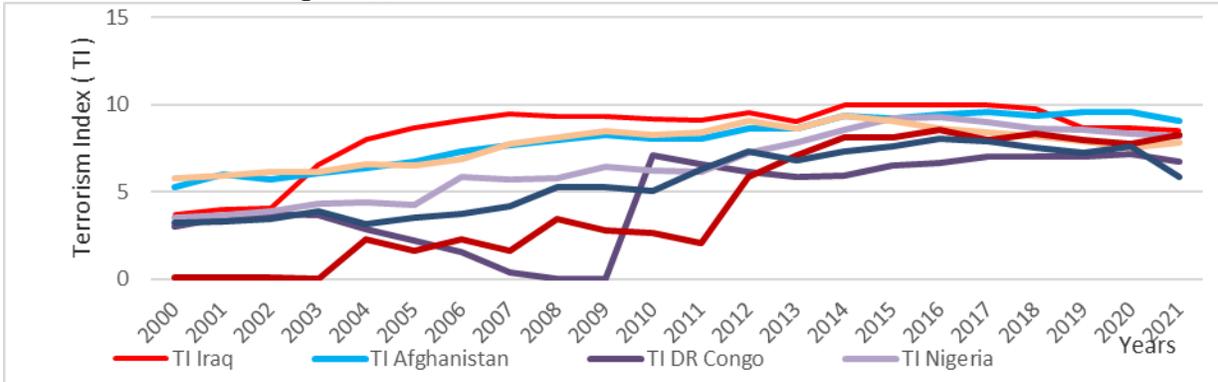
According to Enders and Sandler(2000),the rise in religious terrorism since the fourth quarter of 1991 is attributed to ideological causes. Conomiccauses: Income inequality Poverty,Natural resources,Other,EconomicDeterminants.olitical reasons:Democracy.State Legitimacy Historical and traditions causes.

3. Terrorism Index Trend in the Selected Countries:

The Terrorism Index for any given country, representing the impact of terrorist activities, is determined through the consideration of four types of outcomes: the overall number of fatalities, total injuries, and the complete expenditure on property damage. The calculation of

the terrorist index involves assigning weights to each element and performing various mathematical computations(GTI 2019). Since 2001, there has been a noticeable increase in the magnitude of this indicator across the nations under scrutiny. Figure 1 illustrates that between 2012 and 2020, all seven nations consistently displayed high Terrorism Index(TI) ratings, ranging from 6 to 10. Notably, Iraq and Afghanistan held the highest TI evaluations securing the top two positions due to consistently elevated TI values throughout the research period.

Figure (1)Terrorism Index Trends for the Selected Countries



Source: (Plotted by the researchers based on GTD, 2021)

4. Panel Data Analysis Results

4.1 The Descriptive Statistics:

The descriptive statistics results are shown in Table 2, these statistics were calculated for the seven selected states' indicators from 2000 to 2021, with 154 observations for each variable.

Table (2) Descriptive Statistics of Terrorism Index TI, and the Independent Variables

Variable	Mean	Std. dev.	Min	Max	Observations	
					N=	154
TI	6.477	2.592	0.000	10.000	N=	154
GDPG	3.273	8.501	-36.660	53.390	N=	154
INF	10.043	11.204	-10.100	63.100	N=	154
UEM	7.771	4.083	0.400	16.200	N=	154
G	38.963	7.135	26.646	55.796	N=	154
PS	-2.058	0.669	-3.180	0.280	N=	154
EXI	8.680	1.370	5.400	10.000	N=	154
DP	8.617	0.917	5.500	10.000	N=	154

Source: Researchers' analysis using Stata17.

The average countries is 6.47, falling within the scale of 0.00 to 10.00, with a standard deviation of 2.59. Examining the overall averages of economic factors reveals an annual GDP growth rate of 3.27%. The unemployment rate stands at 7.77%, and the inflation rate is 10%. Additionally, the average economic globalization score is 38.963 on a scale of 100, indicating a relatively low level of economic globalization in the countries being studied.

4.2 Linear Panel Data Modeling: Research by Maddala and Wu(1999) and Im et al.(2003) emphasizes the superior accuracy of panel data procedures compared to country-specific time-series econometric approaches. Panel data analysis is favored due to its ability to generate more precise estimates, offer increased degrees of freedom, and mitigate issues related to variable collinearity(Hsiao 2005). The robustness of panel data approaches becomes evident when dealing with a cluster of nations exhibiting inter or intra cross-sectional features, leading to more reliable conclusions(Baltagi, 2008). In the typical panel data model, information is collected for N distinct entities or nations observed over T various time periods(Baltagi, 2021).

The fundamental panel data model, denoted as(TI_{it}, X_{it}), with i = 1,...N, and t = 1,...T, is expressed as follows: $TI_{it} = \alpha + \beta X_{it} + U_{it}$ (1)

Here, TI represents the terrorism index, Xit signifies the independent variables, and U_{it} represents the error term. With seven states (N = 7) and 22 years of observations (T=22), the dataset is categorized as a long panel data set, given that T exceeds N (Gujarati, 2015). Notably, the dataset is well-balanced, with no missing values for any year, as indicated by Asteriou and Hall (2006) and Stock and Watson (2015). Model specifications for economic variables are outlined as Terrorism Index for the seven

follows: $TI=f(GDPG, INF, UEM, G)$

Additionally, a comprehensive model incorporating economic, political, and demographic variables is presented: $TI=f(GDPG, INF, G, PS, DP, EXI)$

In this context, TI represents the terrorist index, while the other variables include annual GDP growth rate (GDPG), inflation rate (INF), unemployment rate (UEM), globalization of the economy index (G), political stability index (PS), demographic pressures index (DP) and external intervention index (EXI).

4.3 Preliminary Tests:

4.3.1 Check of Cross-Sectional Dependency:

The issue of cross-sectional dependency (CSD) in macro-panels has received considerable attention in recent years, particularly since the 2010s. This type of dependence stems from common shocks that affect nations differently. Events such as the 2007 global financial crisis oil price shocks in the 1970s, and sudden increases in terrorist attacks in the Middle East North Africa, and South Asia have significantly elevated terrorism index records in the past decade. Additionally, CSD can manifest as spillover effects, where domestic repercussions impact other countries or regions. Factors contributing to CSD may include the omission of common effects, geographical influences, and interactions with socioeconomic factors (Atasoy 2017). The prevalence of CSD in panel datasets is well-documented in studies like Atasoy (2017) and Apergis, Christou, and Gupta (2017). In this study, we apply the CD test developed by Pesaran (2004) and the Lagrange Multiplier (LM) test introduced by Breusch and Pagan (BP) in 1980 to assess the presence of CSD in our dataset. The null and alternative hypotheses for each test are formulated as follows:

Null Hypothesis (H₀): Covariance(u_{it}, u_{jt}) = 0, for all t, $i \neq j$, indicating cross-sectional independence of panels. Alternative Hypothesis (H₁): Covariance(u_{it}, u_{jt}) \neq 0, for all t, $i \neq j$ suggesting cross-sectional dependency of panels. Our study subjected the raw data to a group-wise cross-sectional dependency (CSD) test using the Pesaran (2004) CD test and the Breusch-Pagan LM (1980) test. The average correlation coefficients are detailed in Table 3 below:

Table (3) CD and LM Tests for Panels Cross Section Dependence (CSD)

Variable	CD-test		LM-test		Abs. (corr)
	Stat.	p-value	Stat.	p-value	
TI	16.320	0.000	281.197	0.000	0.759
INF	1.160	0.245	23.573	0.314	0.196
GDPG	1.050	0.291	16.252	0.755	0.154
G	2.310	0.021	88.869	0.000	0.359
UEM	10.280	0.000	173.867	0.000	0.547
PS	6.620	0.000	107.018	0.000	0.367
EXI	2.780	0.005	98.178	0.000	0.395
DP	0.100	0.923	77.950	0.000	0.345

Source: Researchers' analysis using Eviews12.

Results from the Pesaran CD test in Table 3 indicate that the p-values for TI, G, UEM, PS and EXI are below the 5% significance level, leading to the rejection of H₀. This implies the presence of CSD. Conversely, INF, GDPG, and DP have p-values exceeding 5%, suggesting cross-sectional independence. Given that T > N in our panel dataset, we also applied the BP

LM test(Bhujabal Sethi and Padhan 2021), yielding consistent findings with the Pesaran CD test, except for the variable DP. We reject H0 for DP, indicating that it is not cross-sectionally independent.

4.3.2 Test of Data Stationarity: To assess the stationary properties of panel datasets, two generations of tests are commonly employed. The first generation assumes cross-sectional independence, while the second generation allows for cross-section dependency(Pesaran 2007). Levin Lin, and Chu(2002) utilized first-generation unit root tests for balanced panel datasets, assuming $N/T \rightarrow 0$. Additionally, the Augmented Dickey Fuller(ADF) test was applied to variables without cross-sectional dependency. Refer to Table 4 for the results, indicating the stability of INF, GDPG, and DP at both levels and first differences.

Table (4) First Generation Unit Root Tests of Levin, Lin and Chu, and ADF

Variable	LLC Level		LLC First Difference		ADF Level		ADF First Difference	
	Constant	Constant and Trend	Constant	Constant and Trend	Constant	Constant and Trend	Constant	Constant and Trend
INF	-4.159***	-3.598***	-7.082***	-4.353***	47.924***	38.428***	94.645***	73.224***
GDPG	-5.840***	-4.750***	-8.272***	-4.914***	53.882***	43.608***	102.568***	71.548***
DP	-0.852	-0.592	-9.977***	-6.744***	23.964**	16.741	93.0006***	65.816***

*** Significant at 1% level, ** Significant at 5% level, *Significant at 10% level.
Source: Researchers' analysis using Eviews12.

Given cross-sectional interdependence, first-generation unit root tests may yield biased results. To address this, second-generation unit root tests are applied to variables with cross-sectional dependenc

Table (5) Second Generation Unit Root Tests of CADF and CIPS

Variable	CADF Level		CADF First Difference		CIPS Level		CIPS First Difference	
	Constant	Constant andTrend	Constant	Constant and Trend	Constant	Constant and Trend	Constant	Constant and Trend
TI	-2.281*	-2.057	-2.941 ***	-3.550 ***	-2.210 *	-2.032	-3.984 ***	-4.137 ***
UEM	-1.272	-1.974	-3.008 ***	-2.805 *	-1.526	-2.501	-4.332 ***	-4.194 ***
G	-1.821	-2.583	-3.474 ***	-3.599 ***	-2.050	-2.538	-4.548 ***	-4.560 ***
PS	-2.521 **	-2.675	-3.407 ***	-3.340 ***	-2.213 *	-2.737 *	-4.170 ***	-3.963 ***
EXI	-1.742	-1.543	-2.295 *	-2.803 *	-1.064	-1.016	-3.833 ***	-4.330 ***
DP	-2.196	-2.194	-2.736 ***	-2.770 *	-2.319 *	-2.327	-4.431 ***	-4.391***

CADF t- bar statistics, CIPS statistics. *Significance levels: *** at 1%, ** at 5%, * at 10%.
Source: Researchers' analysis using Stata17.

y(TI, UEM, G, PS, EXI, and DP) using the Cross Section Augmented Dickey Fuller(CADF) and Im, Pesaran, and Shin(CIPS) tests. Table 5 summarizes the results.

In practical circumstances, alterations in governmental regimes or significant global events are frequently identified as factors contributing to structural breaks. Examples of such occurrences include the aftermath of The Great Depression, oil price shocks, World War II,terrorist attacks, and the Covid-19 epidemic. To address the impact of structural breaks in panel datasets, Karavias and Tzavalis(2014) devised a unit root test. The primary Stata command, "xtbunitroot," is utilized to execute panel unit root tests with the goal of identifying breaks in individual series' intercepts or both intercepts and linear trends.This test accommodates one or two breaks on known or unknown dates, taking into account cross section heteroskedasticity and dependency, as well as non-normal errors. It demonstrates substantial power against both heterogeneous and homogeneous alternatives and is applicable to panels with either large or small time-series dimensions(Karavias& Tzavalis, 2014). Structural breakdowns have the potential to distort traditional unit root testing, leading to the acceptance of the null hypothesis when the unit root is stationary, or vice versa. Insufficient awareness of structural fractures can compromise test power and result in inaccurate conclusions(Chen, Karavias, and Tzavalis, 2022). The outcomes of the KT(Karavias and Tzavalis) unitroot evaluation, accounting for structural breakdowns in panel data, are detailed in Table 6. The hypotheses being tested are outlined as follows:

H0: The series has unit root for all panels.

H1: The series doesn't have unit root for some or all panels.

Table (6) Karavias and Tzavalis KT (2014) Panel Unit Root Test

Variable	Level		First Difference		No. of Structural Breaks	Accept	
	constant	Constant & trend	Constant	Constant & trend			
TI	-7.7875*** (0.1110)	-2.4455**(-2.7162)	-13.5868*** (-3.3680)	-7.2104*** (-3.0783)	1	H1	
UEM	-4.3464*** (0.2600)	-2.5923** (-2.5585)	-14.5475*** (-4.4779)	-8.8961*** (-2.5719)	1	H1	
INF	-7.5420** (-7.7264)	-5.2191(-6.1026)	-19.1472*** (-4.9632)	-10.3016 *** (-3.1908)	1	H1	
GDPG	-14.7027*** (5.0390)	-8.6454***(-3.1356)	-23.3463*** (-1.4356)	-13.6411*** (-1.8089)	1	H1	
G	-4.7457*** (1.9301)	-1.8500(-3.1033)	-14.8115*** (-3.2224)	-7.8696*** (-2.4239)	1	H1	
PS	-1.2878 ** (-0.9441)	-0.7150 (-1.2346)	-6.0677* (-7.6880)	-4.0076* (-5.3155)	1	H1	
D P	CD No CSD	-0.6732 (-1.6009)	-0.2753 (-1.2254)	-8.984 (-3.0940)	-5.4631*** (-2.2411)	1	H1
	LM CSD	-1.1792** (-1.0296)	-0.3799 (-0.8938)	-8.4633** (-3.6181)	-4.9394*** (-2.7952)		
E X I		-0.9264*** (0.0988)	-0.7769**(-0.6960)	-9.0528*** (-3.5603)	-5.6279*** (-2.5913)	1	H1

Numbers in the parentheses denote Bootstrap critical values. The lowest Z-statistic: *** Significance at the 1%, 5%, and 10% levels.

Source: Researchers' analysis using Stata17.

Table 6 presents the results of unit root test conducted by Karavias and Tzavalis(2014) for social, political, and economic variables. Table 6 reports the findings of the Cross-Sectional Dependence(CSD) test, suggesting that all four economic variables exhibit stationary patterns at both the level and the first difference. Consequently, we reject the null hypothesis(H0) and embrace the alternative hypothesis(H1) that one or more panel time series are stationary processes. Similarly, the social and political variables also display stationary patterns at both levels and first differences. In summary, the unit root test by Karavias and Tzavalis(2014) indicates that, under the presence of one structural break and CSD in the dataset, all variables are either stationary at the level or in their first differences. Following Engle and Granger's(1987) concept, a set of variables that are stationary at the first difference(1) implies cointegration. Thus, these I(1) series are in long-run equilibrium, moving together with some random fluctuation. As all considered variables are stationary at the initial difference I(1), we can infer that they are cointegrated in the long run. Subsequently, cointegration tests will be conducted in the subsequent section to further substantiate this finding.

4.3.3 Cointegration Tests: To explore long-term cointegration between panels, we employ first-generation cointegration tests that assume cross-sectional independence among the panels. Specifically, we apply the criteria outlined by Pedroni(2004) and Kao(1999). According to Baltagi(2005, p. 256), the Pedroni test proves more accurate than the Kao test when the time span(T) significantly exceeds the group dimension(N). Larsson et al. (2001) introduced the LR-bar test, which outperforms both Pedroni and Kao tests. Nevertheless, once Cross-Sectional Dependence(CSD) is identified, these tests lose their validity. In response to this issue, Westerlund(2007) introduced a second-generation cointegration test based on error correction, designed to address CSD between panels. This test has become widely recognized for its effectiveness. The primary objective is to investigate the absence of cointegration by assessing whether error correction occurs among all panels or across all panels. The results of both first- and second-generation cointegration analyses for both models are presented in Table 7. One model focuses on economic factors, while the other incorporates a combination of economic, political, and demographic variables.

Table (7) Cointegration Tests

Cointegration test		M1 (Economic variables)	M2 (Economic, Political, and Demographic variables)
Westerlund		Variance ratio sta. = 2.4074, P-value= 0.0080	Variance ratio sta. = 5.139 , P-value= 0.0000
Pedron	test Stat. p-value Modified Phillips Perron t	3.4334 0.0003 Phillips Perron t 2.5176 0.0059 Augmented Dickey Fuller t 3.10020.0010	2.7578 0.0029 Phillips Perron t -1.2838 0.0996 Augmented Dickey Fuller t -0.93000.1762
Kao	test	Stat.	p-value
	Modified Dickey Fuller t	-0.4614	0.3223
	Dickey Fuller t	-1.0575	0.1451
	Augmented Dickey Fuller t	1.2442	0.1067
	Unadjusted modified Dickey Fuller t	-0.7651	0.2221
	Unadjusted Dickey Fuller t	-1.2371	0.1080

Source: Researchers' analysis using Stata17.

Table 7 presents the p-values for the relevant statistics of the Westerlund and Pedroni tests, all of which are below 0.01. This suggests that there is evidence of cointegration among all panels of the economic model. Consequently, we reject the null hypothesis(H0) that posits no cointegration between all panels. It's important to note that the Kao test provides conflicting results. However, due to cross-sectional dependence in the dependent variable and the majority of the regressors, we opt for Westerlund's(2007) second-generation cointegration test. The outcomes of the economic regressors reveal cointegration across all panels. In the case of mixed regressors, testing panels for cointegration leads us to reject H0 and accept H1 indicating that all panels are cointegrated. This decision is based on the p-values of Westerlund and Kao statistics, both of which are below 0.05.

4.3.4 The Break dates:

•Table 8 shows the findings of Ditzen, Karavias, and westerlund's (2021) test for several break dates in the economic model.

H0: No break(s) vs. H1: Two breaks.

Table (8) Break Dates for the Economic Variables Model

Bai & Perron Critical Values				
	Test statistic	1% Critical value	5% Critical value	10% Critical value
supW(tau)	11.17	4.14	3.44	3.15
Estimated break dates	2005 , 2011		Trimming: 0.15	

Source: Researchers' analysis using Stata17.

The supW(tau) statistic has significance at the 1% level, according to Bai and Perron's Critical Values. Thus, we reject H0 and conclude that the economic model exhibits two break points in 2005 and 2011.

•Table 9 displays the findings of Ditzen, Karavias, and Westerlund's(2021) test for multiple break dates in the Mix model of Economic, Political, and Demographic determinants. H0: no breaks vs. H1: one break(s).

Table (9) Break Dates for the Assorted Variables Model

Bai & Perron Critical Values				
	Test statistic	1% Critical value	5% Critical value	10% Critical value
supW(tau)	5.07	4.08	3.35	2.99
Estimated break date	2009		Trimming: 0.15	

Source: Researchers' analysis using Stata17.

Using Bai and Perron Critical Values, we discover that the statistic supW(tau) has significance at the 1% level. As a consequence, we deny the null hypothesis(H0) and adopt the conclusion that the model integrating a combination of economic, political, and demographic data has just one break date, in 2009. The difference in the number of break dates between the two models can be ascribed to the economic indicators suffering more

shocks along their trajectories as a result of the selected nations' economic susceptibility. In contrast, the scale of political and demographic aspects in these nations has remained largely consistent. Furthermore, political, demographic, and foreign actions, as well as their correlation with economic indicators, are less probably to experience large shocks.

4.4 Economic Variables Models

4.4.1 Static Models: Table 10 shows the static models and the tests associated with them. Also included is a comparison of each of the two models examined in order to choose the best static model using the Model Selection Test in the table **Table (10) Estimated POLS, FEM, And REM for the Impact of Economic Determinants on Terrorism**

Variables	POLS			FEM			REM			Accept
	Coef.	Std. Err.	t. stat.	Coef.	Std. Err.	t. stat.	Coef.	Std. Err.	t. stat.	
INF	0.018	0.021	0.88	0.043	0.017	2.58 **	0.04	0.017	2.37 **	
UEM	0.06	0.054	1.12	0.385	0.12	3.20***	0.28	0.099	2.84***	
G	0.001	0.032	0.04	-0.067	0.051	-1.31	-0.071	0.046	-1.55	
GDPG	-0.01	0.027	-0.38	-0.024	0.021	-1.14	-0.025	0.021	-1.19	
Constant	5.806	1.184	4.90 ***	5.739	2.433	2.36 **	6.733	2.144	3.14 ***	
Model statistic	F (4, 149) = 0.830			F (4,143) = 7.06 ***			Chi ² = 23.445 ***			
Mean dependent variable	6.477			6.477			6.477			
Overall R ²	0.022			0.0172			0.017			
R ² within	-			0.1648			0.163			
R ² between	-			0.0034			0.010			
CD- test ¹	5.77***			10.99 ***			9.710 ***			H1
Sigma – u	-			2.377			1.751			
Sigma – e	-			1.980			1.980			
Rho	-			0.590			0.4387			
² Slope heterogeneity	6.472 ***			-			-			H1
Model Preference test	B.P. LM.: Chi-bar ² (01) = 192.44 ***			LR: F (6, 143) = 18.87 ***			Hausman: Chi ² =7.10P-value = 0.1309			RE
Heteroskedasticity	³ B.P. Chi ² (1) = 2.33			Wald Chi ² (7) = 435.46 ***			Wald Chi ² (7) = 2393.62 ***			H1
Autocorrelation	⁴ F (1,6) = 107.297 ***			⁵ Q(p)-stat= 17.68 ***			⁵ Q(p)-stat= 14.41***			H1
⁶ Group wise Correlation of residuals	-			B-P LM test: Chi ² (21) = 175.463, P-V = 0.000			-			
Number of obs.	154			154			154			

1 (Pesaran, 2004, H0: cross-section independence CD ~ N (0,1). 2 (Pesaran, Yamagata, 2008. H0: slope coefficients are homogeneous). 3 (Breusch-Pagan/Cook-Weisberg test for heteroskedasticity, H0 = constant variance). 4 (Wooldridge test for autocorrelation in panel data; hypothesis: no first-order autocorrelation). 5 Bias-corrected Born and Breitung (2016) conducted a Q(p)-test on variables with the hypothesis "no serial correlation up to order 2". Ha, that's right. "Some serial correlation up to order 2." 6 (Breusch-Pagan LM test, H0: Group Residues Independence). *** p<0.01, ** p<0.05, * p<0.

Source: researchers' calculations using Stata17.

The F-statistic's P-value is significant at the 5% level, leading us to reject the null hypothesis(H0) and accept the alternative hypothesis(H1). This indicates the appropriateness of the Fixed Effect Model(FEM) for the analysis. Similarly, the P-value of the BP LM Chi²-bar test is significant at the 5% level, leading to the rejection of H0 and suggesting the presence of random effects. Consequently the Random Effects Model(REM) is considered suitable. The results of the Hausman test show that the P-value of the Chi² statistic is negligible at both the 5% and 10% levels. Therefore, we accept H0, signifying identical coefficients and conclude that the REM is appropriate for the economic predictors.

Interpretation of REM in Table 10: Both INF and TI exhibit a significant positive relationship at the 5% significance level, as do UEM and TI at the 1% significance level. This implies that, holding other factors constant, a 1% increase in the inflation rate corresponds to a 0.04-point increase in terrorism and a 1% rise in the unemployment rate corresponds to a 0.28-point increase in terrorism. Richardson(2011) supports the idea that unemployment leads to an increase in terrorist events. Similar associations between unemployment and terrorist risks have been found by Caruso and Schneider (2011) Goldstein(2005), and Cruz D'Alessio and Stolzenberg(2020). According to Pesaran's(2004) CD test of dependence, the model's error terms exhibit cross-sectional dependence (CD

supporting H1 of dependence based on the CD statistic's significance at the 1% level. This suggests that innovations in variables other than the four economic factors influence terrorism in the seven nations. Additionally, the model displays heteroskedasticity evident from the Wald Chi² statistic's significant P-value at the 1% level. The statistically significant P-value of the F statistic at the 10% level indicates the presence of autocorrelation in the estimated random effect model. Following Balestra and Varadharajan-Krishnakumar(1987), we examine the new estimated model(G2SLS Random-Effects IV Regression) to identify any dynamic patterns it may exhibits in:

$$TI = 0.453 + 0.913 \text{ Lag TI} + 0.007 \text{ INF} - 0.012 \text{ UEM} + 0.009 \text{ G} - 0.013 \text{ GDPG} \quad (2)$$

tsta.	1.05	34.37 ***	1.09	-0.65	0.89	-1.51
-------	------	-----------	------	-------	------	-------

*** p<0.01 , ** p<0.05 , * p<0.1
 Researchers' calculations Stata17.

Using equation(2), we determined that the lag TI is statistically significant at the 5% level, suggesting the necessity of incorporating a dynamic structure into the model. We can now apply mean group, pool mean group, and dynamic fixed effect methods.

4.4.2ARDL Models: In the context of ARDL modeling(Auto Regressive Distributed Lag), Table11 displays error correction models(pool mean group mean group, and dynamic fixed effect) that focus on the economic factors influencing terrorism in selected countries from 2000 to 2021. The results from all three approaches indicate a long-term cointegration among the studied variables, evident through negative error correction terms with a 1% significance level. The confirmation of long-run cointegration aligns with the Granger approximations theorem proposed by Engle and Granger(1987). According to this theorem, if the cointegration score of the model, as observed in Table 8, is significant, then the error correction term also holds significance.

Table (11) ARDL Models depicting the Influence of Economic Determinants on Terrorism

Variables	PMG			MG			DFE			Accept
	-Coef.	Std.Err.	z. stat.	Coef.	Std.Err.	z. stat.	Coef.	Std. Er.	z. stat.	
Long run										
GDPG	0.339	0.118	-2.880 ***	-0.385	0.146	-2.650 ***	-0.294	0.118	-2.480 **	
INF	0.131	0.069	1.880 *	-0.011	0.172	-0.060	0.052	0.063	0.820	
G	0.320	0.206	1.550	0.256	0.192	1.330	0.419	0.221	1.890 *	
UEM	-0.750	0.537	-1.400	-0.027	0.826	-0.030	-0.187	0.442	-0.420	
Short run										
ECT (speed of adjustment)	-0.109 (9.17)	0.018	-6.230 ***	-0.206 (4.854)	0.079	-2.610 ***	-0.137 (7.299)	0.036	-3.78 ***	
D1. GDPG	0.039	0.026	1.490	0.048	0.020	2.430 **	0.022	0.009	2.370 **	
D1. INF	-0.046	0.030	-1.500	0.004	0.019	0.230	-0.004	0.008	-0.460	
D1. G	0.101-	0.038	-2.660 ***	-0.117	0.062	-1.870 *	-0.067	0.034	-1.990 **	
D1. UEM	0.264	0.226	1.170	0.155	0.478	0.330	0.072	0.124	0.580	
Constant	0.095	0.146	0.650	-0.941	2.093	-0.450	-0.907	1.120	-0.810	
Log Likelihood	-99.666			-			-			
² CD- test	CD=-0.17, p-value= 0.861 , corr.= -0.008			CD=-0.45, p-value=0.650 , corr.= -0.021			CD=-0.31, p-value=0.758 , corr.= -0.014			H0
³ Autocorrelation	F(1, 6) = 0.221 Prob. F = 0.655			F (1, 6) = 0.061 Prob. F = 0.8133			F(1, 6) = 0.047 Prob. F = 0.8361			H0
Aka inf cri	1.8917									
Hausman test	MG & PMG: Chi ² = 0.874 , (P-value= 0.759)			DFE & PMG : Chi ² = 0.684 , (P-value = 0.953)						PMG
Obs per group	22			22			22			
Number of groups	7			7			7			
Number of obs.	154			154			154			

¹ECT speed of adjustment in years between the parentheses. ²(Pesaran, 2004, H0: cross-section independence CD ~ N(0,1)). ³(Wooldridge test for autocorrelation in panel data, H0: no first-order autocorrelation).

Source: Researchers' analysis using Stata17.

The Hausman Chi² test is employed to identify the most suitable model among PMG, MG, and DFE. When comparing MG and PMG using the Hausman test PMG is favored due to a negligible p-value of the Chi² statistic, indicating that the PMG model is optimal under H₀. In the comparison between DFE and MG the hypothesis of coefficient Homogeneity cannot be rejected, leading to the inference that the MG model is adequate.

Additionally, the Hausman test for DFE versus PMG confirms the PMG method, as the p-value is insignificant at the five percent level, supporting the hypothesis of coefficient homogeneity. In summary, all three Hausman tests suggest a model that allows for heterogeneity in short-run dynamics while maintaining similar long-run coefficients. Consequently, the PMG model is deemed the most appropriate choice.

Interpretation of the PMG Model in Table 11: the PMG estimator assumes identical long-run coefficients while allowing for differences in short-run coefficients and variances of errors between groups. The long-run component of the PMG model reveals a significant inverse correlation between GDP growth rate (GDPG) and terrorism. Specifically, a 1% increase in GDP growth rate leads to a 0.339-point reduction in the terrorism index at a 1% significance level. Similarly, INF and TI show a positive correlation, supported by Caruso and Schneider (2011). According to the PMG model, a 1% rise in inflation results in a 0.131-point increase in terrorism at the ten percent significance threshold. The short-run component of the PMG model indicates a strong inverse association between economic globalization (G) and terrorism. A one-point increase in the economic globalization index leads to a 0.101-point decrease in the terrorism index at the one percent significance level. Rajput, Khoso, Sial, Dakhan, and Syed (2021) provide supporting evidence for this negative association. The inflation rate coefficient of the REM is consistent with the PMG model's results suggesting a positive and substantial link. Therefore, among the analyzed economic regression factors, the growth rate in GDP and inflation are identified as long-term causing variables for terrorism.

- **Table 11's Error Correction Terms:** We can notice from Table 11 the PMG, MG, and DFE models are in short and long-run equilibrium. The one-period lag residual coefficient indicates a negative and significant association at the 1% level, with an ECT value of -0.109. This implies that the system corrects its preceding period's disequilibrium at a rate of 10.9% annually until reaching equilibrium. The structural break findings in Table 8, examining years 2005 and 2011, confirm significant shifts in the economic model, requiring considerable time to return to normalcy due to susceptibility to shocks.

Post-Estimation Tests of the Selected PMG Model in Table 11: Wooldridge test for autocorrelation in panel data indicates that the null hypothesis (H₀) of No Autocorrelation in the idiosyncratic error terms is accepted. This is supported by the insignificant p-value of the F statistic. Additionally, the p-value of the CD statistic for the PMG error terms is also insignificant, which further confirms the acceptance of H₀, indicating cross-section independence in the idiosyncratic error terms.

4.5 Models Including Economic, Political, and Demographic Variables. 4.5.1 Static Models:

In the combination of economic, political, and demographic indicators, static models (POLs, FEM, and REM) are estimated in Table 12. The LR F test statistic rejects the null hypothesis of all individual particular effects being zero or constants being identical, favoring the use of the Fixed Effect model. The Hausman test further confirms that REM is not the optimum model and the Fixed Effect model is more suitable.

Table (12) Presents the Impact of Mixed Macro Indicators on Terrorism

Variables	POLs			FEM			REM			Accept
	Coef.	Std. Err.	t. stat.	Coef.	Std. Err.	t. stat.	Coef.	Std. Err.	t. stat.	
GDPG	0.009	0.019	0.49	-0.008	.017	-0.49	0.01	0.02	0.48	
INF	-0.001	0.031	-0.06	0.001	0.014	0.11	-0.002	0.016	-0.12	
PS	-2.837	0.408	-6.95 ***	-2.288	0.243	-9.41 ***	-2.837	0.277	-10.24	
EXI	-0.070	0.226	-0.31	-0.05	0.223	-0.22	-0.07	0.138	-0.51	
DP	-0.239	0.652	-0.37	0.657	0.343	1.91 *	-0.239	0.211	-1.14	
G	-0.003	0.063	-0.06	-0.088	0.039	-2.28 **	-0.004	0.025	-0.16	
Constant	3.452	4.154	0.83	-0.002	2.991	-0.00	3.452	1.829	1.89 *	
Model statistic	F (6, 147) = 21.57			F (6, 141) = 23.830 ***			Chi ² = 129.434 ***			
Mean dependent variable	6.477			6.477			6.477			
Overall R ²	0.4682			0.364			0.468			
R ² within	-			0.503			0.432			
R ² between	-			0.168			0.652			
¹ CD- test	6.95 ***			5.27 ***			6.95 ***			H1
Sigma – u	-			1.589			0.000			
Sigma – e	-			1.538			1.538			
Rho	-			0.516			0.000			
² Slope heterogeneity test	4.557 ***			-			-			H1
Model Preference test	B.P. LM.: Chi-bar ² (01) = 0.000 Prob Chi-bar ² = 1.000			LR: F (6, 141) = 15.00 *** Prob. F = 0.000			Hausman: Chi ² = 55.159 *** P-value = 0.000			FE
Heteroskedasticity	³ B.P. Chi ² (1) = 0.09			Wald Chi ² (7) = 380.83*			Wald Chi ² (7) = 6615.48*			H1
Autocorrelation	⁴ F (1,6) = 36.921 *** Prob F = 0.0009			⁵ Q(p)-stat = 14.12 ***			⁵ Q(p)-stat = 13.72 ***			H1
⁶ Group Correlation of the residuals	-			B - P LM test: Chi ² (21) = 87.762 ***, Pr. = 0.000			-			
Number of obs.	154			154			154			

¹In Pesaran's study from 2004, the null hypothesis (H0) posits that cross-section independence is characterized by a normal distribution with a mean of 0 and a standard deviation of 1 (CD ~ N(0, 1)).
²In the work by Pesaran and Yamagata in 2008, the null hypothesis (H0) suggests that the slope coefficients are uniform.
³The Breusch-Pagan/Cook-Weisberg test for heteroskedasticity, with the null hypothesis (H0) assuming constant variance.
⁴The Wooldridge test for autocorrelation in panel data indicates the hypothesis that there is no first-order autocorrelation.
⁵Born and Breitung's (2016) Q(p) test was employed to assess variables with the hypothesis that there is no serial correlation up to order 2. The alternative hypothesis (Ha) proposes some serial correlation up to order two.
⁶The Breusch-Pagan LM test assumes the null hypothesis (H0) that group residues are independent. Note: Significance levels are denoted as *** for p<0.01, ** for p<0.05, and * for p<0.
 Source: Researcher's calculations using Stata17.

From Table 12, Political Stability (PS) has a statistically significant inverse relationship with the Terrorism Index (TI) at the 1% significance level under the specified Fixed Effect Model (FEM). This implies that an increase of one point in the Political Stability Index results in a decrease of 2.288 points in the Terrorism Index, assuming no other changes. Tahir (2020) utilizes a fixed effect model to support this negative correlation and asserts that political instability significantly contributes to terrorism. Similarly, the Globalization of the economy (G) exhibits an inverse relationship with TI at the 5% significance level. Specifically, when G increases by one point, terrorism decreases by 0.088 points, assuming other variables remain constant. On the other hand, at the 10% significance level, Demographic Pressures (DP) show a positive connection with TI. This suggests that when the index of demographic pressures increases by one point, the

terrorism index increases by 0.657 points. The analysis indicates that among various factors, political stability has a noteworthy impact on the frequency of terrorist activities in the seven nations under investigation. The chosen FEM's F statistic is significant at the one percent level, signifying that all independent variables effectively explain the variability in terrorism across the selected nations. The Rho statistic, indicating intra-country correlation, reveals those variations between panels account for 51.6% of the variance. The mean of the dependent variable TI is 6.47 over a 22-year period in the studied nations. Moreover, based on Pesaran's (2004) CD test, we reject the null hypothesis (H0) of cross-section independence and accept the alternative hypothesis (H1) validating the residuals' Cross-Sectional Dependence (CSD). This suggests that innovations in characteristics beyond the six specified social and economic variables impact terrorism in the selected nations. The model also exhibits heteroskedasticity, as indicated by the significant p-value of the Wald Chi² statistic at the 1% level. Autocorrelation in the error terms is detected through the F test, with a significant p-value at the 10% level, highlighting an issue with autocorrelation in the selected fixed effect model. Finally, testing for group correlation of residuals using the B-P LM Chi² reveals significance at the 1% level, leading to the rejection of H0 of no group correlation of residuals and acceptance of H1. Thus, the selected FEM is unreliable, to seek for the validity of its dynamic feature we add lag dependent variable TI_{t-1} or Lag TI, as an extra predictor in order to select a proxy model. But firstly, we need to test the significance of the added variable as the following:

$$TI = 0.189 + 0.808LagTI - 0.014GDPG + 0.002INF - 0.469PS + 0.09EXI - 0.189DP + 0.029G \quad \dots (3)$$

t sta.	0.12	18.43 ***	-1.53	0.26	-2.88 ***	0.77	-1.03	1.34
--------	------	-----------	-------	------	-----------	------	-------	------

*** p < 0.01, ** p < 0.05, * p < 0.1

Source: Researchers' calculations using Stata17.

The t-statistics for the additional lag dependent variable in equation (3)'s right-hand side is significant at the 1% level, suggesting that the newly formulated model is expected to demonstrate a dynamic pattern. Therefore, we can compute models, including MG, PMG, and DFE, incorporating our set of Economic Political, and Demographic predictors.

4.5.2 The Estimated ARDL Models: Table 13 presents the estimated ARDL models, encompassing MG, PMG, and DFE models incorporating a variety of economic, political, and demographic variables that may impact terrorism in the selected states. All three techniques affirm long-run cointegration among the variables, as evidenced by the negative and significantly 1% level ECT. The Hausman Chi² test is employed to identify the most suitable model among PMG, MG, and DFE. In the model preference test between MG and PMG the Hausman Chi² statistic indicates the preference for the PMG model, as its p-value is insignificant, suggesting efficiency under the H0 hypothesis. Additionally, the Hausman test for choosing between DFE and PMG favors the PMG model due to an insignificant p-value, indicating that we cannot reject the homogeneity hypothesis. Finally, the Hausman Chi² statistic for deciding between MG and

DFE is small, leading to the acceptance of the MG model as efficient. Considering the outcomes of these three Hausman tests, the chosen model should accommodate diverse short-run dynamics while maintaining common long-run coefficients. Consequently, the PMG model is selected as the most appropriate choice.

Table (13) The MG, PMG, and DFE Models Illustrating the Impact of Mixed Indicators on Terrorism

Variables	PMG			MG			DFE			Accept
	Coef.	Std. Err.	z. stat.	Coef.	Std. Err.	z. stat.	Coef.	StdErr.	z. stat.	
Long run										
GDPG	-0.081	0.040	-2.040 **	-0.087	0.088	-0.990	-0.161	0.084	-1.930*	
INF	0.052	0.025	2.040 **	-0.140	0.179	-0.790	-0.001	0.052	-0.030	
PS	-2.036	0.247	-8.26 ***	-1.707	3.780	-0.450	-1.923	0.846	-2.27**	
EXI	-0.651	0.307	-2.120 **	1.727	1.797	0.960	0.350	0.772	0.450	
DP	0.755	0.464	1.630 *	1.057	1.813	0.580	-0.838	1.248	-0.670	
G	0.005	0.047	0.100	0.240	0.257	0.940	0.254	0.157	1.620 *	
Short run										
¹ ECT(Speed of adj years)	-0.256 (3.906)	0.087	-2.960***	-0.417 (2.398)	0.114	-3.67 ***	-0.186 (5.376)	0.048	-3.9***	
D1. GDPG	0.038	0.027	1.420	0.059	0.052	1.140	0.016	0.009	1.740 *	
D1. INF	-0.042	0.035	-1.210	0.008	.022	0.380	0.001	0.008	0.100	
D1. PS	-0.196	0.420	-0.470	-0.684	0.80	-0.850	0.049	0.23	0.210	
D1. EXI	0.121	0.193	0.620	-0.639	0.332	-1.930 *	0.106	0.192	0.550	
D1. DP	0.181	0.376	0.480	0.016	0.338	0.050	0.009	0.232	0.040	
D1. G	-0.095	0.042	-2.250 **	-0.107	0.070	-1.530	-0.054	0.034	-1.570	
Constant	0.377	0.174	2.160 **	-1.598	5.676	-0.280	-0.313	1.750	-0.180	
Log Likelihood	-82.328			-			-			
² CD- test	CD=1.510, p-value= 0.132, corr.= 0.070			CD= 5.23, p-value=0.000, corr.= 0.244			CD=2.33, p-value=0.020, corr.= 0.108			H0
³ Autocorrelation	F (1, 6) = 1.712 Prob. F = 0.238			F (1,6) = 4.468 Prob. F = 0.0790			F (1,6) = 0.216 Prob. F = 0.6583			H0
Aka inf cri	1.8743									
Hausman test	MG & PMG: Chi ² = 5.36, (P-value= 0.498) DFE & PMG: Chi ² = 4.51, (P-value = 0.608) DFE & MG: Chi ² = 1.10, (P-value= 0.981)									PMG
Obs per gro	22			22			22			
No. groups	7			7			7			
No. of obs.	154			154			154			

¹ Speed of Adjustment measured in years is enclosed within parentheses for ECT. ² In accordance with Pesaran (2004), the null hypothesis (H0) posits cross-section independence, denoted as CD ~ N(0,1). ³ The Wooldridge test, assessing first-order autocorrelation in panel data, assumes the null hypothesis (H0) of no first-order autocorrelation.

Source: researchers calculations utilizing Stata17.

- Interpretation of the PMG Model in Table 13: The long-term PMG model demonstrates an inverse relationship between the GDPG rate and the Terrorism Index(TI). Specifically, a 1% increase in the GDPG rate leads to a 0.081-point decrease in the terrorism index at the 5% significance level, assuming all other variables remain constant. Conversely, the inflation rate(INF) exhibits a positive association with TI in the long run. A 1% increase in the inflation rate results in a 0.052-point rise in the terrorism index at the 5% significance level, assuming no other changes. Political stability(PS) in the long run displays a significant negative correlation with TI at the 1% significance level. Therefore, a one-point increase in PS reduces terrorism by 2.036 points, assuming all other factors remain constant. Meierrieks and Gries(2013) argue for the interconnectedness of terrorism and political instability. External interventions(EXI), such as economic and political assistance from external sources or the establishment of an international peacekeeping mission, have a long-term inverse relationship with TI at the 5% level. When EXI increases by one point, TI decreases by 0.651 points. The Demographic Pressures Index(DP) evaluates a state's stresses arising from its population or environment, including factors like food supply, drinking water availability, health issues, and epidemics. According to the PMG model, DP is positively correlated with TI in the long run. Thus, a one-point increase in

demographic pressures results in a 0.755-point rise in the terrorism index at the 10% significance level, assuming no other changes. Examining the short-term estimates of the mixed PMG model, economic globalization(G)exhibits a significant negative impact on TI at the 5% level. For each one-point increase in the G index, TI decreases by 0.095 points, assuming other factors remain constant. In summary the PMG model affirms the static FE model of mixed macro factors,as evidenced by the significance of PS, DP, GDPG, INF, and EXI parameters. These factors are identified as the most crucial long-term influences on terrorism in the selected countries between the years 2000 and 2021.

- The Error Correction Terms in Table 13:The error correction coefficients(ECT) from all three AR models indicate both short- and long-term equilibrium, being significant and negative at the 1% level. Specifically, the PMG ECT value of -0.256 suggests that the system corrects its previous period imbalance at a rate of 25.6% per year to achieve equilibrium. This implies that the effects of INF, G DP GDPG PS and EXI result in lasting terrorist implications for approximately $(1/0.256) = 3.9$ years. Table 9 presents a model incorporating various macro determinants with a single break date in 2009. This is likely due to the stability of political and demographic conditions in the analyzed countries albeit negatively stable. The magnitude of the model's error correction coefficient, 0.256, exceeds that of the economic model's coefficient of 0.109. This suggests that a state of equilibrium may be reached in a shorter period around 4 years, compared to the economic model, which takes over 9 years to attain equilibrium.

- Post-Estimation Tests of the Selected PMG Model in Table 13:The Wooldridge test for autocorrelation operates under the null hypothesis of no autocorrelation in the idiosyncratic error components when the p-value of the F statistic is insignificant. Similarly the CD test for cross-section independence in the model's error term yields an insignificant p-value at the 5% level, supporting the null hypothesis of no cross-section dependence in the idiosyncratic error components.

5. Granger Causality: The Granger causality test(Granger, 1969) is a statistical examination that assesses whether one time series can predict another. For panels characterized by a substantial T and limited N, Dumitrescu and Hurlin(2012) introduced the DH test, a statistic specifically designed for heterogeneous panels. In our analysis, we utilized the Stata command "xtgcause," developed by Lopez and Weber(2017), and the results are presented in Table 14. Lag selection optimization in the test was achieved using the Akaike information criterion(AIC). Additionally, in addressing the empirical challenge of cross-sectional dependence, p-values and critical values were computed using a bootstrap technique. Consequently, we hypothesize: Null Hypothesis: Variable Xi does not Granger-cause Terrorism Index(TI) Alternative Hypothesis: Variable Xi Granger-causes TI in at least one panel.

Table (14) The DH Test Examining the Determinants that Granger-Cause Terrorism

Variable Granger cause TI	W-bar	Z-bar	Z-bar tilde	Optimal No. of lags (AIC)	Accept
INF	1.3446	0.6446	0.3314	1	H0
UEM	2.0121	1.8934	1.3387	5	H0
GDPG	9.4185	3.6968***	0.5044	5	H0
G	13.2239	6.8806	1.5050	5	H0
PS	3.6228	4.9068*	3.7694*	1	H1
EXI	10.3652	4.4888	0.7534	5	H0
DP	8.4594	2.8943	0.2523	5	H0

P-values computed using 1000 bootstrap replications, significant at; ***p < 0.01, **p < 0.05, p < 0.1

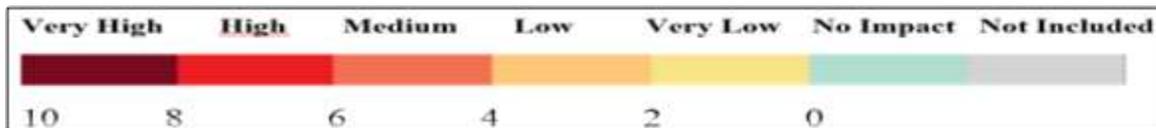
Source: Researchers' analysis using Stata17.

The DH test results indicate that GDP growth exhibits Granger causality with terrorism as the Z-bar statistic is statistically significant at the 1% level. This finding aligns with Meierrieks and Gries(2013), who observed Granger causality between economic growth and terrorism. Moreover, there is evidence to suggest that political stability may Granger cause terrorism in the selected countries, as the corresponding Z-bar statistic is significant at the 10% level. Tahir(2020) also arrived at a similar conclusion through his calculations, highlighting the Granger causation of terrorism by political instability. Consequently, we reject the null hypothesis(H0) for both GDPgrowth(GDPG) and political stability(PS) indicating that they do predict terrorism individually. Hence the growth of GDP and political stability are Granger-promoting factors for terrorism in the considered countries. Finally, we accept the null hypothesis(H0) for the other factors suggesting that they have no significant influence on predictions of the terrorism index(TI).

6. Conclusions: The study's conclusions offer a comprehensive overview of the connection between economic and social factors and terrorism in Iraq Afghanistan, the Democratic Republic of the Congo, Nigeria, Pakistan, Syria and Yemen spanning from 2000 to 2021. The following are the key findings summarized:

i. These countries have been identified as particularly susceptible to terrorist threats over the past decade, with an overall mean of the terrorism index (TI) at 6.47, indicating a high rate, as scaled in Figure 2.

Figure (2) illustrates Global Terrorism Impact Ratings.



Source: (GTI, 2022, p.8)

The general averages for the examined economic factors encompass GDP Growth Inflation(INF), Unemployment(UEM), Government Effectiveness(G), Political Economic Stability(PS), Globalization(EXI), and Demographic Pressures(DP).

ii. When assessing various static models such as POLS, FEM, and REM to identify the most suitable economic model, REM was chosen. This model indicated a positive and significant impact of both inflation and unemployment on terrorism. However limitations in the chosen REM model were identified, including heteroskedastic autocorrelation, and residual CSD. As an alternative dynamic models such as DFE MG, and PMG were computed, considering their advantages.

Static FEM was employed to model economic, political, and demographic factors. The analysis revealed that political stability and economic globalization exerted adverse and significant effects on terrorism, while demographic pressures showed a positive association. Nevertheless, drawbacks in the FEM model, such as heteroskedasticity, autocorrelation, and residual CSD, prompted the exploration of dynamic structures, leading to the utilization of DFE, MG and PMG models as substitutes. After conducting Hausman tests to compare REM MG, and PMG models, it was recognized that the PMG model was the most appropriate for economic and mixed factors encompassing economic, political and demographic aspects.

iii. In the economic PMG model's long-run component, a significant negative association between GDP growth rate and terrorist risks was observed, while the inflation rate exhibited a significant positive relationship with terrorism. Economic globalization, in the short run, demonstrated a significant negative influence on terrorism.

Examining the long-term component of the PMG model, it was found that the inflation rate and demographic pressures had a significant positive association with terrorist risks. Conversely, political stability, external interventions, and GDP growth displayed a significant indirect link with terrorism. In the short term, economic globalization exerted a significant adverse effect on terrorism.

iv. The mixed variables model displayed a higher error correction coefficient (0.256) compared to the economic model (0.109). This suggests that the mixed PMG model reaches equilibrium in less than 4 years, while the economic model requires more than 9 years.

7. The Granger causality test for panel data revealed that GDP growth and political stability both Granger caused terrorism in the studied countries. Consequently, it can be concluded that GDP growth rate is the most influential economic determinant in predicting the terrorism index, while political stability holds the most influence among the non-economic determinants

8. Recommendations: The researchers recommend the counterterrorism establishments in the selected countries should focus on implementing reforms related to economic, political, and demographic issues. Some key areas for the :

9. improvements include: Economic Measures: Monitoring and promoting GDP growth and economic globalization can be effective in reducing terrorism. Efforts to control inflation and unemployment rates are also crucial to address potential drivers of terrorism.

Political Stability: Recognizing the significant impact of political stability on terrorism, attention should be directed towards stabilizing political affairs both within and outside the countries. This can be achieved through enhancing political freedom and fostering negotiations rather than resorting to violence.

Addressing Demographic Pressures: Acknowledging the influence of demographic pressures on terrorism, strategies to address population-related issues should be considered, such as ensuring access to education, healthcare, employment opportunities, and reducing the factors that cause local and outside country's migrations.

i. Strengthening External Relationships: Improving a country's external relations through trade, sports, strategic agreements, and diplomatic efforts can help prevent illegal external interference that may exploit vulnerable circumstances within these countries.

a. Since the factor of Economic Globalization (G) has a significant inverse impact on terrorism in the short run, the economic policies of the studied countries should be directed to expanding extent of trade across borders. Increases in the movement of international capital, and the wide and rapid

dissemination of technology are all contributing to the growing interdependence of world economies, which ultimately lead to reduce terrorism.

REFERENCES

1. Anderson, T. W. and KHSiao, C. (1981) 'Estimation of Dynamic Models with Error Components,' *Journal of the American Statistical Association*, 76(375), pp. 598-606 <https://doi.org/10.1080/01621459.1981.10477691>
2. Apergis, N., Christou, C. and Gupta, R. (2017) 'Are there Environmental Kuznets Curves for US state-level CO2 emissions?,' *Renewable & Sustainable Energy Reviews*, 69, pp. 551–558. <https://doi.org/10.1016/j.rser.2016.11.219>
3. Atasoy, B.S. (2017) 'Testing the environmental Kuznets curve hypothesis across the U.S.: Evidence from panel mean group estimators,' *Renewable & Sustainable Energy Reviews*, 77, pp. 731–747. <https://doi.org/10.1016/j.rser.2017.04.050>
4. Asteriou, D. and Hall, S.G. (2007) *Applied Econometrics: A Modern Approach Using Eviews and Microfit*, Revised Edition. Palgrave Macmillan.
5. Bai, J. and Perron, P. (2003) 'Critical values for multiple structural change tests,' *The Econometrics Journal*, 6(1), pp. 72–78. <https://doi.org/10.1111/1368-423x.00102>
6. Baltagi, B.H. (2021) 'Econometric analysis of panel data,' *ideas.repec.org* [Preprint]. <https://ideas.repec.org/b/spr/sptbec/978-3-030-53953-5.html>
7. Bardwell, H. and Iqbal, M. (2020) 'The Economic Impact of Terrorism from 2000 to 2018 Peace Economics, Peace Science and Public Policy', 27(2), pp. 227–261. <https://doi.org/10.1515/peps-2020-0031>
8. Berrebi, C. and Ostwald, J. (2014) 'Terrorism and the labor force,' *Journal of Conflict Resolution*, 60(1), pp. 32–60. <https://doi.org/10.1177/0022002714535251>
9. Bren, Zeman and, Urban. "The Effect Of Individual Economic Indicators on Social Development National Security and Democracy: A New Perspective - ProQuest," n.d. conference paper 9th International Scientific Conference on Economic and Social Development – "Sustainability from an Economic and Social Perspective" - Lisbon, (April 2019):29-30.
10. Bhujabal, P., Sethi, N. and Padhan, P.C. (2021) 'ICT, foreign direct investment and environmental pollution in major Asia Pacific countries,' *Environmental Science and Pollution Research*, 28(31) pp. 42649–42669. <https://doi.org/10.1007/s11356-021-13619-w>
11. Blackburne, E. (2007) 'Estimation of nonstationary heterogeneous panels' <https://econpapers.repec.org/RePEc:tsj:stataj:v:7:y:2007:i:2:p:197-208>
12. Born, B. and Breitung, J. (2014) 'Testing for serial correlation in Fixed-Effects panel data models,' *Econometric Reviews*, 35(7), pp. 1290–1316. <https://doi.org/10.1080/07474938.2014.976524>
13. Breusch, T. and Pagan, A. (1980) 'The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics,' *The Review of Economic Studies*, 47(1), p. 239 <https://doi.org/10.2307/2297111>
14. Caruso, R. and Schneider, F. (2011) 'The socio-economic determinants of terrorism and political violence in Western Europe (1994–2007),' *European Journal of Political Economy* 27, pp. S37–S49. <https://doi.org/10.1016/j.ejpoleco.2011.02.003>
15. Chen, P., Karavias, Y. and Tzavalis, E. (2022) 'Panel unit-root tests with structural breaks' *The Stata Journal*, 22(3), pp. 664–678. <https://doi.org/10.1177/1536867x221124541>
16. Chuku, C., Abang, D.E. and Ima-Abasi, I. (2017) 'Growth and fiscal consequences of terrorism in Nigeria,' *Defence and Peace Economics*, 30(5), pp. 549–569. <https://doi.org/10.1080/10242694.2017.1389583>
17. Çınar, M. (2017) 'The Effects of Terrorism on Economic Growth: Panel Data Approach.' <https://ssrn.com/abstract=2997408>
18. Cook, R.D. and Weisberg, S. (1983) 'Diagnostics for heteroscedasticity in regression,' *Biometrika*, 70(1), pp. 1–10. <https://doi.org/10.1093/biomet/70.1.1>
19. Cruz, E., D'Alessio, S.J. and Stolzenberg, L. (2018) 'The labor market and terrorism,' *Studies in Conflict & Terrorism*, 43(3), pp. 224–238. <https://doi.org/10.1080/1057610x.2018.1455372>
20. Data and Tools START.umd.edu (2008). <https://www.start.umd.edu/data-and-tools/start-datasets>
21. Das, P. (2019) *Econometrics in theory and practice: Analysis of Cross Section, Time Series and Panel Data with Stata 15.1*. Springer Nature.
22. Davis, P.K. (2009) *Social Science for Counterterrorism: Putting the pieces together*. <https://www.rand.org/pubs/monographs/MG849.html>
23. De Hoyos, R.E. and Sarafidis, V. (2006) 'Testing for Cross-Sectional dependence in Panel-Data models,' *The Stata Journal*, 6(4), pp. 482–496. <https://doi.org/10.1177/1536867x0600600403>

26. Ditzen, J., Karavias, Y. and Westerlund, J. (2021) 'Testing and estimating structural breaks in time series and panel data in STATA,' arXiv(Cornell University)[Preprint]. <https://doi.org/10.48550/arxiv.2110.14550>
27. 'Does Terrorism Affect the Stock-Bond Covariance? Evidence from European Countries on JSTOR'(no date) www.jstor.org [Preprint]. <http://www.jstor.org/stable/23809495>
28. Dumitrescu, E.I. and Hurlin, C.(2012) 'Testing for Granger non-causality in heterogeneous panels,' 298.Economic Modelling, 29(4), pp. 1450–1460. <https://doi.org/10.1016/j.econmod.2012.02.014>
- Enders, W., Sandler, T. and Gaibullov, K.(2011) 'Domestic versus transnational terrorism Data, 30.decomposition, and dynamics,' Journal of Peace Research,48(3), pp. 319–337. <https://doi.org/10.1177/0022343311398926>
31. Engle, R.F. and Granger, C.W.J. (1987) 'Co-Integration and error correction: representation estimation, and testing,' Econometrica, 55(2), p. 251. <https://doi.org/10.2307/1913236>
32. Executive Order 13224-United States Department of State(2023). <https://www.state.gov/executive-order-13224/>
33. Gaibullov, K. and Sandler, T. (2011) 'The adverse effect of transnational and domestic terrorism on growth in Africa,' Journal of Peace Research, 48(3), pp.355–371. <https://doi.org/10.1177/0022343310395798>
34. Global Terrorism Database (no date). <https://www.start.umd.edu/gtd/>
35. Granger, C.W.J. (1969) 'Investigating causal relations by econometric models and cross-spectral methods,' Econometrica, 37(3), p. 424. <https://doi.org/10.2307/1912791>
36. Herre, B.(2023b) Terrorism. <https://ourworldindata.org/terrorism#how-many-people-are-killed-by-terrorists-worldwide>
37. Herre, B.(2023) Terrorism. <https://ourworldindata.org/terrorism> Hsiao,C.(2005)'Why panel data?,' Social Science Research Network[Preprint]. <https://doi.org/10.2139/ssrn.820204>
38. Im, K.S., Pesaran, M.H. and Shin, Y. (2003) 'Testing for unit roots in heterogeneous panels Journal of Econometrics, 115(1), pp. 53–74. [https://doi.org/10.1016/s0304-4076\(03\)00092-7](https://doi.org/10.1016/s0304-4076(03)00092-7)
39. Ito, H. and Lee, D. (2005) 'Assessing the impact of the September 11 terrorist attacks on U.S. airlines demand,' Journal of Economics and Business, 57(1), pp.75–95. <https://doi.org/10.1016/j.jeconbus.2004.06.003>
40. Kao, C. (1999) 'Spurious regression and residual-based tests for cointegration in panel data Journal of Econometrics, 90(1), pp. 1–44. [https://doi.org/10.1016/s0304-4076\(98\)00023-2](https://doi.org/10.1016/s0304-4076(98)00023-2)
41. Karavias, Y. and Tzavalis, E. (2014) 'Testing for unit roots in short panels allowing for a structural break,' Computational Statistics & Data Analysis, 76, pp.391–407. <https://doi.org/10.1016/j.csda.2012.10.014>
42. Kis-Katos, K., Liebert, H. and Schulze, G.G.(2011) 'On the origin of domestic and international terrorism,' European Journal of Political Economy, 27, pp. S17–S36. <https://doi.org/10.1016/j.ejpoleco.2011.02.002>
43. LaFree, G., Morris, N.A. and Dugan, L.(2009) 'Cross-National Patterns of Terrorism: Comparing Trajectories for total, attributed and fatal attacks, 1970-2006,' The British Journal of Criminology, 50(4), pp. 622–649. <https://doi.org/10.1093/bjc/azp066>
44. LaFree, G., Yang, S. and Crenshaw, M. (2009) 'Trajectories of terrorism,' Criminology & Public Policy, 8(3), pp. 445–473. <https://doi.org/10.1111/j.1745-9133.2009.00570.x>
45. Levin, A.T., Lin, C.F. and Chu, C.-S.J. (2002) 'Unit root tests in panel data: asymptotic and finite-sample properties,' Journal of Econometrics, 108(1), pp.1–24. [https://doi.org/10.1016/s0304-4076\(01\)00098-7](https://doi.org/10.1016/s0304-4076(01)00098-7)
46. Lopez, L. and Weber, S. (2017) 'Testing for Granger Causality in Panel Data,' Stata Journal 17, (4), pp. 972–984. <https://doi.org/10.1177/1536867x1801700412>
47. Maddala, G.S. and Wu, S. (1999) 'A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test,' Oxford Bulletin of Economics and Statistics, 61(s1), pp. 631–652. <https://doi.org/10.1111/1468-0084.61.s1.13>
48. Meierrieks, D. and Gries, T. (2013) 'Causality between terrorism and economic growth Journal of Peace Research, 50(1), pp. 91–104. <https://doi.org/10.1177/0022343312445650>
49. Nasir, M., Ali, A. and Rehman, F.U. (2011) 'DETERMINANTS OF TERRORISM: A PANEL DATA ANALYSIS OF SELECTED SOUTH ASIAN COUNTRIES,' The Singapore Economic Review, 56(02), pp. 175–187. <https://doi.org/10.1142/s0217590811004225>
50. Pedroni, P. (2004) 'PANEL COINTEGRATION: ASYMPTOTIC AND FINITE SAMPLE PROPERTIES OF POOLED TIME SERIES TESTS WITH AN APPLICATION TO THE PPP HYPOTHESIS,' Econometric Theory, 20(03). <https://doi.org/10.1017/s0266466604203073>
51. Pesaran, M.H. and Yamagata, T. (2008) 'Testing slope homogeneity in large panels,' Journal of Econometrics, 142(1), pp. 50–93. <https://doi.org/10.1016/j.jeconom.2007.05.010>
52. Piazza, J.A. (2011) 'Poverty, minority economic discrimination, and domestic terrorism Journal of Peace Research, 48(3), pp. 339–353. <https://doi.org/10.1177/0022343310397404>

53. Rajput, S.M. et al. (2021) 'Do economic, social and political globalization affect terrorism? Fresh evidence from international panel data,' Journal of Aggression, Conflict and Peace Research, 13(4), pp. 186–188. <https://doi.org/10.1108/jacpr-12-2020-0566>
54. Sandler, T. (2013) 'The analytical study of terrorism,' Journal of Peace Research, 51(2), pp. 257–271. <https://doi.org/10.1177/0022343313491277>
55. Tahir, M. (2018) 'Terrorism and its Determinants: Panel Data Evidence from 94 Countries Applied Research Global economy, worlde conomy TheGlobalEconomy.com (no date). <https://www.theglobaleconomy.com/>
56. The Fund for Peace FFP : <https://www.theglobaleconomy.com/in> Quality of Life, 15(1), pp. 1–16. <https://doi.org/10.1007/s11482-018-9660-x> U.S. Department of State – home (2024). <https://www.state.gov/UNAMI/OHCHR> Baghdad, October (2014), p.9.
57. Westerlund, J. (2007) 'Testing for error correction in panel data*,' Oxford Bulletin of Economics and Statistics, 69(6), pp. 709–748. <https://doi.org/10.1111/j.1468-0084.2007.00477.x>
58. 'What makes a terrorist: Economics and the Roots of Terrorism (New Edition) on JSTOR (2007) www.jstor.org [Preprint]. <http://www.jstor.org/stable/j.ctt7t153>
59. Wooldridge, J.M. (2010) Econometric Analysis of Cross Section and Panel Data, second edition. MIT Press.
60. World Bank Open Data (no date b). <https://data.worldbank.org/>
61. KOF Globalisation Index (2023). <https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html>
62. International Monetary Fund (2018). <https://www.imf.org/en/Data%20%20World%20Bank:%20https://www.theglobaleconomy.com>