International Journal of Social and Administrative Sciences
ISSN(e): 2521-0556
DOI: 10.18488/journal.136.2019.41.44.56
Vol. 4, No. 1, 44-56

URL: www.aessweb.com

MIGRATION POLICY UNCERTAINTY AND TERRORIST ATTACKS: EVIDENCE FROM THE US

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Article History
Received: 10 January 2019
Revised: 18 February 2019
Accepted: 20 March 2019
Published: 3 April 2019

Keywords
Migration policy uncertainty
Terrorist attacks
Vector autoregression
Granger causality test
Impulse response function
Variance decomposition.

JEL Classification
F52; E70.

ABSTRACT

To examine the potential relationship between migration policy uncertainty and terrorist attacks, this study uses the migration policy uncertainty index based on newspaper coverage frequency under the empirical framework of Vector Autoregression (VAR) model. The main findings of this study are as follows: (1) Based on the Granger causality test, migration policy uncertainty increases the occurrence of terrorist attacks. (2) From impulse response analysis, the exogenous shock to migration policy uncertainty has a significant and persistent impact on terrorist attacks. (3) By forecast error variance decomposition, migration policy uncertainty contributes to more than 24% of the forecast error variance of terrorist attacks. (4) The nexus between migration policy uncertainty and terrorist attacks only exists in typical migration countries, such as the U.S. Therefore, this paper first documents the causal relationship between terrorist attack and migration policy uncertainty. In practice, policymakers should decrease migration policy uncertainty in order to prevent the likelihood of future terrorist attacks.

Contribution/ Originality: This study contributes to the existing literature by investigating the potential relationship between migration policy uncertainty and terrorist attacks. This paper documents the following results that migration policy uncertainty does increase the occurrence of terrorist attacks and this nexus only exists in a typical migration country.

1. INTRODUCTION

Terrorism is not a new phenomenon (Carter, 1998). After 9.11 terrorist attacks in the United States, the issue of global terrorist attacks has become increasingly severe. In recent decades, the global terrorist attacks exhibit a wider range and rising occurrence Figure 1. The number of terrorist attacks rose sharply rise from about 1000 in 2004 to almost 17000 in 2014 (Smith and Zeigler, 2017) which implies a worsening global security environment. Terrorist attacks have a long-lasting effect compared to another incidence, such as traffic accidents. On one side, terrorist attacks directly result in severe loss of lives and properties. On the other hand, the mental stress of the victims caused by the terrorist attacks and the subsequent series of social issues magnify the impact of terrorist attacks. A number of researchers has turned to explore the negative effects of terrorist attacks from macroeconomic perspectives, such as the reduction of foreign direct investment inflows (Bandyopadhyay *et al.*, 2013; Shah *et al.*, 2016) the decrease in the number of tourists (Sönmez, 1998; Rittichainuwat and Chakraborty, 2009; Liu and Pratt,

2017) and the decline in the expected return on corporate stocks (Arin *et al.*, 2008; Aslam and Kang, 2015; Halkos *et al.*, 2017). Abadie and Gardeazabal (2003) emphasize that terrorist attacks can deteriorate the economy.

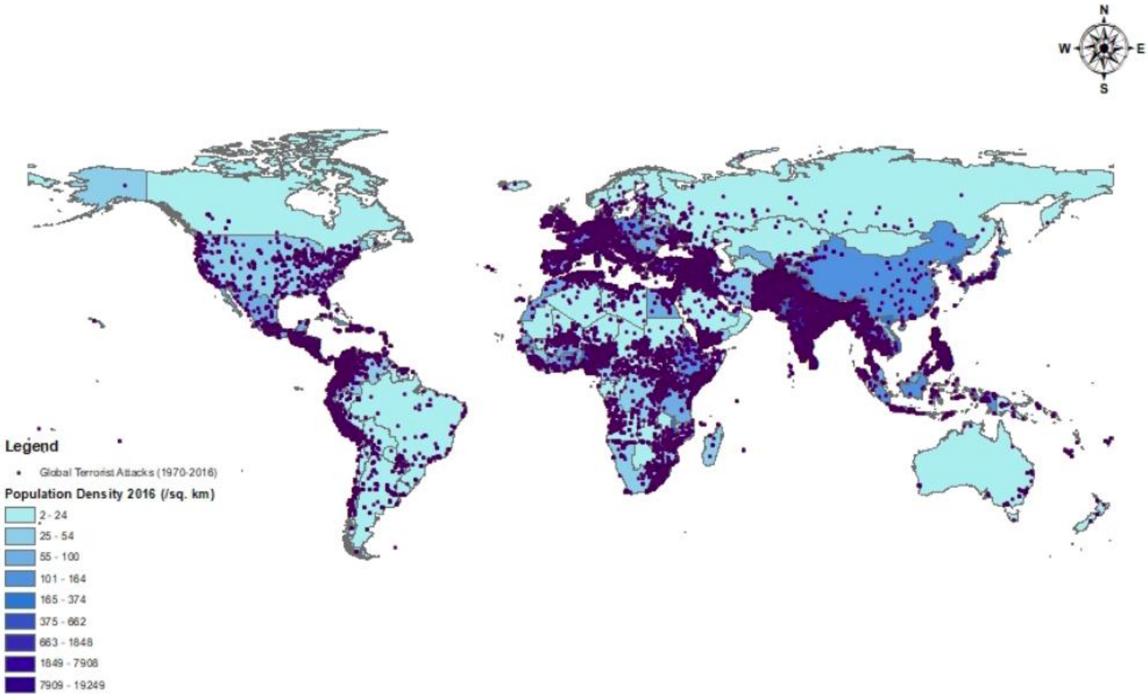

Figure-1. Global Terrorist Attacks Distribution (1970-2016).
Source: Global Terrorism Database, University of Maryland.

One of the significant changes after 9.11 terrorist attacks in the United States is a series of immigration acts that have been enacted and implemented, like Enhanced Border Security and Visa Entry Reform Act (2002), Real ID Act (2005), Comprehensive Immigration Reform Act (2007), DACA Dream Act (2012) and Travel Ban (2017). After the Travel Ban of 2017 is in effect, the relationship between migration and potential threats from terrorist attacks has become the focus of related debate. In other words, as an important control instrument, the migration policy is closely related to terrorist attacks. In addition, with the frequent implementation of immigration acts, the uncertainty of migration policy also increases over this period.

It is worth noting that the negative impact of higher migration policy uncertainty on migration. First of all, increasingly restrictive migration policies increase the risk of radicalization. Next, it is more difficult for migrants to plan their lives in the host country because the future is uncertain, increasing the risk of their failure to integrate into the host society. Briefly speaking, migrations who fail to integrate into the host societies might turn against the host societies.

Therefore, the aim of this paper is to explore the possible relationship between migration policy uncertainty and terrorist attacks. Specifically, will the consistent migration policy be more effective to decrease potential terrorist attacks than uncertain migration policy? Or will migration policy uncertainty be regarded as a supplementary interpretation to explore the contributing factors of terrorist attacks from the political perspective. To the best of my knowledge, none of the existing studies have explored the relationship between terrorist attacks and migration policy uncertainty. One possible explanation is that it is difficult to quantify the migration policy uncertainty. Baker *et al.* (2016) use text mining approach to construct the policy uncertainty index. In practice, policymakers might want to understand how migration policy uncertainty plays a potential role in increasing terrorist attacks. Therefore, this paper examines the potential relationship between migration policy uncertainty and terrorist attacks using vector autoregression (VAR) by utilizing the uncertainty index constructed by Baker *et al.* (2016).

The rest of the paper is organized as follows. Section II summarizes the related literature on the determinants of terrorist attacks and the effects of terrorist attacks. Section III presents the variables and the VAR model. Section IV describes the descriptive statistics for the data used in my paper. Section V interprets and discusses the technological results from the VAR model. Section VI moves ahead and compares the difference between migration policy uncertainty and terrorist attacks across countries to provide a comprehensive analysis. Section VII concludes and explores policy implications.

2. A BRIEF LITERATURE REVIEW

Terrorist attacks are a complicated social phenomenon. The current studies on terrorist attacks focus on two aspects: the determinants of terrorist attacks and the effects of terrorist attacks. Four important impacts caused by terrorist attacks include the decline of capital stock (including human capital and material capital), the rising of economic instability factors, the increase in anti-terrorism expenditures, and the deterioration of domestic tourism.

Enders and Sandler (1996) point out that the terrorist attacks in Spain from 1976 to 1991 lead to a 13.5% decrease in FDI, and an 11.9% decrease in Greece as a consequence of terrorist attacks. Becker and Murphy (2001) estimate that the occurrence of 9.11 Terrorist Attacks results in a loss of 0.06% of the production capital of the United States and the long-term negative impact on the US economy is 0.3%. Drakos (2010) uses financial market data from 22 different countries and find that there is a significantly negative shock on stock returns after a terrorist attack. Kollias *et al.* (2011) employ event study approach and GARCH model to analyze the effects of two different terrorist attacks occurring in Madrid (March 11, 2004) and London (July 7, 2005) on the stock sector and conclude that the terrorist attacks lead to permanent damage to Madrid's economy while London has a greater ability to recover from terrorist attacks.

Some studies consider the impact of terrorist attacks on tourism. Llorca-Vivero (2008) evaluates the difference of 134 travel destinations from 2001 to 2003 and finds that both domestic and international terrorist attacks have a moderately negative impact on tourism. Particularly, terrorist attacks have a more substantial effect on the tourism of developing countries than that of developed countries. Saha and Yap (2014) use data of 139 countries from 1999 to 2009 to analyze the relationship between political stability, terrorist attacks, and tourism development and conclude that terrorist attacks have an adverse impact on tourism. Liu and Pratt (2017) use panel data from 95 different countries to show that after controlling for income variables, terrorist attacks have no long-term impact on international tourism, but they have a significant short-term impact on some countries.

Some studies investigate the relationship between immigration and terrorist attacks. Karyotis (2007) points out that the connection between immigration and terrorist attacks has been exaggerated. More researchers (Bove and Böhmelt, 2016; Nail, 2016) conclude that there is a potential relationship between immigration and terrorist attacks, but the causal relationship between them remains unclear. Nail (2016) believes that immigrants are regarded as potential terrorists because of their special status. Bove and Böhmelt (2016) also mention that immigrants from terrorist-prone countries have led to the spread of terrorism. However, seldom existing studies have ever explored the relationship between migration policy uncertainty and terrorist attacks. A possible explanation is migration policy uncertainty is difficult to quantify.

3. EMPIRICAL MODEL

I estimate a vector autoregression model in line with Enders and Sandler (1991) in which the two key variables are migration policy uncertainty and terrorist attacks. VAR model is one the of most flexible models for the analysis of multivariate time series, especially useful for characterizing the dynamic behaviors of economic variables. In addition, the VAR model also provides a valid approach to forecast economic variables. The VAR model is specified as follows:

$$\begin{bmatrix} MPU_t \\ TT_t \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \cdot \begin{bmatrix} MPU_{t-1} \\ TT_{t-1} \end{bmatrix} + \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \cdot \begin{bmatrix} MPU_{t-2} \\ TT_{t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad (1)$$

Rewrite Equation 1 in a compact form,

$$\boldsymbol{X}_t = \boldsymbol{A} \cdot \boldsymbol{X}_{t-1} + \boldsymbol{B} \cdot \boldsymbol{X}_{t-2} + \boldsymbol{\varepsilon}_t$$

$\boldsymbol{X}_t = [\ MPU_t\ \ TT_t]'$, where MPU_t and TT_t are endogenous variables, $\boldsymbol{A}$ and $\boldsymbol{B}$ are coefficient matrices. $\boldsymbol{\varepsilon}_t$ is a vector of two distinct exogenous shocks, $\boldsymbol{\varepsilon}_t \sim WN(0, \Sigma_\varepsilon)$. The matrix dimensions of $\boldsymbol{A}$ and $\boldsymbol{B}$ are 2*2 and 2*2, respectively. When estimating the regression Equation 1, I will take the logarithmic of migration policy uncertainty for better interpretation, that is how terrorist attacks affect percentage change of migration policy uncertainty.

Because each equation of migration policy uncertainty and terrorist attacks has the same variables on the right-hand side, therefore ordinary lease squares can provide an efficient estimation. The characteristic roots of VAR model should be less than one to guarantee a stable condition. The optimal lag order can be chosen by a series of information criterion (e.g., AIC and BIC).

In addition, this study perform a Granger causality test (Granger, 1969) to identify the causation between migration policy uncertainty and terrorist attacks. Although Granger causality does not imply that two variables have the real effect, at least from the forecasting perspective, Granger causality can help us better understand the potential causal direction. In the Equation 1, if $A_{12} = B_{12} = 0$, then terrorist attacks do not Granger-cause migration policy uncertainty. Similarly, if $A_{21} = B_{21} = 0$, then migration policy uncertainty doesn't Granger cause terrorist attacks.

However, Granger causality can't tell the complete story about the interactions between the migration policy uncertainty and terrorist attacks. Therefore, in most applied works, it is often of interest to know the impact of shocks to one specific variable on other variables, so this study further analyze the impulse response functions as well as variance decomposition of forecasting error in VAR analytical framework. All empirical results are performed through EViews 9.0 software.

4. DATA DESCRIPTION

Before turn to introduce the data source and variable choices, the definition of terrorist attacks and migration policy uncertainty are clarified first. The word "terrorism" can be traced back to the late 18th century during the French Revolution. According to Global Terrorism Database, terrorist attack means that incidents were collected according to the following definition of terrorism, that is "…the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation." As for migration policy uncertainty, it is migration-related policy uncertainty. It is a kind of risk based on the uncertainty of future government actions on migration-related issues.

The sample length is 1990Q1-2016Q4 as this period exhibits the rising number of terrorist attacks. The total observations are 108. The number of terrorist attacks is collected from Global Terrorism Database published by the University of Maryland. The migration policy uncertainty is collected from the website[1]. To construct the migration policy uncertainty index, Baker et al. count the number of newspaper articles with at least one term from

[1] http://www.policyuncertainty.com/immigration_fear.html

each of the migration, policy and uncertainty term sets, and then divide by the total count of newspaper articles (in the same calendar quarter and country).

Table 1 summarizes the descriptive statistics for terrorist attacks and migration policy uncertainty in the U.S. The average number of terrorist attacks is approximately 7.55 times, and the maximum of terrorist attacks is 32 occurring in the third quarter of 2016. The average value of migration policy uncertainty index is 118.54, and the maximum index happens in the third quarter of 2016. Figure 1 further represents the relationship between the number of terrorist attacks and the migration policy uncertainty index. We can find that before the 9.11 terrorist attacks, the number of terrorist attacks is much larger than the number of terrorist attacks after the 9.11 attack. Since the 9.11 terrorist attacks, the U.S. government takes a stricter security strategy, such as the establishment of the Department of Homeland Security as well as the implementation of Patriot Act. A remarkable phenomenon is the number of terrorist attacks has risen significantly after the European Refugee Crisis.

Table-1. Descriptive Statistics.

Variables	Observation	Mean	Std Dev	Maximum	Minimum
TERR ATTACKS	108	7.55	5.88	32	0
MPU	108	118.54	80.76	660.75	32.68

Note: The sample period is from 1990Q1-2016Q4.

Figure 2 shows the time trend between migration policy uncertainty and terrorist attacks during the sample period. Before 9.11 terrorist attacks, migration policy uncertainty and terrorist attacks seem to have a closer relationship. However, such nexus breaks down after 9.11 terrorist attacks. In recent years (especially after the European Refugee Crisis), it shows a closer and stronger relationship since 9.11 terrorist attacks. Therefore, I further calculate the simple correlation coefficients in three sub-samples Table 2. The simple correlation coefficients are consistent with my previous analysis. In the first and third subsamples, migration policy uncertainty and terrorist attacks have a positive relationship (0.1563 and 0.1221) and the relationship becomes weaker and even opposite in the second sub-sample (-0.0276).

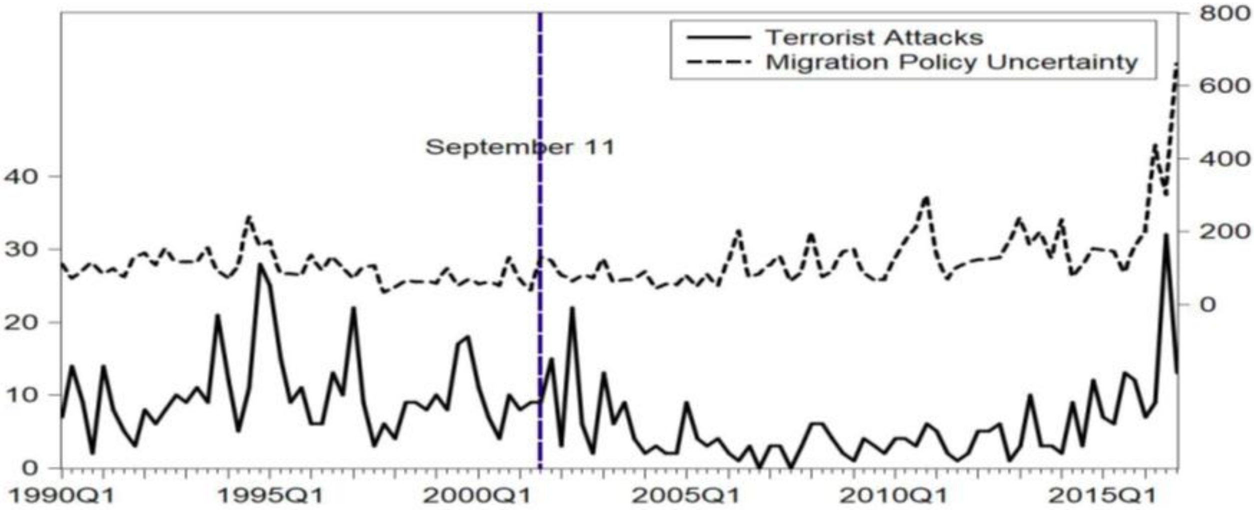

Figure-2. The Time Trend between Terrorist Attacks and Migration Policy Uncertainty.

Note: The sample range is from 1990Q1-2016Q4. The left axis is the number of terrorist attacks and the right axis is migration policy uncertainty index. The dash line represents 9.11 Terrorist Attacks in 2001, which belong to the 4th quarter of 2001.

Table-2. Correlation Coefficients in Sub-samples.

Sample Period	Description	Correlation
1990Q1-2001Q3	Pre-9.11 Terrorist Attack	0.1563
2001Q4-2015Q1	Post-9.11 and Pre-European Refugee Crisis	-0.0276
2015Q2-2016Q4	Post- European Refugee Crisis	0.1221
1990Q1-2016Q4	Full Sample	0.1388

Note: The sample period is from 1990Q1-2016Q4.

5. EMPIRICAL RESULTS

Before estimating the results of any time series model, the first step is to examine the variable stationarity to avoid the potential issue of the spurious regression. Follow this procedure, I consider augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test to achieve above goal, in which the Dickey-Fuller test involves a parametric extension for higher-order correlation in the residuals and the Phillips-Perron test developed as a nonparametric approach also controls for serial correlation in the residuals. The unit root test results are reported in Table 3. The second column shows that Dickey-Fuller test and the third column presents that Phillips-Perron test. We can reject the null hypothesis that variable has a unit root at 1% significance level, this indicates that the data generating processes for both time series variables are stationary according to the test results. So, we don't need to worry about the potential issue led by non-stationary variables and then turn to the Granger causality analysis.

Table-3. Unit Root Test.

Variable	ADF	PP
Terrorist Attacks	-6.51*** (0.00)	-6.96*** (0.00)
MPU	-4.79*** (0.00)	-5.10*** (0.00)

Note: The null hypothesis of augmented Dickey–Fuller test (ADF) and Phillips-Perron test are the variable has a unit root. The p-value reports in the parenthesis. *** represents significance level at 1%.

One of the advantages of the VAR model is to help us clarify the possible causal directions between migration policy uncertainty and terrorist attacks. As discussed earlier, although Granger causality doesn't prove the real causation. This method provides a valid way to define the causation from the perspective of forecasting. In the VAR model, I perform the Granger causality test by constructing an F-statistic to examine whether the joint hypothesis is correct. However, Thornton and Batten (1985) point out that arbitrary lag length specifications in the Granger causality test might obtain misleading results and an extensive search of lag space is the safest approach when we know nothing about the lag order. So, I choose four different lag orders (2, 4, 6 and 8) to guarantee the robustness of the Granger causality test, the results are reported in Table 4.

. **Table-4.** Granger Causality Test: US.

Null hypothesis	Lags	F-statistic (p-value)
TT does not Granger Cause MPU	2	0.388 (0.679)
	4	0.538 (0.708)
	6	0.341 (0.913)
	8	0.307 (0.962)
MPU does not Granger Cause TT	2	4.351**(0.015)
	4	4.165*** (0.004)
	6	3.253*** (0.006)
	8	2.760*** (0.009)

Note: The null hypothesis of Granger causality test is a joint hypothesis. The Granger causality test statistic is a F-statistic. P-value reported in the parenthesis. ***, ** represent the significance level at 1% and 5%, respectively.

The first null hypothesis is that terrorist attacks do not Granger cause migration policy uncertainty and the second null hypothesis is that the migration policy uncertainty does not Granger cause terrorist attacks. Table 4 shows that we cannot reject the first null hypothesis and reject the second null hypothesis, so we can conclude that the migration policy uncertainty and terrorist attacks only have a unidirectional relationship, that is from migration policy uncertainty to terrorist attacks. Furthermore, all preceding results are robust even though I choose different lag lengths

The possible explanation behind the above phenomenon may attribute to two reasons. First, the enactment and implementation of migration policy rely on different factors, such as social, political and economic factors. Terrorist attacks play a limited role in the change of migration policy compared with other factors which are more critical. For example, how to protect domestic residents from the competition of migration in the labor market could be a more important issue. Second, I did not distinguish the type of terrorist attacks into domestic and transnational terrorist attacks[2] due to the data limitation. If the terrorist attacks data has more domestic terrorist attacks, it may weaken the causational relationship between terrorist attacks and migration policy uncertainty.

Next, I perform innovation accounting by getting the impulse response functions and forecasting error variance decompositions from a Cholesky decomposition of the regression residuals. We should notice that the Cholesky decomposition is sensitive to the order of variables in the VAR model. According to the Granger causality test, we have already known the causal ordering is from migration policy uncertainty to terrorist attacks, so the order of variables in Cholesky decomposition is from migration policy uncertainty to terrorist attacks. As shown by regression Equation 1 in section III, I follow this order to set up the basic VAR model.

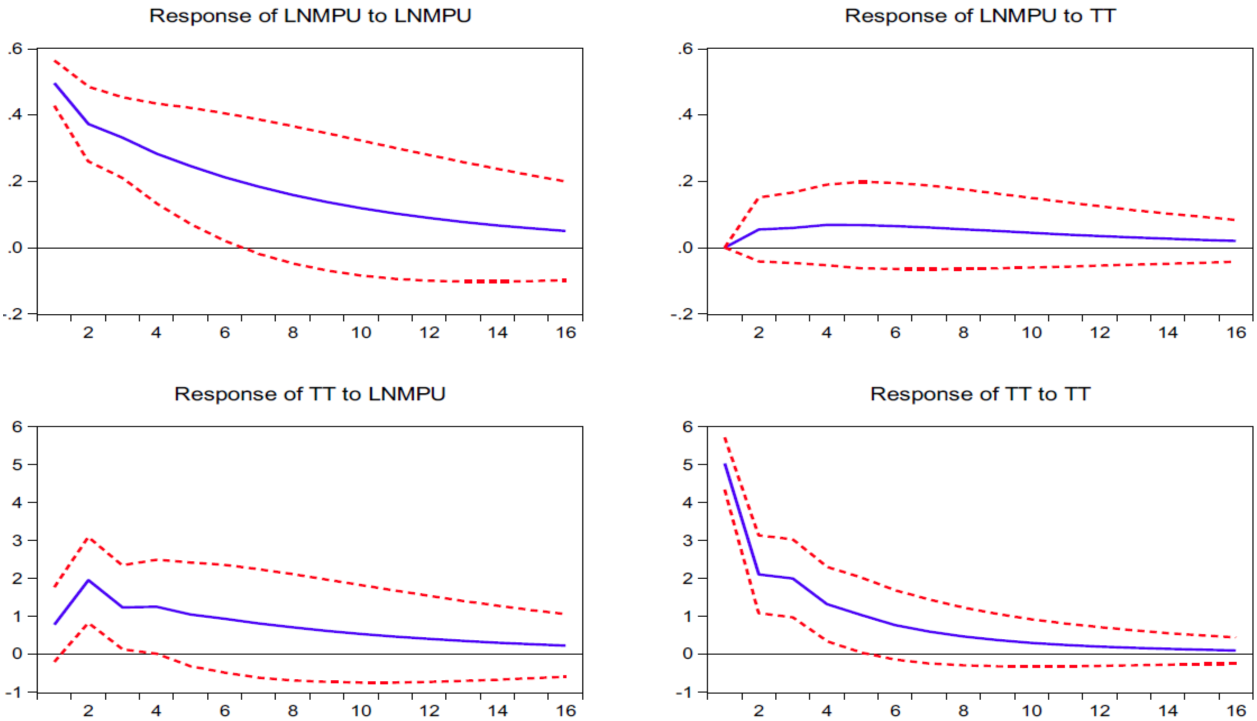

Figure-3. Impulse Response Functions: U.S.

Note: The red dash lines represent upper and lower 95% confidence interval. This study uses Cholesky approach to orthogonalize the impulses, in which migration policy uncertainty causally prior to terrorist attacks.

The four panels of Figure 3 exhibit the impulse response functions when we treat the migration policy uncertainty is causally prior to terrorist attacks. The solid blue lines in the figure are impulse responses, and the dashed red lines represent upper and lower 95% confidence interval. What we care more about is the response of terrorist attacks to migration policy uncertainty based on the results of Granger causality test. In the top left panel, a one-unit standard deviation shock to migration policy uncertainty ε_{1t} in Equation 1 will result in the increase of itself around 0.5% in the first quarter, and then the impact of shocks dies out after the 16th quarter. So, the exogenous shock to migration policy uncertainty has a persistent and significant effect on itself. The top right panel shows that the terrorist attack shock will have the largest impact on migration policy uncertainty in the second quarter and then impact begins to weaken. The diminishing of terrorist attack shock is persistent. Furthermore, the

[2] Enders, Sandler and Gaibulloev (2011) collect the terrorist attacks data from Global Terrorist Database and decompose the terrorist attacks into domestic and transnational parts.

bottom right panel shows how the terrorist attack responds to its own shock ε_{2t} in Equation 1. The number of terrorist attacks increase almost 5 times in the first quarter when suffer from one-unit exogenous shock. In addition, the diminishing of the terrorist attack is faster than that of migration policy uncertainty the in top left panel.

Finally, we will further consider the response of terrorist attacks to migration policy uncertainty shown in the bottom left panel. A one-standard deviation shock to migration policy uncertainty is persistent with the subsequently induced shocks remaining statistically significant until the 16th quarter. The number of terrorist attack occurrence arrives at the maximum value (approximately two times) in the second quarter to respond to the migration policy uncertainty shock. Therefore, the larger uncertainty of migration policy increases the occurrence of terrorist attacks after half a year and the subsequent impact of migration policy uncertainty is also significant.

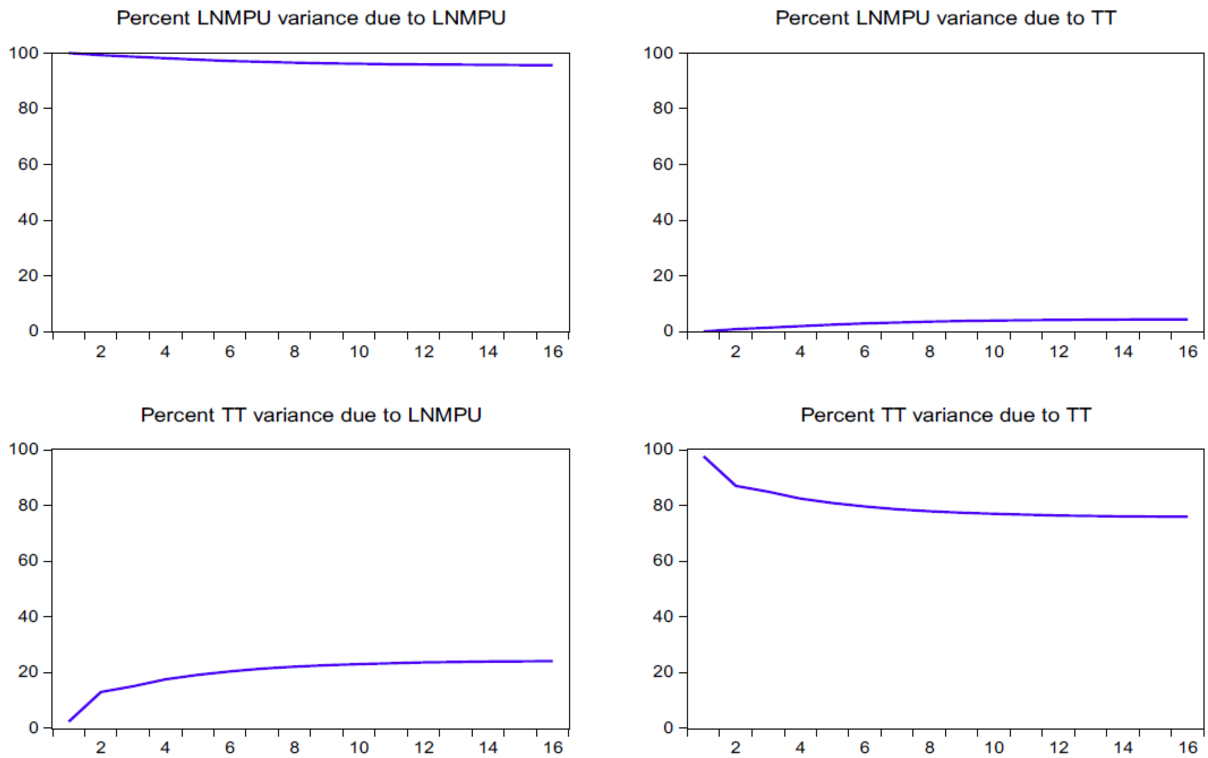

Figure-4. Forecast Error Variance Decomposition: U.S.

The four panels of Figure 4 show the forecasting error variance decomposition when migration policy uncertainty is causally prior to terrorist attacks. Two supplementary tables are reported in the Appendix A. The forecast error variance decomposition tells the proportion of the movements in a sequence due to its own shocks versus shocks to the other variable. The top portion of Figure 4 provides the information on the variance decomposition of migration policy uncertainty. Approximately all the variation of migration policy uncertainty attribute to its own shocks, which dominates in the forecasting error variance relative to the shocks coming from terrorist attack.

6. AN EXTENSION: COMPARISON ACROSS COUNTRIES

To provide a complete analysis on the relationship between migration policy uncertainty and terrorist attacks as well as a better comparison between the US and other countries, I utilize the data for France, UK and Germany to further explain the relationship between migration policy uncertainty and terrorist attacks.

Table 5 reports the Granger causality test from three European countries. To remove the potential impact from the choice of lag order, I also use different lag lengths to guarantee the robustness of conclusions. For these countries, we can't reject the null hypotheses, which means that there does not have Granger causality between migration policy uncertainty and terrorist attacks in these three countries. Therefore, the unidirectional relationship from migration policy uncertainty to terrorist attacks only exists in the US. Appendix B further shows the impulse response functions in UK, Germany and France. By comparing the impulse response function in all of the four countries, we can conclude that Germany is similar to the US, but UK and France are different. For example, in the UK, the impulse responses from both sides are negative.

Table-5. Granger Causality Test: UK, Germany and France.

Country	Null hypothesis	Lags	F-statistic (p-value)
UK	TT does not Granger Cause MPU	2	0.555 (0.576)
		4	0.395 (0.812)
		6	0.695 (0.655)
		8	1.629 (0.129)
	MPU does not Granger Cause TT	2	1.509 (0.226)
		4	0.996 (0.414)
		6	0.684 (0.662)
		8	0.475 (0.871)
Germany	TT does not Granger Cause MPU	2	1.898 (0.155)
		4	0.464 (0.762)
		6	0.528 (0.786)
		8	0.400 (0.917)
	MPU does not Granger Cause TT	2	0.488 (0.615)
		4	1.384 (0.245)
		6	1.233 (0.297)
		8	1.042 (0.412)
France	TT does not Granger Cause MPU	2	0.297 (0.744)
		4	0.918 (0.466)
		6	0.760 (0.603)
		8	0.759 (0.639)
	MPU does not Granger Cause TT	2	0.496 (0.610)
		4	1.440 (0.227)
		6	1.419 (0.216)
		8	1.267 (0.272)

Note: P-value reported in the parenthesis. ***, ** represent the significance level at 1% and 5%, respectively.

7. CONCLUSION

To explore the potential relationship between migration policy uncertainty and terrorist attacks as well as further discuss the above question, and further address the following question whether the consistent migration policy be more effective to decrease potential terrorist attacks than uncertain migration policy. This study utilizes the VAR model to analyze above relationship from different perspectives and arrive at the following conclusions: (1) migration policy uncertainty increases the occurrence of terrorist attacks. (2) From impulse response analysis, the exogenous shock to migration policy uncertainty has a significant and persistent impact on terrorist attacks. (3) Migration policy uncertainty contributes to more than 24% of the forecast error variance of terrorist attacks. (4) The nexus between migration policy uncertainty and terrorist attacks only exist in typical migration countries, such as the U.S. Therefor, this paper also confirms the previous study on the basis of counting model .

However, two more potential issues are still unsolved in my paper. First, I didn't distinguish the domestic and transnational terrorist attacks due to the data limitation. By referring to Enders *et al.* (2011) I might separate the Global Terrorism Database (GTD) into transnational and domestic terrorist incidents in the future, since this decomposition is essential for the understanding of some terrorism phenomena when the two types of terrorism are hypothesized to have different impacts. For the second extension, from the time trend shows in Figure 2, we can find that there is a potential structural break before and after 9.11. Therefore, for the next step, I will conduct the structural break analysis pre and post 9.11 to have an in-depth study of the relationship between the two.

Funding: This study received no specific financial support.
Competing Interests: The authors declare that they have no competing interests.
Contributors/Acknowledgement: All authors contributed equally to the conception and design of the study.

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Appendix A

Table-A.1. Forecast Error Variance Decomposition: U.S.

Variance Decomposition of MPU				Variance Decomposition of TT			
Period	**S.E.**	**MPU**	**TT**	**Period**	**S.E.**	**MPU**	**TT**
1	0.496	100	0	1	5.096	2.367	97.633
2	0.623	99.227	0.773	2	5.853	13.015	86.985
3	0.708	98.687	1.313	3	6.309	15.052	84.948
4	0.766	98.077	1.923	4	6.568	17.553	82.447
5	0.807	97.562	2.438	5	6.733	19.147	80.853
6	0.837	97.124	2.876	6	6.842	20.422	79.578
7	0.86	96.768	3.232	7	6.916	21.37	78.63
8	0.876	96.485	3.515	8	6.969	22.092	77.908
9	0.888	96.262	3.738	9	7.006	22.638	77.362
10	0.897	96.089	3.911	10	7.033	23.05	76.95
11	0.904	95.955	4.045	11	7.053	23.361	76.639
12	0.909	95.852	4.148	12	7.068	23.596	76.404
13	0.913	95.774	4.226	13	7.079	23.773	76.227
14	0.916	95.714	4.286	14	7.087	23.906	76.094
15	0.918	95.669	4.331	15	7.093	24.006	75.994
16	0.92	95.635	4.365	16	7.098	24.082	75.918

Appendix B

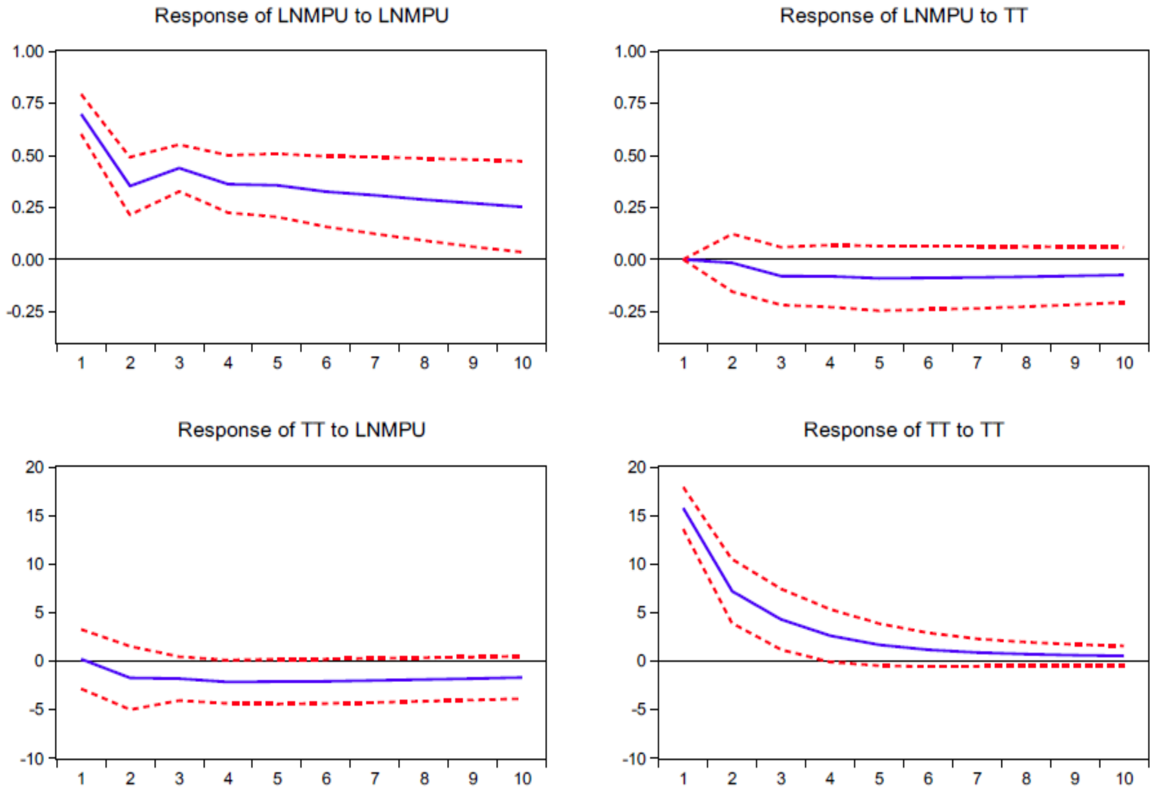

Figure-B.1. Impulse Response Functions: UK.

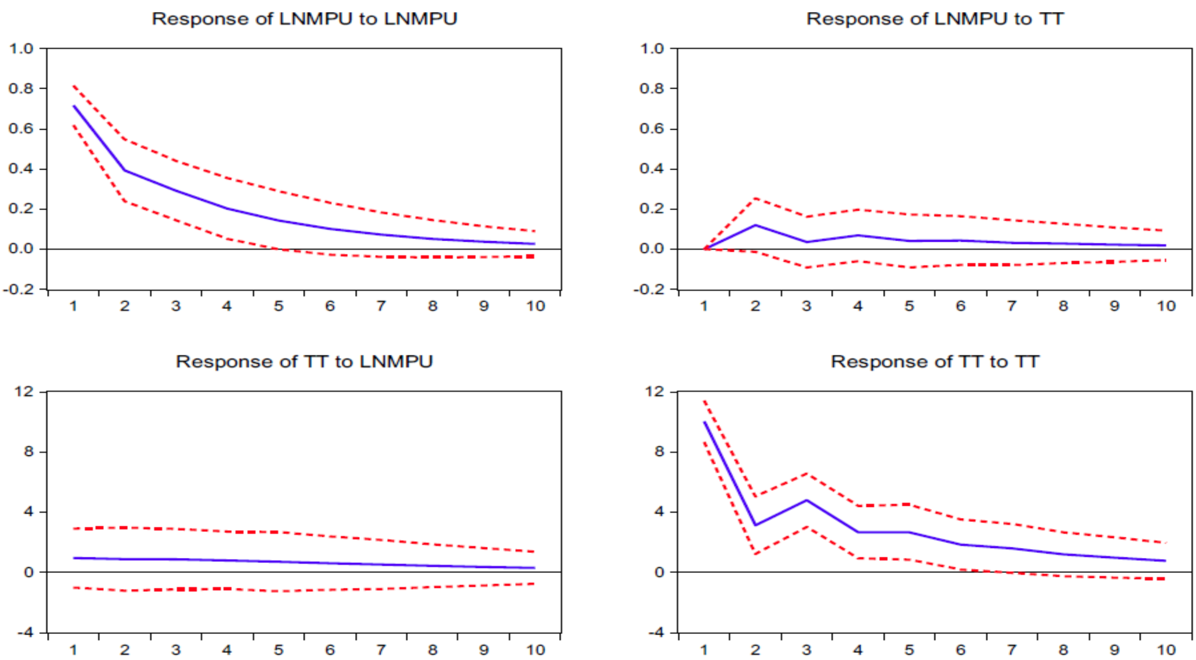

Figure-B.2. Impulse Response Functions: Germany.

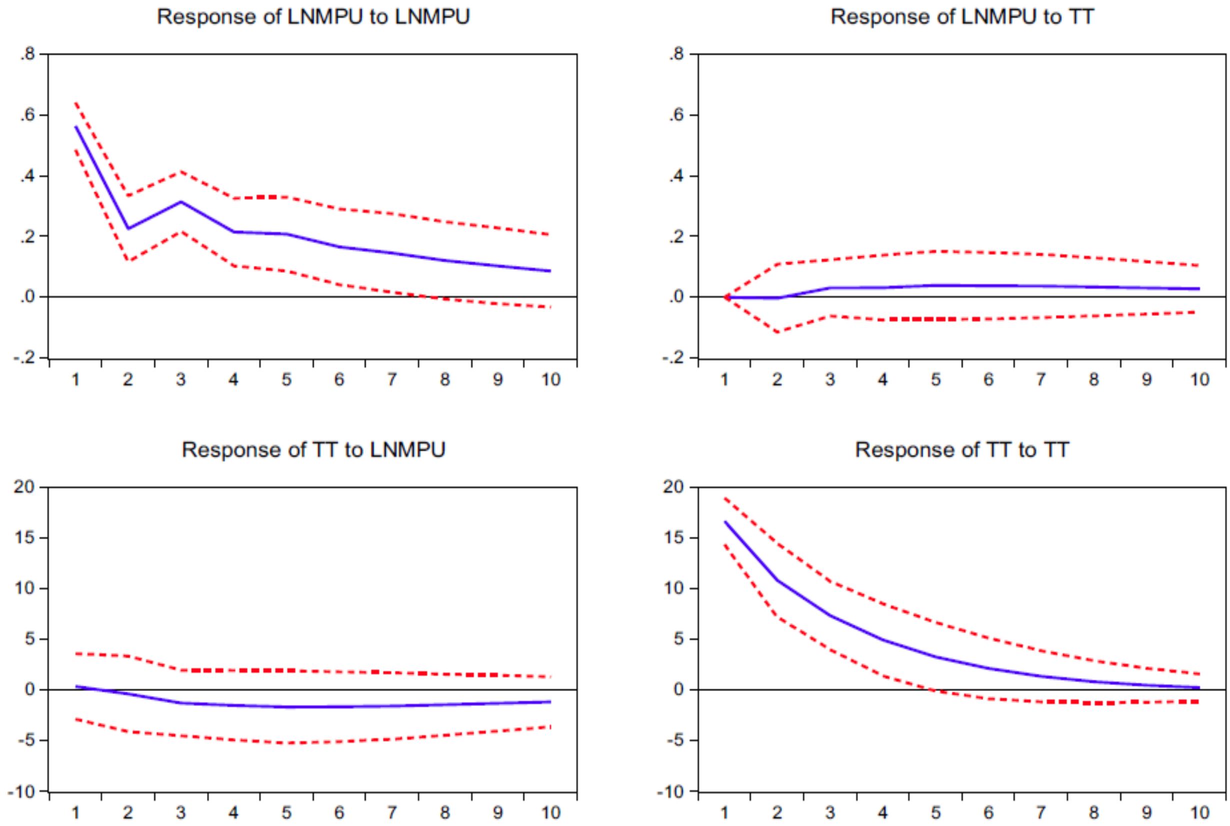

Figure-B.3. Impulse Response Functions: France.

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