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Terrorism Shocks and Public Spending: Panel VAR Evidence from Europe[*]

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Abstract

Based on a trivariate panel VAR and utilizing Generalized Impulse Responses, we explored the dynamic impacts of terrorism and crime risks on public order and safety spending across European countries during the period 1994-2006. Our findings suggest that both a shock in terrorism risk or in crime, significantly increase the subsequent trajectory of public order and safety spending. As a by-product we find that public spending is ineffective in reducing observed crime or terrorism risks.

Keywords: Panel VAR, Public Order and Safety Spending, Terrorism Activity

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1. Introduction

The extant empirical literature has established that terrorism activity leads to a wide range of adverse economic effects (see Brock and Wickstrom 2004; Brock *et al.*, 2008). In this study we are interested in exploring terrorism's potential effects on fiscal expenditure. In principle, one may consider indirect fiscal costs, for instance the erosion of tax base via a disruption in economic activity, or direct costs such as the increase in the terrorism-related public spending. Moreover, another important dimension is the possibility of "crowding out effects", which can be of two forms. Either affecting the composition of public spending, whereby an increase in terrorism-related expenditure reduces the resources dedicated to other public uses, and/or the more traditional case where increased terrorism-related spending crowds out private spending. The sparse literature on the issue has produced evidence for a limited terrorism fiscal impact (Hobijn, 2002; Lenain, *et al.*, 2002; Wildasin, 2002; Eichenbaum and Fisher, 2004; Gupta, *et al.*, 2004). It should be noted however, that these studies have either relied on overall fiscal expenditure or employed defence spending. Thus, it becomes apparent that identifying terrorism's impact using such metrics is rather hard. Perhaps a more promising avenue would be to rely on public spending that is more likely to be classified as terrorism-related. However, such data are difficult to obtain mainly for two reasons: : (i) the fact that state budgets incorporate several scattered funds, that are related either to the prevention of terrorism (counterterrorism) or coping with the consequences of terrorism, and (ii) the fact that anti-terrorism fiscal expenditures are not directly observed, either because they are classified or because they are embedded in other more general expenditures.

In order to circumvent these problems we adopt the pragmatic approach that terrorism is a criminal activity. Hence, the natural source for locating anti-terrorism

expenditures is the spending on **public order and safety**. Of course, such spending is targeted towards crime as well and therefore, any econometric analysis must take this into account. In other words, in order to avoid biases in inference a complete econometric model requires the use of public order spending, terrorism activity as well as crime activity. Moreover, one cannot simply rely on a single equation context where public spending is projected on terrorism and crime since, leaving aside the endogeneity issues, it might be difficult to distinguish public spending's responses to the two stimuli (terrorism, crime). To tackle these issues we employ a panel vector autoregressive (PVAR) approach that overcomes endogeneity issues, while at the same time allowing for country-specific unobserved heterogeneity – largely absent from time series analyses. Our approach also allows us to isolate the effect of these two types of risk on public order and safety spending, as well as the effectiveness of spending in reducing these types of risk. The latter is explored by examining a set of identification free impulse responses, the so-called Generalized Impulse Responses (GIRs) suggested by Koop *et al*. (1996) and Pesaran and Shin (1998) of the variable of interest, namely public order and safety spending.

Our paper makes a twofold contribution to the security economics literature: (*i*) we provide empirical evidence for a panel of European countries using public order and safety spending data, which clearly are more relevant for the issue at hand, and (*ii*) we employ generalized rather than orthogonalized impulse-response functions, that free our results from stringent identification restrictions, usually employed in time series analysis. Moreover, by means of our impulse response analysis, we are able to separate the response of public order and safety to *historical* shocks to either terrorism or crime risk.

## 2.	Data Issues and Background Analysis

We use panel data for 29 European Countries to study the dynamic relationship between the levels of risk, be it terrorism or crime, a country faces and the level of public order and safety spending. The countries under scrutiny are: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Turkey, UK. The time span of our data covers the time period from 1994 to 2006 , and is dictated by data availability.

We obtained our data by combining various sources. Data on public order spending were obtained by the IMF's **Government Financial Statistics** (**GFS**), which provides measures in terms of domestic currency.[1] These were then converted into real US dollars per person measured at 2005 PPP. Original series were deflated using the GDP deflator and expressed in per capita terms (both derived from IMF's **International Financial Statistics** (**IFS**)). The series were then converted into US dollars using 2005 PPP rates, obtained from World Bank's **World Development Indicators** (**WDI**). Furthermore, in order to proxy for country-level terrorism and crime risks, we make use of the annual count of terrorism events and total registered crimes, which were obtained from the **Global Terrorism Database (GTD)** and from **Eurostat** respectively.

Letting i and t denote country and year respectively we define the following variables, which we employ in our analysis:

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[1] The reported values in GFS measure the variable of interest either in *cash* or in *accrual* basis. In our work we employ *cash* measures, when these are available, albeit the two numbers rarely differ. We are thankful to Athanasios Tagkalakis for discussions on this issue.

- *POSS$_{it}$* : the logarithm of public order and safety spending, measured in real per capita US dollars at 2005 PPP;

- *TRISK$_{it}$* : the logarithm of one plus the number of per capita terrorist attacks[2];

- *CRISK$_{it}$* : the logarithm of one plus the number of per capita crimes.

3. Econometric Methodology

In our analysis we employ a Vector Autoregressive (VAR) methodology, applied to panel data (PVAR). A VAR methodology squares well with our purposes here, as there is no *a priori* theory regarding the causal relations between the variables of interest, namely country spending on safety and country security risks. In such a framework, all variables are treated as endogenous in a system of equations, while the short-run dynamics may be identified at a later stage (Lütkepohl, 2006). In particular a VAR model allows us to explore the causal relationships between the variables of interest, with causality running in either direction: from risk to spending and from spending to risk.[3]

The PVAR technique combines the traditional VAR approach, which treats all the variables in the system as endogenous, with the panel-data approach, which allows for unobserved individual heterogeneity. To begin, we specify a panel VAR model with *k* lags as follows:

$$\mathbf{y}_{it} = \boldsymbol{\mu}_0 + \mathbf{A}_1 \mathbf{y}_{it-1} + ... + \mathbf{A}_k \mathbf{y}_{it-k} + \boldsymbol{\alpha}_i + \boldsymbol{\lambda}_t + \mathbf{u}_{it}, \ i = 1,...,N; \ t = 1,...,T \qquad (1)$$

where $\mathbf{y}_{it} = (POSS_{it}, TRISK_{it}, CRISK_{it})'$ is a three-variable random vector, composed of a measure of public ordered and safety spending, a measure of terrorism activity risk and a measure of crime activity risk; $\mathbf{A}_j$ are a 3×3 matrices of estimable

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[2] Both risks are expressed in per capita terms in order to account for the country size.
[3] This *causality* is not restricted by any means to be Granger-Causality.

coefficients; $\boldsymbol{\alpha}_i$ denotes unobserved country-affects; $\boldsymbol{\lambda}_t$ denotes time-effects; and $\mathbf{u}_{it}$ is a 3×1 vector of well behaved disturbances.

As is common in panel data studies, we need to impose the restriction that the underlying structure is the same for each cross-sectional unit, i.e. the coefficients in the matrices $\mathbf{A}_j$ are the same for all countries in our sample. Since this assumption is likely to be violated, our model allows for "individual heterogeneity" in the levels of the variables by introducing fixed effects, denoted by $\boldsymbol{\alpha}_i$ in the model. Then our model (1) is a *system* of dynamic panel data equations. It is known, however, that the fixed effects are correlated with the regressors due to lags of the dependent variables (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998), so the usual *within* transformation to eliminate fixed effects would create biased coefficients.[4] Hence, we employ *forward orthogonal deviations* (Arellano and Bover, 1995) to eliminate the fixed effects. This procedure removes only the forward mean, i.e. the mean of all the future observations available for each country-year. This transformation preserves the orthogonality between transformed variables and lagged regressors, so we can use lagged regressors as instruments and estimate the coefficients by system GMM (Arellano and Bover, 1995).[5]

The reduced form VAR is useful, in that it allows implementing dynamic simulations, once the unknown parameters are estimated. This usually involves impulse response (IR) analysis and variance decompositions (VD) that allow one to examine the impact of *innovations* to any particular variable to other variables in the

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[4] Individual heterogeneities have been a major issue in dynamic panel models, as they render the standard fixed and random effects estimators inconsistent (Arellano and Bond, 1991; Arellano and Bover, 1995).

[5] See also Love and Zicchino (2006) and Arias and Escudero (2007) for different applications of the PVAR techniques employed in this paper.

system. Such exercises require solving a delicate identification issue.[6] The most common way to deal with this problem is to choose a *causal ordering* so that more exogenous variables impact on the more endogenous ones in a sequential order.[7]

As we are unwilling to defend any particular causal ordering, we opt for the use of Generalized Impulse Responses (GIR) and variance decompositions (GVD) suggested by Koop *et al.* (1996) and Pesaran and Shin (1998), which aim avoiding particular orthogonalizations of the shocks. In particular, a GIR measures the effect of a *typical (historical)* shock in variable $y_{l,it}$ on the system of equations. One way to interpret these is as the effect a change $y_{l,i}$ by ζ_l at time *t* has on the expected values of the whole stochastic vector $\mathbf{y}_{it}$ at time *t+h*. In addition, Pesaran and Shin (1998) show that GIRs in linear systems will be invariant to history (the information set on which we condition) and will depend only on the composition of the shocks, i.e. the vector ζ we choose.

4.   Empirical Results

Before proceeding with estimating the panel VAR, we need to make a choice regarding the number of lags to use in the system of equations (Lütkepohl, 2006). To do so, we employ the Arellano-Bover GMM estimator for lags between one and four, and employ standard information criteria (e.g. Akaike and Schwarz) to select the appropriate lag-length. Both the AIC and SIC indicate that two lags should be used (see Table A.1 in the Appendix). However, the estimated parameters for the second lag were not statistically significant, and we finally opted for a PVAR of order one,

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[6] A more detailed discussion of the identification issues is discussed in the Appendix.

[7] This assumption is implicit in the Cholesky decomposition of the covariance matrix of the error terms, which imposes a recursive orthogonal structure (causal ordering) on the identified shocks.

which preserves the information in the low frequency data we use, while also economizes on the degrees of freedom.[8]

Furthermore, in order to be able to analyze the impulse-response functions we need an estimate of their confidence intervals. As the estimated impulse response functions is based on the estimated VAR coefficient, sampling uncertainty needs to be taken into account. We obtain standard errors for the impulse response functions by means of Monte Carlo simulations. In particular, we randomly generate random draws of the VAR coefficients, using the estimated coefficients and the estimated covariance matrix of the errors, to recalculate the impulse responses (see Love and Zicchino, 2006; Arias and Escudero, 2007).[9]

The estimated parameters of the panel VAR(1) specification are reported in Table 1. Our results show that public order and safety spending responds positively to its lagged value, and positively to lagged terrorism and crime risk, albeit the coefficient on terrorism risk is insignificant. On the other hand, terrorism risk is influenced positively by past terrorism risk and past crime risk, but also – somewhat surprisingly – positively by lagged *POSS*. However, the coefficient estimates are insignificant. Finally, we see the crime risk is responds positively and significantly to past crime risk, and positively insignificantly to past terrorism risk. We find again that crime risk is influenced positively by lagged *POSS*, however the coefficient estimate is insignificant.

[Insert Table 1 about here.]

One might question the meaningfulness of these findings. Our point of view is that the results in Table 1, being estimates from a reduced form model do not convey

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[8] Results are available upon request.

[9] In practice we repeat this procedure 1000 (experimenting with more replications delivers similar insights). We generate the 16th and 84th (68%) percentiles of this distribution is generated and we use this as a confidence interval for the impulse responses.

much information. Instead, one should pay attention to the underlying moving average (MA) representation of the VAR model, namely the impulse response functions (IRs) and the associated variance decompositions (VDs). These two combined, convey information on how each variable responds to a surprise change (a *shock*) to another variable in the system.

As we agued above, IRFs and VDs may be obtained for various identification schemes, based on different orderings of the variables. However, such identifying assumptions are hard to stomach, as they require strong exogeneity assumptions that are probably violated in our data. Hence, we opt for the use of generalized impulse response functions (GIRs) and variance decompositions (GVDs) that do not depend on the particular ordering of the variables in the system.

The GIRs from are plotted in Figure 1, and are normalized to correspond to a one percent increase of *POSS* (first column), *TRISK* (second column) and *CRISK* (third column) respectively. We first note that a 1% increase in *POSS* persists over time, as it takes roughly five years to return to its previous level. It is also clear, that such a policy change does not have any significant impact on crime risk. We also find that an increase of *POSS*, leads to an increase of terrorism risk on impact, but this effect becomes insignificant after one year. These findings taken at face value, imply that public order spending is at best ineffective in reducing terrorism or crime risk. Similar evidence for terrorism has been reported by Kollias *et al*. (2009) who study the effectiveness of public spending on terrorism activity.

[Insert Figure 1 about here.]

Next, we turn our attention to the IRF's of main interest, i.e. those that trace out the dynamic impacts of risks on public spending. We find that an increase in terrorism risk by one percentage point dies out pretty quickly, while exerting a

negative effect on crime risk – although this effect is insignificant as can be seen from the wide confidence intervals. Importantly though, we find that such a shock leads to an increase of *POSS* by roughly 0.05 percent on impact. The peak response of *POSS* is after one year, and then it converges to its pre-shock level smoothly. In other words, public spending is responsive to observed terrorism risk. Turning now to crime risk we see that it has pronounced effects. In particular, we find that even six years after the shock, it does not return to its pre-shock level. More importantly though we see that it has a strong and long-lasting positive effect on both *POSS* and *TRISK*.[10] In particular, we find that *POSS* increases on impact by 0.08 percent, and its response peaks after four years (having increased by 0.6 percent). Similarly, we find that *TRISK* increases on impact (by 0.16 percent) and its response reaches its peak after two years (0.69 percent).

In Table 2, we report the GVDs for *POSS*, *TRISK* and *CRISK*, which provide evidence of the importance of terrorism risk and crime risk for public order and safety spending, as well as of the importance of *POSS* for *TRISK* and *CRISK*. These results are in line with the GIRs analysis above. In particular, at a horizon of five years, about 4% of the *POSS* forecast error variance is attributed to terrorism risk, while about 13% is due to crime risk. At longer horizons (10, 20 and 30 years) *TRISK* becomes less important, whereas the importance of *CRISK* increase over time (accounting for 25%, 32% and 33% respectively). Turning to *TRISK*, we see that about 3% of its forecast error variance is accounted for by variations in *POSS*, for all horizons, while variations in *CRISK* are becoming more important over time accounting for 3% at a five year horizon, 5% at ten years, and about 7% at a thirty year horizon.

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[10] The largest eigenvalue of the companion matrix $\mathbf{A}_1$ which determines the stability properties of the VAR is 0.919, hence the VAR is stable. On the other hand, the fact that this eigenvalue is large enough, explains why the impulse responses to *CRISK* – the most persistent variable in our analysis – have long-lasting but by no means permanent effects on the other two variables in the system.

4.1 Sensitivity Analysis

A natural question that arises is how robust are the results we have reported thus far to the number of lags employed in the PVAR. A second question pertains to whether our results are robust to the measure of *POSS* employed.[11] We assess these issues in turns.

First, we assess the robustness of our results to varying the number of lags in the analysis. To this end, we have re-estimated PVAR models with two, three and four lags. Estimating a model with two lags, delivers similar - if not identical – insights both in terms of impulse responses and variance decompositions. Increasing the number of lags to three or four, however we now find both terrorism and crime risk have a more pronounced and significant effects on public safety spending. In particular, we find that an increase in either type of risk induces and increase of *POSS* on impact, the response being significant for roughly five years. Furthermore, in these cases we find that the fraction of variance share of *POSS* explained by innovations to *CRISK* is roughly equal that reported in our results. What becomes much more pronounced is the extent of variability of *POSS* explained by innovations in *TRISK*, which at horizons of thirty years after the shock, explains a good 40% of the *POSS* variation.

Secondly, in order to assess the sensitivity of our results to the particular measure of *POSS* we have employed, as an alternative we have opted for the ratio of *POSS* relative to GDP, as the relevant variable. As in our main results, standard information criteria suggest that a PVAR(2) is appropriate, but the coefficients on the second lag are statistically insignificant; hence we have opted for a model with one

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[11] Recall that *POSS* is measured in real US dollars per capita using 2005 PPPs.

lag. Based on this, the results we obtained are in line with those we discussed above. We have also experimented with varying the lag length, which again provided us with results, that are similar to those obtained using our benchmark measure of *POSS*.

5.   Conclusions

Based on a trivariate panel VAR and in particular the Generalized Impulse Responses, we explored the dynamic impacts of terrorism and crime risks on public order and safety spending across European countries during the period 1994-2006. Our findings suggest that a shock in terrorism risk leads to an increase of public order and safety spending by roughly 0.05 percent on impact, with the response peaking after one year. In addition, a shock in crime risk also leads to an increase in public spending, by 0.08 percent on impact, and the response peaking after four years. These findings are also confirmed by the Generalised Variance Decompostions, which suggest that terrorism risk and crime risk tend to increase public order and safety spending.

We see two natural extensions of the present study. First, one could enlarge the sample by considering non-European countries as well. Second, it would be fruitful to investigate the potential interplay between public spending and observed risks with perceived risks.

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Tables

Table 1: Panel VAR Estimates

Dependent Variable	Equation		
	$POSS_{it}$	$TRISK_{it}$	$CRISK_{it}$
$POSS_{it-1}$	0.586***	0.097	0.003
[t-stat]	[4.953]	[0.354]	[0.053]
$TRISK_{it-1}$	0.020	0.156	-0.015
[t-stat]	[0.429]	[1.238]	[-0.835]
$CRISK_{it-1}$	0.313*	0.600	0.930***
[t-stat]	[1.924]	[0.989]	[10.081]
Nobs.	281	281	281
$\hat{\sigma}_u \times 100$	2.636	28.823	0.553

Notes for **Table 1**: $POSS_{it}$ stands for the logarithm of public order and safety spending, measured in real per capita US dollars (2005 PPP); $TRISK_{it}$ denotes the logarithm of one plus the number of terrorist attacks per person; $CRISK_{it}$ denotes the logarithm of one plus the number of crimes per person. The PVAR model is estimated using system GMM. Reported numbers show the coefficients of regressing the dependent variables on lags of the independent variables. The two largest eigenvalues of the companion matrix, which determine the stability of the PVAR, are 0.919 and 0.591. Heteroskedasticity adjusted *t*-statistics are in square brackets. *,**, and *** indicate significance at the 10%,5% and 1% level respectively.

Table 2: Variance Decompositions

	$POSS_{it} - E_t(POSS_{it})$			$TRISK_{it} - E_t(TRISK_{it})$			$CRISK_{it} - E_t(CRISK_{it})$		
	Generalized Innovations to								
h	$POSS_{it}$	$TRISK_{it}$	$CRISK_{it}$	$POSS_{it}$	$TRISK_{it}$	$CRISK_{it}$	$POSS_{it}$	$TRISK_{it}$	$CRISK_{it}$
1	100.00	2.83	0.12	2.83	100.00	0.05	0.12	0.05	100.00
2	98.18	4.10	2.06	3.07	99.24	0.79	0.09	0.40	99.41
3	95.13	4.24	5.38	3.12	98.33	1.66	0.08	0.62	99.09
4	91.44	4.08	9.26	3.12	97.50	2.47	0.07	0.75	98.91
5	87.72	3.88	13.07	3.11	96.79	3.17	0.07	0.82	98.81
10	75.19	3.37	25.46	3.04	94.53	5.42	0.06	0.96	98.61
20	68.32	3.17	32.12	3.00	93.15	6.79	0.06	1.01	98.54
30	67.16	3.14	33.24	2.99	92.90	7.04	0.06	1.02	98.53

Notes for **Table 2**: The table reports the fraction (in percentage points) of the *h*-years ahead forecast error variance of each variable, that is attributable to generalized innovations in $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$. The variance shares may not sum to 100 (Pesaran and Shin, 1998). See also notes for **Table 1**.

Figures
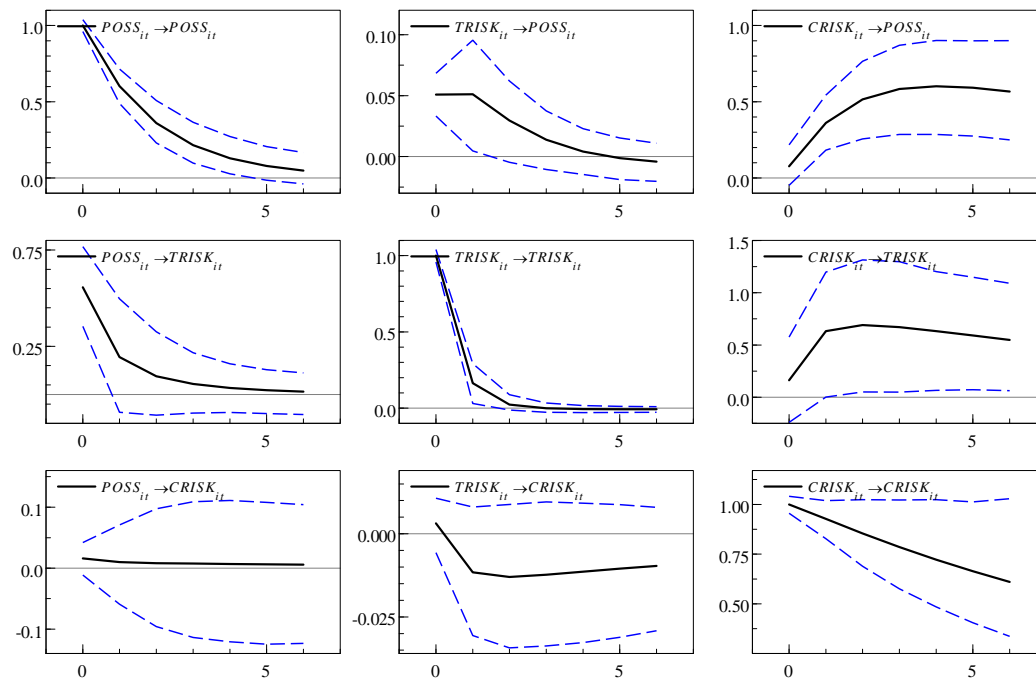
Figure 1. Generalized Impulse Responses of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$.

Notes for Figure 1: The figure displays the generalized impulse responses of the column variable ($POSS_{it}$, $TRISK_{it}$, $CRISK_{it}$) to a one percent shock the row variable ($POSS_{it}$, $TRISK_{it}$, $CRISK_{it}$). $POSS_{it}$ The dashed lines show the one standard deviation standard errors generated by Monte Carlo simulation with 1000 replications. The horizon is in years after the shock.

Appendix

A.1 Generalized Impulse Responses

The effects of shocks in the variables are easily seen from the Wold moving average (MA) representation of $\mathbf{y}_{it}$:

$$\mathbf{y}_{it} = \mathbf{u}_{it} + \mathbf{C}_1\mathbf{u}_{i,t-1} + \mathbf{C}_2\mathbf{u}_{i,t-2} + \mathbf{C}_3\mathbf{u}_{i,t-3} + ... \tag{A.1}$$

The coefficient matrices of this representation may be obtained by recursive formulas from the coefficient matrix $\mathbf{A}_j$ (see Lütkepohl, 2006; or Hamilton, 1994). The elements of the $\mathbf{C}_s$'s may be interpreted as the responses to impulses hitting the system. In particular, the *kl*-th element of $\mathbf{C}_s$ represents the expected marginal response of $y_{k,it}$ to a unit change in $y_{l,it}$ holding constant all past values of the process.

Since the components of $\mathbf{u}_{it}$ may be instantaneously correlated, orthogonal innovations are often preferred in impulse response analysis. Using a Cholesky decomposition of the covariance matrix $\mathrm{E}(\mathbf{u}_{it}\mathbf{u}_{it}') = \boldsymbol{\Sigma}_\mathbf{u}$ is one way to obtain uncorrelated innovations. Let $\mathbf{B}$ be a lower-triangular matrix with the property that $\boldsymbol{\Sigma}_\mathbf{u} = \mathbf{BB}'.$. Then orthogonalized shocks are given by $\boldsymbol{\varepsilon}_{it} = \mathbf{B}^{-1}\mathbf{u}_{it}$. Substituting in (A.1) and defining $\mathbf{D}_s = \mathbf{C}_s\mathbf{B}$ ($s = 0,1,2, ...$) gives

$$\mathbf{y}_{it} = \mathbf{D}_0\boldsymbol{\varepsilon}_{it} + \mathbf{D}_1\boldsymbol{\varepsilon}_{it-1} + \mathbf{D}_2\boldsymbol{\varepsilon}_{it-2} + ... \tag{A.2}$$

Notice that $\mathbf{D}_0 = \mathbf{B}$ is lower triangular so that the first shock may have an instantaneous effect on all the variables, whereas the second shock can only have an instantaneous effect on $y_{2,it}$ to $y_{n,it}$ but not on $y_{1,it}$. This way a recursive Wold causal chain is obtained. The effects of the shocks $\boldsymbol{\varepsilon}_{it}$ are sometimes called *orthogonalized impulse responses* because they are instantaneously uncorrelated (orthogonal).

A well-known drawback is that many matrices $\mathbf{B}$ exist which satisfy $\mathbf{BB}' = \boldsymbol{\Sigma}_\mathbf{u}$ – the Choleski decomposition is to some extent arbitrary if there are no good reasons for a particular recursive structure. Clearly, if a lower triangular Choleski decomposition is used to obtain $\mathbf{B}$, the actual innovations will depend on the ordering of the variables in the vector $\mathbf{y}_{it}$ so that different shocks and responses may result if the vector $\mathbf{y}_{it}$ is rearranged.

As we mentioned, the results of analyses based on orthogonalization assumptions depend on the ordering of the variables to obtain $\mathbf{B}$ and hence the orthogonalized shocks. Recent results by Koop *et al.* (1996) and Pesaran and Shin (1998) though have re-examined the concept of orthogonalized impulse responses, aiming to remove this shortcoming. Instead of orthogonalized impulse responses from a Choleski decomposition, they suggested *generalized impulse responses* (GIR henceforth) that are based on a "typical" shock to the system.

The argument about GIR may be explained as follows. Let the Vector Moving Average (VMA) representation of the *n*-variable PVAR model be given by

$$\mathbf{y}_{it} = \boldsymbol{\kappa}_0 + \boldsymbol{\kappa}_i + \boldsymbol{\kappa}_t + \sum_{s=0}^{+\infty} \mathbf{C}_s\mathbf{u}_{s,t-j} \tag{A.3}$$

where $\boldsymbol{\kappa}_o$ is a vector of constants, $\boldsymbol{\kappa}_i$ are country-effects, $\boldsymbol{\kappa}_t$ are time effects, and $\mathbf{u}_{it}$ is a vector of unobserved "shocks", where $\mathbf{u}_{it} \sim \mathbf{IIDN}_n\left(\mathbf{0}, \boldsymbol{\Sigma}_u\right)$ and let σ_{lm} be a typical element of $\boldsymbol{\Sigma}_u$. Then it holds that

$$\mathrm{E}\left(\mathbf{u}_{it}\middle|u_{i,lt} = \zeta_l\right) = \boldsymbol{\Sigma}_u \mathbf{e}_l \sigma_{ll}^{-1} \zeta_l \tag{A.4}$$

where $\mathbf{e}_l$ is a $(n \times 1)$ selection vector with element l equal to unity and zeroes elsewhere. Then the GIR of the effect of a "unit" shock to the *l-th* disturbance term at time t on $\mathbf{y}_{i,t+h}$ is

$$GIR_{\mathbf{y}_{i,t+h}}\left(h,l\right) = \left(\frac{\mathbf{C}_h \boldsymbol{\Sigma}_u \mathbf{e}_l}{\sqrt{\sigma_{ll}}}\right)\left(\frac{\zeta_l}{\sqrt{\sigma_{ll}}}\right), \ h = 0, 1, 2, ..., \tag{A.5}$$

and the GIRs are measured h periods after the shock has occurred.[12]

In general, Pesaran and Shin (1998) show that one can interpret generalized impulse responses for a stationary vector process $\mathbf{y}_{it}$ as

$$GIR_{\mathbf{y}_{i,t+h}}\left(\zeta, \mathfrak{I}_{t-1}\right) = \mathrm{E}\left(\mathbf{y}_{i,t+h}\middle|\mathbf{u}_{it} = \zeta, \mathfrak{I}_{t-1}\right) - \mathrm{E}\left(\mathbf{y}_{i,t+h}\middle|\mathfrak{I}_{t-1}\right).$$

They also explain that in a linear system, the impulse responses will be invariant to history (the information set on which conditioning is made), and so the GIR will depend only on the composition of the shocks as defined by ζ. In addition, they demonstrate that the GIR will be numerically equivalent to the standard impulse response function based on Cholesky decompositions, only if $\boldsymbol{\Sigma}_u$ is diagonal.

Furthermore, the share of variance of $y_{k,it}$ explained by a shock in variable $y_{k,it}$ is given by

$$\theta_{kl}(h) = \frac{\sigma_{kk}^{-1}\sum_{s=1}^{h}\left(\mathbf{e}_k^{'}\mathbf{C}_s\boldsymbol{\Sigma}_u\mathbf{e}_l\right)^2}{\sum_{s=1}^{h}\mathbf{e}_k^{'}\mathbf{C}_s\boldsymbol{\Sigma}_u\mathbf{C}_s^{'}\mathbf{e}_l} \tag{A.6}$$

Note that due to the non-zero covariance between the original (non-orthogonalized) shocks, in general, the variance shares may not sum to unity.

A.2 Data Background and Summary Statistics

Data Sources
IMF's Government Financial Statistics: http://www2.imfstatistics.org/GFS/
IMF's International Financial Statistics: http://www.imfstatistics.org/imf/
World Bank's World Development Indicators: http://data.worldbank.org/data-catalog/world-development-indicators
Global Terrorism Database: http://www.start.umd.edu/start/
Eurostat: http://epp.eurostat.ec.europa.eu/portal/page/portal/eurostat/home/

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[12] By letting $\zeta_l = (\sigma_{ll})^{1/2}$, we obtain the scaled generalized impulse response function by $GIR_{\mathbf{y}_{i,t+h}}\left(h,l\right) = \mathbf{C}_h \boldsymbol{\Sigma}_u \mathbf{e}_l (\sigma_{ll})^{-1/2}$ which measures the effect of one standard error shock to the *l*-th equation at time t on expected values of y_i at time $t+h$.

A.3 Lag-Length Selection for PVARs

Table A.1: Information Criteria

lags	AIC	SIC
1	-10.043	-9.746
2	**-10.574**	**-9.918**
3	-10.472	-9.374
4	-10.262	-8.599

Notes for Table A.1: The table reports the Akaike and Scwarz information criteria, employed in determining the appropriate number of lags in the PVAR models.

Not for Publication Appendix: *Further Results*

Table A.I: Panel VAR(2) Estimates

Dependent Variable	Equation		
	$POSS_{it}$	$TRISK_{it}$	$CRISK_{it}$
$POSS_{it-1}$	0.643***	-0.055	0.008
[t-stat]	[4.273]	[-0.168]	[0.105]
$TRISK_{it-1}$	0.017	0.201	-0.001
[t-stat]	[0.301]	[1.398]	[-0.065]
$CRISK_{it-1}$	0.118	0.332	0.985***
[t-stat]	[0.810]	[0.430]	[7.379]
$POSS_{it-2}$	-0.018	0.150	-0.019
[t-stat]	[-0.239]	[0.828]	[-0.706]
$TRISK_{it-2}$	-0.017	-0.060	0.000
[t-stat]	[-0.339]	[-0.625]	[-0.028]
$CRISK_{it-2}$	0.110	-0.053	-0.046
[t-stat]	[1.261]	[-0.119]	[-0.707]
Nobs.	248	248	248
$\hat{\sigma}_u \times 100$	1.833	23.254	0.525

Notes for Table: The two largest eignevalues of the companion matrix are 0.924 and 0.635. See also notes for **Table 1**.

Table A.II: Panel VAR Estimates

Dependent Variable	Equation		
	$POSS_{it}$	$TRISK_{it}$	$CRISK_{it}$
$POSS_{it-1}$	0.603***	19.244	1.122
[t-stat]	[7.151]	[1.022]	[0.405]
$TRISK_{it-1}$	0.000	0.156	-0.015
[t-stat]	[0.610]	[1.277]	[-0.830]
$CRISK_{it-1}$	0.003*	0.583	0.927***
[t-stat]	[1.653]	[1.080]	[13.243]
Nobs.	281	281	281
$\hat{\sigma}_u \times 100$	2.636	28.823	0.553

Notes for **Table 1**: $POSS_{it}$ stands for the ratio of public order and safety spending relative to GDP; $TRISK_{it}$ denotes the logarithm of one plus the number of terrorist attacks per person; $CRISK_{it}$ denotes the logarithm of one plus the number of crimes per person. The PVAR model is estimated using system GMM. Reported numbers show the coefficients of regressing the dependent variables on lags of the independent variables. The two largest eigenvalues of the companion matrix, which determine the stability of the PVAR, are 0.924 and 0.612. Heteroskedasticity adjusted *t*-statistics are in square brackets. *,**, and *** indicate significance at the 10%,5% and 1% level respectively.
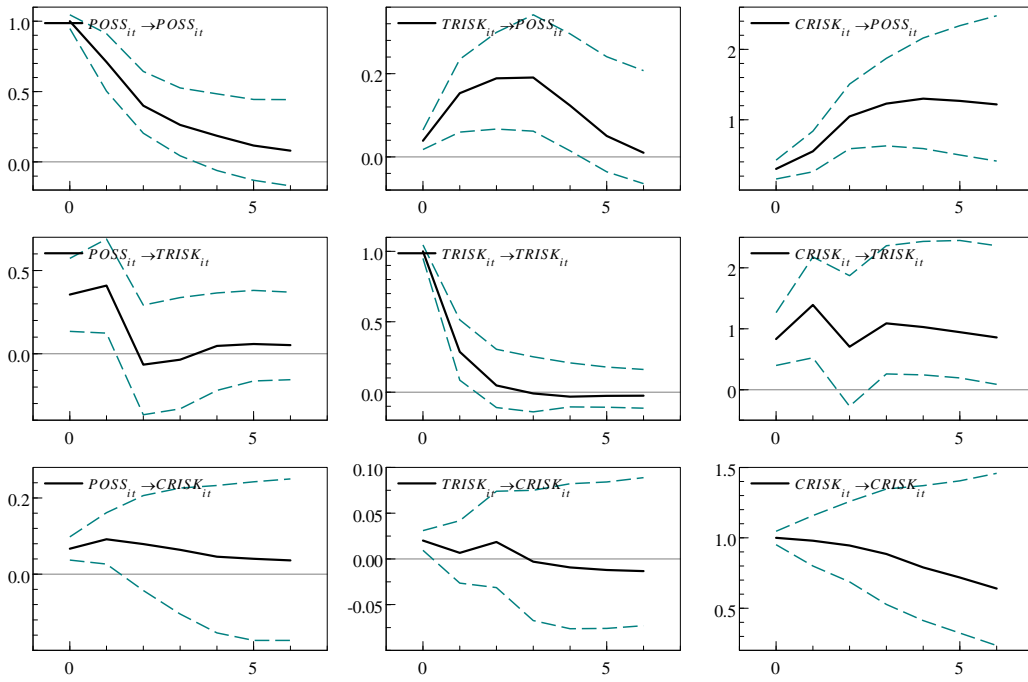
Table A.III: Variance Decompositions

	$POSS_{it} - \mathrm{E}_t(POSS_{it})$			$TRISK_{it} - \mathrm{E}_t(TRISK_{it})$			$CRISK_{it} - \mathrm{E}_t(CRISK_{it})$		
	Generalized Innovations to								
h	$POSS_{it}$	$TRISK_{it}$	$CRISK_{it}$	$POSS_{it}$	$TRISK_{it}$	$CRISK_{it}$	$POSS_{it}$	$TRISK_{it}$	$CRISK_{it}$
1	100.00	1.22	0.00	1.22	100.00	0.02	0.04	0.09	100.00
2	98.56	2.71	0.00	1.98	98.85	0.28	0.02	0.34	99.99
3	96.62	3.09	0.37	2.31	97.68	0.44	0.02	0.49	99.98
4	94.30	3.11	1.14	2.43	96.69	0.56	0.03	0.57	99.98
5	91.86	3.03	2.17	2.47	95.84	0.70	0.03	0.61	99.98
10	82.61	2.72	7.61	2.45	93.07	1.38	0.05	0.68	99.97
20	76.69	2.57	12.07	2.40	91.26	1.92	0.07	0.71	99.97
30	75.56	2.55	12.93	2.39	90.90	2.03	0.07	0.71	99.97

Notes for **Table A.III**: The table reports the fraction (in percentage points) of the *h*-years ahead forecast error variance of each variable, that is attributable to generalized innovations in $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$. The variance shares may not sum to 100 (Pesaran and Shin, 1998).
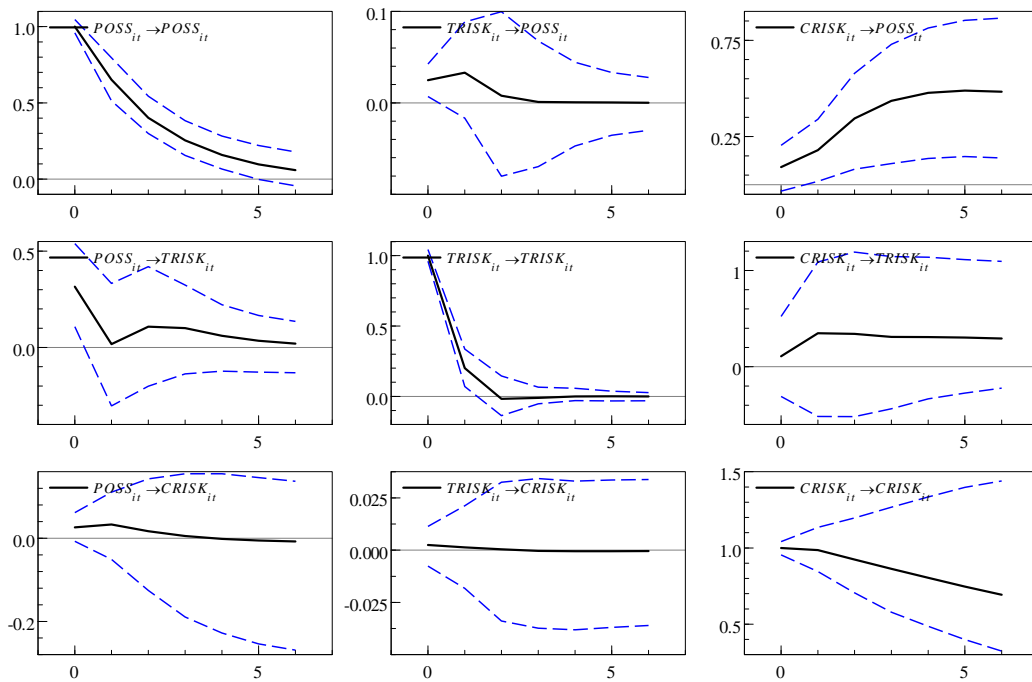
Figure A.1. Generalized Impulse Responses of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a VAR(2).

Notes for Figure A.1: See notes for Figure 1.

Figure A.2. Generalized Impulse Responses of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a VAR(3).
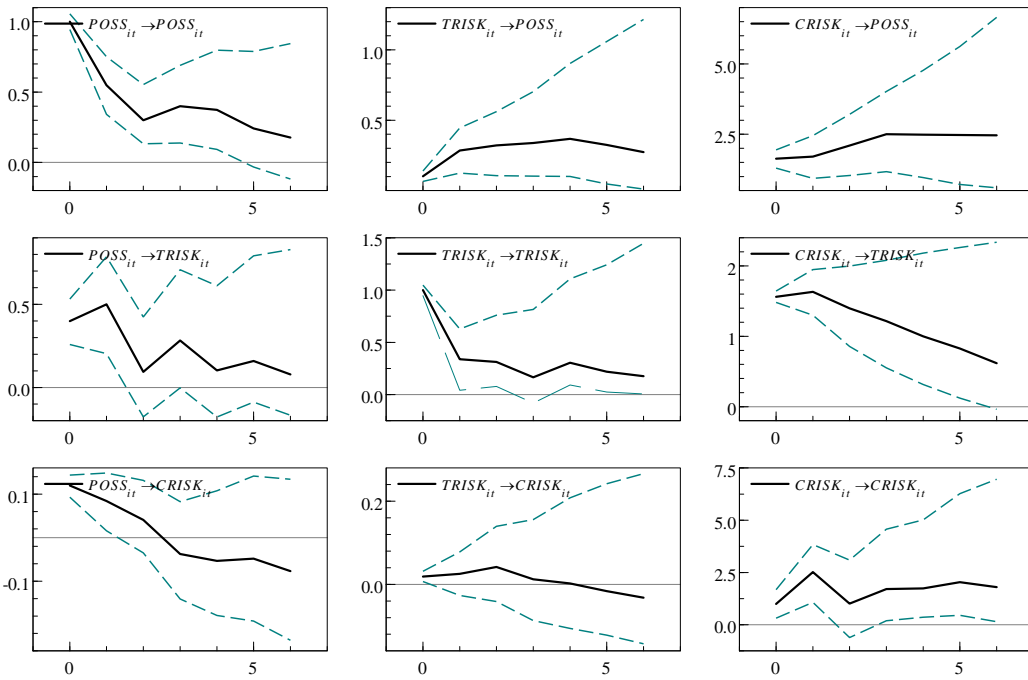
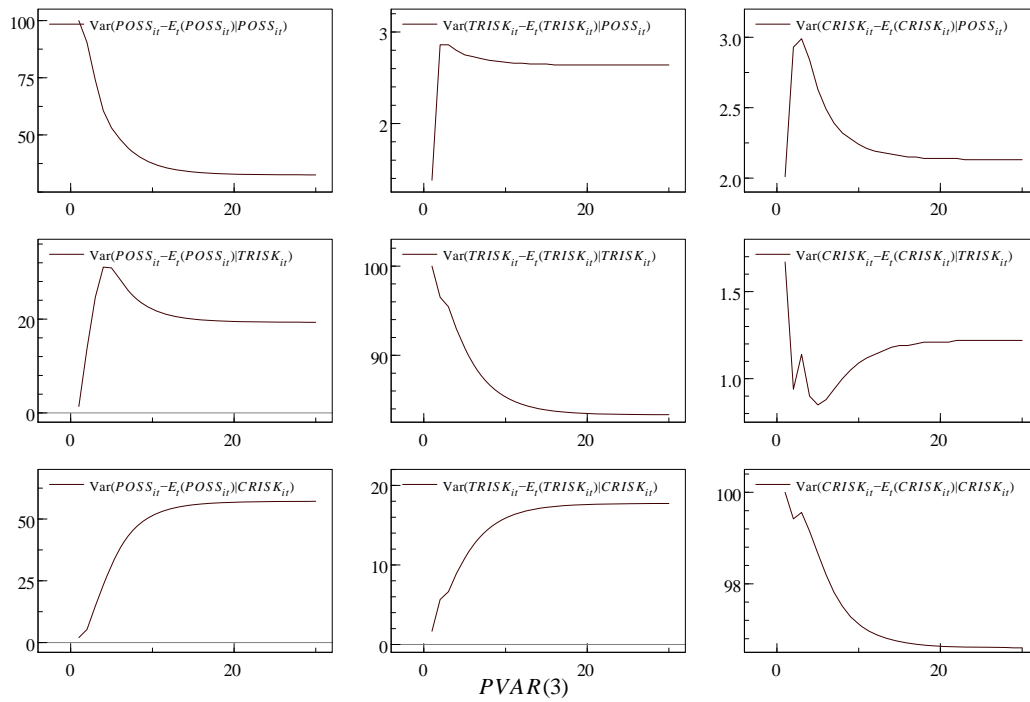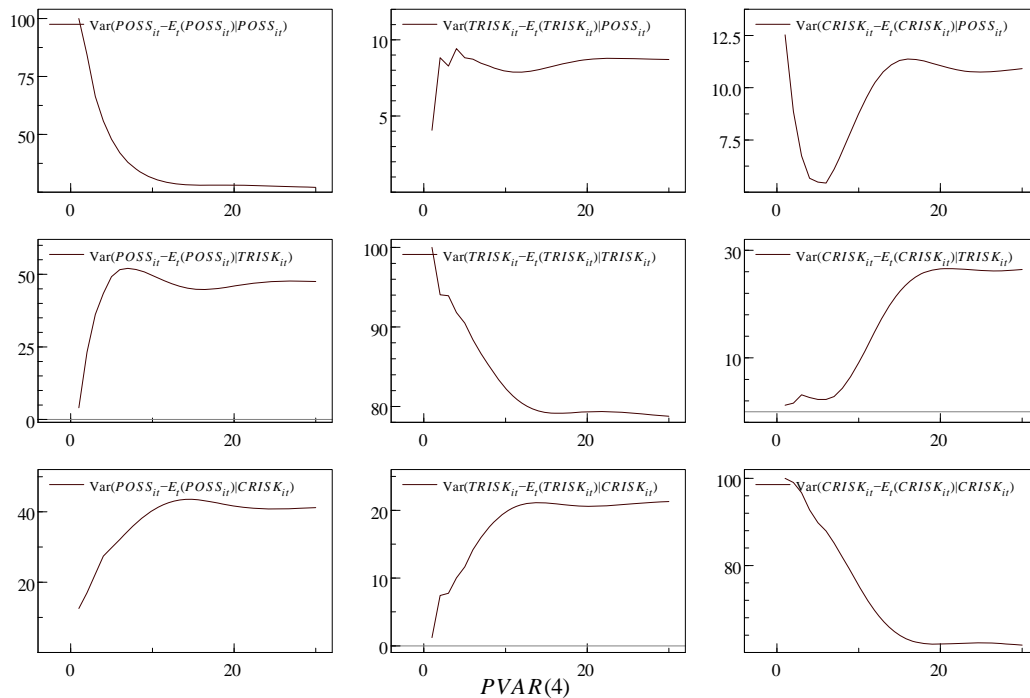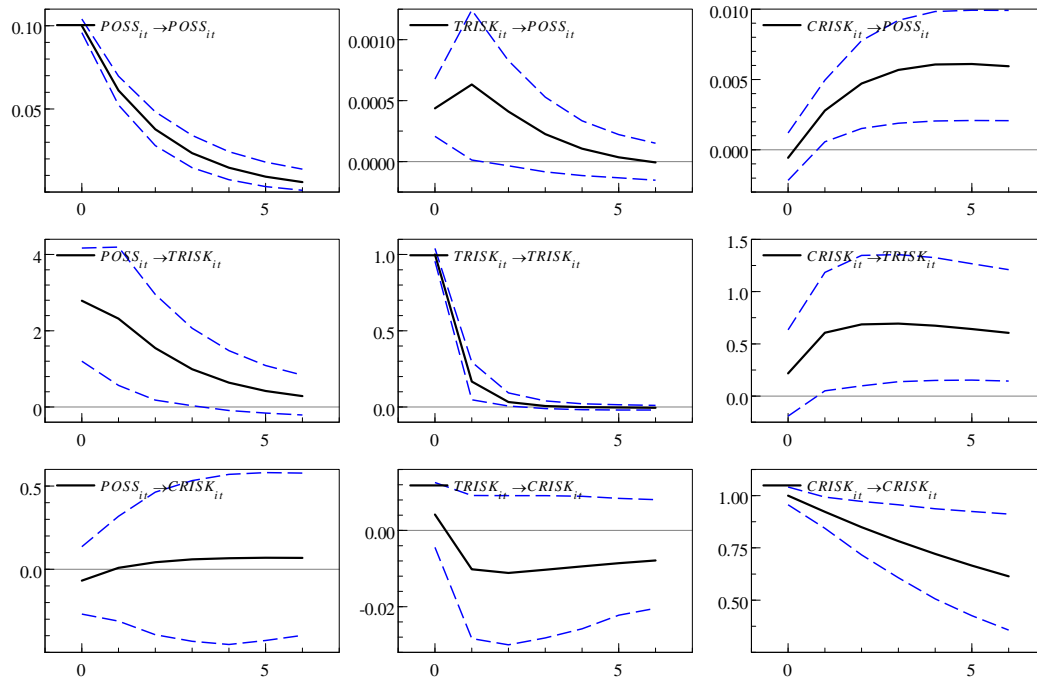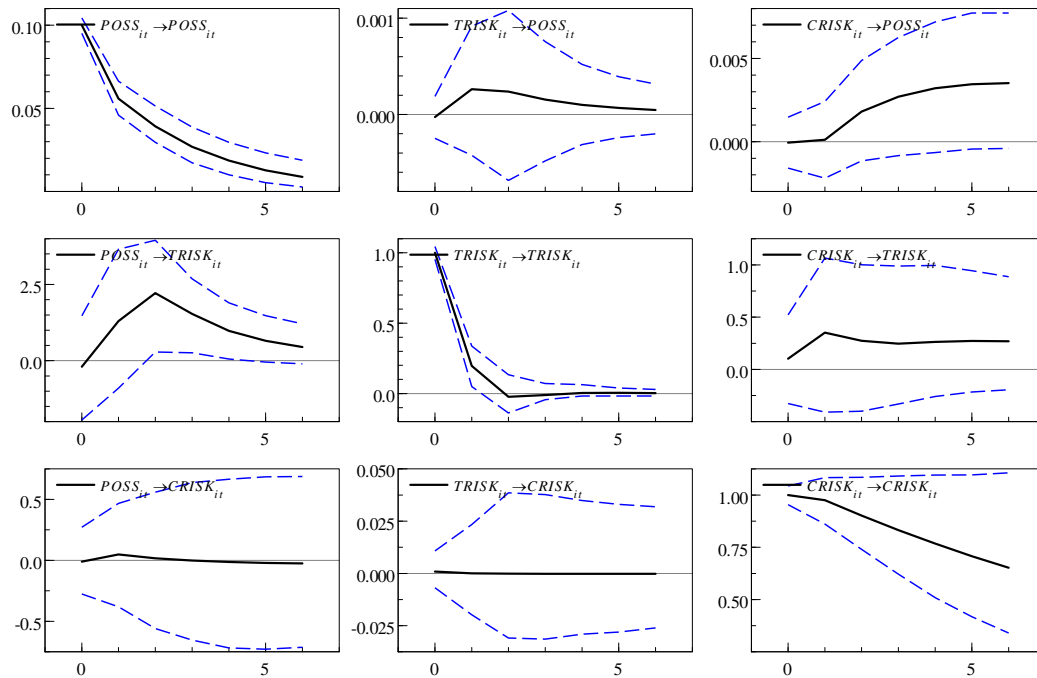**Figure A.3**. Generalized Impulse Responses of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a VAR(4).
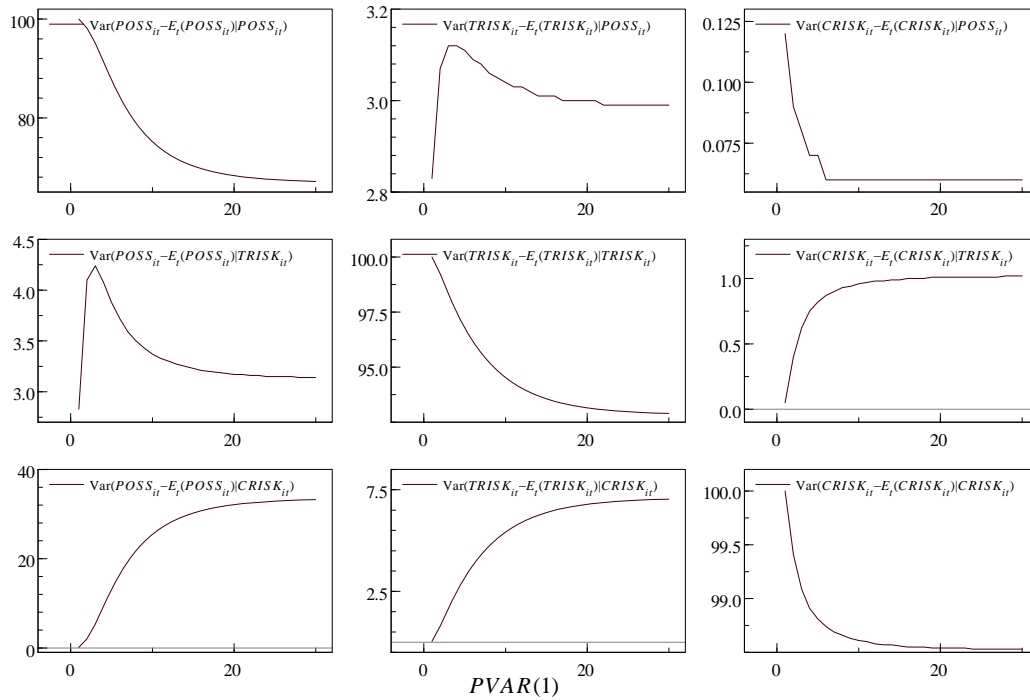
Figure A.4. Generalized Forecast Error Variance Decomposition of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a PVAR(1).

Notes for **Figure A.4**: Each row shows the share (percent) of forecast error variance explained by a shock in column variable. For instance, the first column shows the forecast error variance explained by shocks to *POSS*, and the first row displays the fraction of forecast error variance of *POSS* explained by each shock.
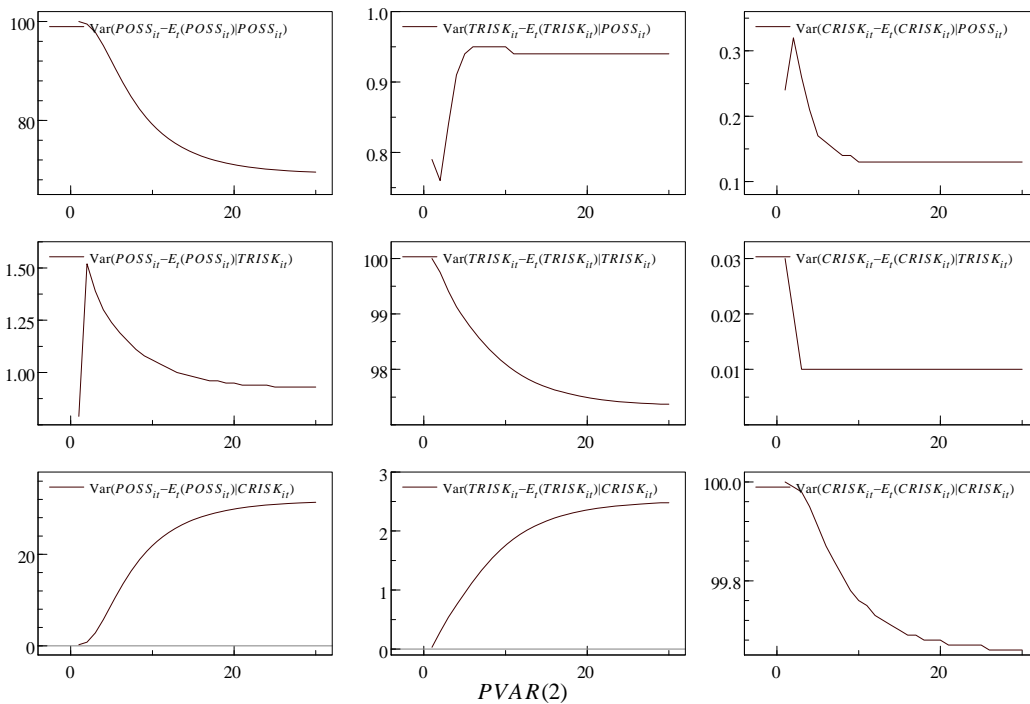
Figure A.5. Generalized Forecast Error Variance Decomposition of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a PVAR(2).
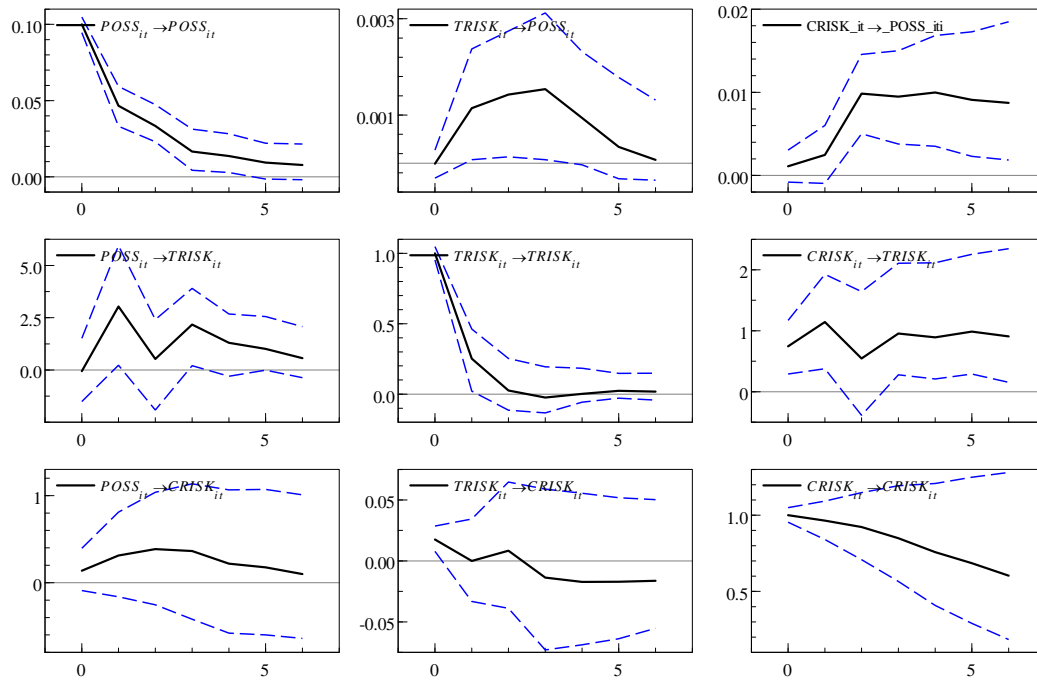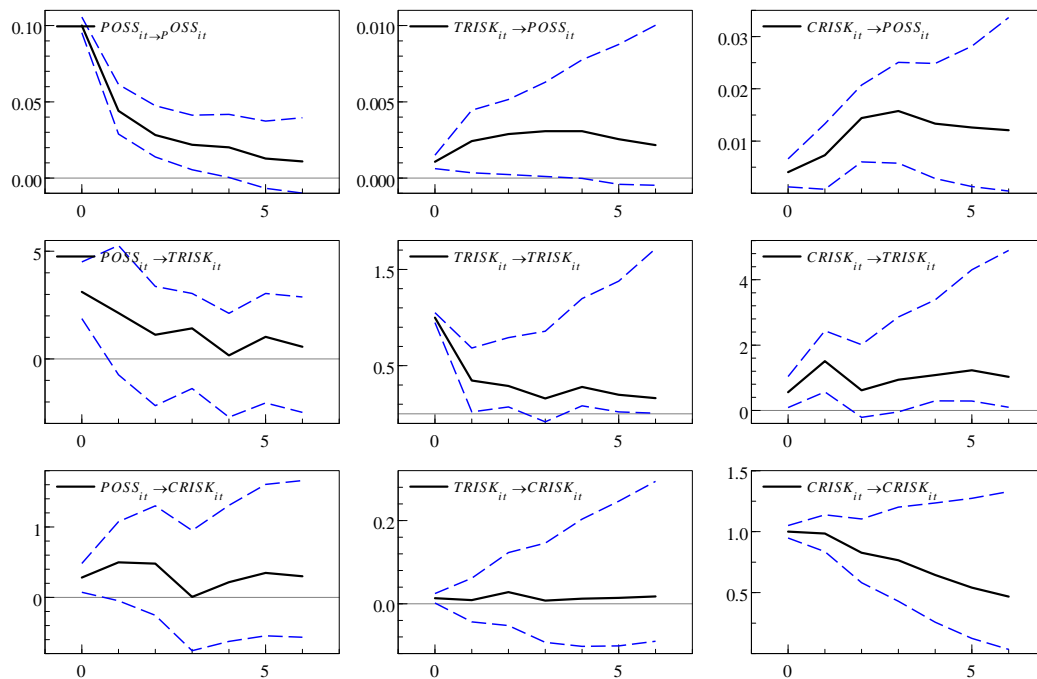
Notes for **Figure A.5**: See notes for **Figure A.4**.

Figure A.6. Generalized Forecast Error Variance Decomposition of $POSS_{it}, TRISK_{it}$ and $CRISK_{it}$ from a PVAR(3).

Notes for **Figure A.6**: See notes for **Figure A.4**.

Figure A.7. Generalized Forecast Error Variance Decomposition of $POSS_{it}, TRISK_{it}$ and $CRISK_{it}$ from a PVAR(4).

Notes for **Figure A.7**: See notes for **Figure A.4**.

Figure A.8. Generalized Impulse Responses of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a PVAR(1).

Notes for Figure A.8: $POSS_{it}$ denotes the ratio of *POSS* spending to GDP. See also notes for **Figure A.3**.
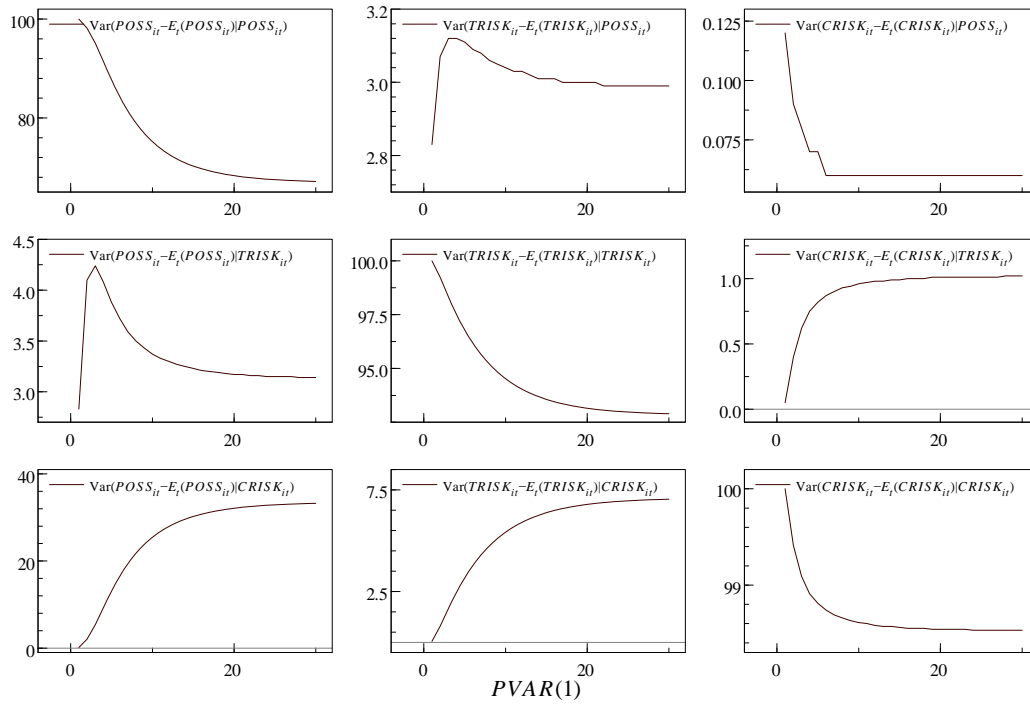

Figure A.9. Generalized Impulse Responses of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a PVAR(2).

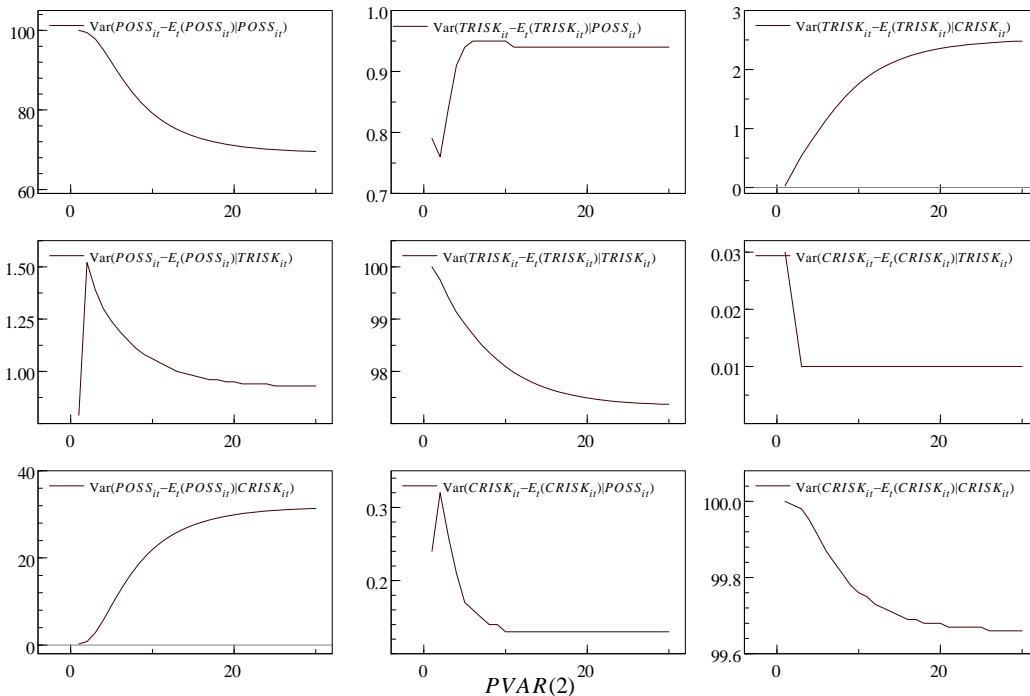Notes for Figure A.9: $POSS_{it}$ denotes the ratio of *POSS* spending to GDP. See also notes for **Figure A.3**.

Figure A.10. Generalized Impulse Responses of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a PVAR(3).

Notes for Figure A.10: $POSS_{it}$ denotes the ratio of *POSS* spending to GDP. See also notes for **Figure A.3**.

Figure A.11. Generalized Impulse Responses of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a PVAR(4).

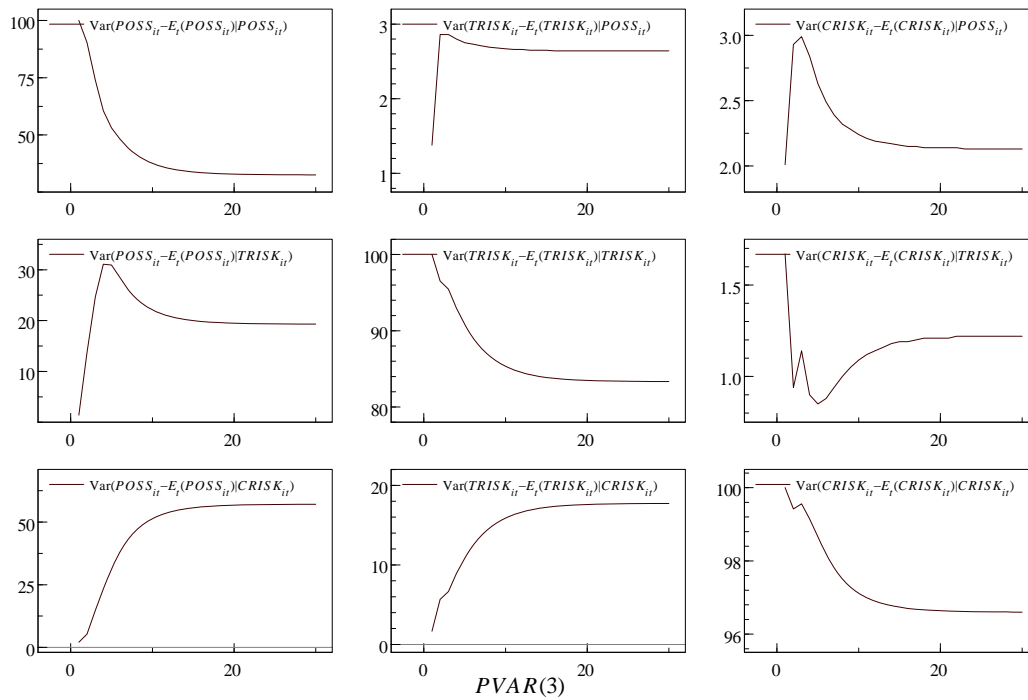Notes for Figure A.11: $POSS_{it}$ denotes the ratio of *POSS* spending to GDP. See also notes for **Figure A.3**.

Figure A.12. Generalized Forecast Error Variance Decomposition of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a PVAR(1).

Notes for **Figure A.12**: $POSS_{it}$ denotes the ratio of *POSS* spending to GDP. See also notes for **Figure A.4**.
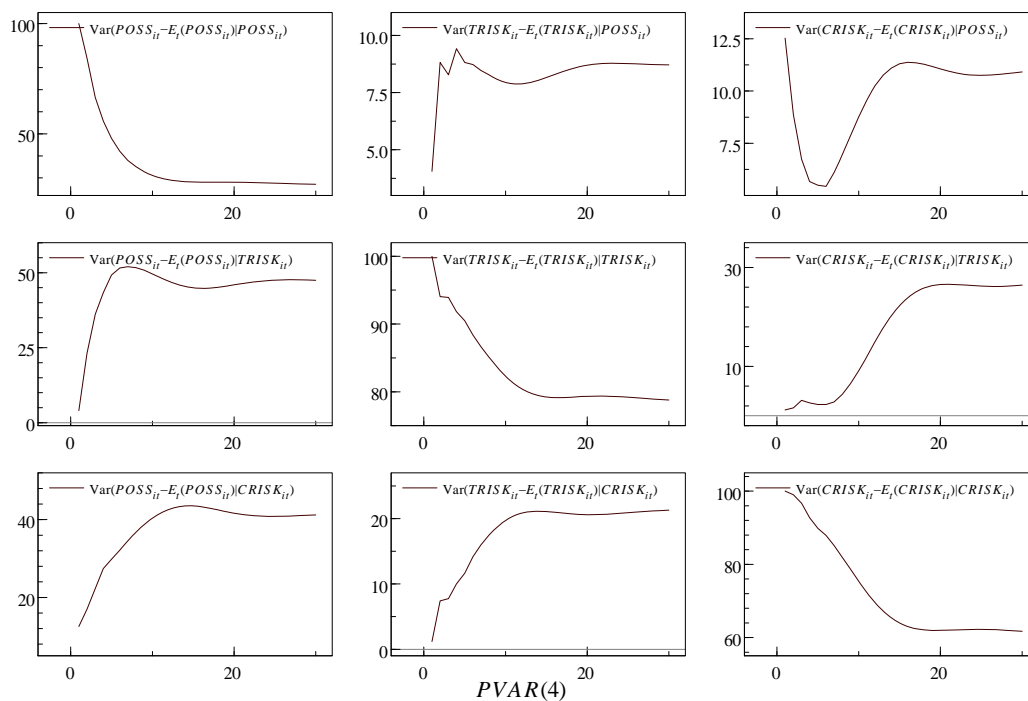

Figure A.13. Generalized Forecast Error Variance Decomposition of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a PVAR(2).

Notes for **Figure A.13**: $POSS_{it}$ denotes the ratio of *POSS* spending to GDP. See also notes for **Figure A.12**.

Figure A.14. Generalized Forecast Error Variance Decomposition of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a PVAR(3).

Notes for **Figure A.14**: $POSS_{it}$ denotes the ratio of *POSS* spending to GDP. See also notes for **Figure A.12**.

Figure A.15. Generalized Forecast Error Variance Decomposition of $POSS_{it}$, $TRISK_{it}$ and $CRISK_{it}$ from a PVAR(4).

Notes for **Figure A.15**: $POSS_{it}$ denotes the ratio of *POSS* spending to GDP. See also notes for **Figure A.12**.