Informing *ex-ante* event studies with macro-econometric evidence on the structural and policy impacts of terrorism

Jason Nassios[1,*,3] and James A. Giesecke[2,*,3]

[*] Centre of Policy Studies
Victoria University Flinders Street Campus
Melbourne Australia

Abstract

In modeling the economic impact of a hypothetical terrorism event, details describing two broad sets of shocks are typically required: (1) Physical impacts on observable variables, e.g., asset damage; and (2) Behavioral impacts on unobservable variables, e.g., investor uncertainty. Assembling shocks related to the physical characteristics of a terrorism event is relatively straightforward, since estimates are either readily available or plausibly inferred. However, assembling shocks describing impacts on agent behavior is more difficult. Values for behavioral variables, e.g., impacts on required rates of return, are typically inferred or estimated by indirect means. Generally, this has been achieved via reference to extraneous literature or ex-ante surveys. How confident can planners be that the impact magnitudes produced by this methodology are plausible? Ex-post econometric studies of terrorism by Blomberg *et al.*[1] yield models for the response of observable economic variables, e.g., real GDP, investment and government expenditure, to terrorism and other forms of conflict. In this article, we use the findings of Blomberg *et al.*[1] to determine point estimates for relevant (unobservable) structural variables impacted by terrorism events, using the USAGE 2.0 dynamic CGE model of the U.S.A.[2, 3]. This allows us to: (i) explore the relative contributions of implicit structural and policy shifts in the results for observable variables reported in Blomberg *et al.*[1]; and (ii) compare these implicit structural shocks with assumed structural shocks in earlier ex-ante CGE studies of terrorism.

Keywords: Terrorism, Economic impact; Dynamic CGE modelling.

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[1] Jason.Nassios@vu.edu.au

[2] James.Giesecke@vu.edu.au

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1 INTRODUCTION

Terrorism events such as the 2001 World Trade Center bombing, the Bali bombings and the recent Paris attacks illustrate the disparate nature of this form of conflict. Whilst highly localized geographically, the direct economic and social impacts of each of these incidents, while diverse, can typically be classified under two broad categories: (1) physical consequences (fatalities, asset damage or business interruption); and (2) behavioral consequences (arising from heightened fear and uncertainty)[4,5,6]. These direct effects drive a variety of regional and macroeconomic consequences of terrorism[1,7,8,9].

In making contingency plans for diverse threat scenarios, emergency management decision makers are aided by the findings of economic research undertaken using a number of different research methodologies. At the level of the macro economy, time series analysis has been applied by Blomberg *et al.*[1] to study a panel dataset of three distinct forms of conflict: (i) terrorism (as defined by Mickolus *et al.*[10]), (ii) internal conflict and (iii) external conflict. The econometric models presented by Blomberg *et al.*[1] identified three key macroeconomic impacts of terrorism in the terrorism event-year[3]: (1) a reduction in the ratio of investment-to-GDP; (2) an increase in the ratio of public-consumption-to-GDP; (3) a reduction in the rate of real GDP growth. In later work, Blomberg and Hess[11] modelled the impact of the three aforementioned forms of conflict on bilateral trade.

More recently, CGE models have been used to analyze the impact of terrorism events. Early work in this approach to costing the impact of terrorism by Rose *et al.*[12] considered the economic effects of the 9/11 attack, with particular emphasis on the impacts of both business interruption and the associated reductions in air travel. Giesecke *et al.*[8,9] later explored the *ex-ante* impact of (hypothetical) radiological dispersal device attack and a chlorine attack in the Los Angeles Financial District. On the basis of independently formulated scenarios and analyses, inputs to the CGE model were calculated to describe property damage, casualties and business interruption[13,14]. A similar approach was recently applied to explore the *ex-ante* impact of an Ebola epidemic in Liberia[15].

Such *ex-ante* studies are helpful to government decision makers, who must make plans for a wide range of terrorism threat scenarios. In the formulation and evaluation of these plans, economic consequence analysis plays an important role in elucidating the benefits of successful deterrence, mitigation, and post-event management. However, planning in this regard is not easy, particularly when terrorism events have diverse characteristics defined along many dimensions, including the method, location, scale and frequency of attack(s). As discussed in previous work by Giesecke *et al.*[9], CGE models are well-suited to the analysis of the economic consequences of a diverse range of threat scenarios. With a large number of exogenous variables, CGE models can be used to

[3] Tavares[27] utilized an alternative dataset of terrorism events to present a similar analysis of the macroeconomic impact of terrorism, with real GDP growth taken as a measure of the welfare impact of terrorism.

impart shocks related to the many particular characteristics that can define a given individual terrorism event. This also makes them well suited to the analysis of the many hypothetical scenarios and risks that must be investigated in contingency planning by defense and emergency management agencies. In defining a terrorism event for input to a CGE model, two broad sets of shocks are typically recognized: (1) physical impacts on observable economic variables, e.g., fatalities, asset damage, business interruption; and (2) behavioral impacts on unobservable structural variables, e.g., the effects of fear and uncertainty on the preferences of workers, investors, and consumers. Assembling shocks related to the physical characteristics of a terrorism event is relatively straightforward, since estimates are either readily available or plausibly inferred. However, assembling shocks describing the behavioral characteristics of terrorism events is more difficult. In Giesecke *et al.*[8,9], these were inferred from extraneous literature on stigmatized asset values, e.g., see Davis[16], and from survey work on the public's behavioral responses to actual and hypothetical threat scenarios, e.g., see Burns *et al.*[17,18].

Given the growing use of CGE models in ex-ante studies of hypothetical threat scenarios, an important research question is: given the uncertainties relating to the inputs to such ex-ante studies, how confident can planners be that the reported impact magnitudes are plausible? This paper seeks to address this question, by informing shocks to a CGE model with output from the time-series econometric model by Blomberg *et al.*[1]. The implicit movements in the CGE model's structural variables are subsequently compared with those assumed in earlier ex-ante CGE studies.

Following a similar methodology to Giesecke *et al.*[9], we utilize a dynamic CGE model to consider the impact of a single terrorism event. Rather than adopting a regional focus, we consider the epicenter to be general and occurring within the U.S.A. We apply the USAGE 2.0 (U.S.A. General Equilibrium) model to investigate the impact of the terrorist event. This model is based on the MONASH model of Australia and the USAGE model of the U.S.A.[2,3]. The terrorism event is described in terms of the econometric models of Blomberg *et al.*[1]; that is, the effects of the terrorist event are described in terms of impacts on variables that are typically endogenous in a standard closure of the USAGE 2.0 model, viz. real GDP, the ratio of real-investment-to-real-GDP, and the ratio of real-public-consumption-to-real-GDP.

These variables must be exogenous in USAGE 2.0 if they are to be shocked with values from Blomberg *et al.*[1]. Dixon and Rimmer[2] showed how observed results for naturally endogenous variables can be imposed on a CGE model as exogenous shocks, via the endogenous determination of certain (normally exogenous) structural variables, which are most relevant to the determination of the (normally endogenous) observable variables. As we shall discuss in the context of the present application, closure changes of this type highlight three CGE variables as being central to carrying the structural and behavioral forces underlying the Blomberg *et al.*[1] econometric estimates, namely: (1) the relationship between capital formation and required rates of return; (2) real public consumption spending; and (3) total primary factor augmenting technical change. Our work generates time-paths for these structural variables in response to a single terrorist attack in the U.S.A. Importantly, while the general response of these structural variables has been discussed extensively, point estimates for their potential magnitudes have not been established.

The outline of proceeding sections is as follows. In section 2, we summarize the key findings and equations arising from econometric analyses of terrorism. Section 2.3 focuses explicitly upon the CGE approach to modelling, with particular emphasis on the USAGE 2.0 model applied in this article. A discussion of key macro results and comparison to past work is then provided in section 3, before we present concluding remarks in section 4.

2 PAST WORK

2.1 Econometric study by Blomberg *et al.*[1]

As discussed in section 1, the macroeconomic impacts of terrorism (and internal and external conflict) were quantified by Blomberg *et al.*[1] via a series of panel regressions. Three response variables were considered, namely real GDP growth (ΔY_t), and real investment and government spending as proportions of real GDP (IYR_t and GYR_t respectively); see equations 2.1 - 2.3, which are reproduced herein from Blomberg *et al.*[1],[4]. Equation 2.4 is reproduced from Blomberg and Hess[11] and will be discussed shortly.[5]

[4] We follow the convention in Blomberg *et al.*[1], with the notation ***, ** and * used to represent statistical significance of the estimated coefficients at the 1%, 5% and 10% levels respectively.

[5] The models were derived using annual observations from 177 countries over the period 1968 to 2000; this dataset was an amalgamation of the Penn World Table data set, the ITERATE data set[10], and data sets of external and internal conflict. Given the nature of the data and the composition of multiple data sources, it is not possible to confirm that some instances of terrorism (as defined by Mickolus *et al.*[10]) are not duplicated in the data set as larger-scale instances of internal conflict.

$$IYR_{t,\text{Blom}} - IYR_{t,\text{Base}} = 3.307^{***} \ln\left(\frac{BYR_{t-1,\text{Blom}}}{BYR_{t-1,\text{Base}}}\right) + 0.496 \ln\left(\frac{Y_{t-1,\text{Blom}}}{Y_{t-1,\text{Base}}}\right) - 0.389^{**} \frac{T_t}{P_t}, \quad 2.1$$

$$GYR_{t,\text{Blom}} - GYR_{t,\text{Base}} = 3.043^{***} \ln\left(\frac{BYR_{t-1,\text{Blom}}}{BYR_{t-1,\text{Base}}}\right) - 2.117^{***} \ln\left(\frac{Y_{t-1,\text{Blom}}}{Y_{t-1,\text{Base}}}\right) + 0.412^{*} \frac{T_t}{P_t}, \quad 2.2$$

$$\Delta Y_{t,\text{Blom}} - \Delta Y_{t,\text{Base}} = 0.184 \ln\left(\frac{BYR_{t-1,\text{Blom}}}{BYR_{t-1,\text{Base}}}\right) - 7.959^{***} \ln\left(\frac{Y_{t-1,\text{Blom}}}{Y_{t-1,\text{Base}}}\right) + 0.341^{***}\left(IYR_{t-1,\text{Blom}} - IYR_{t-1,\text{Base}}\right) - 0.513^{***} \frac{T_t}{P_t}, \quad 2.3$$

$$\ln\left(\frac{BYR^{\text{US}}_{t,\text{Blom}}}{BYR^{\text{US}}_{t,\text{Base}}}\right) = 0.502^{***} \ln\left(\frac{\Delta Y^{\text{US}}_{t,\text{Blom}}}{\Delta Y^{\text{US}}_{t,\text{Base}}}\right) + 0.502^{***} \ln\left(\frac{\Delta Y^{\text{RoW}}_{t,\text{Blom}}}{\Delta Y^{\text{RoW}}_{t,\text{Base}}}\right) - 0.188^{***} \ln\left(\frac{P^{\text{US}}_{t,\text{Blom}}}{P^{\text{US}}_{t,\text{Base}}}\right) - 0.188^{***} \ln\left(\frac{P^{\text{RoW}}_{t,\text{Blom}}}{P^{\text{RoW}}_{t,\text{Base}}}\right) - 0.043^{***} TV_t. \quad 2.4$$

In equations 2.1 - 2.4, the explanatory variables include the natural logarithm of (lagged) real bilateral trade as a proportion of GDP (BYR_{t-1}) and real GDP (Y_{t-1}), as well as lagged investment to GDP (IYR_{t-1}); see Table I for definitions of all variables used herein. We also apply the following notational conventions:

- A subscript "Blom" denotes a variable that follows a time-path described by Blomberg *et al.*[1] and/or Blomberg and Hess[11] in response to a terrorist attack. This time-path is referred to herein as the *Blomberg Simulation*;
- A subscript "Base" denotes a variable following a Baseline Simulation path, e.g., a business-as-usual time-path where no terrorist event is observed. This scenario is denoted as the *baseline* herein;
- In section 2.3.1, we will introduce and discuss a third simulation, which we denote the *Structural Simulation*;
- T_t is the number of recorded terrorist events within a country per year; and
- P_t is the population in million persons.

2.1.1 Findings

Equation 2.3 shows that in any given year from 1968 to 2000, a unit increase in the number of terrorist events per one million persons (T_t / P_t=1) drives an (on average) fall of 0.513% in real GDP growth, i.e., real GDP growth in the Blomberg simulation is 0.513% below the baseline. From a theoretical standpoint, the authors advanced three mechanisms through which terrorist events can disrupt the real economy in this way: (1) destruction of economic inputs; (2) disruption of household and business spending; (3) reallocation of economic activity to security. In part these mechanisms are captured by the direct effect term (T_t /P_t) in equation 2.3. But their modelling also recognized indirect paths via which these mechanisms might operate, by modelling: (i) the impact of terrorist events and other conflict on the ratio of investment-to-GDP via the variable IYR_t; and (ii) the response of government to the terrorist event and the subsequent impact this has on the ratio of public-consumption-to-GDP via the variable GYR_t. Examining equation 2.1, we see that one event per million persons reduces the investment / GDP ratio in the event year by 0.389%. Examining equation 2.2, we see that each event per million persons is met with a rise in government spending relative to GDP of 0.412%.

2.2 Findings by Blomberg and Hess[11]

In later work, Blomberg and Hess[11] studied the impact of terrorism and other conflicts on real bilateral trade as a proportion of GDP (BYR_t); this yielded equation 2.4, where the terrorism predictor is defined as:

$$TV_t = \begin{cases} 0 \text{ if both the home country or trading partner experience no terrorist events,} \\ 1 \text{ otherwise.} \end{cases} \qquad 2.5$$

The use of the predictor TV_t in this study (instead of T_t /P_t) restricted our capacity to model shocks to bilateral trade via equation 2.4, in conjunction with equations 2.1 - 2.3. This is because the dummy explanatory variable TV_t in equation 2.4, unlike the explanatory variable T_t /P_t in equations 2.1 – 2.3, does not control for the number of distinct terrorist events that occurred in a given period. For this reason, in this paper we focus on the shocks implied by equations 2.1 – 2.3.

2.3 USAGE 2.0: A Dynamic CGE model of the U.S. economy

In this paper, we use the econometric equations for the three key macroeconomic indicators IYR_t, GYR_t and ΔY_t derived by Blomberg *et al.*[1] to define terrorism-related shocks to a CGE model of the U.S. economy (the USAGE 2.0 model). In a standard closure of the CGE model, these three variables are naturally in the set of endogenous or dependent variables. For these variables to carry terrorism-related shock values from the Blomberg equations, they must be exogenous. We move these variables to the set of exogenous variables via the endogenous determination of structural variables that are typically exogenous in a standard implementation of the CGE model. Herein, the impact of a terrorism event on a set of underlying structural variables is therefore inferred using the CGE model. In the work presented in this paper, we refer specifically to the following three variables as structural variables:

1. Shifts in the required rate-of-return on new units of physical capital, denoted by the variable Λ;
2. Shifts in real public consumption spending, denoted as G;
3. Total primary-factor-augmenting technical change, denoted by the variable A.

With paths determined for a set of independent structural variables in response to a terrorism event, a decomposition analysis is then performed to analyze their respective impacts on the overall macro economy. Our approach contrasts to previous work in this field, which has focused on a direct analysis of the macroeconomic or regional consequences of terrorism, using movements in structural variables estimated from surveys or extraneous literature, and resource-loss estimates. Next, we present the USAGE 2.0 model in more detail, before outlining an appropriate "back-of-the-envelope" (BOTE) model in section 2.3.2. The paths taken by all shocked variables are then summarized in section 2.3.3.

2.3.1 The USAGE 2.0 model

USAGE 2.0 is a dynamic CGE model of the U.S. economy based on the MONASH model[2] and developed in collaboration with the U.S. International Trade Commission. The USAGE 2.0 model and its predecessor (USAGE) have been widely applied as tools for forecasting and policy analysis; see Dixon and Rimmer[3],[19], Gehlhar *et al.*[20] and Dixon *et al.* [21]. So that readers do not need to be familiar with the details of the full USAGE 2.0 model to follow this paper, in section 2.3.2 we present a back-of-the-envelope (BOTE) representation of the full model tailored to describe the key mechanisms within USAGE 2.0 that are relevant to the present paper. Before proceeding to the BOTE model, we first provide an overview of USAGE 2.0.

USAGE 2.0 is a disaggregated CGE model recognizing many industries, capital creators, a representative household, government, and a foreign sector. Industries, investors and households are modelled as constrained optimizers. Each industry minimizes unit costs subject to given input prices and a constant-returns-to-scale (CRS) production function. Consumer demands are modelled via a representative utility maximizing household. Units of new industry-specific capital are formed as cost minimizing combinations of construction, machinery and other capital goods. Imperfect substitutability between imported and domestic varieties of each commodity is modelled using the Armington constant-elasticity-of-substitution (CES) specification. Export demand for any given U.S. commodity is inversely related to its foreign currency price. Capital accumulation is specified separately for each industry. An industry's capital stock at the start of year $t+1$ is its capital at the start of year t plus its investment during year t, less depreciation. Industry-specific investment in year t is determined as a positive function of the expected rate of return on industry-specific capital.

A USAGE 2.0 simulation of the effect of a shock (such as a reduction in ratio of real-investment-to-real-GDP) typically requires two runs of the model: a business-as-usual run (referred to as a "baseline" herein) and a perturbed run (typically referred to as a "counterfactual run"). The baseline is intended to be a plausible forecast, while in general the counterfactual run generates deviations away from the baseline caused by the shock under consideration. As we shall discuss in section 2.3.2, in this paper we require two counterfactual simulations. First, we impose on USAGE 2.0 results for ΔY_t, IYR_t and GYR_t that track the implied paths in Blomberg *et al.*[1] under a scenario of a single U.S.-located terrorist event. USAGE 2.0 then determines the required movements in all structural variables (as discussed in section 2.1, we refer to this counterfactual run as the

Blomberg Simulation). We then take the values for the Blomberg Simulation structural variables, and impose them on USAGE 2.0 under a standard closure. Hereafter, we denote this second simulation as the *Structural Simulation*.

2.3.2 A BOTE model of USAGE 2.0

In this section, we introduce a BOTE model of USAGE 2.0 tailored to highlight the main economic mechanisms that are relevant to the application in this paper. We begin with a description of equations 6.1 - 6.13 that are summarized in Table II, which provide a stylized representation of the key macroeconomic relationships in USAGE 2.0. Equations 6.1 - 6.13 are defined herein as the BOTE (back-of-the-envelope) model.

To begin, consider equations 6.1 - 6.11, which relate a general set of variables *within* any given year of a multi-year dynamic simulation of USAGE 2.0. Equation 6.1 describes the GDP identity in real terms. Equation 6.2 describes a CRS production function, relating real GDP to inputs of labor, capital and primary-factor-augmenting technical change. Equation 6.3 relates real private consumption spending to real GDP and a function of the terms of trade.[6] Equation 6.4 makes investment an increasing function of the ratio of (i) the rate-of-return on physical capital; and (ii) the required rate-of-return on physical capital. Equation 6.5 defines the gross capital growth rate. Since the production function is CRS, marginal product functions are homogeneous of degree zero and thus can be expressed as functions of the ratio of labor and capital inputs. This accounts for equations 6.6 and 6.7. Equation 6.6 is the first-order-condition for the profit maximizing use of labor.[7] Equation 6.7 is the first-order-condition for the profit maximizing use of capital.[8] Equation 6.8 summarizes the determination of import volumes. In USAGE 2.0, demands for commodity-specific imports by each agent are related to each agent's activity level (proxied in equation 6.8 by *Y*) and the ratio of the domestic-to-import price for each commodity (proxied in equation 6.8 by the terms of trade, *TOT*). Commodity exports in USAGE 2.0 are inversely related to foreign currency prices via commodity-specific constant-elasticity-of-demand (CED) functions. This is summarized by equation 6.9, which relates the terms of trade (the ratio of export prices to import prices) to the volume of exports (*X*, movements along foreign demand schedules for U.S. exports) and a shift variable (*V*, movements in foreign demand schedules for U.S. exports).

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[6] The origin of equation 6.3 is $P_c \times C = APC \times Y \times P_O$, where P_O and P_c are the GDP and consumption deflators respectively, and all other variables are as described in Table I. Noting that that P_O / P_C is a positive function of the terms of trade, *g(TOT)*, we have equation 6.3.

[7] Via equation 6.2, and noting that $f(L,K)$ is homogenous of degree 1, the marginal product of labor is $f_L(L,K) / A$. The profit maximizing use of labor requires: $P_O \times f_L(L,K) / A = W \times P_C$, where P_O and P_C are the price of output and consumption respectively, and all other variables are as defined in Table I. Noting that P_O / P_C is an increasing function of the terms of trade, $g(TOT)$, we have equation 6.6.

[8] Via equation 6.2, and noting that $f(L,K)$ is homogenous of degree 1, the marginal product of capital is $f_K(L,K) / A$. The profit maximizing use of capital requires: $P_O \times f_K(L,K) / A = ROR \times P_I$, where P_O and P_I are the price of output and investment respectively, and all other variables are as defined in Table I. Noting that P_O / P_I is an increasing function of the terms of trade, $h(TOT)$, we have equation 6.7.

Equations 6.10 and 6.11 define key variables from Blomberg *et al.*[1]; these variables are used to deliver our shocks under the Blomberg Simulation in section 3. Under a standard closure in the baseline simulation, these are endogenous variables.

In defining a standard closure for the equations in Table II , we refer specifically to equations that describe economic relationships *within* any given year (6.1 - 6.9 and 6.10 - 6.11), as opposed to equations that govern the *inter-year dynamics*, e.g., movements in stock variables (6.12) and the sticky wage adjustment (6.13). Within any given year, capital (*K*) can be considered exogenous (we refer the reader to Table I for the definition of all variables). The movement in this variable between years depends on investment within years and is described by equation 6.12. When operational in each year of the respective counterfactual simulations, equation 6.13 gradually moves the labor market from a short-run situation of exogenous real wage (*W*) and endogenous employment (*L*), to a long-run situation of exogenous employment (*L*) and endogenous real wage (*W*).

Recognizing that equations 6.12 and 6.13 govern dynamics across years, our task of characterizing the BOTE model closure narrows to choosing appropriate short-run and long-run closures for equations 6.1 - 6.11, which comprise 11 equations in 18 unknowns. In Table II, model closure is described by rendering exogenous variables in **bold**. Two closures are presented: a short-run closure and an ‘effective’ long-run closure. By ‘effective’ long-run closure, we mean that while *ROR*, *K* and *L* are presented as long-run exogenous, no such exogeneity is actually imposed on these variables in USAGE 2.0 simulations; rather, equations 6.4, 6.12 and 6.13 lead the economy to a long-run position that can be satisfactorily described by exogenous status of *ROR*, *K* and *L*.

A conventional short-run closure of equations 6.1 - 6.11 would have *X*, *Y*, *C*, *I*, Ψ, *L*, *ROR*, *M*, *TOT*, *IYR* and *GYR* determined endogenously, given exogenous values for *A*, *K*, *G*, *APC*, Λ, *W* and *V* (see Table I for a definition of all variables). Under this closure, each equation can be readily associated with the determination of a specific endogenous variable. With relatively high export demand and import supply elasticity’s, scope for significant movements in *TOT* is constrained. Hence, with *W*, *K*, and *A* exogenous, equation 6.6 can be identified with the determination of *L*. Hence, with *K* and *A* exogenous, equation 6.2 determines *Y*. With *Y* thus determined, and *APC* exogenous, equation 6.3 determines real private consumption. Again, leaving aside for the moment the possibility of movements in *TOT*, with *Y* determined by equation 6.2, equation 6.8 determines *M*. With *L* determined by equation 6.6, and *K* and *A* exogenous, equation 6.7 determines *ROR*. This determines *I* via equation 6.4. With *I* thus determined, equation 6.5 determines Ψ. With *Y*, *C*, *I*, *G* and *M* explained, equation 6.1 determines *X*. With *X* determined and *V* exogenous, *TOT* is given by equation 6.9. With all of *X*, *M*, *I* and *Y* determined, and *G* exogenous, equations 6.10 and 6.11determine *IYR* and *GYR*.

Our description of the USAGE 2.0 long-run behavior differs in two respects from the short-run closure described above:

1. Equation 6.13 ensures that the counterfactual simulation level of *L* is eventually returned to its baseline level via real wage (*W*) adjustment. This is represented by long-run exogeneity of *L* and endogeneity of *W* in the second column of Table II.

2. The short-run operation of equations 6.4 and 6.12 gradually drive rates-of-return (*ROR*) towards baseline via capital stock (*K*) adjustment. The end-point of this process can be represented by long-run exogeneity of *ROR* and endogeneity of *K*.

With *ROR* exogenous in the long-run, equation 6.7 largely determines *K*. With *L* also exogenous in the long-run, equation 6.6 largely determines *W*.

2.3.3 Paths for shocked variables

As with all CGE models, an initial solution of the model is required. For USAGE 2.0, this calibration is based on 2011 data. In this article, we assume the initial solution period (2011) proceeds as per the baseline, i.e., no terrorist event occurs in the U.S. in 2011. We then investigate the impact of a single terrorism event occurring in 2012. That is, in terms of Blomberg *et al.*[1] equations 2.1 - 2.3, we assume:

$$T_2 = 1, \qquad 2.6$$

where the subscript "2" denotes that the terrorism event occurs in the second period (2012) of the Blomberg simulation, relative to the baseline where no terrorism event occurs in any simulation period.[9] For simplicity, we regard the population at the end of period 1 of each simulation to be the population of the U.S. as at 2014; this was sourced from the IMF and stood at 318.5 million.[10] The required shock in equations 2.1 - 2.3 is therefore:

$$\frac{T_2}{P_2} = 0.00314. \qquad 2.7$$

Next, consider two sets of equations 2.1 - 2.3, with one set specifying the Blomberg simulation levels of *IYR* and *GYR* and the growth rate of real GDP (ΔY_t), and the second set describing the corresponding quantities in the baseline simulation. Taking the difference between the two sets of equations, we arrive at equations 2.8 and 2.9. These equations describe the cumulative difference (in percentage form) of the investment and public consumption to GDP ratios at period *t*, i.e., $\Delta IYR_{t,\text{Blom-Base}}$ and $\Delta GYR_{t,\text{Blom-Base}}$, between the Blomberg simulation results and the baseline. Equation 2.10 is the corresponding expression for the growth rate in real GDP.

[9] Period 1 of the Blomberg simulation is therefore equivalent to period 1 of the baseline.

[10] See http://www.economywatch.com/economic-statistics/economic- indicators/Population/

$$\Delta IYR_{t,\text{Blom-Base}} = \frac{1}{IYR_0}\left(3.307^{***}\ln\left(1+\frac{\Delta BYR_{t-1,\text{Blom-Base}}}{100}\right) + 0.496\ln\left(1+\frac{\Delta Y_{t-1,\text{Blom-Base}}}{100}\right) - 0.389^{**}\frac{T_t}{P_t}\right), \quad 2.8$$

$$\Delta GYR_{t,\text{Blom-Base}} = \frac{1}{GYR_0}\left(3.043^{***}\ln\left(1+\frac{\Delta BYR_{t-1,\text{Blom-Base}}}{100}\right) - 2.117^{***}\ln\left(1+\frac{\Delta Y_{t-1,\text{Blom-Base}}}{100}\right) + 0.412^{*}\frac{T_t}{P_t}\right), \quad 2.9$$

$$\Delta Y_{t,\text{Blom-Base}} = \left(0.184\ln\left(1+\frac{\Delta BYR_{t-1,\text{Blom-Base}}}{100}\right) - 7.959^{***}\ln\left(1+\frac{\Delta Y_{t-1,\text{Blom-Base}}}{100}\right) + 0.341^{***}\left(\Delta IYR_{t-1,\text{Blom-Base}}\right) - 0.513^{***}\frac{T_t}{P_t}\right), \quad 2.10$$

In equations 2.8 - 2.10, IYR_0 is the base period (or initial) investment-to-GDP ratio in percentage form, e.g., a number like 14.7[11]. Similarly, GYR_0 is the initial public-consumption-to-GDP ratio while we define:

$$\Delta IYR_{t,\text{Blom-Base}} = \frac{IYR_{t,\text{Blom}} - IYR_{t,\text{Base}}}{IYR_0}, \quad 2.11$$

$$\Delta GYR_{t,\text{Blom-Base}} = \frac{GYR_{t,\text{Blom}} - GYR_{t,\text{Base}}}{GYR_0}, \quad 2.12$$

and as before, "Blom" denotes the Blomberg Simulation and "Base" denotes the Baseline Simulation. We have assumed the impact of a single terrorism event on the relative populations between the two simulations to be small, i.e., fewer than 100 fatalities. This assumption is consistent with Sandler and Enders[22], who show that terrorism incidents in general result in few deaths (albeit for outlier events where this is not so, such as the 9/11 attack). In addition, a study of the ITERATE terrorism database by Anderton and Carter[23] showed an average of 2.6 casualties (fatalities plus injuries) were reported across all terrorist events within ITERATE from 1968 to 2000.

As previously discussed, we do not consider the equation derived by Blomberg and Hess[11] for BYR_t in response to shocks in the variable TV_t; see Table I and equations 2.4 and 2.5. In order to close the system of equations 2.8 - 2.10, we model $\Delta BYR_{t,\text{Blom-Base}}$ endogenously using USAGE 2.0 across all years t. Under this approach, we omit all

[11] This data is sourced directly from the USAGE 2.0 database.

terms involving $\Delta BYR_{t,\text{Blom-Base}}$ from equations 2.8 - 2.10; this yields a suitable closed system of equations to derive exogenous shocks for $\Delta IYR_{t,\text{Blom-Base}}$, $\Delta GYR_{t,\text{Blom-Base}}$ and $\Delta Y_{t,\text{Blom-Base}}$ over the full simulation time period.

2.3.4 Simulations

Using the methodology outlined in section 2.2.3, paths are derived for $\Delta IYR_{t,\text{Blom-Base}}$, $\Delta GYR_{t,\text{Blom-Base}}$ and $\Delta Y_{t,\text{Blom-Base}}$ over a 6 year time period in response to the shock defined in equation 2.7. These paths are summarized in Table III, with plots provided in Figure 1.

Next, we apply the BOTE model to describe the required Blomberg Simulation closure modifications to model the impact of terrorism.

2.3.4.1 Shock to investment relative to GDP

Slovic[6] postulated that certain events drive economic disruption beyond their direct impacts, through a signaling mechanism of heightened uncertainty due to increases in perceived future risk. This concept was considered formally in the context of a terrorist attack by Burns and Slovic[24]. In this paper, we follow the convention established in ex-ante studies of terrorism by Giesecke *et al.*[8,9] and utilize this risk perception mechanism as a premise for modelling terrorism-related movements in IYR_t in the U.S. This is achieved via endogenization of a shift variable in the required rate-of-return Λ, and exogenization of the ratio *IYR* (see Table II), i.e. Blomberg-determined reductions in *IYR* are accommodated as an increase in the degree of risk aversion of investors in response to the terrorist event, achieved via movements in Λ.

2.3.4.2 Shock to public consumption relative to GDP

In both the short- and long-run, we endogenize public consumption (*G*) and exogenize *GYR*. Government expenditure is therefore permitted to adjust in order to yield the required path for *GYR*, i.e., an increase in *GYR* (all else being equal) would therefore be accommodated via an endogenous increase in *G* within the Blomberg simulation relative to the baseline (see Table III).

2.3.4.3 Shocks to Real GDP

In line with previous work by Pan *et al.*[25] and Giesecke *et al.*[8], the impact of shocks to real GDP are delivered via endogenization of total primary-factor augmenting technology (*A*), and exogenization of real GDP growth. This represents the impact of business interruption driven by terrorism.

3 RESULTS

This section is structured as follows. In section 3.1, we discuss the relaxation paths recovered from the Blomberg simulation in response to the shocks in Table III. Our explanation of the macroeconomic modelling results is presented in section 3.2. This focuses on a series of decomposition figures. The decomposition figures are created by running the CGE model five times: one full (Blomberg) simulation in which all three sets of Blomberg *et al.*[1] results (as reported in Table III) are implemented as simultaneous shocks to USAGE 2.0; a second (Structural) simulation in which the structural responses derived from the first simulation (as described in section 3.1 and summarized in Table IV) are passed as exogenous shocks into the model (see section 2.3.1 for a full description of this process); and a further three simulations in which each of the three sets of structural shocks are implemented individually, i.e., one simulation for each of columns (1) – (3) in Table IV. We focus explicitly on the percentage deviations between the Structural simulation results and the Baseline simulation results; the Blomberg results are also included for the reader's reference, and as expected are in line with the Structural simulation results. We conclude with a comparison of our results with previous ex-ante work in section 3.3. This allows us to make inferences about how future ex-ante CGE studies of hypothetical terrorism events might be informed by structure shifts implicit in Blomberg's findings.

3.1 Shocks and Responses

The exogenous shocks and subsequent structural responses are graphically illustrated in Figure 1 and Figure 2, while numerical summaries are given in Table III and Table IV. By choice of convention, a positive value for Λ describes an increase in the required rate-of-return on capital. We observe such an outcome in the terrorist event-year (2012) in Figure 2. This implies that, when considered jointly with the effects in 2012 of the rise in *G* (which will tend to raise *IYR* relative to baseline) and *A* (which will tend to lower *IYR* relative to baseline) we require a rise in Λ to explain the observed outcome for *IYR*. This is consistent with heightened perceptions of risk and uncertainty on the part of investors, and a compensating increase in required rates of return on new units of capital.

Again, by choice of convention, a positive outcome for primary-factor augmenting technical change (*A*) corresponds to diminished productivity. We observe such an outcome in the Blomberg simulation relative to the baseline (see Table IV). That is, the decline in real GDP observed in the Blomberg results is too high to be explained by the joint effects alone of the rise in *G* and rise in Λ. A positive deviation in *A* in the event-year is consistent with a short-term reduction in the efficiency with which inputs are translated into output, as might be caused, for example, by business interruption.

The sign convention for *G* is as expected, i.e., a positive value for *G* implies higher public consumption in the Blomberg simulation relative to the baseline. This is consistent with a policy proclivity for fiscal stimulus in an environment of weakened economic activity.

3.2 Macroeconomic deviations

To study the interaction of the imposed shocks and their impact on the U.S. economy, we begin in section 3.2.1 with a discussion of the relative impact of each shock on employment (*L*), capital (*K*) and real GDP (*Y*). This leads to a discussion of rates-of-return on capital (*ROR*) and real investment (*I*) in section 3.2.2, and the balance of trade in section 3.2.3. Influences on the terms of trade (*TOT*) are considered in section 3.2.4, before we conclude with some remarks on long-run trend behavior in section 3.2.5.

3.2.1 Employment, capital and real GDP in the event-year

A striking feature of the deviation in employment (*L*) shown in Figure 3 is the absence of a change in *L* in the event-year. The decomposition simulation shows that this outcome is the net result of the *L*-damping effects of the rise in required rates-of-return (Λ) and the productivity deterioration (*A*), and the expansions in *L* due to the rise in public consumption (*G*).

The consequences of the shocks to Λ, *A* and *G* are transmitted throughout the economy via direct and indirect means. To illustrate, consider BOTE equation 6.6. As discussed in section 2.3.1, an important feature of the USAGE 2.0 model in this simulation is short-run wage stickiness. With the real wage sticky in the terrorist event-year, a rise in *A* drives a direct fall in *L* as it appears explicitly in equation 6.6. In Figure 3, we see this direct impact expressed as a negative contribution by primary-factor technical change to event-year *L*. Also from Figure 3, it is clear that the rise in Λ has the largest (negative) impact on event-year *L*. This results via indirect means, namely, the rise in Λ causes a negative deviation in the terms of trade (*TOT*) in the event year. This is shown in Figure 5, and will be discussed in section 3.2.4. With the real wage sticky in the event-year, the negative terms of trade deviation generates a positive deviation in the real producer wage. Because *TOT* (and not Λ) appears in the relevant equation (equation 6.6) we classify this as an indirect avenue via which the terrorism-related shocks affect *L* relative to baseline.

Importantly, Figure 3 shows that the negative impacts on *L* in the event year of the rise in *A* and Λ are offset by the employment-expanding effects of the rise in *G*. A rise in *G* has a positive impact on *L* in two ways:

1. Via direct means, as public consumption is labor intensive;
2. Via indirect means, as it generates a positive deviation in *TOT* (see Figure 5).

It is important to note that the magnitude of the job creation driven by the rise in *G* is not imposed upon the system: it is a realization of the path outlined for *GYR* by Blomberg *et al.*[1]. As we discuss in section 3.3, this has potential implications for future modelling of the economic consequences of terrorism events.

As discussed in section 2.3.2, industry-specific *K* in USAGE 2.0 adjusts in year $t + 1$ to movements in year *t* net investment. As such, there is no scope for *K* to adjust in the event-year. This is shown in Figure 8, where we plot the (rental-weighted) sum of the percentage deviations in industry-specific *K*.

Having considered outcomes for *L* and *K* in the event year, we now turn to the outcome for real GDP (*Y*), reported in Figure 4. Our discussion is framed in terms of BOTE equation 6.2. As there is no scope for event-year adjustments in capital (see Figure 8), we focus explicitly on the impact of movements in event-year employment (*L*) and productivity (*A*). Event-year *L* is influenced by the three structural shocks (see Figure 2 and Figure 3). This impacts event-year *Y* via equation 6.2. Specifically, the negative deviation in *L* driven by the rise in Λ generates a negative contribution to *Y* of approximately -0.0007 percentage points (see Figure 4). This GDP impact is partly offset in the event year by the positive deviation in event-year *L* driven by the positive deviation in *G*. However the largest contributor to the negative deviation in *Y* in the event-year is the rise in *A*, contributing approximately -0.0016 percentage points to the net outcome (Figure 4). The deterioration in event-year *A* affects *Y* via two routes:

1. Via equation 6.2, productivity has a direct impact on the capacity of a given level of primary factor input(s) to generate *Y*;
2. The deterioration in productivity has an indirect impact via equation 6.6 and the fall in event-year *L*. This also drives *Y* lower via equation 6.2.

3.2.2 Rates-of-return and investment in the event-year

Figure 7 describes the deviation path for real investment (*I*), and its decomposition into the individual contributions made by the three structural shocks. From BOTE equation 6.4, we can rationalize short-run movements in *I* in terms of outcomes for the ratio of realized rates-of-return to required rates-of-return (*ROR* and Λ respectively).

As discussed in reference to Figure 2, the Blomberg simulation generates a large positive deviation in Λ in the event-year. When applied as part of the set of shocks in the Structural simulation, the rise in Λ explains the bulk of the event-year decline in *I* (Figure 7). This is also clear from equation 6.4, where a positive deviation in Λ has a direct negative impact on *I*.

However, each of the three shocks also causes indirect movements in *I*, via movements in *ROR*. These indirect effects can be studied via equation 6.7. We can explain the impact of Λ, *G* and *A* on *ROR* (and thus the indirect impact on *I*) in terms of direct channels (in the case of *A*, it appears in equation 6.7) and indirect channels (in the cases of Λ and *G*, which exert an influence on *I* via their impacts on event-year employment (*L*) and the terms of trade (*TOT*)).

We begin with the effect of the rise in *A* on *ROR*. *Ceteris paribus*, a rise in *A* reduces the marginal product of capital and thus has a direct impact on *ROR* in the short-run. As discussed in section 3.2.1, the rise in *A* also reduces *L* and increases the *TOT*, thereby having indirect impacts on *ROR* through two channels:

1. Via equation 6.7, the fall in *L* reinforces the direct impact of the movement in *A* on *ROR* by increasing the capital-to-labor ratio K / L;
2. Via equation 6.7, the rise in the event-year *TOT* increases *ROR* in the event-year, because output prices rise by more than capital construction costs. This attenuates the aforementioned deterioration in the event-year *ROR*.

Nevertheless, as is clear from Figure 6, the *net* effect on *ROR* of the deviation in event-year productivity is negative. This accounts for the negative contribution made to event year investment by the deviation in productivity (Figure 7).

Turning now to the positive deviation in public consumption spending (*G*), this also exerts an indirect influence on short-run *ROR* and thus *I* via its impacts on *L* and the *TOT*:

1. As discussed in section 3.2.1, the positive deviation in event-year *G* increases *L* relative to baseline. *Ceteris paribus*, via BOTE equation 6.7, this raises the marginal product of capital, and with it, *ROR*;

2. The value of the marginal product of capital increases by more than capital construction costs due to a positive deviation in event-year *TOT* (see Figure 5, to be discussed in section 3.2.4), adding to the positive deviation in *ROR* in the event year.

Both indirect channels thus lead the positive deviation in *G* to make a positive deviation in *ROR* (Figure 6). Via BOTE equation 6.4, this explains the positive contribution to *I* in the event-year made by the rise in *G* (Figure 7).

Finally, the rise in Λ causes a negative indirect impact on *I* in the event-year. As discussed in section 3.2.1, the rise in Λ imparts negative contributions to the deviations in *L* and the *TOT* from baseline. From equation 6.7, it is clear that a decline in *L* and *TOT* (for any given level of *K* and *A*) requires *ROR* to fall. Via equation 6.4, the decline in *ROR* induced by the rise in Λ reinforces the direct effect of the rise in Λ on *I*. These direct and indirect effects of the rise in Λ in the event-year therefore drive a large proportion of the decline in event-year *I*.

3.2.3 Real GNE and the balance of trade

We turn now to the effects of the structural shocks on real GNE and the balance of trade. With employment (*L*) largely determined by equation 6.6, and with capital (*K*) sticky in the short-run, real GDP (*Y*) in the short-run is largely determined by equation 6.2. This allows us to rely on equation 6.1 to explain movements in the real balance of trade by focusing on movements in real gross national expenditure (GNE) relative to *Y*.

Figure 2, Figure 7 and Figure 9 describe the (respective) movements in the three components of real GNE: (i) public consumption (*G*), (ii) investment (*I*) and (iii) private consumption (*C*). We have explained *I* in our discussion in section 3.2.2, while the outcome for *G* is imposed exogenously (see section 3.1). We therefore now focus on the outcome for *C*.

From equation 6.3, movements in *C* are determined by movements in both *Y* and *TOT*.

1. The outcome for *Y* was discussed in section 3.2.1, where we noted that the rise in *A* explains much of the event year negative deviation in *Y*. *Ceteris paribus*, the fall in *Y* reduces national income and thus reduces *C* via equation 6.3;
2. *C* is also affected by the *TOT*, via the latter's influence on real (consumption price deflated) national income.
    a. In section 3.2.2 we saw that the rise in *G* and Λ cause a negative deviation in the *TOT* in the event year. These indirect channels, via the terms of trade, reinforce the impact of the change in *Y* on *C*.
    b. As we shall discuss in greater detail in section 3.2.4, the rise in *A* increases *TOT* relative to baseline (see Figure 5). While the contribution of the rise in *A* on *C* remains negative in the event-year (Figure 9) via the direct impact of *A* on *Y*, the net impact (relative to that given by the GDP effect alone) is damped by the positive contribution made by *TOT*.

The net outcome for GNE resulting from the movements in its components (*C*, *I* and *G*) is a negative deviation, and one that exceeds (that is, lies below) the negative deviation in real GDP. Via equation 6.1, this generates a positive deviation in the balance-of-trade-to-GDP ratio in the event-year (Figure 10). This deviation is overwhelmingly driven by the rise in Λ, which causes a negative deviation in *I*. Via 6.1, this in turn generates a positive deviation in the balance of trade. However, the net movement towards balance of trade surplus in the event-year is attenuated by the rise in *A* and *G*. In terms of BOTE equations 6.1 and 6.2, the rise in *A* reduces *Y* relative to GNE, and the rise in *G* increases GNE relative to *Y*. The effect of both is to move *X* - *M* towards deficit, which is clearly apparent in the decomposition results for Λ and *G* in Figure 10.

3.2.4 The terms of trade

In our previous discussions, we have made frequent reference to the deviation in the terms of trade (*TOT*). As described by BOTE equation 6.9 and discussed in section 2.3.2, movements in *TOT* are explicable in terms of movements in export volumes (*X*). In Figure 5, we see that *TOT* increases relative to baseline in the event-year. This is the net outcome of a negative contribution made by the rise in Λ, and positive contributions made by the rise in *A* and *G*. We consider these factors in turn.

As discussed in section 3.2.3, the positive deviation in Λ moves the balance of trade towards surplus in the event-year. In Figure 11 and Figure 12, we see this expressed as a fall in import volumes (*M*) and a rise in export volumes (*X*). Via equation 6.9, the rise in *X* involves a movement down foreign export demand schedules, requiring export prices (and thus *TOT*) to fall in foreign currency terms.

As discussed in section 3.2.3, the balance of trade is moved towards deficit relative to baseline by both the rise in *A* and *G*. These movements more than offset the effect on the *TOT* of the increase in Λ. In Figure 11 and Figure 12, we see this expressed as contributions by the *A* and *G* shocks to a positive deviation in *M* and a negative deviation in *X*. Via BOTE equation 6.9, the negative contributions to the deviation in *X* cause positive contributions to the deviation in *TOT* in the event-year.[12]

3.2.5 Long-run behavior

In the long-run, the shock to the required rate of return (Λ) on capital abates. Whilst employment (*L*) returns to its baseline value also, capital (*K*) remains sluggish in its recovery; however, with a lower base from which to cover depreciation costs and Λ in line with the baseline, the increasing trend in capital formation observed in Figure 8 is expected to drive *K* back to base line over a longer time scale. The lower level of *K* however continues to depress the real wage and drives the rental price on capital (*ROR*) higher, due to the diminished (higher) marginal product of labor (capital)

[12] In our description of BOTE in section 2.3.2, we noted that the variable *TOT* served the dual function of describing both the *TOT* and the real exchange rate (ϕ), the latter being defined as $\phi = P_O / P_M$ where, as before, P_O is the output price index, while P_M is the import price deflator in domestic currency. The close correspondence between these two variables in the present USAGE 2.0 simulation is apparent by comparing the *TOT* results (Figure 5) with those for ϕ (Figure 13); the economic mechanisms driving movements in ϕ in response to the (respective) rise in Λ, *A* and *G* are therefore similar to those discussed in this section for the *TOT*.

respectively. Despite this diminished capital stock, real GDP (Y) is in line with the baseline due to improved overall productivity, while public consumption (G) remains slightly elevated relative to baseline. Importantly, both private consumption (C) and household income are broadly in line with the baseline in the long-run; consequently, the impact from lower real wages on household income is offset by the marginally higher *ROR* on capital.

3.3 Comparison with previous work

As discussed in section 1, an important application of CGE models is the *ex-ante* analysis of hypothetical terrorism events. These studies can be of value to policy makers in planning for diverse threat scenarios. In previous studies, e.g., Giesecke *et al.*[8,9], values for shocks to variables such as required rates-of-return (Λ), business interruption (A), and public consumption spending (G) have typically been assembled from independent sources before input to the model. This paper presents an opportunity to assess some of the assumptions adopted in these papers against the movements in CGE structural variables implicit in the Blomberg *et al.*[1] econometric results. In so doing, we remain cognizant of the fact that the Blomberg results are based upon the ITERATE database of broad-ranging, global terrorism events, whereas Giesecke *et al.*[8, 9] relate to unique terrorism events in a specific locale.

Nevertheless, Table V attempts a comparison of the studies, by scaling relevant region-specific shock inputs in Giesecke *et al.*[8, 9] up to the U.S.-wide level. Beginning with the first column, we see that the shifts in required rates-of-return (Λ) in Giesecke *et al.*[8, 9] are about five times larger than those in the Blomberg simulation herein. Given that the two sets of studies come to the task of assessing the change in required rates of return from different directions, this result is encouraging. Indeed, given that the two ex-ante studies are high-casualty events (see column 4 of Table V), with both using means (radiological dispersion and chlorine) likely to generate high degrees of dread and uncertainty, which are likely to evoke high levels of aversion behavior, the higher assumed values for Λ in the ex-ante studies relative to the implied Λ in Blomberg *et al.*[1] for an average terrorism event look reasonable.

Turning to column 2, we see that the extent of business interruption (A) is similar for Blomberg *et al.*[1] and Giesecke *et al.*[9] ($200 m. and $149 m. respectively) but significantly larger for Giesecke *et al.*[8] ($1,427). Again, this points to the specific nature of the latter study, which notes a long and extensive period of shutdown of affected areas as radiological contamination is removed.

Column 3 highlights the large shift in public consumption spending (G) based on the Blomberg simulation herein, which is absent in the two comparison studies. This highlights a hitherto overlooked role for endogenous fiscal response in future ex-ante studies, specifically in abating the macroeconomic impacts of terrorism in the event-year through efforts to support employment (L). This is evident in our discussion in section 3.2.1, where we highlight that the impact on L of the rise in Λ and A are offset entirely in the event-year by an increase in G.

4 CONCLUDING REMARKS

We have used independent macro-econometric equations describing the impacts of terrorism estimated by Blomberg *et al.*[1], to trace time paths for three key macroeconomic variables in response to a terrorism event: (i) real GDP growth (ΔY); (ii) the ratio of investment to GDP (*IYR*); (iii) and the ratio of government consumption to GDP (*GYR*). The paths for these variables were then imposed as exogenous shocks to a CGE model of the U.S. under an unconventional closure of the model, allowing us to uncover time paths for underlying variables describing economic structure and policy. In particular, we uncover values for CGE model variables describing investor uncertainty (Λ), productivity (A), and public consumption (G). When results for Λ, A and G are imposed on the CGE model as exogenous shocks under a conventional closure of the model, the model reproduces the Blomberg *et al.*[1] results for GDP, *IYR* and *GYR*. This allows us to do three things: (i) explain the econometrically-estimated impacts of terrorism in terms of movements in underlying structural and policy variables in a CGE model; (ii) compare the assumed values for structural and policy variables in recent ex-ante studies of terrorism with those implicit in Blomberg's results; and (iii) draw conclusions that might be helpful to future researchers undertaking ex-ante studies of hypothetical terrorism events.

How should future researchers undertaking ex-ante CGE studies of hypothetical terrorist events use the findings in this paper? First, it appears that a comprehensive ex-ante assessment of the economy-wide consequences of a terrorism event should take account of the possibility that fiscal policy (via public consumption) will adjust in response to the event. In this paper, we found the public consumption response to be of sufficient magnitude to neutralize broader adverse employment effects. This might be an appropriate way of benchmarking the size of the fiscal stimulus in future ex-ante studies. Second, we found that the magnitude and pattern of the movements in required rates-of-return and productivity implicit in the Blomberg study were in broad conformity with those assumed in previous ex-ante studies. This should provide some comfort to researchers undertaking ex-ante studies as they assemble the inputs necessary to drive shocks to exogenous variables, particularly those describing business interruptions, behavioral effects and heightened perceived investment risks. Finally, the Blomberg results suggest some scope for post-event recovery of lost production, as evidenced by the positive deviation in post-event primary factor productivity. It may therefore be appropriate to give some consideration to this effect in future work. This would be consistent, for example, with the emphasis by Rose[26] on resilience as a potential factor in mitigating post-event damages.

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6 TABLES AND FIGURES

Table I: Summary of key variables and their respective mathematical abstraction.

(a) Macroeconomic variables introduced by Blomberg *et al.*[1]			
IYR	Real investment as a proportion of real GDP.	*GYR*	Real public consumption as a proportion of real GDP.
BYR	Real imports plus exports as a proportion of GDP.	TV_t	Dummy variable defined in equation 2.5
ΔY_t	Real GDP growth over year *t*.	P_t	Population at time *t* in millions
T_t	Number of terrorist events recorded in a particular country in year *t*.		
(b) Back-of-the-envelope (BOTE) model variables.			
A	Primary factor augmenting technical change	*ROR*	Rate of return on capital.
APC	Average propensity to consume.	*TOT*	Terms of Trade.
C	Real private consumption.	*V*	Shift in export demand schedule.
G	Real public consumption.	*W*	Real (CPI-deflated) wage.
I	Real Investment.	*X*	Export volumes.
K	Capital stock.	*Y*	Real GDP.
L	Employment.	Λ	Shift in rate of return schedule for *I*.
M	Import volumes.	Ψ	Investment-to-Capital ratio.
W_t^s	Real (CPI-deflated) wage at time *t* for $s \in$ {Policy, Base}.	ΔK_t	Change in *K* between years *t* and *t* -1.
		W_t^s	Employment at time *t* for $s \in$ {Policy, Base}.

Table II: Back-of-the-envelope (BOTE) representation of USAGE 2.0

	(a) Short-run closure.	(b) Effective long-run closure.
	(i) Equations holdings within any given year of a year-on-year simulation.	
6.1	$Y = C + I + \boldsymbol{G} + X - M$	$Y = C + I + \boldsymbol{G} + X - M$
6.2	$Y = f(L, \boldsymbol{K}) / \boldsymbol{A}$	$Y = f(\boldsymbol{L}, K) / \boldsymbol{A}$
6.3	$C = \boldsymbol{APC} \cdot Y \cdot g(TOT)$	$C = \boldsymbol{APC} \cdot Y \cdot g(TOT)$
6.4	$I = u(ROR / \Lambda)$	$I = u(\boldsymbol{ROR} / \Lambda)$
6.5	$\Psi = I / \boldsymbol{K}$	$\boldsymbol{\Psi} = I / K$
6.6	$f_L(\boldsymbol{K} / L) \cdot g(TOT) = \boldsymbol{W} \cdot \boldsymbol{A}$	$f_L(K / \boldsymbol{L}) \cdot g(TOT) = W \cdot \boldsymbol{A}$
6.7	$f_K(L / \boldsymbol{K}) \cdot h(TOT) = ROR \cdot \boldsymbol{A}$	$f_K(\boldsymbol{L} / K) \cdot h(TOT) = \boldsymbol{ROR} \cdot \boldsymbol{A}$
6.8	$M = j(Y, TOT)$	$M = j(Y, TOT)$
6.9	$ToT = z(X, \boldsymbol{V})$	$ToT = z(X, \boldsymbol{V})$
6.10	$IYR = I / Y$	$IYR = I / Y$
6.11	$GYR = G / Y$	$GYR = G / Y$
	(ii) Relevant equations holding between consecutive years of a year-on-year simulation.	
6.12	$\Delta K_t = I_{t-1}$	
	(iii) Lagged wage adjustment.	
6.13	$\frac{W_t^{\text{Policy}}}{W_t^{\text{Base}}} = \left(\frac{W_{t-1}^{\text{Policy}}}{W_{t-1}^{\text{Base}}} - 1 \right) + \alpha \cdot \left(\frac{L_t^{\text{Policy}}}{L_t^{\text{Base}}} - 1 \right)$	

Table III: Shock and subsequent relaxation paths for the variables described by Blomberg *et al.*[1] as presenting a measurable and significant response to terrorism. All results are presented to six decimal places as percentage deviations of the Blomberg simulation from the baseline.

Period	$\Delta IYR_{t,\text{Blom-Base}}$	$\Delta GYR_{t,\text{Blom-Base}}$	$\Delta Y_{t,\text{Blom-Base}}$
2011	0	0	0
2012	-0.008277	0.008751	-0.001611
2013	-0.000054	0.000231	-0.000288
2014	-0.000010	0.000041	0.000020
2015	0.000001	-0.000003	-0.000002
2016	0	0	0

Table IV: Deviations in the structural response variables from the baseline, driven by the Blomberg simulation shocks in Table III. The required rate of return in period t is denoted by $\Lambda_{t,\text{Blom-Base}}$, while the deviation in the rate of growth in public consumption is $g_{t,\text{Blom-Base}}$ and all primary-factor augmenting technical change is $a_{t,\text{Blom-Base}}$

Period	$\Lambda_{t,\text{Blom-Base}}$ (1)	$g_{t,\text{Blom-Base}}$ (2)	$a_{t,\text{Blom-Base}}$ (3)
2011	0	0	0
2012	0.000019	0.007134	0.001354
2013	-0.000005	-0.000055	-0.000174
2014	-0.000003	0.000064	-0.000364
2015	0	-0.000003	-0.000301
2016	-0.000001	0.000002	-0.000259

Table V: Comparison of event-year shocks, standardized to a U.S.A.-wide basis

	Required rate of return (U.S.-wide, change)	Business interruption & other direct resource loss impacts (U.S.-wide, $m.)	Government consumption (U.S.-wide, $m.)	Casualties (fatalities and serious injuries)
	(1)	(2)	(3)	(4)
Blomberg *et al.*[1] [Event: average event]	0.000019[(a)]	$200[(b)]	$155[(c)]	2.6[(h)]
Giesecke *et al.* (2012)[8] [Event: dirty bomb]	0.000110[(d)]	$1,427[(e)]	$0[(f)]	450[(i)]
Giesecke *et al.* (2015)[9] [Event: chlorine gas]	0.000100[(d)]	$149[(e)]	$4[(g)]	286[(j)]

Notes to Table V:

(a) See Table IV.

(b) Percentage change in productivity (Table IV) multiplied by GDP.

(c) Percentage change in public consumption (Table IV) multiplied by government expenditure.

(d) Change in required rate of return in downtown Los Angeles, multiplied by share of downtown Los Angeles investment in economy-wide U.S. investment.

(e) Business interruption, fatalities and capital damage.

(f) No change in government consumption in Giesecke *et al.* [8].

(g) Event-related medical expenditure only.

(h) Anderton and Carter[23] studied the ITERATE database upon which the analysis by Blomberg *et al.*[1] is based. Anderton and Carter[23] did not distinguish between fatalities and injuries in their analysis, combining the two to study overall casualties of terrorism. Average casualties per incident from 1968 to 2001 quoted herein were calculated from the average number of casualties per terrorism event per year and the number of terrorism events per year reported by Anderton and Carter[23].

(i) 180 fatalities and 270 serious injuries.

(j) 182 fatalities and 104 serious injuries.

Figure 1: Plot of shocks from Table III

% Deviation from Baseline

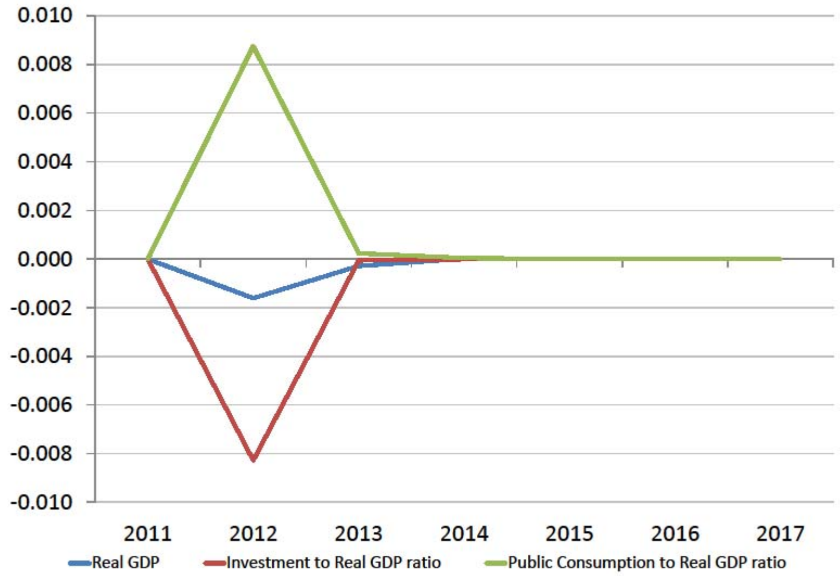

Figure 2: Plot of structural variable responses from Table IIV

% Deviation from Baseline

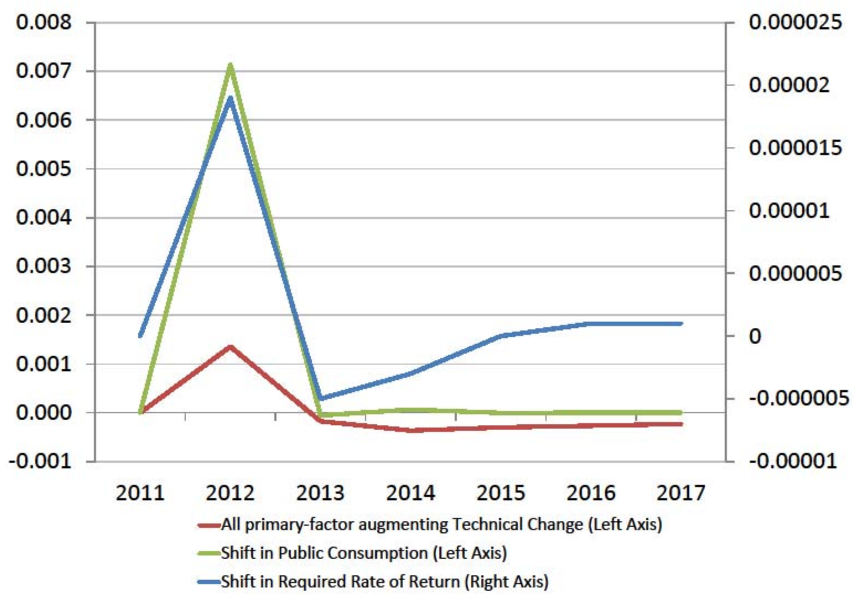

Figure 3: Aggregate Employment

% Deviation from Baseline

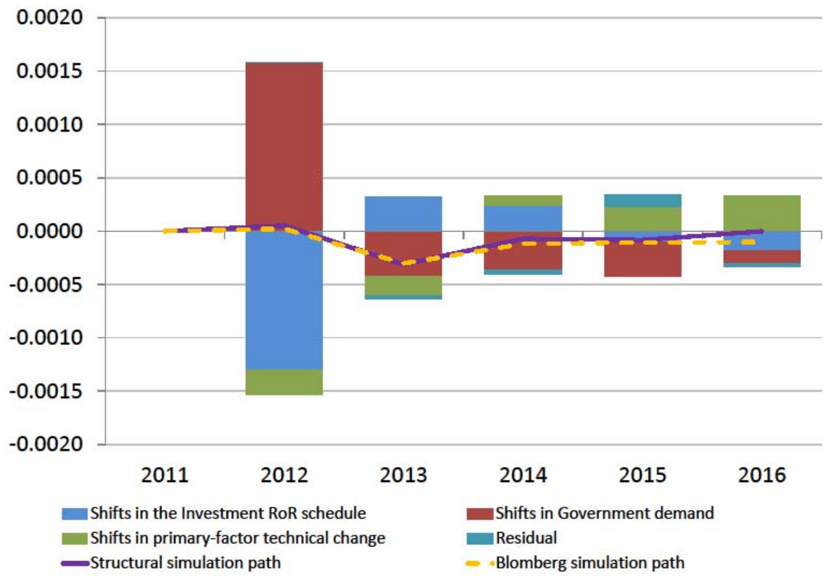

Figure 4: Real GDP

% Deviation from Baseline

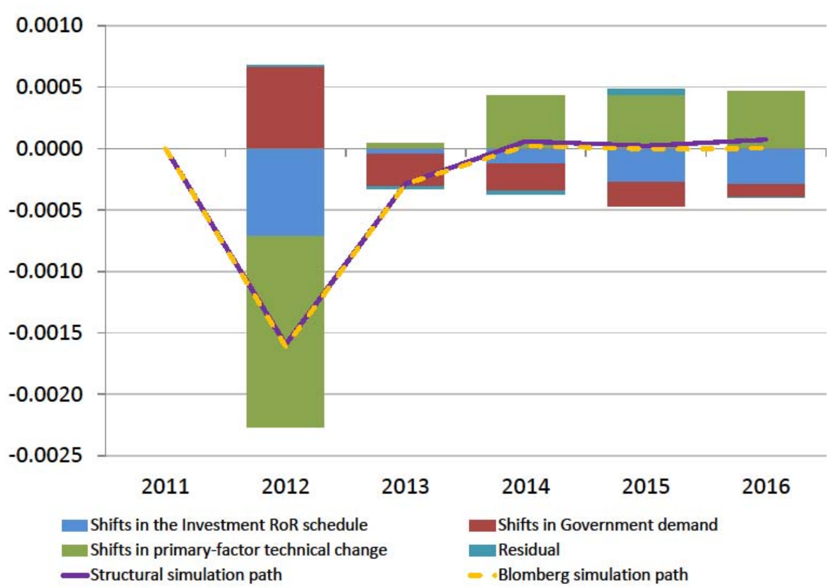

Figure 5: Terms of Trade

% Deviation from Baseline

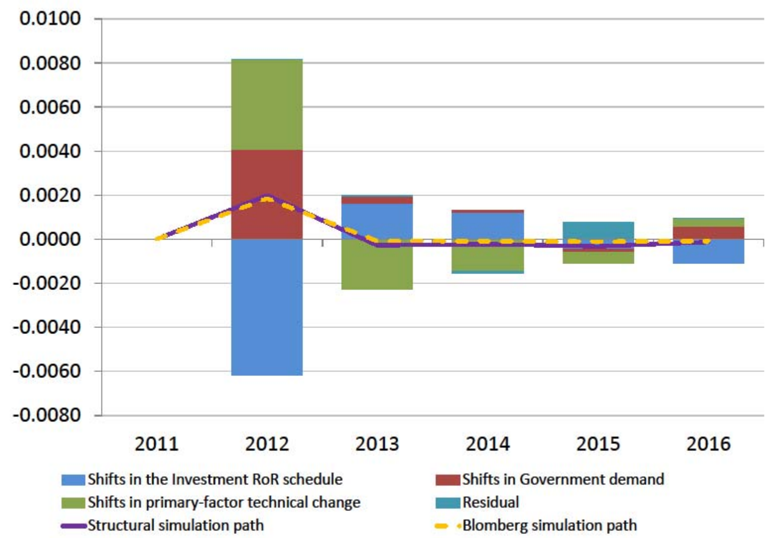

Figure 6: Ratio of the Average Capital Rental Price to the Investment Price Deflator

% Deviation from Baseline

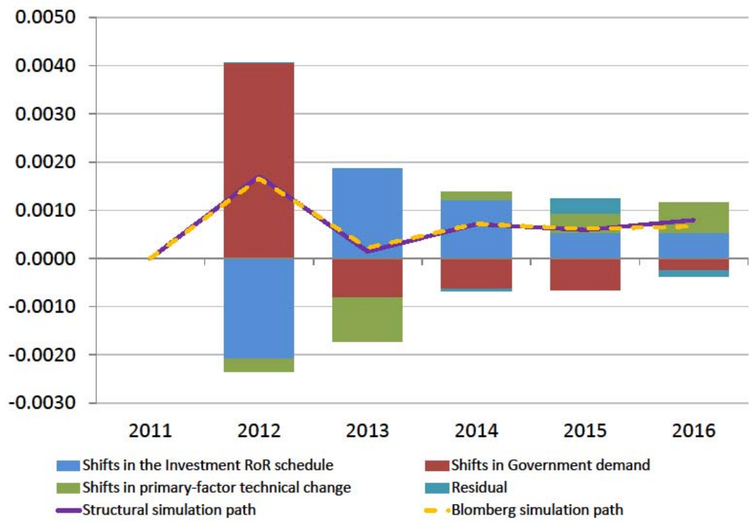

Figure 7: Real Investment

% Deviation from Baseline

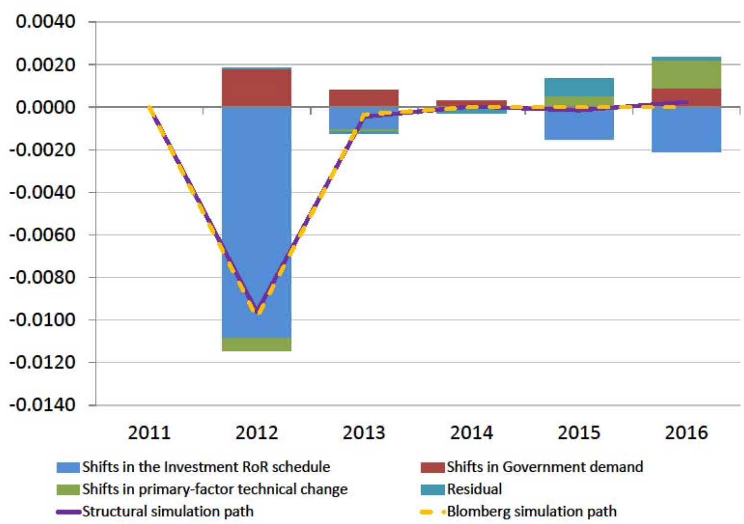

Figure 8: Capital stock (Rental-weighted)

% Deviation from Baseline

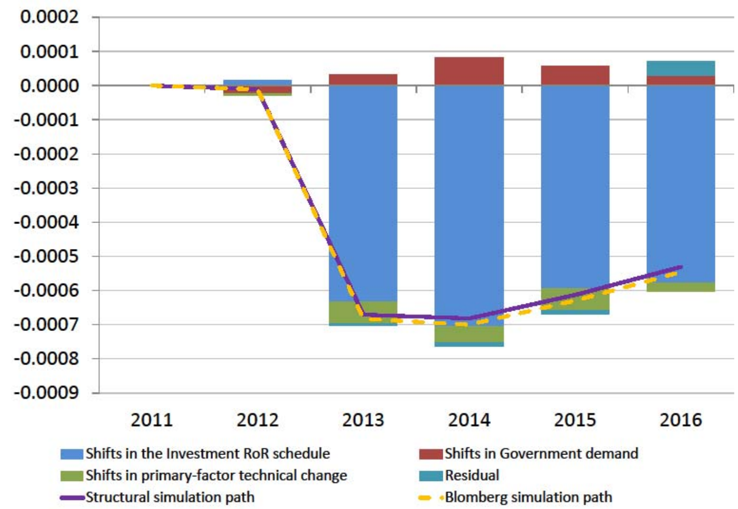

Figure 9: Real Private Consumption

% Deviation from Baseline

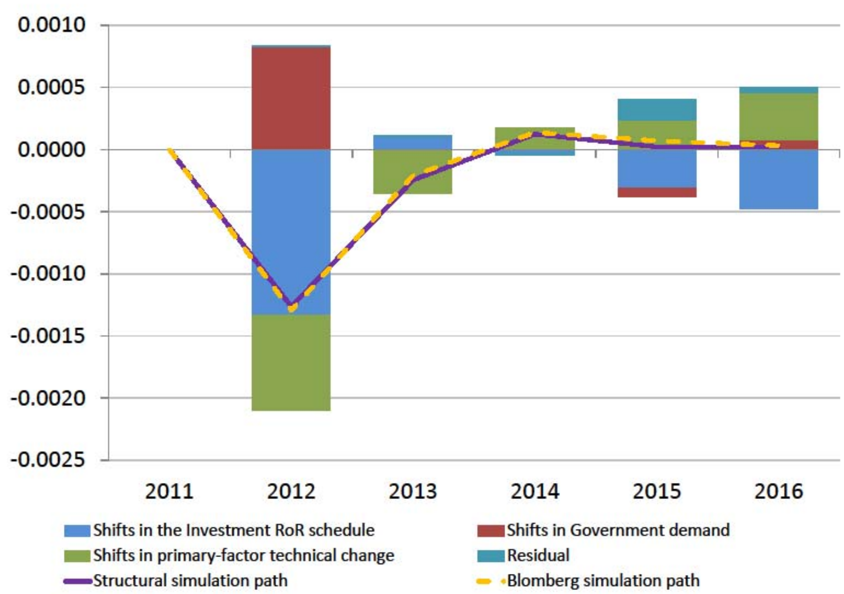

Figure 10: Balance of Trade / GDP ratio

% Deviation from Baseline

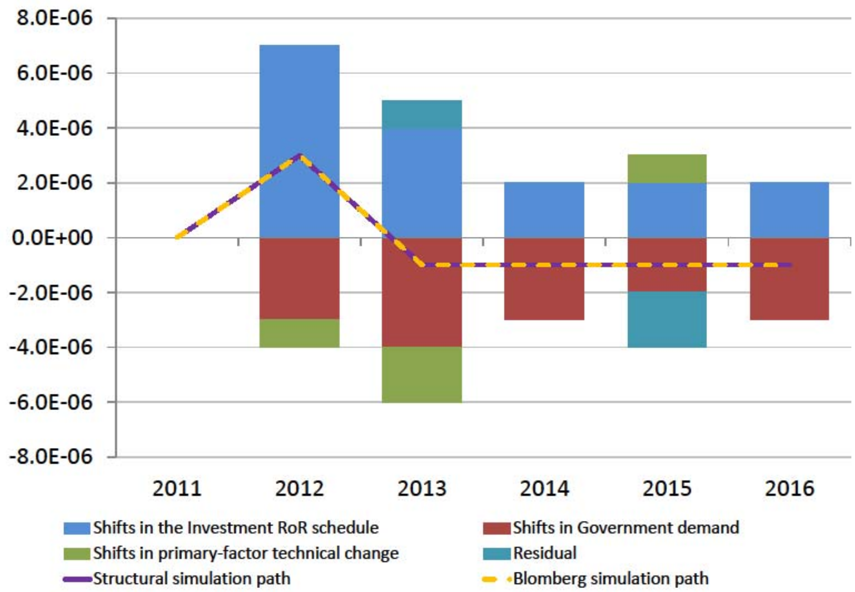

Figure 11: Import Volumes

% Deviation from Baseline

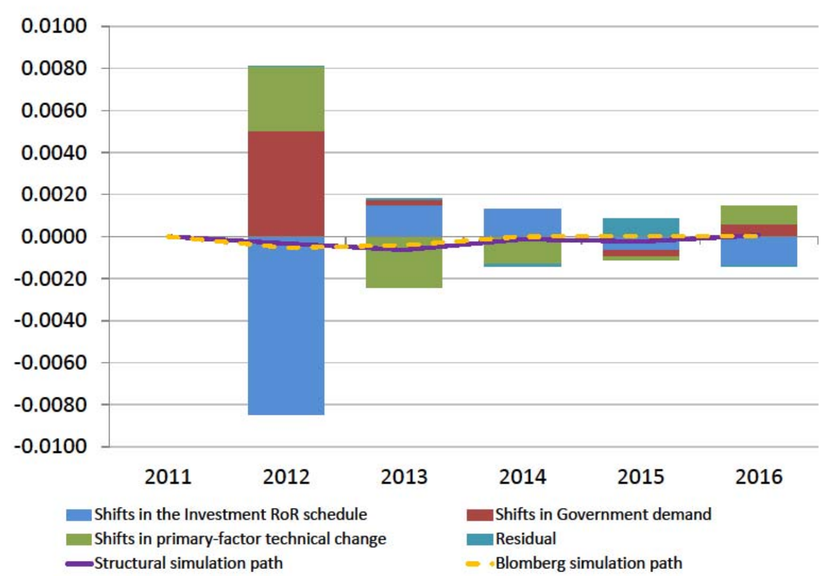

Figure 12: Export Volumes

% Deviation from Baseline

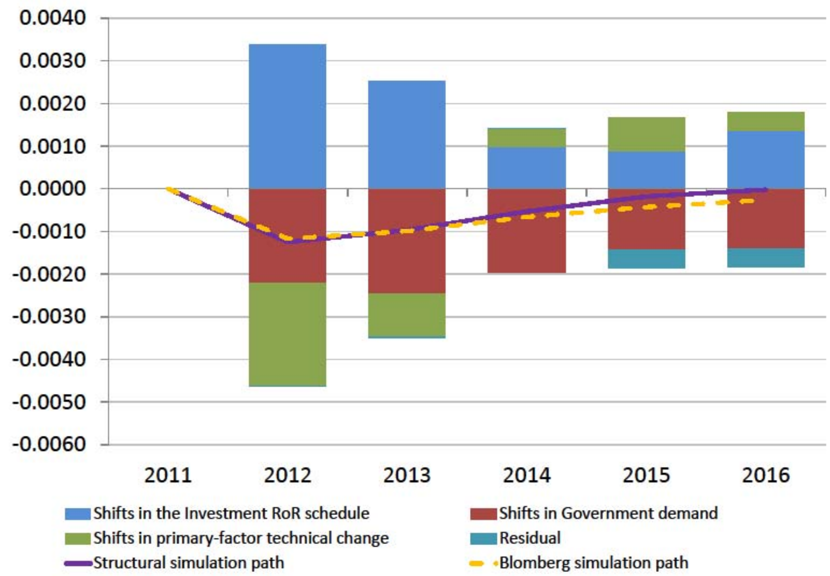

Figure 13: Real Exchange Rate

% Deviation from Baseline