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Abstract

This paper investigates the impact of economic policy uncertainty shocks and shocks to commodity prices on the realized stock market volatility of the CARB (Canada, Australia, Russia, and Brazil) countries. The CARB countries are important countries to study because they are major commodity exporters. The analysis is conducted using sign restricted impulse response functions (IRFs) and structural vector-autoregressive IRFs. There are some common results across the CARB countries. A positive shock to commodity prices lowers realized stock market volatility while a shock to economic policy uncertainty has a significant positive impact on realized stock market volatility. The magnitudes of the initial impact of these two shocks are similar. Shocks to global economic activity and short-term interest rates lower realized stock market volatility. The impacts of these shocks are more pronounced in models that use sign restrictions. These results have implications for investors and policy makers.

JEL Classification: E60, G15, G18

Keywords: Economic policy uncertainty; commodity prices; stock market volatility, sign restricted VAR.

1. Introduction

"In short, governments set the rules of the game."
Pastor and Veronesi (2012, p.1219).

Government policy affects decision making by individuals and firms and changes in monetary or fiscal policy can impact financial markets. When policy changes are anticipated the impact on financial markets is likely weak but if there is uncertainty about economic policy then the effects on financial markets can be strong. For firms, economic policy uncertainty creates an option value of waiting to resolve the uncertainty before making any strategic decisions and this creates an incentive to postpone decision making. Pastor and Veronesi (2012) develop a theoretical model to analyze the impact of government policy uncertainty on stock prices. Their model shows that, on average, stock prices fall after the announcement of a policy change. Economic policy uncertainty increases stock price volatility and correlations among stocks.

Up until recently measuring the impact of economic policy uncertainty (EPU) on stock market volatility has been difficult due to the lack of a standardized measure of EPU. Now, thanks to the work of Baker et al. (2016) there are standardized measures of EPU. The construction and publication of these indices has created a rapidly growing field investigating the impact of EPU on stock prices and stock price volatility. Baker et al. (2016), Brogard and Detzel (2016), and Yu et al. (2018) find that stock market volatility and EPU are closely correlated. Liu and Zhang (2015) find that higher EPU leads to significantly higher stock market volatility and that forecasting models with EPU provide better out of sample prediction compared to models that do not include EPU. Several other authors have found a significant relationship between economic policy uncertainty and stock prices (Arouri et al., 2016; Bekiros et al., 2016a, 2016b; Chen et al., 2017; Dakhlaoui and Aloui, 2016; Kang et al., 2015; Kang and Ratti, 2013; Li and Peng, 2017; Ozturk and Sheng, 2018; Tsai, 2017).

There is one strand of literature on (i) the impact of EPU on stock prices, and (ii) there is another strand of literature on the impact of commodity prices on stock prices. Our objective is to combine these two strands of literature to see which impact is greater on stock market volatility in the case of commodity producing countries. This is an important topic to study for several reasons because the results of our analysis have implications for investors and policy makers. If EPU is the dominant source of stock market volatility then stock market volatility can be reduced by mitigating domestic economic policy uncertainty. For example, efficient, effective and transparent monetary and fiscal policies can help to reduce EPU which is beneficial to investors. If, however, commodity prices are the dominant source of stock market volatility then there is little a major commodity producing country can do to mitigate stock market volatility because commodity prices are determined by global supply and demand for commodities. In this case, investors can hedge their exposure to commodity prices. Consequently, the sources and magnitude of stock market volatility affects government policy responses and investors' risk management strategies.

We do the analysis for the CARB (Canada, Australia, Russia, and Brazil) countries because the CARB countries are richly endowed with natural resources and are four major commodity exporters with high stock market liquidity for which the EPU index is available.[1] Based on 2017 dollars, Canada is the third largest wheat exporter[2], fourth largest crude oil exporter[3], fourth largest iron ore exporter[4], fifth largest copper ore exporter[5], and sixth larger exporter of gold[6]. Australia is the world's leading exporter of iron ore and coal[7], third largest copper ore exporter, fourth largest exporter of wheat, and seventh largest exporter of gold. Russia is the second largest exporter of crude oil and wheat, third largest exporter of coal and sixth largest exporter of corn[8]. Brazil is the second largest exporter of corn and iron ore, and sixth largest exporter of copper ore. Understanding the impacts of commodity prices and economic policy uncertainty on stock market volatility is import because stock price volatility is often measured by variance and variance is an important component to risk management topics like portfolio construction, hedging, and option pricing.

We make several important contributions to the literature. First, we use a structural vector autoregression (SVAR) and sign restricted VARs to investigate the impact of EPU on stock market volatility in the CARB countries. A VAR framework is also appropriate because of the endogeneity of policy changes (which are captured by the EPU) and the consequent implications on stock price volatility. In particular, when policy changes are uncertain, "policy changes raise

[1] They represent the world's key commodity markets.
[2] http://www.worldstopexports.com/wheat-exports-country/
[3] http://www.worldstopexports.com/worlds-top-oil-exports-country/
[4] http://www.worldstopexports.com/iron-ore-exports-country/
[5] http://www.worldstopexports.com/copper-ore-exports-by-country/
[6] http://www.worldstopexports.com/gold-exports-country/
[7] http://www.worldstopexports.com/coal-exports-country/
[8] http://www.worldstopexports.com/corn-exports-country/

the volatility of the stochastic discount factor. As a result, risk premia go up and stock returns become more volatile and more highly correlated across firms" (Pastor and Veronesi, 2012, p. 1221). Second, because the CARB countries are major commodity exporters we include commodity prices in the model. We are interested not only in the impact of EPU on stock market volatility but also whether EPU has a larger or smaller impact compared to commodity prices. Including EPU and commodity prices helps to determine the impact of domestic economic policy uncertainty and global commodity price shocks on country stock market volatility. Third, we compare the results from a standard SVAR with short-run exclusion restrictions to those from a VAR with sign restrictions (Uhlig, 2005). Standard SVARs impose some zero-value restrictions on the contemporaneous effects of structural shocks for certain variables, which means representing them with a value of zero in the variance-covariance matrix of error terms in the structural VAR for within-period (contemporaneous) covariances. The sign-restrictions approach has several advantages over the standard SVAR: (i) Sign restrictions are often used implicitly in SVARs in order to assess ex-post the validity of the identifying exclusion restrictions imposed by checking whether the impulse responses derived have the anticipated signs. In the sign-restrictions approach these restrictions are explicitly imposed a priori. (ii) Impulse responses estimated with sign restrictions use simulation to account for both data and identification uncertainty. (iii) Sign restrictions are weaker than zero restrictions. This avoids the use of zero restrictions to impose identification. (iv) The sign-restriction approach uses Bayesian Monte Carlo sampling which does not require differencing of the data thereby avoiding the specification issues of whether to estimate the VAR in levels or differences (Sims, 1988).

Our analysis of the CARB countries reveals several important results. A positive shock to commodity prices lowers stock market volatility while a shock to economic policy uncertainty has a significant positive impact on realized volatility. The magnitudes of the initial impact of these two shocks are similar. Both SVAR and sign restricted VARs produce these results although the magnitude of the impacts are larger with sign restricted VAR. Sign restricted IRFs show that a shock to global economic activity has a negative impact on realized volatility as does a shock to interest rates.

The paper is organized as follows. Section 2 presents a brief overview of the relevant literature. Section 3 discusses the econometric approach in some detail, and Section 4 describes the data. Section 5 offers the empirical results while Section 6 reports robustness. Section 7 concludes the paper.

2. Literature review

We review briefly the two strands of literature in turn, the literature that analyzes the relationship between commodity prices and stock market return volatility, and the literature that explores economic policy uncertainty and its link to stock markets. The first strand of literature is very large, whereas the second strand is comparatively small. However, there is a growing amount of empirical work relating economic policy uncertainty to stock market volatility, although most empirical work still focuses on U.S. data. Economic theory postulates that an asset price is determined by its discounted cash flow (Fisher, 1930). Hence, any new information that changes the expected cash flow of an asset will affect its price. Thus, an oil price increase that affects relative input costs and future cash flows, dividends and earnings of a firm will affect its stock price (e.g., Jones and Kaul, 1996).[9] For example, Bjørnland (2009) points out that Norway, which is a net oil exporter, has benefited from oil price increases, showing temporary increases in economic growth, but Canada, also a net-oil exporter, has shown declines in economic growth.

The literature on commodity prices and stock markets is dominated by empirical research on one specific commodity and that is oil. This is due on the one hand to the important role of oil as an input in the production of many goods and services and, in the form of gasoline, its role in the expenditure budget of households, and on the other hand to the relatively large fluctuations of oil prices over time.[10] The main focus of this first strand of the literature has been on the U.S. and developed economies. There are relatively few papers that study oil-exporting countries and often, if they are included, they are generally not analyzed as a separate group. We consider for our literature review only a few selected studies that are directly relevant for our research.

Numerous articles research the bilateral relationship between commodity prices and stock market returns. Some studies focus on the transmission of prices fluctuations, whereas others focus on the transmission of volatilities from one market to another. These are often based on time-varying correlation analysis between the price or return volatility of a specific commodity or

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[9] Oil price volatility can also affect the risk premium component of the discount rate and the cash flow. Furthermore, oil price shocks may also lead to misperceptions about future inflation and hence about expected real interest rates that are used for discounting future flows (e.g., Smyth and Narayan, 2018).
[10] The history of oil price fluctuations over the past forty years is studied in Baumeister and Kilian (2016).

of a commodity price index on the one hand, and the return or return volatility of a stock market index on the other hand. Filis et al. (2011) survey the literature on time-varying dynamic conditional correlations of volatilities, where volatility of a time series is measured by some form of its general autoregressive heteroskedasticity. They present bi-variate results for crude oil prices and various stock markets of oil-importing (Germany, Netherlands and U.S.) and oil exporting (Brazil, Canada, and Mexico). Filis et al. (2011) find that lagged oil prices have negative effects in all current stock markets, with the exception of the 2008 global financial crisis when the effect is positive. The findings do not differ for oil-importing and oil-exporting countries.[11] However, the literature does not agree on this finding. A complicating feature of bi-variate analysis is that a third factor that is not controlled for may be driving relationships.

Kang et al. (2018) construct a multivariate structural VAR model with time-varying parameters that combines country-specific variables (industrial production, consumer price indexes, and short-term interest rates) with a global commodity price index and a global stock return volatility index. They find that stock market volatility and commodity prices affect each other in a gradual endogenous adjustment process. Aside from the U.S., they analyze four developing and 12 developed countries. Generally, shocks to global stock volatility cause negative effects on global commodity prices in the first year, and shocks to global commodity prices have persistent positive effects on global stock volatility, especially during the recent global financial crisis.

Smyth and Narayan (2018) review the various branches of literature on the relationship between oil prices and stock returns that use bi-variate and multi-variate methods. They focus primarily on the period since 2008. Kilian and Park (2009) is an often cited paper that uses a structural VAR model for the oil market. They model world oil production (oil supply), the price of crude oil, and world oil demand (measured by an index of global economic activity) in a VAR that includes U.S. stock returns. They conclude that 22% of the long-run variations in U.S. real stock returns are explained by oil demand and oil supply shocks together. Further, they argue that, regardless of the source of the oil shock, the impact response of stock returns is driven by fluctuations in expected real dividend growth and time-varying risk premia.[12] We discuss next the literature on the role of risk, as measured by the EPU, for stock returns.

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[11] See also Creti et al. (2013) for an extension of this type of analysis to 25 commodities and their relationship to U.S. S&P 500 stock returns.
[12] Smyth and Narayan (2018) discuss various other studies on oil prices and stock returns based on the VAR approach. Recent examples are Basher et al. (2018) focusing on major oil-exporting countries and Degiannakis et

We review a number of studies which focus on the effects of EPU on stock market volatilities in CARB countries. Kang and Ratti (2013) extend the structural VAR model of Kilian and Park (2009) by adding the economic policy uncertainty index of Baker et al. (2013).[13] Based on monthly observations over the period 1990-2011, they find that an unanticipated increase in policy uncertainty reduces real stock returns in Canada, an energy-exporting country. In a multi-country empirical study, Christou et al. (2017) examine the role of EPU on the stock market returns for six Pacific-rim countries including Australia and Canada.[14] Based on monthly observations over the period 1998 to 2014, they find that an increase in the U.S. EPU negatively (positively) affects stock market returns in Canada (Australia). The difference in results may be explained by the fact that Canada is the U.S.'s second largest trade partners, while Australia ranks far below other trading partners.

Ferreira et al. (2018) find that over the period 1996-2016, political uncertainty (measured by the EPU index) is positively and significantly related to the volatility and correlation of stock returns in the Brazilian capital market. However, they did not find a significant relationship between political uncertainty and the equity risk premium, which is likely due to two opposing forces with respect to the effect of political uncertainty on the equity risk premium in a weaker economy. As argued by Pastor and Veronesi (2013), on the one hand, a government's concern for investors' interest pulls down the risk premium, while on the other hand, the lack of clarity concerning the outcome of a government's action pushes up the risk premium. Xavier and de Vasconcelos (2018) examine whether and how EPU is related to momentum return in the Brazilian stock market. Using monthly data over the period 2001-2017, they find that local momentum is stronger in months followed by high EPU, both domestic and foreign EPU. Furthermore, foreign EPU (particularly of the United States) plays a more prominent (mostly negative) role than the country-specific EPU for the Brazilian momentum strategy.

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al. (2014) on various European stock index volatility measures. Bastianin et al. (2016) instead analyzed oil price shocks and stock return volatility in G-7 countries.

[13] On the other hand, Kang et al. (2015) use instead of the EPU index the Chicago Board of Options Exchange's VIX fear index. It measures investors' uncertainty, inferred from option prices, about both fundamental values of an asset and the behaviour of other investors over the next 30 calendar days.

[14] Unlike most previous studies, they use a panel VAR framework to capture the international transmission of different shocks including return spillovers and financial contagion. In addition, their panel VAR permits for heterogeneous coefficients which generate country-specific impulse response functions, rather than an average impulse response obtained under standard panel data approaches. To compensate for the overparameterization of their panel VAR, they use the Bayesian method proposed by Koop and Korobilis (2016), which offers a parsimonious panel VAR framework.

Liu and Zhang (2015) examine whether adding EPU to an existing volatility prediction model improves forecasting ability. Using the 5-minute high-frequency return of the U.S. S&P 500 and eight popular models of realized volatility, they find that EPU helps to predict both in-sample and out-of-sample stock market volatility. The predictability of stock volatility with EPU is explained through the reasoning of Pastor and Veronesi (2012), who argue that policy uncertainty and stock price volatilities are endogenous. Pastor and Veronesi (2013) examine the effects of political uncertainty, proxied by the EPU index of Baker et al. (2012), on stock prices and find that political uncertainty makes the stock more volatile (through an increase in the risk premium) and more correlated, and the effects are stronger in weaker economies.

The main message of the earlier studies is that the global stock markets cannot afford to ignore political dangers. At the time of this writing (mid 2019), both the VIX and EPU climbed to their near high levels of uncertainty in the wake of escalating trade tension between China and the U.S. The trade tension is just one of the myriad sources of political uncertainty rippling through the global financial markets.

3. Empirical methodology

3.1 The sign restricted model

We use a vector autoregressive (VAR) model with dynamic sign restrictions in order to identify structural shocks, based on Bayesian methods. We include the procedures described in Uhlig (2005), in particular his rejection and penalty function approach. We also employ Fry and Pagan's (2011) median target method. We will apply Uhlig's (2005) procedures but will choose the final model with the median target method of Fry and Pagan (2011).

The first step of the analysis is to consider the structural equations underlying a reduced-from VAR:

$$A_0 y_t = A(L) y_{t-1} + \varepsilon_t, \tag{1}$$

where y_t is a vector of n endogenous variables of interest, for time periods t=1, …, T; ε_t denotes the (nx1) vector of serially and mutually uncorrelated structural innovations, which have an economic interpretation as shocks. They are assumed to follow a standard normal distribution with zero mean and constant variance. The orthogonal structural innovations have to be estimated from the reduced form:

$$y_t = A_0^{-1} A(L) y_{t-1} + e_t, \tag{2}$$

with e_t a vector of VAR errors such that $A_0 e_t = \varepsilon_t$. The reduced form VAR errors, e_t , have no economic interpretation as they are correlated with each other. In order to identify the n^2 parameters in A_0 one has to impose enough restrictions on this matrix to be able to identify the structural shocks. This process allows recovering the relationships between reduced form shocks e_t and structural shocks ε_t, which is given by $A_0 e_t = \varepsilon_t$. Identification is necessary to carry out impulse response function analysis. The identification of A_0 usually requires at least n(n-1)/2 restrictions in order to identify the elements of A_0. Often, recursive structures (Cholesky decompositions) or zero restrictions are used for contemporaneous relationships between the structural shocks in period t and the variables in y_t, based on information lags or nominal rigidities found in previous studies. It is also possible to impose restrictions that last many time periods, so-called long-run restrictions. Another alternative is to impose sign restrictions for the effects of shocks on a specific variable only over a certain number of time periods. Uhlig (2005) shows how structural VAR models can incorporate prior beliefs about the signs of the impact of certain shocks, as suggested by theoretical models. It would be difficult to impose sign restrictions directly on the coefficient matrix of the model. Therefore, they are imposed ex-post on a set of orthogonalized impulse response functions to see whether the responses are consistent with the imposed sign restrictions. Thus, Uhlig (2005) argues that this procedure makes explicit what restrictions are used for judging whether impulse response functions produce reasonable results. In addition to specifying the sign of the response of a variable to a shock, one has to choose for how many time periods the sign restriction applies and what variables are restricted. Hence, one imposes a joint set of dynamic sign restrictions.

Uhlig's (2005) method identifies structural shocks using a rejection method applied to a reduced-from VAR model that is estimated with Bayesian methods, using a flat Gaussian-inverse Wishart prior distribution for the reduced-from parameters.[15] As implemented in R, the size of the shock is one standard deviation and only one shock of interest is identified at a time by a set of sign restrictions imposed. The Markov chain Monte Carlo (MCMC) routine stops once enough draws have been found that satisfy the sign restrictions or the maximum number of draws is reached. The method is based on a certain, user-specified, number of draws from the posterior distribution and a specified number of sub-draws for each posterior draw to generate an impulse

[15] Baumeister and Hamilton (2015) show that informative priors work only in very special circumstances.

vector and the candidate impulse responses to which a rejection algorithm is applied. This involves calculating the impulse responses and an orthogonal impulse vector that is drawn randomly from the unit sphere that maps the loading of the shock onto the variables. This vector is decomposed based on so-called "Givens" rotations. Impulse responses are then checked to see if they match the imposed signs for every restricted period. Uhlig's (2005) algorithm checks whether the impulse response functions have the appropriate sign. The above sub-draws generate a number of impulse response vectors for each posterior draw. His algorithm finds an impulse vector by minimizing a function that penalizes sign restriction violations. Next, an impulse vector is selected that minimizes the total penalty for the restricted variables at all restricted horizons. Minimization is carried out over the unit sphere of the penalty function. The routine, as implemented in R, stops once a sufficient number of accepted draws is reached. Also, the procedure in R currently allows only one shock to be fully identified at a time for a set of restrictions only. Mountford and Uhlig (2009) provide an extension of the penalty function approach for dealing with multiple shocks simultaneously. Furthermore, the number of rejected draws provides an indication of the number of other models that may fit the data.

Often, results have been presented by taking the posterior median response function, e.g., Uhlig (2005). However, summarizing the responses by the median response reflects the distribution across models and not, as necessary, the sampling uncertainty. In other words, the median impulse response does not, in general, correspond to the impulse responses of a single model. Therefore, we follow Fry and Pagan's (2011) suggestion to pick, instead of a median response, a single impulse vector and the corresponding model that is closest to the median response. This is Fry and Pagan's (2011) median-target method. It finds the single best draw for the impulse vector by minimizing the sum of squared standardized gaps between the impulse responses given the test rotation and the sign restricted responses of the model that is tested.[16]

3.2 VAR specification and sign restrictions imposed

We select for our VAR the following variables: real global economic activity (denoted "gea") to reflects global business cycle fluctuations and to proxy for the global demand for commodities

[16] Furthermore, Fry and Pagan (2011) explain why variance decompositions carried out in order to assess the contribution of a specific structural shock to fluctuations and forecast-errors is generally flawed in sign restricted VARs of the type that we analyse here. See also Kilian and Lütkepohl (2013, Ch. 13).

in general;[17] the country-specific commodity price index in constant US dollars ("comprice"), weighted by the importance of the included commodities in global economic production; the country-specific economic policy uncertainty index ("epu"); a country-specific short-term interest rate ("rate") that reflects monetary and fiscal government policies; and country-specific realized stock market volatility ("RV"). All variables are treated as endogenous. Data are monthly observations.

Table 1 shows the sign restrictions for the impulse response functions. The sign restrictions are imposed on months 1 through 6.[18] A positive shock to gea is assumed to have a positive impact on gea and comprice and a negative impact on epu and RV. A positive shock to comprice is assumed to have a negative impact on gea and RV. The impact that commodity prices have on RV for commodity exporting countries is difficult to determine a priori since higher commodity prices are beneficial to the commodity producing sectors but not beneficial to the non-commodity producing sectors. The assumption that comprice has a negative impact on RV is based on preliminary IRF analysis that indicates a better fit based on the Pagan-Fry impulse responses than those obtained assuming commodity prices have a positive impact on RV. For commodity producing countries higher commodity prices increase cash flows which should increase stock market prices and lower stock market volatility. A shock to epu is assumed to have a positive impact on itself and RV. A positive shock to rate has a positive impact on itself and a negative impact on RV. Interest rates affect the discount rate used to value stocks. Higher interest rates are often indicative of tighter monetary policy which lower stock prices and stock market volatility.

VARs with sign restrictions are estimated using 24 lags, a constant in the model and 48 steps for the impulse response functions. IRFs are calculated using 200 draws from the posterior and

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[17] Kilian and Park (2009) include the global production of oil in their structural VAR of the oil market. Hence, they model oil supply along with oil demand, which allows them to identify the source of oil price shocks. This is not feasible for the various country-specific commodities that we consider, in part due to a lack of appropriate production data. Moreover, we are not interested in the sources of the commodity price shocks, and we follow instead an approach similar to Wong (2015), among others, looking at oil price shocks without exploring their origins in supply or demand shifts. Also, Kilian and Park (2009) argue for the oil market that, regardless of the source of the oil shock, the impact response of stock returns is driven by fluctuations in expected real dividend growth and time-varying risk premia.

[18] We glean the signs of the various effects from previous studies. In particular, we rely on: Schwert (1989), who studies U.S. historic stock volatility and its association with various economic and financial activities; Paye (2012), who explores the forecastability of U.S. S&P500 stock returns with macroeconomic variables; and Kang et al. (2018), who use a VAR with time-varying parameters and global stock volatility and global commodity prices for various countries, including the CARB countries. We should note that we focus instead on country-specific stock volatility and country-specific commodity prices and in addition include the EPU.

200 sub-draws for each posterior draw. The first 1000 accepted draws are kept. IRFs are plotted along with the 68% confidence bands which is standard in this type of analysis. The restrictions are assumed to apply from the first period (point of impact) until the sixth period. In the literature this is known as setting KMIN=1 and KMAX=6.[19] Section 6 presents some results regarding the robustness of these assumptions.

4. Data

The variables used in the analysis consist of realized stock market volatility, global economic activity, commodity prices, economic policy uncertainty, and short term interest rates. Monthly realized stock market volatility is obtained by summing squared daily returns within each month (rv_t) and then applying the natural log transformation as in Paye (2012, pp. 529-530), $RV_t = \ln((12rv_t)^{(1/2)})$. The measure of realized volatility is the natural logarithm of annualized volatility. Daily stock market data in local currency are obtained from Yahoo Finance.

The index of global economic activity, gea, is the one used by Kilian (2009) with updates and corrections available from his website (https://sites.google.com/site/lkilian2019/research/data-sets; last accessed 22 August 2018). This measure of global economic activity is: "an index of cyclical variation in global real economic activity based on percentage changes in representative single-voyage ocean shipping freight rates available for various bulk dry cargoes, consisting of grain, oilseeds, coal, iron ore, fertilizer, and scrap metal, further differentiated by the size of the vessel and the shipping route. These rates of growth are averaged and adjusted for U.S. CPI inflation and for the long-run trend in the cost of the shipping. This approach effectively controls for increases in the size of vessels over time." (Kilian and Zhou, 2018, 57).

The commodity price data is specific to each country. For Canada, the Bank of Canada commodity price index is used (https://www.bankofcanada.ca/rates/price-indexes/bcpi/). This index is a chain Fisher price index of the spot or transaction prices in U.S. dollars of 26 commodities produced in Canada and sold in world markets. For Australia, the RBA Index of Commodity Prices is used (https://www.rba.gov.au/statistics/frequency/commodity-prices/2019/). The index measured in US dollars includes 21 major commodities that are exported from Australia. The commodity price index for Brazil is obtained from ITAU (https://www.itau.com.br/itaubba-

[19] We use the "VARsignR" package written for R: https://rdrr.io/cran/VARsignR/f/vignettes/VARsignR-vignette.Rmd, written by Christian Danne; last accessed 8 May 2019.

en/economic-analysis/our-economic-series/ici-commodities). ITAU is Latin America's largest Corporate & Investment Bank. The index consists of 16 major export commodities in agriculture, base metals, and energy. The index is in US dollars and the commodities are weighted according to their importance in global economic production. For Russia, Brent oil prices in $US are used to proxy commodity price movements. For each commodity price, real values are obtained by dividing by the US consumer price index. The variable comprice denotes the natural logarithm of the commodity price index.

Country specific data on economic policy uncertainty come from the Economic Policy Uncertainty organization (https://www.policyuncertainty.com/). In the case of Canada, for example, the EPU index is constructed by searching 5 Canadian newspapers and the Canadian newswire for terms referencing uncertain, uncertainty, economic or economy. Policy related terms include 'policy', 'tax', 'spending', 'regulation', 'central bank', 'budget', and 'deficit'. These search terms are then aggregated into an index. Full details on the calculation of the EPU index are provided on their website. The variable epu denotes the economic policy uncertainty index. Short term interest rates (rate) are obtained from the Federal Reserve Economic Database (https://fred.stlouisfed.org/). All of data ends in June of 2018 but the start date for each country varies depending upon data availability.[20]

Table 2 presents descriptive statistics for the data of the CARB countries used. There are 402 monthly observations for Canada. The gea variable has the largest range. The coefficient of variation, which applies to data with positive mean values, indicates that the interest rate variable has the most variation while the commodity price variable has the least. Each of the variables exhibit non-normality as indicated by the W (Shapiro-Wilk) test. For Australia, Russia and Brazil, the variable gea has the largest coefficient of variation (Tables 3, 4 and 5). Russia has the highest mean value of RV (3.348) while Canada has the lowest (2.408).

Figure 1 plots the data for Canada. Global economic activity rose considerably between 2000 and 2008. The upward trend was broken by the economic recession of 2008-2009. After the recession, economic activity fell to new lows in 2015 before rebounding. The Canadian commodity price index shows a similar pattern to gea. Canadian short term interest rates have declined over the sample period. Realized volatility was highest in the late 1980s and the peak of the 2008-2009

[20] See the footnotes to Tables 2 to 5 for exact start dates.

financial crises. Economic policy uncertainty was range bound up until 2008-2009 before trending higher.

In the case of Australia, Australian commodity prices have remained strong even when global economic activity weakened (Figure 2). Australian interest rates have mostly trended down after 2008-2009 although the financial crisis did not impact in Australia to the extent that it did in North American and Europe. Realized volatility was highest in 2008 and economic policy uncertainty shows no obvious trend.

Russian short-term interest rates and realized volatility have been trending down over the sample period while economic policy uncertainty has been climbing higher (Figure 3). Brazilian short term interest rates and realized volatility have trended down while commodity prices and economic policy uncertainty have increased (Figure 4).

5. Empirical results

SVAR impulse responses for each country are calculated using the variable ordering gea, comprice, epu, rate, and RV, i.e., a recursive Cholesky ordering with contemporaneous exclusion restrictions only for the effects of structural shocks. The lag length for each variable in the VAR is set at 24, which is consistent with Kilian and Park (2009). The choice of 24 lag lengths accounts for seasonality, ensures the residuals are random, and the roots of the characteristic polynomial are less than unity. A block recursive structure is used where gea has no contemporaneous correlation with other variables, comprice responds contemporaneously to shocks to itself and shocks to gea. epu is assumed to respond to gea and comprice shocks immediately but with a delay of at least one period to rate and RV. In other words, epu responds only to sustained movements in rate and RV and not to every one-period change by itself. The interest rate variable, rate, responds contemporaneously to shocks to itself and shocks to gea, comprice and epu. RV responds contemporaneously to shocks to itself and shocks to each of the other variables.

For Canada, a one-standard deviation positive shock to comprice has a negative and significant impact on RV for three months (Figure 5). A positive shock to epu has a significant positive impact on RV for two months. This is expected since an increase in economic policy uncertainty creates an option value to weighting to invest in stocks (Pastor and Veronesi, 2012). The impact of a one-standard-deviation shock to epu is almost double that of a comprice shock (in absolute terms). Figure 6 reports the results of impulse responses calculated using sign restrictions.

Confidence bands for 68% coverage are shown. The pattern of sign restrictions is described in Table 1. A positive shock to gea lowers RV and this impact is significant for 5 months. A positive shock to commodity prices decreases RV and this effect is significant for 6 months. A positive shock to epu has a positive impact on RV and this impact is significant for 8 months. A positive shock to interest rates has negative and statistically significant on RV for 12 months. Notice that the magnitude of an initial shock to epu on RV is similar in magnitude to an initial shock to commodity prices.

The IRFs from the SVAR for Australia, like in the case of Canada show that a shock to epu has a positive and significant initial impact on RV while a shock to commodity prices has a negative and significant impact on RV (Figure 7). In addition, a shock to gea has a positive and significant impact on RV. The IRFs from sign restrictions show that a positive shock to gea has a negative and significant impact on RV for 5 months (Figure 8). A commodity price shock has a statistically significant negative impact on RV for 5 months. A positive shock to epu has a positive and significant impact on RV for 10 months. As in the case of Canada, the magnitudes of the initial impacts of an epu shock and a commodity price shock on RV are similar.

The SVAR impulse responses for Russia indicate that a positive shock to commodity prices initially reduces RV while a positive shock to epu initially increases RV (Figure 9). Sign restricted IRFs indicate that a positive shock to gea has a negative and significant impact on RV for 5 months (Figure 10). A positive shock to commodity prices decrease RV for five months. A positive shock to epu has a positive significant impact on RV for five months.

In the case of Brazil, the SVAR IRFs indicate that shocks to global economic activity, commodity prices and economic uncertainty have initial significant impacts on RV (Figure 11). Sign restricted IRFs show these effects to be more pronounced (Figure 12).

In summary, there are some common results across the CARB countries regarding how realized stock market volatility responds to shocks to global economic activity, commodity prices, and economic policy uncertainty. For both the SVAR IRFs and sign restriction IRFs a positive shock to commodity prices has a significant negative impact on RV and a positive shock to economic policy uncertainty has a significant positive impact on RV. The magnitudes of the initial impact of these two shocks are similar. A shock to gea reduces RV as does a shock to interest rates. Notice that in each case, the Fry-Pagan responses are very close to the median IRFs indicating a good fitting sign restricted VAR. The IRFs from the sign restricted approach are more pronounced than those from SVAR.

This sign restricted VAR analysis also offers some insight on how short term interest rates respond to shocks in global economic activity, commodity prices and economic policy uncertainty. Since short term interest rates are affected by monetary policy these results can be interpreted as how monetary policy in each country responds to these shocks. A shock to gea has no significantly significant impact on Canadian or Australian short term interest rates (Figures 6 and 8). A shock to gea has a negative and significant impact on Russian short term interest rates for between 2 and 9 months (Figure 10). For Brazil, a shock to gea has a negative and significant impact on short term interest rates around months 6-8 (Figure 12). A shock to commodity prices has no significant impact on Canadian, Australian or Brazilian interest rates and a negative impact on Russian interest rates (months 4-7).[21] A shock to economic policy uncertainty has no significant impact on Canadian or Brazilian interest rates, a negative and significant impact on Australian interest rates (months 10 to 20), and a positive impact on Russian interest rates (between 2 and 10 months). In summary, Australian and Canadian monetary policy is not very responsive to shocks in global economic activity, commodity prices or economic policy uncertainty whereas Russian monetary policy is responsive.

6. Robustness

The IRFs from the sign restricted VAR were estimated assuming the restriction were in place from month one to month six. Figure 13 shows IRFs from a one standard deviation shock to economic policy uncertainty computed with the restrictions in place from month one to month three. For each country the results are similar to what is observed when the restrictions are imposed from month one to month six. Figure 14 shows IRFs from a one standard deviation shock to commodity prices computed with the restrictions in place from month one to month three. For each country the results are similar to what is observed when the restrictions are imposed from month one to month six. Doubling the number of draws from the posterior distribution or doubling the number of accepted draws does not change the IRFs results.

[21] Monetary policy frameworks in both Australia and Canada are centered on an inflation target. Therefore, temporary factors such as changes in gasoline prices do not warrant a monetary policy response.

7. Conclusions

This paper studies the impact that commodity prices and economic policy uncertainty have on realized stock market volatility in the CARB (Canada, Australia, Russia, and Brazil) countries. The CARB countries are major commodity exporters and commodity price shocks are expected to have a significant impact on stock market volatility. What is not known, however, is how the impact of a commodity price shock on stock market volatility compares to an economic policy uncertainty shock. These impacts are analyzed using both SVARs and sign restricted VARs.

The analysis reveals several important results. A positive shock to commodity prices lowers realized stock market volatility while a shock to economic policy uncertainty has a significant positive impact on realized volatility. The magnitudes of the initial impact of these two shocks are similar. Both SVAR and sign restricted VARs produce these results although the magnitude of the impacts is larger with sign restricted VARs. Sign restricted VARs are thus important in establishing the impact of EPU shocks and commodity price shocks on realized volatility is larger than those found under more conventional identification methods. Sign restricted IRFs show that a shock to global economic activity has a negative impact on realized volatility as does a shock to interest rates. These results are consistent with the growing literature showing that economic policy uncertainty shocks impact stock market returns and volatility. These results also deepen the understanding of the importance of commodity prices for realized stock market volatility in commodity exporting countries.

These results have several practical implications. First, since economic policy uncertainty can be influenced by domestic government policy a country can lessen the impact of economic policy uncertainty shocks on stock market volatility by pursuing better more transparent economic decision making. Second, in the case of the CARB countries positive shocks to commodity prices reduce stock market volatility. The concern is that negative shocks to commodity prices (large drops in commodity prices) will increase stock market volatility. For investors in CARB countries adverse commodity price shocks can be offset by hedging.

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Table 1. Sign restrictions.

From =>	gea	comprice	epu	rate
To:				
Gea	+	-		
comprice	+	+		
epu			+	
rate				+
RV	-	-	+	-

Table 2. Descriptive statistics for Canada.

	gea	comprice	epu	rate	RV
nbr.val	402	402	402	402	402
Min	-164.000	4.817	28.537	0.376	1.459
Max	188.000	6.006	449.624	13.818	4.400
Range	352.000	1.189	421.087	13.442	2.941
median	-9.035	5.288	107.426	4.226	2.341
mean	-0.438	5.326	126.397	4.648	2.408
SE.mean	2.939	0.011	3.681	0.172	0.024
std.dev	58.926	0.222	73.799	3.456	0.483
coef.var	-134.520	0.042	0.584	0.744	0.201
skewness	0.879	0.291	1.522	0.793	0.872
kurtosis	1.017	-0.434	2.738	-0.270	1.072
normtest.W	0.941	0.981	0.869	0.911	0.958
normtest.p	0.000	0.000	0.000	0.000	0.000

Notes: Monthly data from January 1985 to June 2018.

Table 3. Descriptive statistics for Australia.

	gea	comprice	epu	rate	RV
nbr.val	246	246	246	246	246
min	-164.000	3.139	25.662	1.700	1.558
max	188.000	4.475	337.044	7.900	4.129
range	352.000	1.337	311.382	6.200	2.571
median	-9.525	3.744	86.711	4.815	2.508
mean	5.861	3.695	99.418	4.419	2.526
SE.mean	4.603	0.025	3.731	0.102	0.027
std.dev	72.197	0.399	58.513	1.596	0.422
coef.var	12.318	0.108	0.589	0.361	0.167
skewness	0.561	0.109	1.481	-0.142	0.565
kurtosis	-0.367	-1.229	2.275	-0.870	0.687
normtest.W	0.958	0.929	0.867	0.949	0.981
normtest.p	0.000	0.000	0.000	0.000	0.002

Notes: Monthly data from January 1998 to June 2018.

Table 4. Descriptive statistics for Russia.

	gea	comprice	epu	rate	RV
nbr.val	258	258	258	258	258
min	-164.000	1.787	12.399	4.200	1.978
max	188.000	4.108	400.017	45.300	5.186
range	352.000	2.321	387.618	41.100	3.208
median	-10.700	3.162	99.726	8.710	3.251
mean	4.957	3.151	118.087	11.389	3.348
SE.mean	4.397	0.034	4.764	0.466	0.037
std.dev	70.622	0.553	76.515	7.487	0.602
coef.var	14.248	0.175	0.648	0.657	0.180
skewness	0.608	-0.266	1.153	2.037	0.512
kurtosis	-0.227	-0.828	1.084	4.228	-0.006
normtest.W	0.956	0.966	0.908	0.758	0.979
normtest.p	0.000	0.000	0.000	0.000	0.001

Notes: Monthly data from January 1997 to June 2018.

Table 5. Descriptive statistics for Brazil.

	gea	comprice	epu	rate	RV
nbr.val	282	282	282	282	282
min	-164.000	2.808	12.690	6.140	2.423
max	188.000	4.124	676.955	84.574	4.819
range	352.000	1.316	664.265	78.434	2.396
median	-8.405	3.364	109.546	14.804	3.213
mean	5.023	3.422	132.406	17.540	3.259
SE.mean	4.044	0.020	5.439	0.587	0.025
std.dev	67.915	0.340	91.329	9.855	0.423
coef.var	13.520	0.099	0.690	0.562	0.130
skewness	0.622	0.250	2.145	2.489	0.919
kurtosis	-0.034	-1.018	6.670	9.797	1.554
normtest.W	0.961	0.960	0.816	0.789	0.953
normtest.p	0.000	0.000	0.000	0.000	0.000

Notes: Monthly data from January 1995 to June 2018.

Figure 1. Plots of the data for Canada.

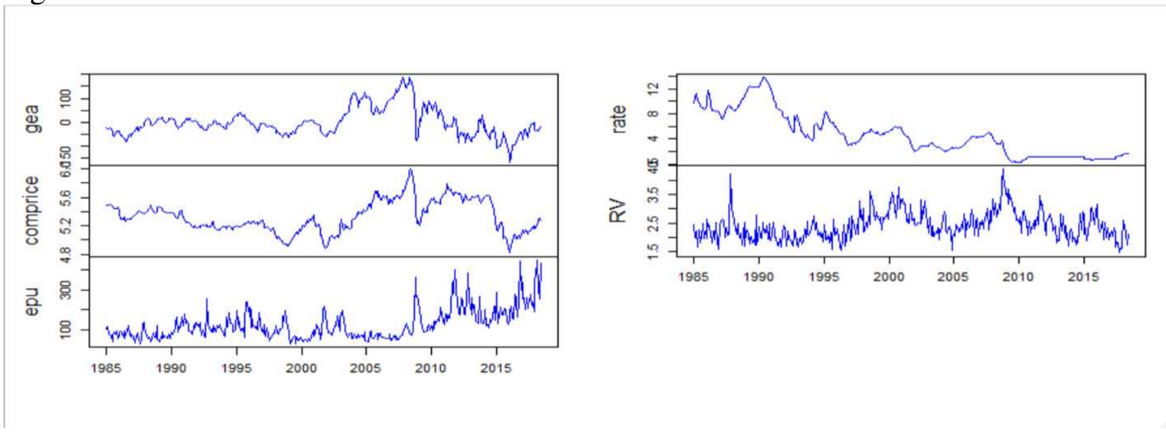


Figure 2. Plots of the data for Australia.

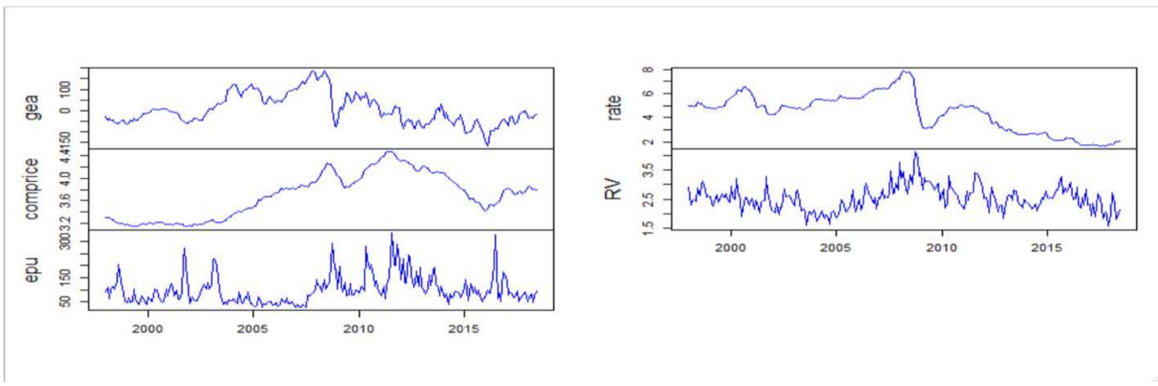


Figure 3. Plots of the data for Russia.

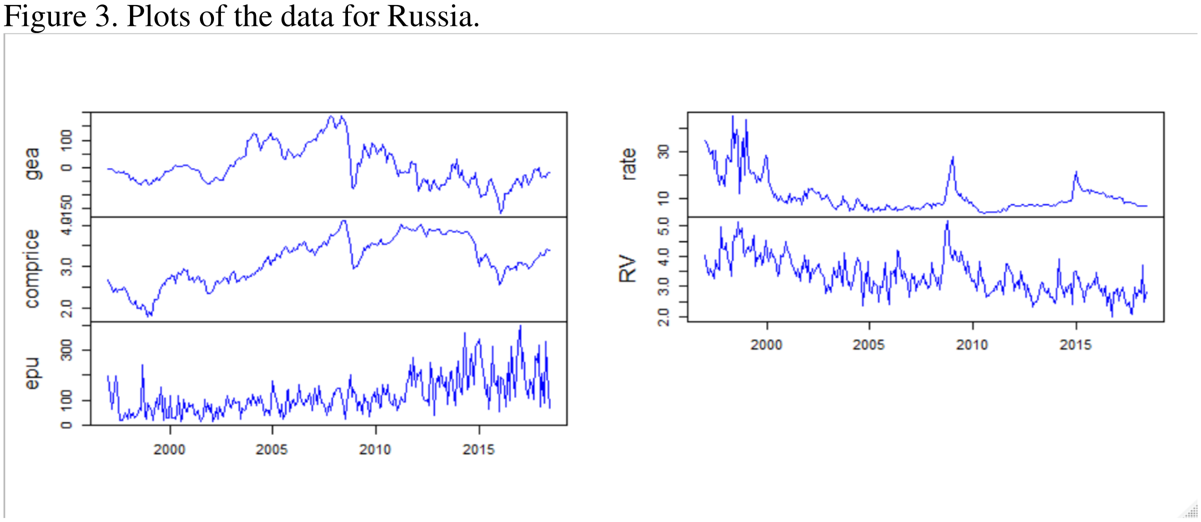


Figure 4. Plots of the data for Brazil.

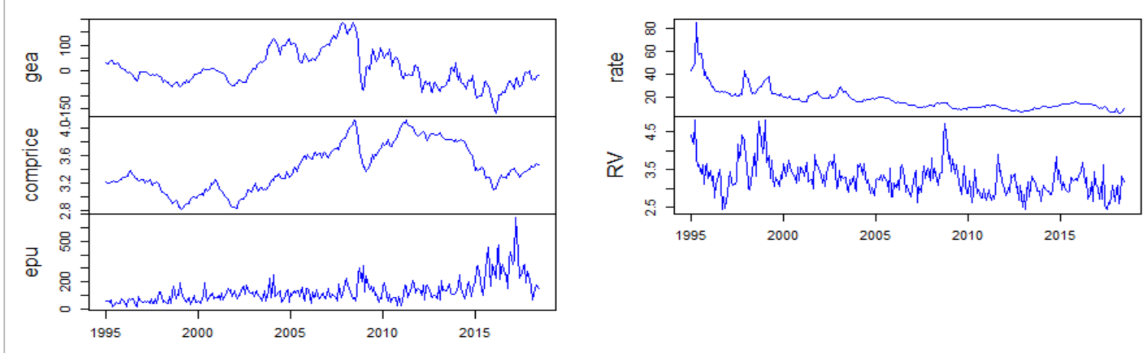


Figure 5. SVAR impulse responses for Canada.

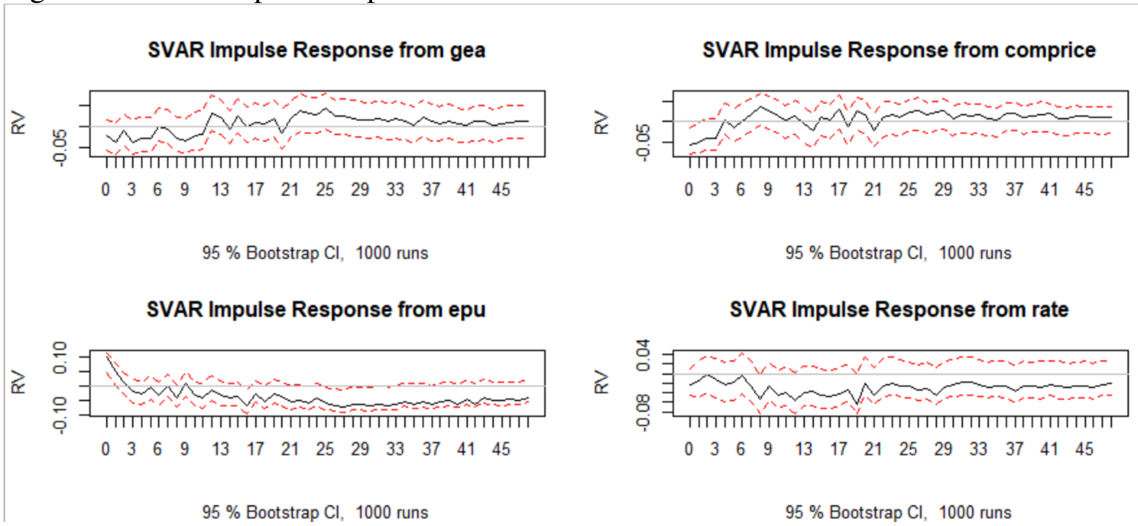
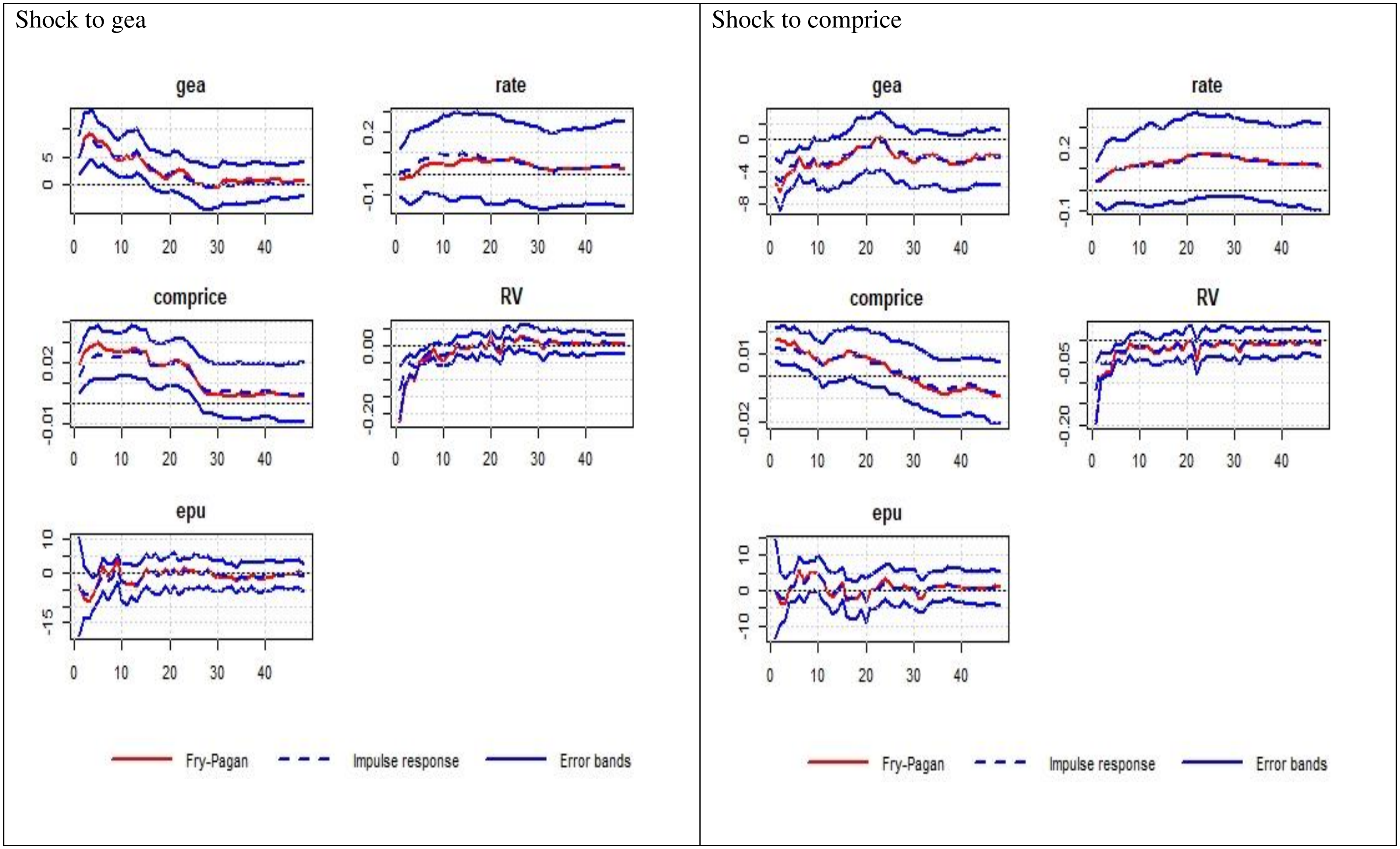


Figure 6. Sign restriction impulse responses for Canada.



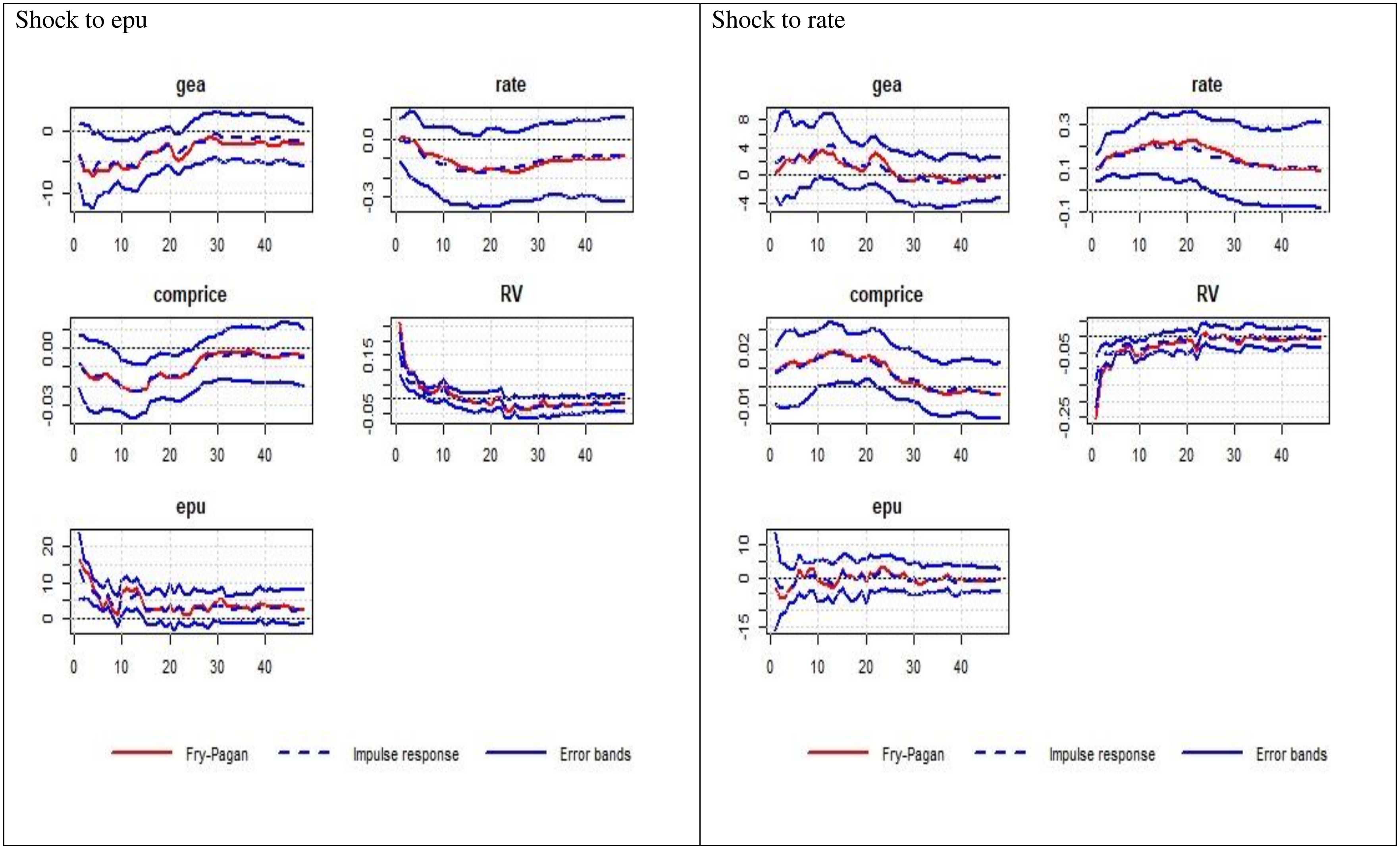

Shock to epu
Shock to rate
gea
rate
comprice
RV
epu
Fry-Pagan
Impulse response
Error bands

Figure 7. SVAR impulse responses for Australia.

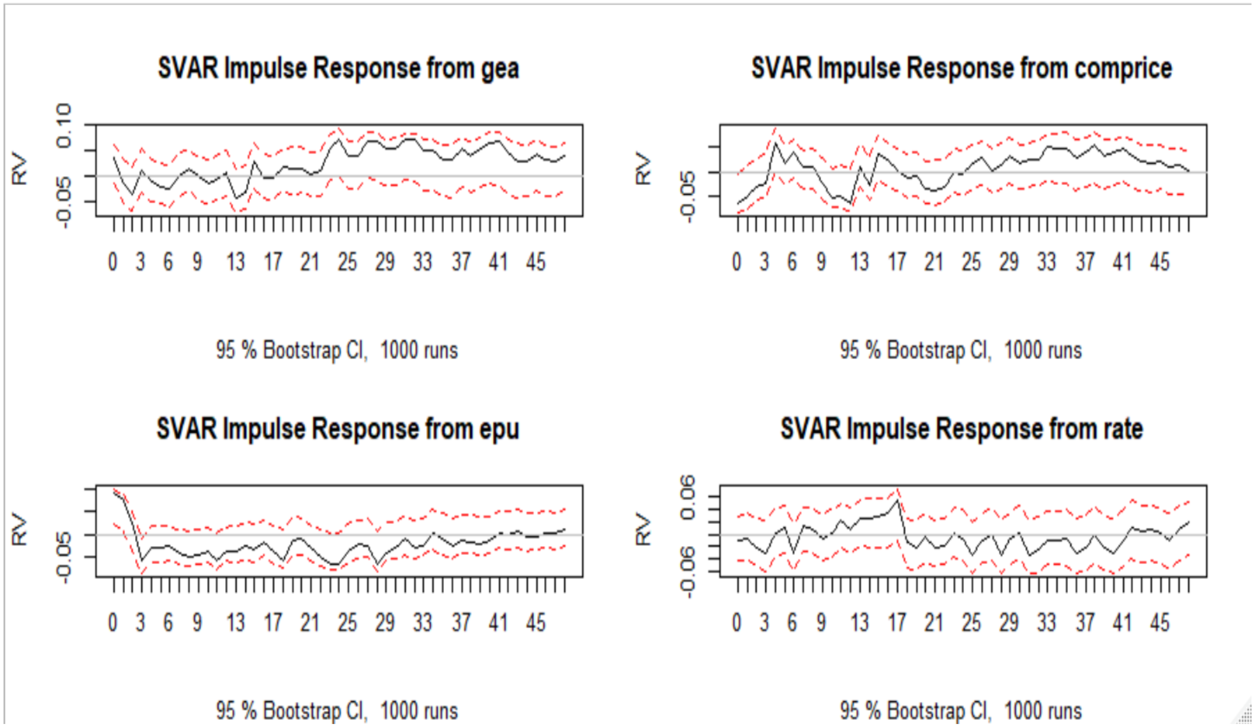
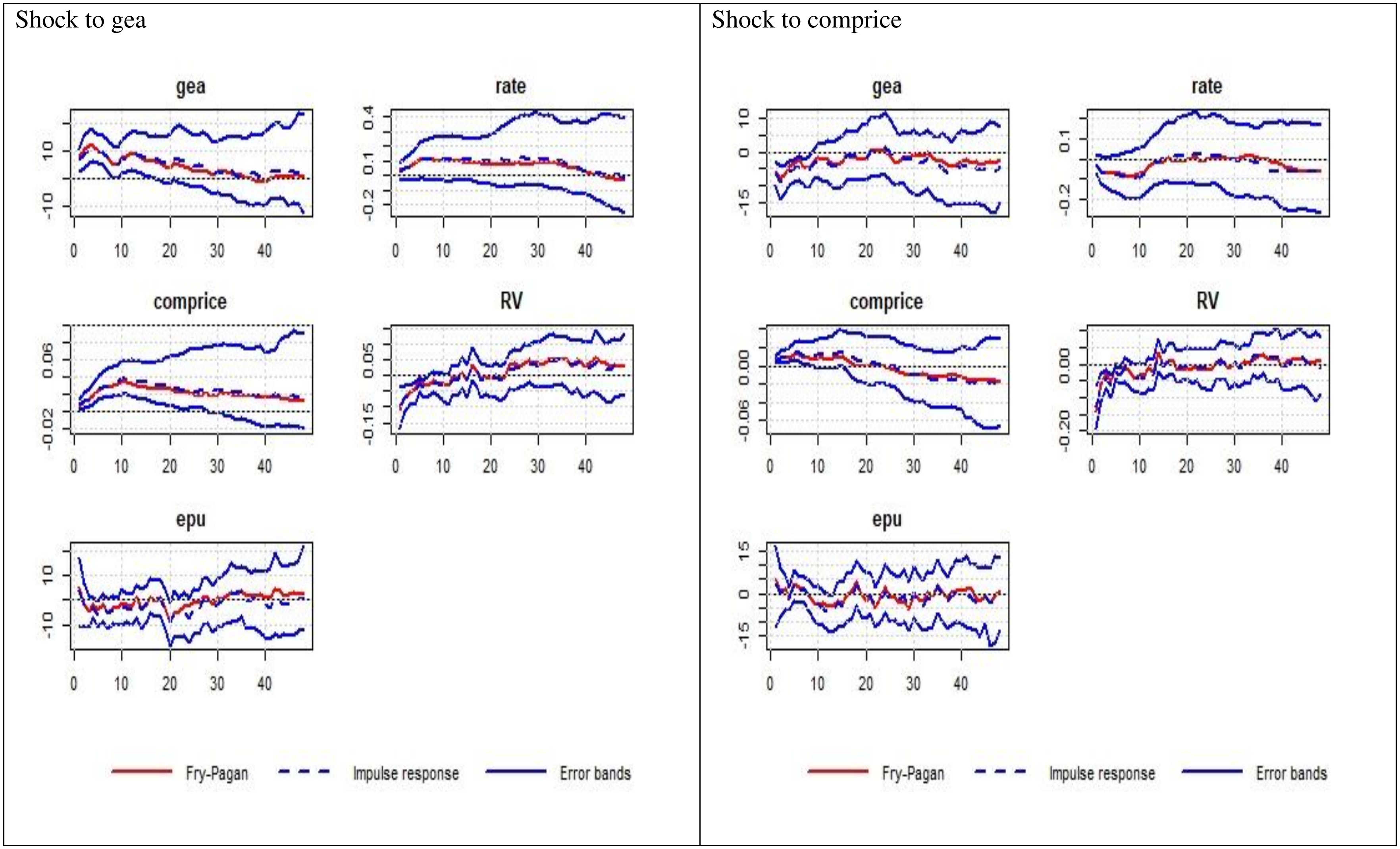
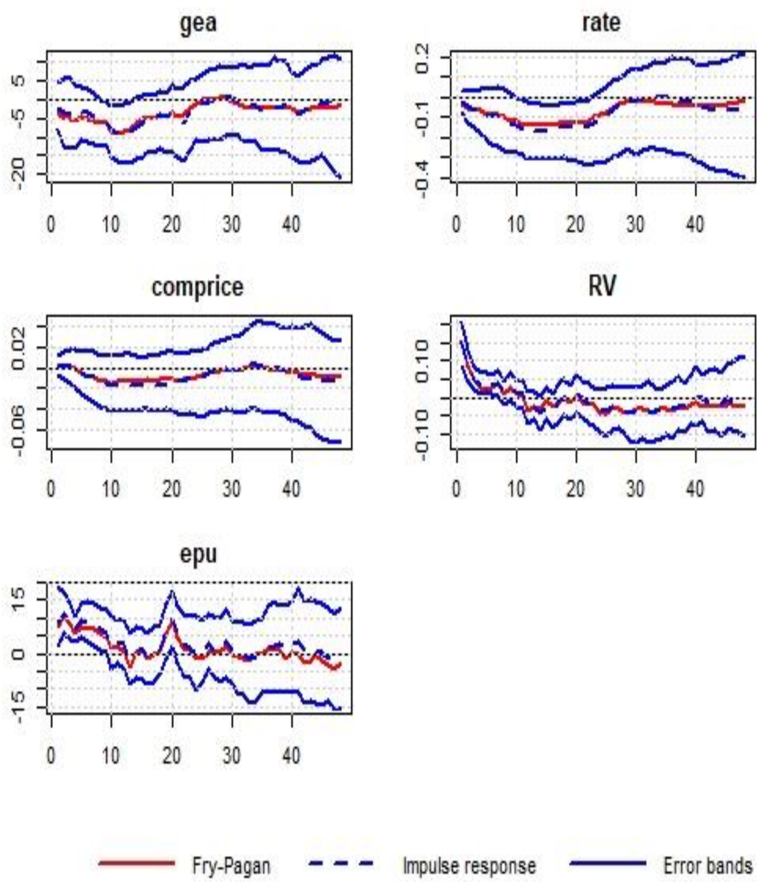


Figure 8. Sign restriction impulse responses for Australia.



Shock to epu



Shock to rate

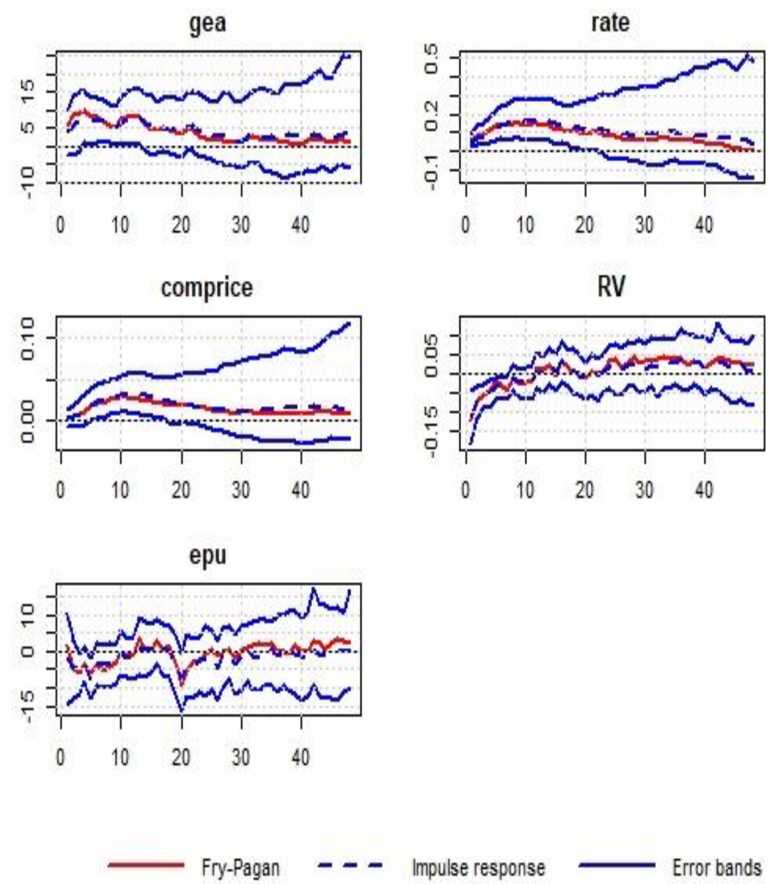


Figure 9. SVAR impulse responses for Russia.

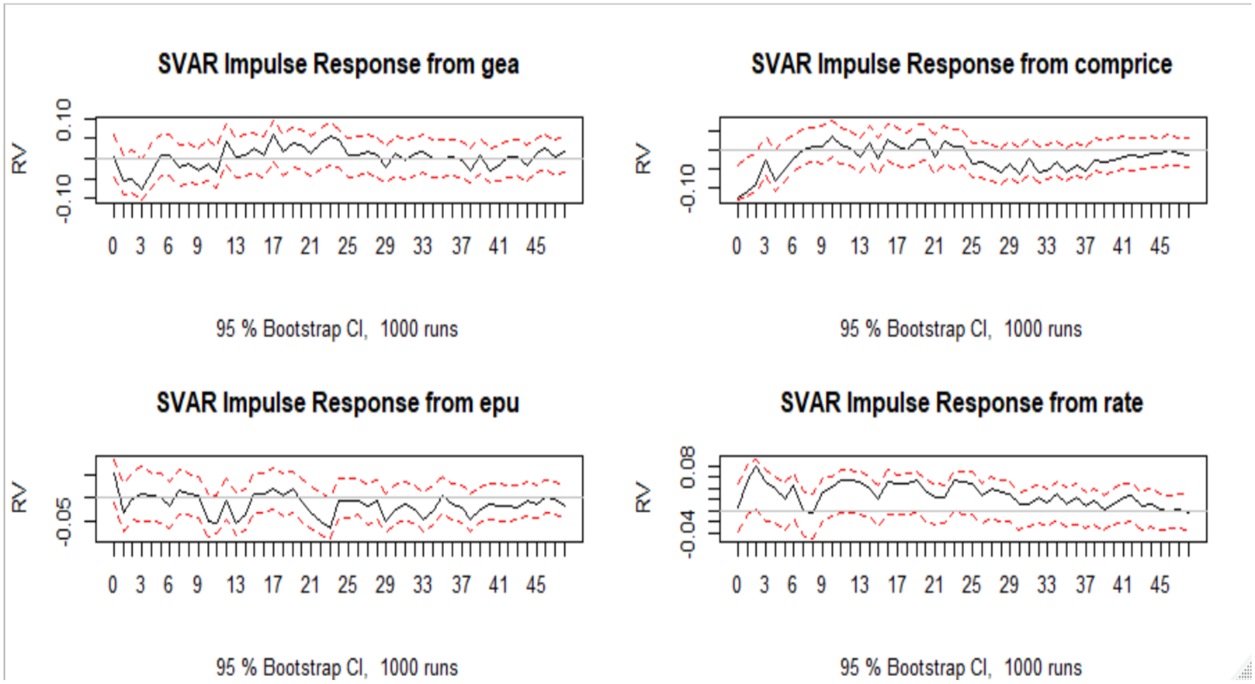
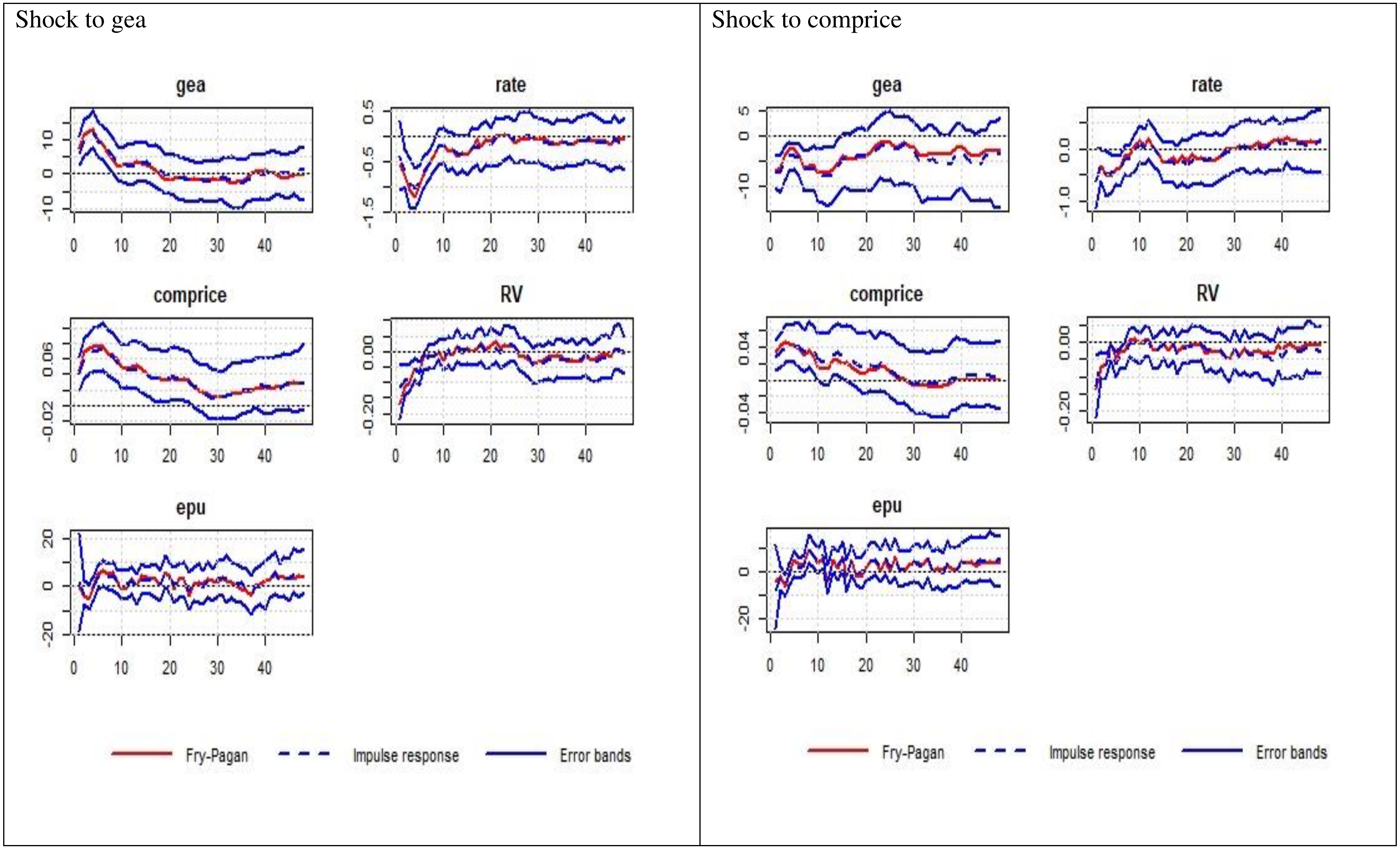
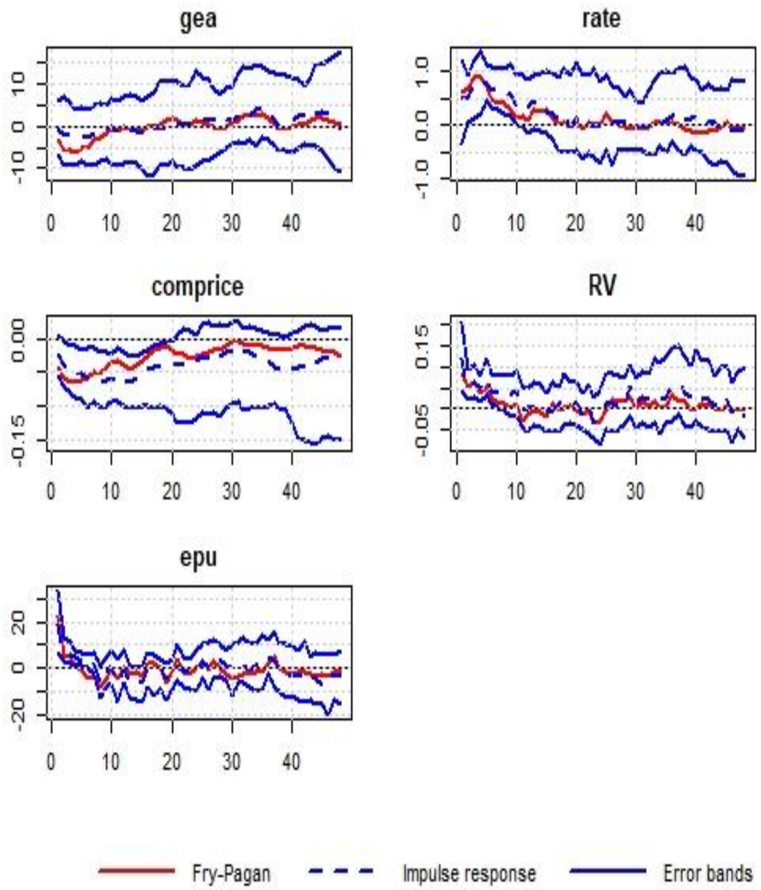


Figure 10. Sign restriction impulse responses for Russia.



Shock to epu



Shock to rate

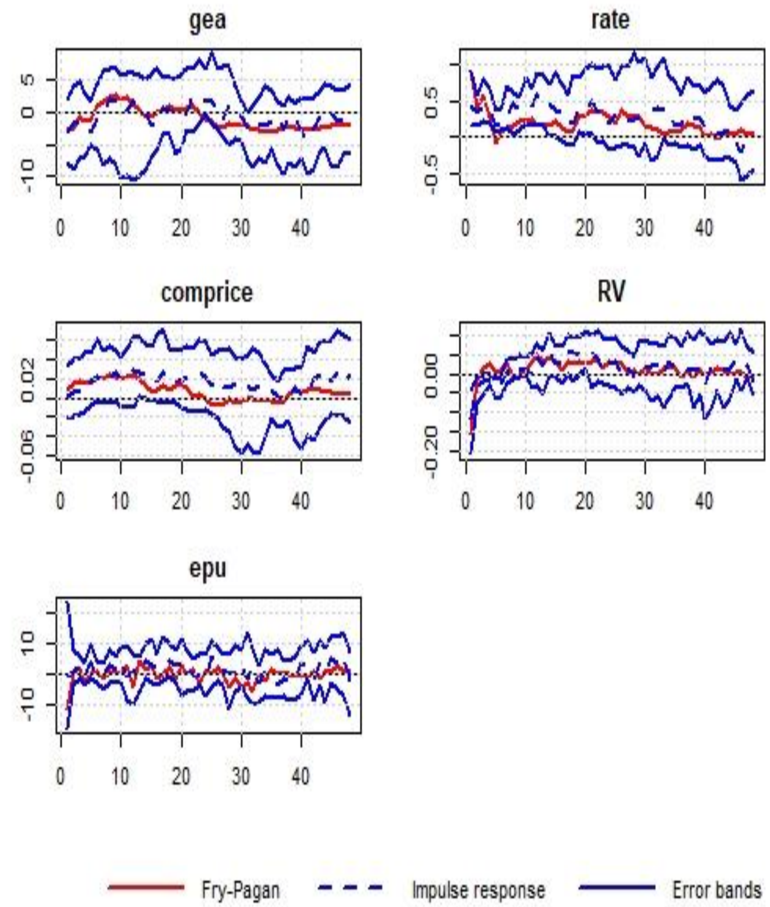


Figure 11. SVAR impulse responses for Brazil.

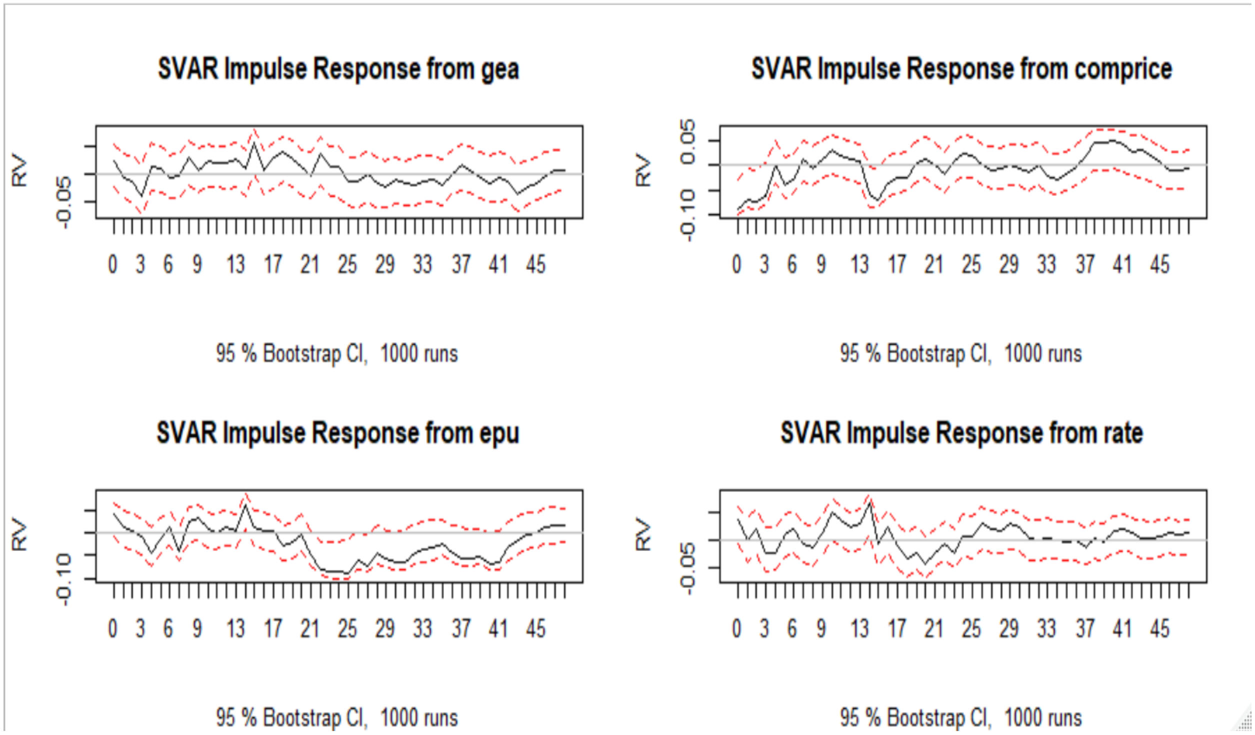
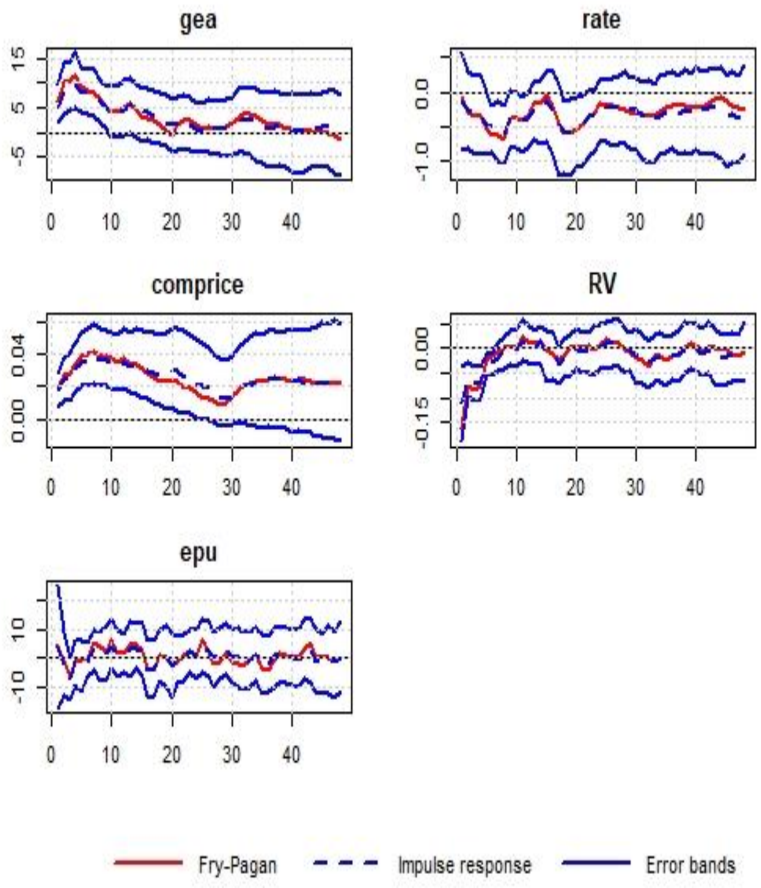
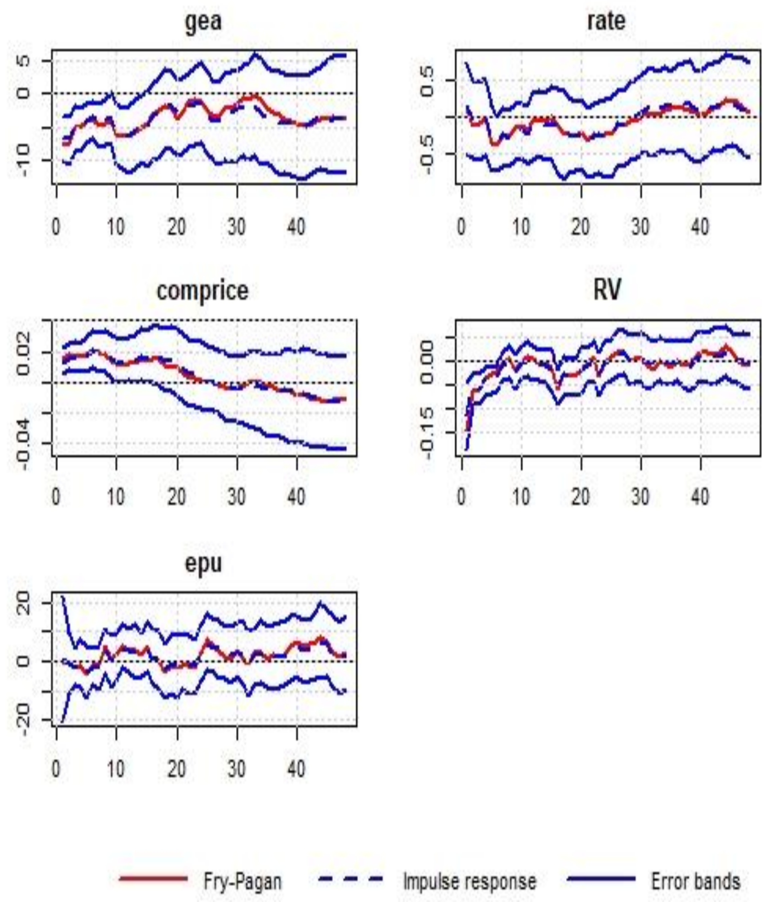


Figure 12. Sign restriction impulse responses for Brazil.

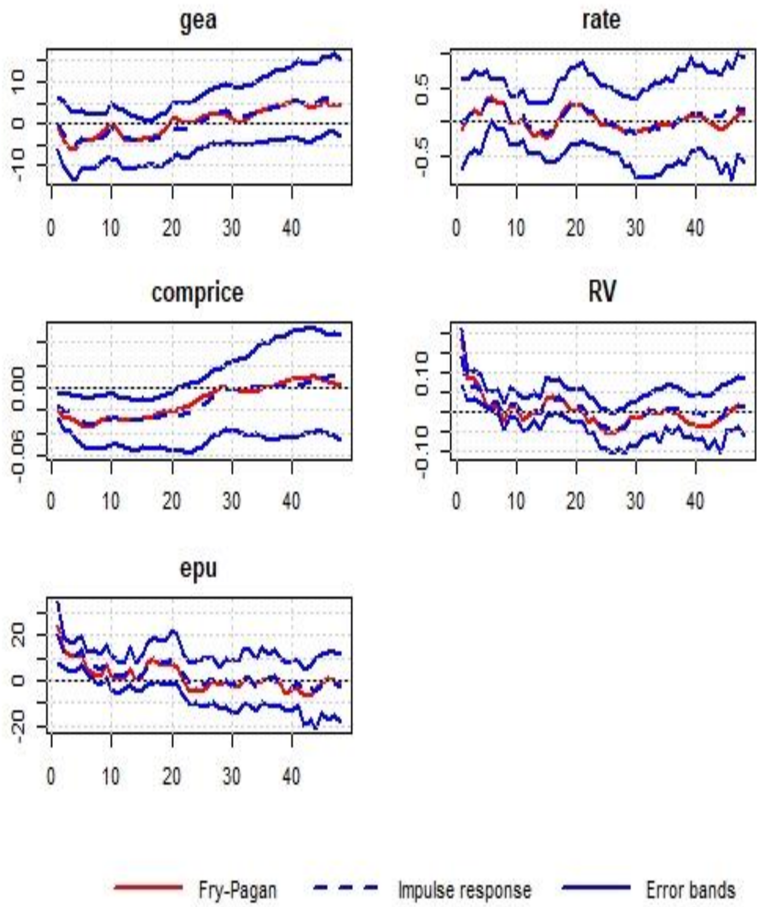
Shock to gea



Shock to comprice



Shock to epu



Shock to rate

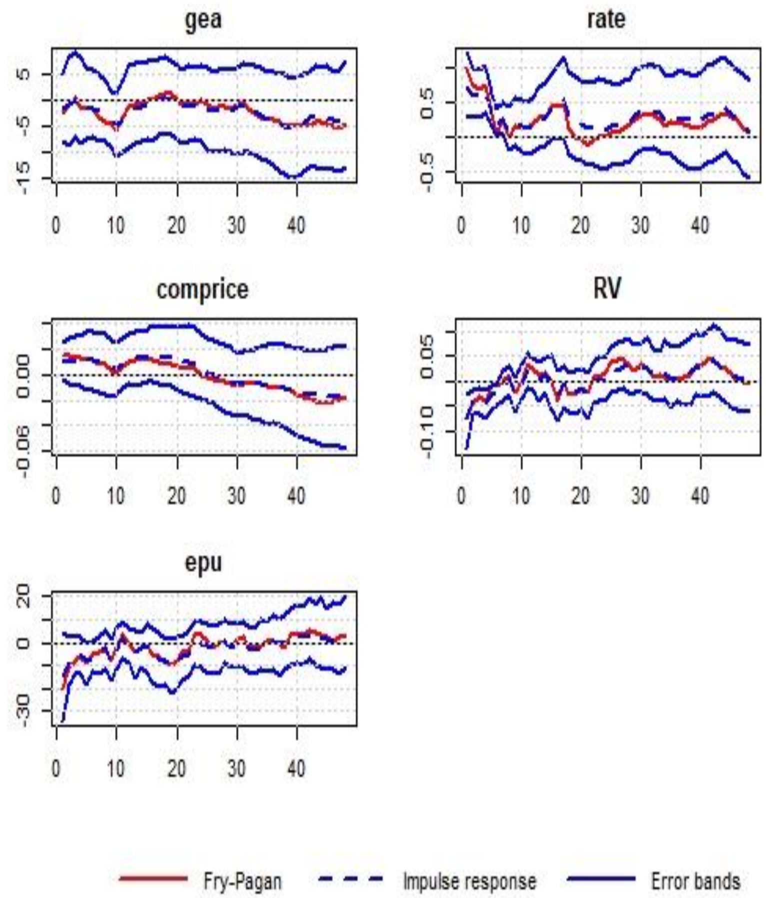
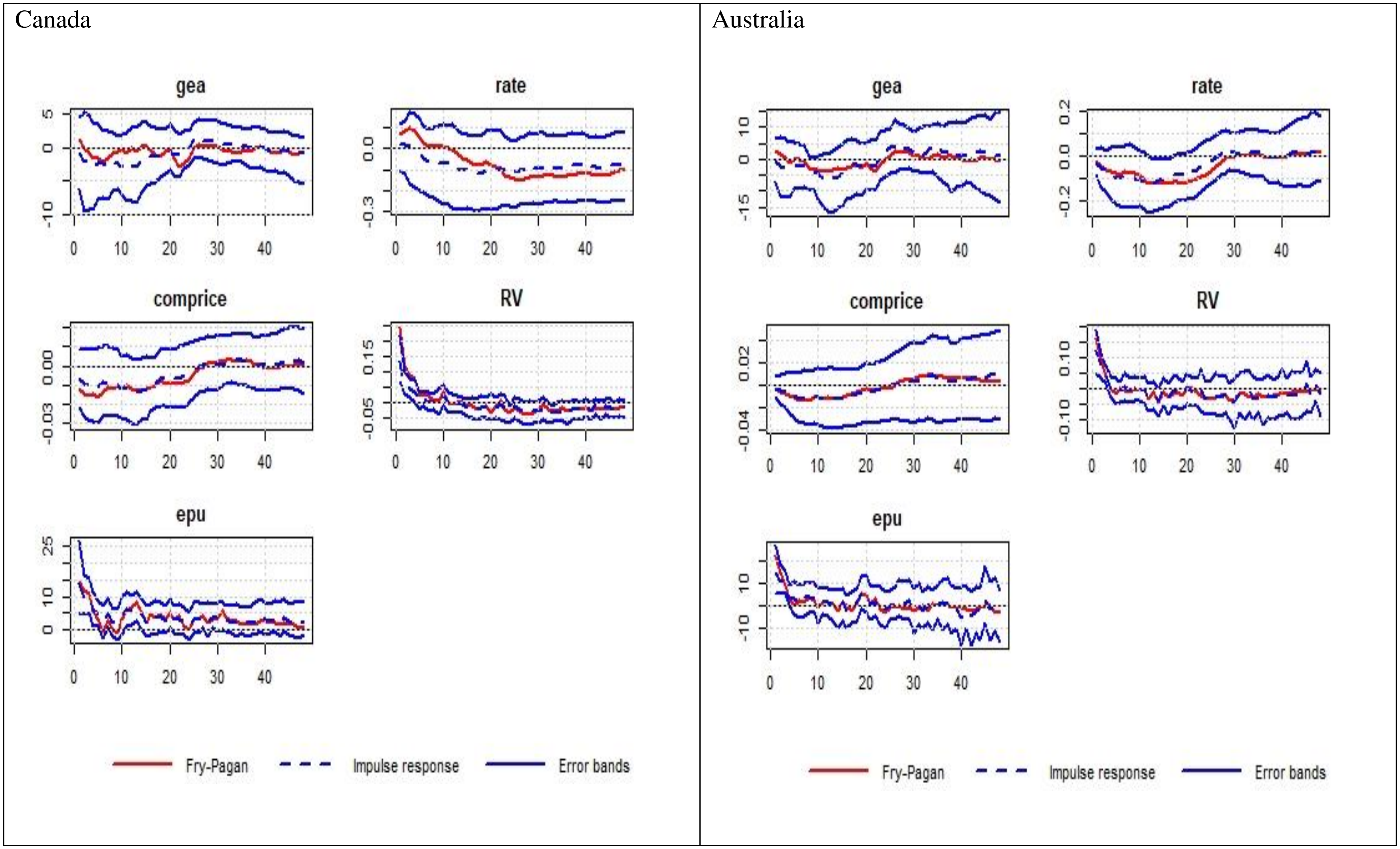
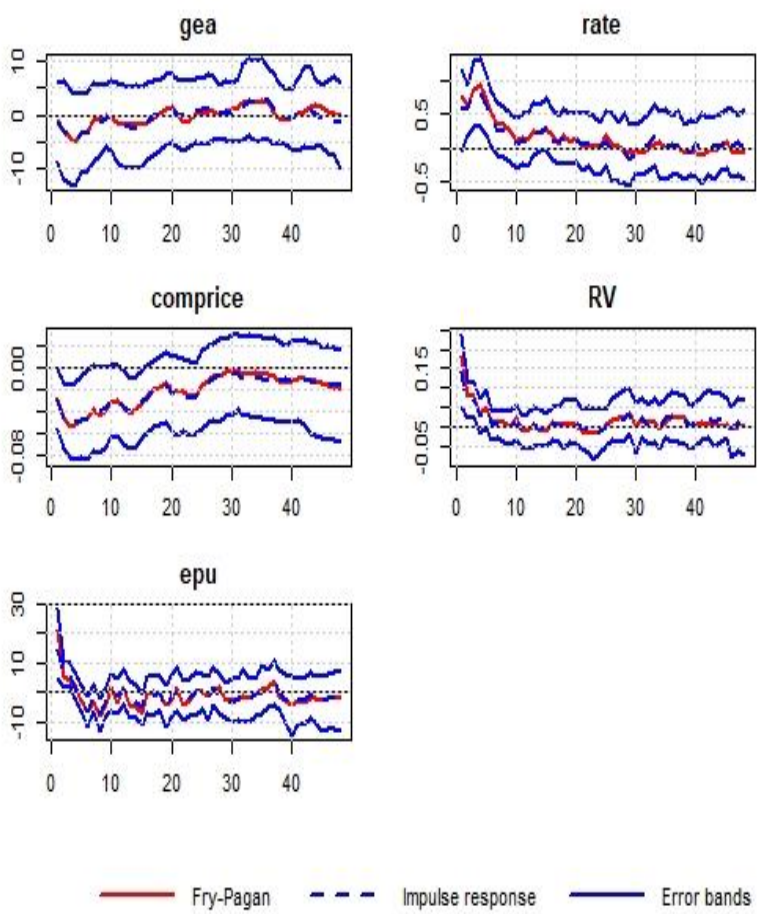


Figure 13. Sign restriction impulse responses (KMAX = 3) for shock to EPU.



Russia



Brazil

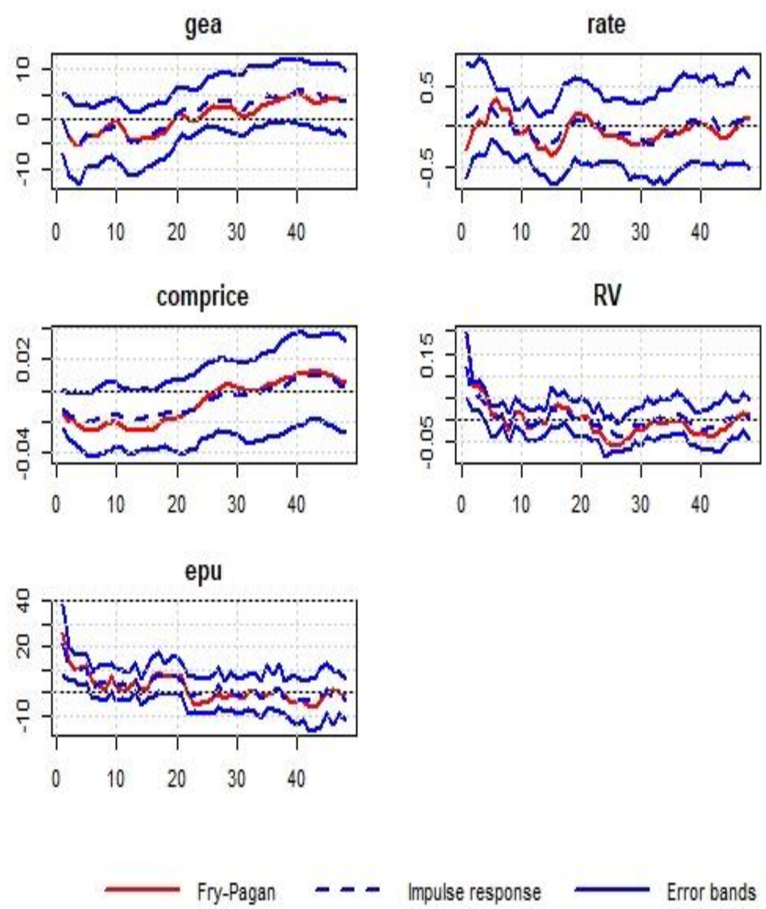
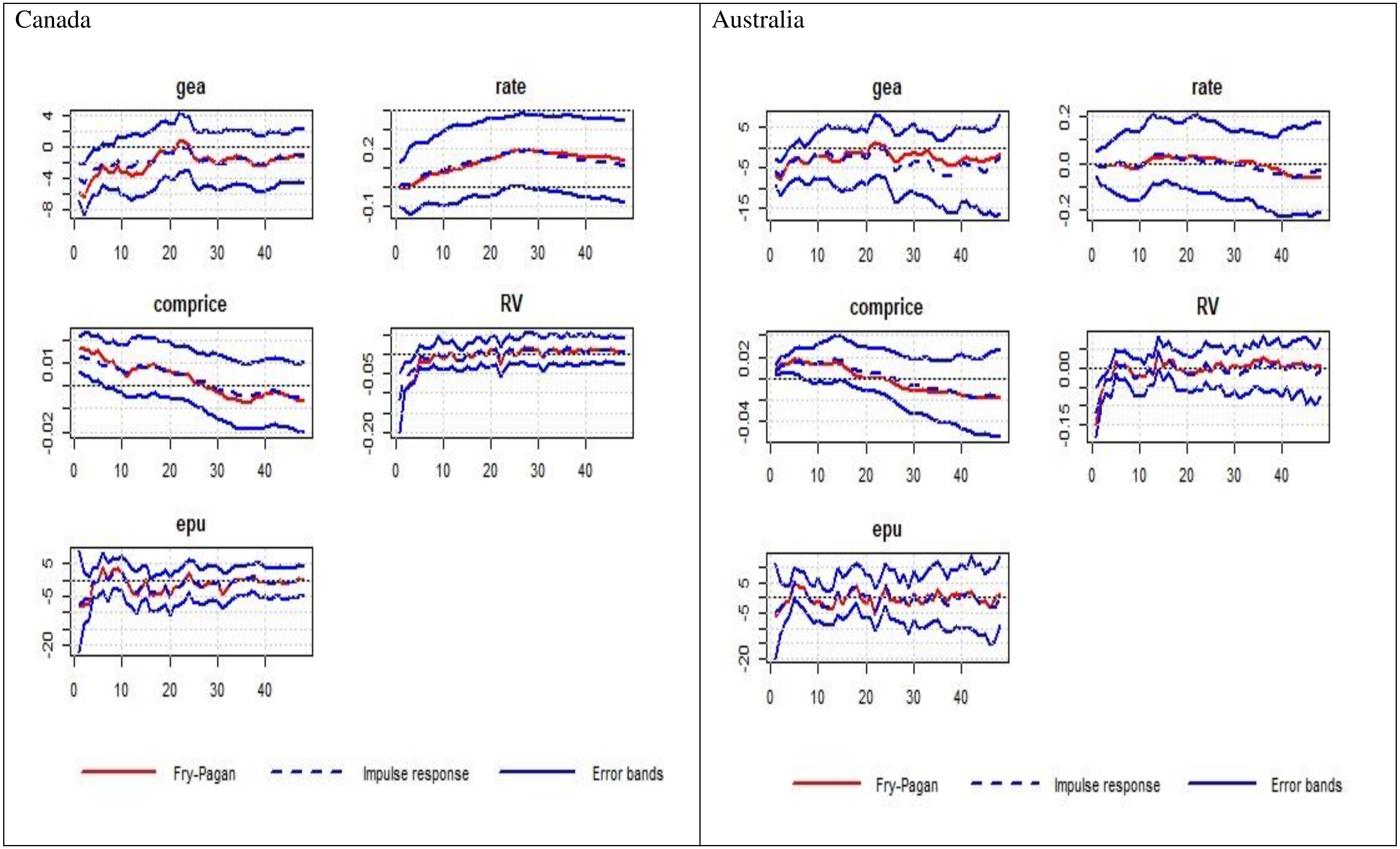
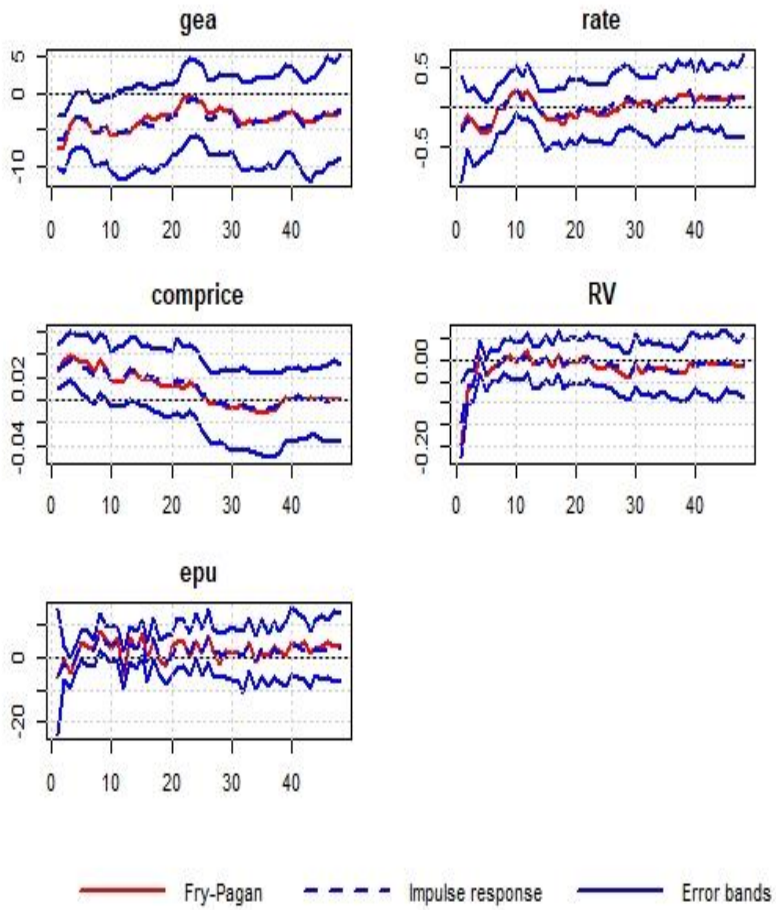


Figure 14. Sign restriction impulse responses (KMAX = 3) for shock to commodity prices.



Russia



Brazil