The effects of global shocks on small commodity-exporting economies: Lessons from Canada

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This paper presents a structural dynamic factor model of a small commodity-exporting economy, using Canada as a representative case study. Combining large panel data sets of the global and Canadian economies, we first use sign restrictions to identify those relevant demand and supply shocks that explain most of the volatility in real commodity prices. Next, we proceed to quantify the dynamic effects of these shocks on a wide variety of macro variables for Canada. We are able to reproduce all the main stylized features at business-cycle frequencies documented in the literature on these economies. These include a Dutch disease effect which has proven difficult to find in models where the underlying sources of sudden changes in commodity price are not properly identified. Our results are fairly robust to alternative identification schemes of the shocks and to several sensitivity checks.

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As stressed by Kilian (2009), not all oil price shocks should be considered alike when assessing the implications of sudden changes in this price on the economy. Fluctuations in the real price of oil may have very different dynamic effects on macroeconomic aggregates depending on their underlying sources (de-

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mand/supply, global/specific shocks). Moreover, it is essential to address the problem of reverse causality from these aggregates to the oil price in order to get correct estimates of the magnitude and persistence of these effects. Accordingly, a growing number of recent contributions to this literature have adopted structural VAR (SVAR) models to identify relevant shocks to the global crude oil market, including those coming from the global business cycle (see Kilian and Murphy, 2012; Lippi and Nobili, 2012). However, while most of these studies have focused on how different shocks impinge on oil-importing economies (especially on the US), much less attention has been devoted to analyze their effects on exporters of oil and other primary commodities.

Our aim here is to fill this gap. Using a structural dynamic factor model framework, we investigate the effects (at business-cycle frequencies) of different global shocks driving real commodity prices (not all oil) on a large set of macro variables in a prototypical small commodity-exporting economy (henceforth SCEE). In particular, our focus lies on the Canadian economy. The choice of this case study is dictated by the fact that Canada is a general commodity exporter, and not only an oil exporter, as well as by the availability of data on this economy, something which is not so common for other SCEEs. This facilitates carrying out our analysis in a data-rich environment where the effects and propagation mechanisms of the different shocks can be studied in a comprehensive way.

One convenient starting point for the rest of the paper is to briefly summarize the main predictions (hereafter denoted as features) which have been highlighted in the literature about the effects of these shocks on SCEEs.

(I) *External balance effect*, according to which trade and current account balances in SCEEs are usually positively correlated with their terms of trade (i.e., the ratio of export and import prices) and the world prices of exported commodities in real terms. When real commodity prices go up, the revenue from exports exceeds the cost of imports, leading to an accumulation of foreign assets (or to a reduction of foreign debt). For the specific case of oil-exporting economies, Kilian, Rebucci and Spatafora (2009) find that this effect is almost fully due to changes in the trade balance of primary commodities

(II) *Commodity currency effect*, whereby real exchange rates in SCEEs are strongly correlated with commodity prices in real terms.[1] Thus, as documented by Chen and Rogoff (2003) and Cashin, Cespedes and Sahay (2004), an increase in real commodity prices results in an appreciation of the real exchange rate

(III) *Spending effect*, meaning that windfall income gains from commodity exports are partially spent inside SCEEs, driving up domestic demand. For example, Spatafora and Warner (1999) find in general a strong positive effect of the terms of trade shocks on all aggregate domestic spending components: consumption, investment and government expenditures

(IV) *Dutch disease effect*, whereby raising real commodity prices, again via an appreciation of the real exchange rate, lead to a fall in competitiveness and thus to a decrease in the output of the non-commodity tradable sectors in SCEEs, in contrast to the nontradable and commodity sectors where output grows (see Corden and Neary, 1982).[2] Despite its popularity, it is somewhat surprising that there is a striking lack of agreement on the relevance of this effect (see, e.g., Spatafora and Warner (1999) and Stijns (2003) for unfavorable and favorable evidence, respectively).[3]

Most of the empirical literature documenting these features suffers, however, from two limitations. First, in general, fluctuations in world commodity prices

[1]Hereafter, real exchange rate is defined as a price of foreign consumption in terms of consumption in the domestic economy, i.e. $RER_t = NER_t \cdot P_t^*/P_t$, where NER_t is a nominal exchange rate in terms of domestic currency per unit of foreign currency, P_t^* and P_t are, respectively, foreign and domestic consumer price indices.

[2]The terms 'non-commodity tradable goods' and 'manufacturing goods' are used interchangeably in this paper.

[3]Notice that most of the literature on the Dutch disease has focused on its long-run effects rather than adopted a business cycle perspective, as we do here. Hence, a more accurate interpretation of this phenomenon in our setup would be an adjustment with Dutch-disease-like properties.

are treated as exogenously determined and reverse causality problems are ignored. Secondly, even in those studies where these problems have been properly addressed, the above-mentioned effects have been often analyzed separately rather than jointly.[4] In view of these shortcomings, our goal is to use an empirical methodology that is free from these criticisms to check if it allows us to reproduce simultaneously all the previous effects in our representative SCEE, including the controversial Dutch disease effect.

As already mentioned, Canada becomes an attractive case study because its exports cover manufactured goods and a wide variety of primary commodities, not only energy resources, as has been the focus of the previous literature on this topic. In effect, although energy products represent 23.5 percent of total merchandise exports in 2010, other basic products and materials related to agriculture sector, forestry and mining account for about 40 percent of those exports. An additional advantage is the availability for this country of a fairly rich quarterly data set covering a long period, 1975q1-2010q4. Combining this information with other rich data sets capturing aggregate changes at the worldwide level which affect the performance of the Canadian economy is particularly useful to tackle the reverse causality problem. In this respect, it is worth stressing that, despite the fact that the US is the main trade partner of Canada, exclusive focus on the US economy, rather than on worldwide variables, may lead to misleading results when identifying shocks. For instance, it may underestimate a global commodity demand shock, like the one starting from the late-1990s, which was driven to a large extent by developments in East and South Asia rather than in the US.

Our proposed methodology combines two strands of the empirical literature dealing with large panel data sets. First, in line with Kilian (2009) and Kilian and Murphy (2012), we use the SVAR methodology to identify the main global shocks driving up the world commodity prices. More precisely, we consider three

[4]Examples are Kilian, Rebucci and Spatafora (2009) and Jaaskela and Smith (2011) who use SVAR methodology and carefully designed measures of global activity to document, respectively, the external balance effect in a large set of fuel-exporting countries, and the commodity currency effect in the Australian economy.

common factors which respectively explain the volatility of three large sets of macro variables at the worldwide level: global economic activity, global inflation and a world commodity price index in real terms.[5] Our benchmark identification scheme for these shocks relies on sign restrictions (combined with bounds on some elements of the impact matrix as in Kilian and Murphy (2012)), supplemented for sensitivity purposes by a more conventional recursive scheme. Three main global shocks are identified during the sample period: (i) a global demand shock (GD), (ii) a global non-commodity supply shock (GS), and (iii) a global commodity-specific shock (GC).

Examples of positive and negative GD shocks include the global expansions and recessions that have taken place since the mid-seventies. Regarding GS shocks, the surge of information and communication technology innovations, productivity growth in emerging economies or the deepening of trade liberalization in the 1990s could be associated to positive (favorable) shocks whereas sudden increases in inflation expectations or natural disasters affecting non-commodity exporting countries provide examples of negative (unfavorable) shocks. Finally, negative GC shocks could be associated with increasing world commodity prices, whose origin can range from wars or natural disasters in commodity-producing countries to unexpected changes in precautionary demand for these commodities in fear of future supply shortages or to speculative trading.

Next, we analyze the propagation mechanisms of these shocks on the Canadian economy, allowing explicitly for dynamic interactions with the global economy in a data-rich environment. A natural empirical framework for this exercise is provided by structural dynamic factor models (SDFM) (Stock and Watson, 2005; Forni et al., 2009) and factor-augmented VARs (FAVAR) (Bernanke and Boivin,

[5]Notice that the set of variables in our model differs slightly from that in Kilian (2009) and Kilian and Murphy (2012). Our model includes global inflation but lacks global commodity supply, given that supply data for many primary commodities are not so readily available as for the oil market. Thus, our GC shocks should be interpreted as accounting for both unexpected changes in the supply and demand of primary commodities which are orthogonal to the changes explained by the remaining two shocks. Yet, this is unlikely to be restrictive, since these authors find that the relative contribution of the oil supply shocks (including those originated in Canada) to fluctuations in real oil price is minor.

2003; Bernanke, Boivin and Eliasz, 2005; Boivin and Giannoni, 2007; Mumtaz and Surico, 2009) estimated by modern Bayesian techniques. Both methodologies turn out to be rather convenient to analyze the effect of a small number of structural shocks on a large set of macroeconomic variables often exceeding the number of observations. Thus, in line with (Boivin and Giannoni, 2007; Mumtaz and Surico, 2009), we construct a recursive SDFM model containing two blocks of common factors: (i) one corresponding to the global economy, and (ii) another pertaining to the SCEE economy.

Our main findings can be summarized as follows. First, we confirm the results obtained by Kilian (2009) and Kilian and Murphy (2012) about real commodity prices being driven by a variety of global shocks rather than by any specific one. More specifically, we find that GD and GC shocks play a more important role than GS shocks in explaining the volatility of these prices. Secondly, focusing exclusively on these two shocks, we find that a rise in commodity prices generated by either a positive GD shock or a negative GC shock generates a positive effect on external balances and commodity currency effects. The fact that the source of shocks does not matter for these two effects (features I and II in the previous list) may explain why they have been found in standard reduced-form specifications where fluctuations in real commodity prices are assumed to be exogenous. However, regarding the other two effects (features III and IV), we find that the source of the shocks matters a lot. For example, the manifestation of the Dutch disease effect at business cycle frequencies in the Canadian manufacturing sector is detected when the rise in the price of commodities is due to a negative GC shock. This is not the case under a positive GD shock which stimulates real output and real expenditures uniformly across industries and sectors. Given that GD shocks contribute significantly to explain commodity price volatility, this result illustrates why it is hard to detect such an effect when the source of shocks are ignored.

This rest of the paper is organized as follows. Section I presents the main features of our modeling approach for a SCEE, including the identification of the global shocks, a brief description of the data and the basics of the estimation strategy. Section II reports the empirical results. In particular, using the dynamic responses of the global and Canadian economies to a positive GD shock and a negative GC shocks, we illustrate the specific channels that give rise to the different stylized features in our specific SCEE. Section III provides a sensitivity analysis of our results regarding subsample estimation, alternative measure of global activity, etc. Finally, Section IV concludes. Two appendices provide further explanations on our estimation and identification approaches.

I. A Structural Dynamic Factor Model

In this section we lay out the basics of our unifying empirical framework which allows for the identification of the main shocks driving the world commodity prices and for the analysis of their transmission mechanisms to our representative SCEE.

Our approach combines two strands of literature. The first one is related to the identification of the main underlying sources of shocks driving changes in commodity prices, which so far has been mainly restricted to the global crude oil market (Kilian, 2009; Lippi and Nobili, 2012; Kilian and Murphy, 2012). An important finding in this literature is that world commodity prices are driven by many shocks and their effects on the global economy can differ a lot. For example, both a global demand shock and an unanticipated disruption of oil supply generate an increase in oil prices. Yet, while the first shock stimulates global economic activity, the second shock reduces it. In other words, proper identification of the sources of changes in these prices is crucial for the analysis of their impact on the global economy and the formulation of appropriate policy responses.

The second one relates to the literature about SDFM (Stock and Watson, 2005; Forni et al., 2009) and factor-augmented VARs (FAVAR) (Bernanke and Boivin, 2003; Bernanke, Boivin and Eliasz, 2005; Boivin and Giannoni, 2007; Mumtaz and Surico, 2009) which is useful to analyze the effect of small number of structural shocks on a large set of macroeconomic variables.

A. Empirical Model

In line with Boivin and Giannoni (2007) and Mumtaz and Surico (2009), our model consists of two blocks. The first block corresponds to the global economy, while the second one summarizes specific detailed information about the SCEE. The state of the economy in these two regions is characterized by a small number K of unobserved factors, $(\mathbf{F}_t^{*\prime},\ \mathbf{F}_t^{\prime})$, where the vector with asterisks denotes three global factors, $\mathbf{F}_t^* = (F_{Y,t}^*,\ F_{\pi,t}^*,\ F_{C,t}^*)^{\prime}$. Following Mumtaz and Surico (2009), global factors are required to have an economic interpretation. Specifically, the first factor, $F_{Y,t}^*$, summarizes information about global economic activity and is extracted from a panel of international series, $\mathbf{X}_{Y,t}^*$, characterizing global and regional output, industrial production and trade. The second factor, $F_{\pi,t}^*$ approximates global inflation and is extracted from international data on consumer/producer prices and GDP deflators, $\mathbf{X}_{\pi,t}^*$. Finally, the third factor, $F_{C,t}^*$, captures the development of real world commodity price index and is obtained from panel data on the price of a wide variety of primary commodities, $\mathbf{X}_{C,t}^*$.[6] The state of the SCEE is measured by a large set of macroeconomic and financial series for Canada, $\mathbf{X}_t$, from which the $K-3$ domestic factors, $\mathbf{F}_t$, are extracted. Given that domestic factors are just used to provide a summary of the business cycle fluctuations in the large panel of Canadian economic variables, they do not require an economic interpretation.

[6] The real world commodity price index estimated in this paper is more closely correlated with the measured export price index for primary commodities in Canada than with the real oil price. This is not surprising since, as explained above, Canada exports a wide range of commodities.

The different panel data sets and the factors are related in the following way:

$$
\begin{pmatrix} \mathbf{X}^*_{Y,t} \\ \mathbf{X}^*_{\pi,t} \\ \mathbf{X}^*_{C,t} \\ \mathbf{X}_t \end{pmatrix} = \begin{pmatrix} \mathbf{\Lambda}^*_Y & 0 & 0 & 0 \\ 0 & \mathbf{\Lambda}^*_\pi & 0 & 0 \\ 0 & 0 & \mathbf{\Lambda}^*_C & 0 \\ \mathbf{\Lambda}_Y & \mathbf{\Lambda}_\pi & \mathbf{\Lambda}_C & \mathbf{\Lambda}_H \end{pmatrix} \begin{pmatrix} F^*_{Y,t} \\ F^*_{\pi,t} \\ F^*_{C,t} \\ \mathbf{F}_t \end{pmatrix} + \begin{pmatrix} \mathbf{e}^*_{Y,t} \\ \mathbf{e}^*_{\pi,t} \\ \mathbf{e}^*_{C,t} \\ \mathbf{e}_t \end{pmatrix} \tag{1}
$$

where $\mathbf{X}^*_t = (\mathbf{X}^{*\prime}_{Y,t},\ \mathbf{X}^{*\prime}_{\pi,t},\ \mathbf{X}^{*\prime}_{C,t})'$ and $\mathbf{X}_t$ are data for the global and domestic economies; $\mathbf{F}^*_t = (F^*_{Y,t},\ F^*_{\pi,t},\ F^*_{C,t})'$ and $\mathbf{F}_t$ denote the corresponding unobservable factors; $\mathbf{\Lambda}^*_i$ and $\mathbf{\Lambda}_j$ are loading matrices for global and domestic factors, respectively; and $\mathbf{e}^*_t = (\mathbf{e}^{*\prime}_{Y,t},\ \mathbf{e}^{*\prime}_{\pi,t},\ \mathbf{e}^{*\prime}_{C,t})'$ and $\mathbf{e}_t$ are zero-mean i.i.d. measurement errors which are assumed to be uncorrelated with the corresponding common components. Lastly, notice that the global factors are included explicitly into domestic block of the model as illustrated by the last row of (1).

Regarding the dynamics of the common factors, they are modeled as a restricted SVAR:

$$
\begin{pmatrix} \mathbf{F}^*_t \\ \mathbf{F}_t \end{pmatrix} = \begin{pmatrix} \mathbf{\Psi}_{11}(L) & \mathbf{0} \\ \mathbf{\Psi}_{21}(L) & \mathbf{\Psi}_{22}(L) \end{pmatrix} \begin{pmatrix} \mathbf{F}^*_{t-1} \\ \mathbf{F}_{t-1} \end{pmatrix} + \mathbf{u}_t \tag{2}
$$

where $\mathbf{\Psi}_{ij}(L)$ are lag polynomials of the finite order p, $\mathbf{u}_t$ denote reduced-form residuals, such that $\mathbf{u}_t \sim N(\mathbf{0}, \mathbf{\Omega})$ and $\mathbf{u}_t = \mathbf{A}_0 \boldsymbol{\epsilon}_t$, with structural shocks $\boldsymbol{\epsilon}_t \sim N(\mathbf{0}, \mathbf{I})$ and $\mathbf{\Omega} = \mathbf{A}_0 \mathbf{A}_0'$. Given the small size of the domestic economy, we impose the restriction that domestic factors have no effect on global factors.[7] Moreover, it is assumed that global shocks are ordered first and that domestic structural shocks have no contemporaneous effect on global factors. Hence, the right upper $3 \times (K-3)$ block of the matrix $\mathbf{A}_0$ is taken to be zero. Additional identifying restrictions on this matrix will be discussed further below.

[7]Estimation of an unrestricted VAR model provides very similar dynamic responses of domestic variables to global shocks.

B. Data

The data base consists of a large balanced panel of quarterly data from 1975q1 to 2010q4 which spans 281 series characterizing both the global and domestic economies. Those variables which are nonstationary are first differenced and all variables are demeaned and standardized prior to estimation. Further details about these series are provided in the online appendix.

The foreign block includes data for the world economy (if available) as well as for the large regional blocks (OECD, EU, G7) and the U.S.[8] This block contains three large categories of variables, namely, real activity, inflation and real commodity prices. Real activity is measured by real GDP, industrial production, volume of exports and imports, plus the index of global real economic activity constructed by Kilian (2009), which is based on representative freight rates for various bulk-dry cargoes.[9] Global inflation summarizes data on implicit price deflators of GDP, consumer and producer prices. Real commodity prices consist of a range of commodity price indices for energy, food, agricultural raw materials, base metals and fertilizers collected by the World Bank.

The data for Canada contain many different real activity indicators, inflation series, exchange rates and financial variables. In addition to these macro variables, a large number of disaggregated deflators and volume series for consumer expenditure drawn from CANSIM are included. Interestingly, we also extend this block of data by including sixteen relative indicators of Canadian aggregate expenditure, employment and output variables in relation to the corresponding indicators in the US. The insight for using these relative indicators is to provide

[8]Unfortunately, quarterly GDP and industrial production data for BRIC countries are only available during the 1990s. However, our global block contains quarterly data on world exports and imports from the OECD data base which captures the effect of growth in the BRIC economies on global economic activity since that decade.

[9]The Kilian's index of real activity as reported by Kilian (2009) (in percent deviations from linear trend) is significantly more persistent than our (log) differenced series of world output and trade and, as a result, our global activity index has practically zero correlation with it. To make Kilian's index comparable to our, we transformed this index to log-deviations from trend as $log(1 + x/100)$ and then computed the first differences of transformed series. Our global economic activity index has higher, but still very low correlation (equal to 0.07) with this transformed index.

comparisons of the Canadian experience with that of a commodity-importing country, like the US, for which one would not expect to observe symptoms of some of the previously listed features, notably the spending and Dutch disease effects.

Finally, to put the data into perspective, Table 1 summarizes the sectoral composition of the Canadian economy whereas Table 2 illustrates its main business cycle statistics during the sample period. As shown in Table 1, although primary commodity sectors (agriculture, forestry, fishing, mining and quarrying) represent only a small fraction of overall GDP (8.4 percent) and employment (5.5 percent), they have a disproportionately large effect on the Canadian trade balance. In particular, net exports of primary commodities represents on average 2.2 percent of GDP, whereas those of manufacturing goods and of services and utilities reach -2.4 and 0.8 percent of GDP, respectively.

As regards Table 2, the main lesson to be drawn is that the business cycle statistics of the Canadian economy, though similar to those observed in the US (e.g. Backus, Kehoe and Kydland, 1995; Schmitt-Grohe, 1998), exhibit important differences which are closely related to the effects of real commodity prices. In particular, the latter are positively correlated with trade balance and negatively correlated with the real exchange rate, illustrating somewhat the presence of external balances and commodity currency effects in the raw data. Yet, at first sight there is no sign of a Dutch disease since real commodity prices are positively correlated with real output in all sectors, including the tradable sectors (excluding commodities), like manufacturing. It is precisely for this reason the decomposition of the real commodity price changes into several structural shocks becomes key to ascertain whether this controversial feature remains absent once we account for the source of these innovations.

Table 1—: Sectoral composition of the Canadian economy: average shares over 1975-2010

	Gross Value Added (percent of total GDP)	Employment (percent of total employment)	Export (percent of the industry production)	Net export (percent of total GDP)
Primary Commodity Sector	*8.4*	*5.5*	*32.7*	*2.2*
Agriculture, forestry and fishing	3.0	4.0	17.3	0.6
Mining and quarrying	5.4	1.5	45.1	1.6
Non-Commodity Tradable Sector	*16.4*	*15.4*	*42.3*	*-2.4*
Manufacturing	16.4	15.4	42.3	-2.4
Non-tradable Sector	*75.2*	*79.1*	*5.7*	*0.8*
Utilities	3.1	0.9	6.0	0.2
Construction	6.1	6.0	-	-
Services	66.0	72.2	6.9	0.6

Data: CANSIM Canada, annual, sample period is 1975-2010

Table 2—: Business cycles in Canada: 1975q1-2010q4

	Volatility	Correlation	Cross-correlations with (leads/lags of) real commodity price								
	(percent per quarter)	with GDP	lags					leads			
			-6	-4	-2	-1	0	1	2	4	6
GDP	1.48	1.00	-0.28	-0.11	0.24	0.36	0.42	0.41	0.34	0.17	-0.01
primary commodity sector	2.37	0.48	-0.46	-0.23	0.29	0.41	0.39	0.27	0.20	0.09	0.01
non-commodity tradable sector	4.06	0.91	-0.42	-0.23	0.16	0.33	0.44	0.43	0.36	0.17	0.02
nontradable sector	1.10	0.85	-0.08	0.00	0.26	0.36	0.41	0.38	0.28	0.08	-0.09
Consumption	1.20	0.83	-0.12	0.00	0.21	0.28	0.37	0.39	0.30	0.01	-0.10
Investment	5.19	0.65	-0.03	0.10	0.32	0.41	0.40	0.29	0.16	-0.08	-0.18
Employment	1.15	0.78	-0.06	0.15	0.37	0.45	0.45	0.37	0.26	0.03	-0.12
Government purchases	1.08	-0.09	0.01	-0.05	-0.08	-0.06	-0.09	-0.15	-0.20	-0.13	0.00
Net export (percent of GDP)	0.92	0.00	-0.12	-0.13	0.14	0.29	0.39	0.35	0.21	0.12	0.03
Real exchange rate	4.03	0.12	-0.03	0.02	0.03	-0.03	-0.09	-0.13	-0.08	0.18	0.33
Real commodity price	8.71	0.42	-0.19	-0.05	0.36	0.74	1.00	0.74	0.36	-0.05	-0.19
GDP in United States	1.42	0.80	-0.34	-0.22	0.04	0.19	0.30	0.34	0.31	0.17	0.07

Data sources: CANSIM Canada, OECD; sample period is 1975:1-2010:4; all variables except net export are in logarithms; all variables are filtered with HP-filter ($\lambda = 1600$); primary commodity sector - agriculture, forestry and fishing, mining and quarrying; non-commodity tradable sector - manufacturing; nontradable sector - utilities, construction, services.

C. Estimation

Following Bernanke, Boivin and Eliasz (2005), Boivin and Giannoni (2007) and Mumtaz and Surico (2009), the model is estimated using a two-step principal component analysis (PCA). In the first step, the largest PC are extracted from each of the panel data sets $\mathbf{X}^*_{Y,t}$, $\mathbf{X}^*_{\pi,t}$, $\mathbf{X}^*_{C,t}$ and $\mathbf{X}_t$ to consistently estimate common factors driving the global and Canadian economies. In the second step, these factors are used for estimation of the restricted VAR in (2).[10]

Note that, in the first step, we impose the constraint that global factors are included into the PC for domestic block of the model. So, if these global factors are really common components, they should be captured by the PC of $\mathbf{X}_t$. To extract the remaining $K-3$ domestic factors from the space spanned by the PC of $\mathbf{X}_t$, we use the approach advocated by Boivin and Giannoni (2007). Accordingly, the following iterative procedure is adopted at the first step of the estimation. Starting from the initial estimates of the $K-3$ principal components $\mathbf{F}_t$ of the domestic block of variables $\mathbf{X}_t$, denoted by $\mathbf{F}_t^{(0)}$, iteration proceeds through the following steps:

1) Regress $\mathbf{X}_t$ on $\mathbf{F}_t^{(0)}$ and estimates of the global factors $\hat{F}^*_{Y,t}$, $\hat{F}^*_{\pi,t}$ and $\hat{F}^*_{C,t}$, to obtain $\hat{\mathbf{\Lambda}}_H^{(0)}$, $\hat{\mathbf{\Lambda}}_Y^{(0)}$, $\hat{\mathbf{\Lambda}}_\pi^{(0)}$ and $\hat{\mathbf{\Lambda}}_C^{(0)}$
2) Compute $\tilde{\mathbf{X}}_t^{(0)} = \mathbf{X}_t - \hat{\mathbf{\Lambda}}_Y^{(0)}\hat{F}^*_{Y,t} - \hat{\mathbf{\Lambda}}_\pi^{(0)}\hat{F}^*_{\pi,t} - \hat{\mathbf{\Lambda}}_C^{(0)}\hat{F}^*_{C,t}$
3) Estimate $\mathbf{F}_t^{(1)}$ as the first $K-3$ principal components of $\tilde{\mathbf{X}}_t^{(0)}$
4) Back to the Step 1. The algorithm is repeated until convergence in $\mathbf{F}_t^{(j)}$ is achieved.

On the basis of several information criteria for the choice of the number of factors, we end up including 8 common factors for Canada. At any rate, the

[10]We do not explicitly model an uncertainty in the measurement of factors, as in Bernanke, Boivin and Eliasz (2005). The problem is that this procedure becomes extremely time consuming when sign identification is used since it requires running the Kalman filter to draw the latent factors from their posterior distribution in each iteration of Gibbs sampler. Thus, this approach becomes unfeasible in practice.

impulse response functions (IRFs) hardly change if additional domestic factors are considered.[11] This choice implies that the second step in our estimation procedure involves the estimation of a restricted VAR with 11 endogenous variables, namely 3 global and 8 domestic factors. The use of the AIC criterion indicates that two lags are enough to adequately capture its dynamics. Since this choice implies a large number of free parameters in the VAR system to be estimated with 144 observations for each variable, a Bayesian estimation procedure is used in this restricted VAR. Further details about the estimation procedure are provided in Appendix A.

D. Identification of Structural Shocks

This section discusses the identification of the three global structural shocks: i) an unanticipated expansion of global demand (GD), $\epsilon^*_{D,t}$, ii) a global supply shock, unrelated to commodity markets (GS), $\epsilon^*_{S,t}$, and iii) a global commodity-specific shock (GC), $\epsilon^*_{C,t}$. The last shock is aimed to catch unanticipated changes in the real commodity prices orthogonal to the first two innovations stemming from an unexpected contraction of the global commodity supply as well as by commodity-specific demand shocks, such as an increase in the precautionary demand on commodities.

The benchmark identification scheme for these global shocks is based on a mixture of sign and impact matrix restrictions, although we also provide results using a more conventional recursive ordering (see Kilian, 2009), as a robustness check of our results. Global factors are ordered first, implying that the rest of the world does not react instantaneously to domestic conditions in Canada.

Sign restrictions combined with short-run elasticity bounds. — In the benchmark identification scheme, we impose sign restrictions on the IRFs of global

[11] Bai and Ng (2002) provide several criteria to determine the number of factors present in the data set, $\mathbf{X}_t$. Their panel information criteria IC_{p1} and IC_{p2}, for example, suggest the presence respectively of 8 and 7 factors in the panel for Canada. However, these criteria do not address directly the question of how many factors should be included in the VAR.

factors to global shocks. In particular, we assume that IRFs accumulated over 4 quarters should have the signs reported in Table 3.

Table 3—: Sign restrictions on impulse response functions

	GD Shock, $\epsilon^*_{D,t}$	GC Shock, $\epsilon^*_{C,t}$	GS Shock, $\epsilon^*_{S,t}$
Global Economic Activity, $F^*_{Y,t}$	+	–	–
Real Commodity Price, $F^*_{C,t}$	+	+	–
Global Inflation, $F^*_{\pi,t}$	+	+	+

These sign restrictions are imposed using the rotation procedure proposed by Rubio-Ramirez, Waggoner and Zha (2010), as described in Appendix B. Accordingly, a GD shock is associated with an increase in global activity, inflation, and real commodity prices. A negative GS shock implies a rise in inflation, and a fall in both real activity and real commodity prices. Finally, a negative GC shock results in increasing commodity prices, higher inflation and declining real activity.

A fundamental problem of the VAR model being identified through sign restrictions is that, in contrast to the exactly-identified VAR, it does not provide a point estimate of the IRFs which are only set identified. In other words, this implies that there is not a unique structural model characterized by the single impact matrix $\mathbf{A}_0$, but a set of models (and a set of matrices $\mathcal{A}_0 = \{\mathbf{A}_0 | \mathbf{A}_0\mathbf{A}_0' = \mathbf{\Omega}\}$) that satisfy the identifying assumptions. This complicates interpretation of the results because medians (or other quantiles) of the IRFs computed for different time horizons often correspond to different structural models.

To alleviate this problem, we adopt the approach proposed by Kilian and Murphy (2012), where the set of admissible structural models is narrowed down by imposing bounds on some of the elements in the impact matrix $\mathbf{A}_0$. In particular, these authors assume a very small short-run elasticity of oil prices to the oil supply as well as a small contemporaneous response of global real activity to oil-market specific demand shocks. Accordingly, we impose here the additional restriction on $\mathbf{A}_0$ that the short-run elasticity of the real global activity to GC shocks is small. Specifically, we assume that corresponding element of the matrix $\mathbf{A}_0$ is in the range from -10 to 5 percent: $-0.1 \leq \mathbf{A}_0(1,2) \leq 0.05$ which, after proper scaling, corresponds roughly to the estimates of the short-run elasticity of the US GDP to real oil price reported in the literature (see, for example, Rotemberg and Woodford, 1996; Hamilton, 2008).[12] Thus, only those structural models satisfying these sign and bound restrictions will be kept for constructing the reported IRFs in the sequel. Following Kilian and Murphy (2012), these will be depicted as the area between the 16 percent and 84 percent quantiles of the posterior distribution.[13] Notice that structural models with a very large negative value of $\mathbf{A}_0(1,2)$ are associated with larger commodity price responses to GD shocks and smaller price responses to GC shocks. As a result, they may lead to counterintuitive results, like, e.g., that the oil crisis of 1979-1980 was mostly due to a positive GD shock rather than to a negative GC shock.[14]

Recursive identification. — To check how sensitive are the results of our benchmark scheme, an alternative scheme based upon recursive ordering is also considered. In particular, as presented in Table 4, the impact matrix corresponding to the foreign 3×3 block is taken to be lower triangular. The global economic activity factor $F^*_{Y,t}$ is ordered first, followed by the real commodity price index $F^*_{C,t}$ and global inflation $F^*_{\pi,t}$ respectively. This ordering implies that the GS shock has no contemporaneous effect on both global economic activity and real commodity prices, while a GC shock is allowed to affect global inflation on impact since the

[12]Mork, Olsen and Mysen (1994), using data for 1967-1992, estimated real GDP responses to negative and positive oil price increases for the US, Canada, Japan, Germany (West), France, the UK, and Norway. Estimated short-run elasticities for all these countries are small. Yet, for Japan, Germany and the UK, they are a bit higher than for the US (one percent increase in oil price implies immediate fall of GDP by 0.022 percent in Japan, 0.036 percent in Germany, 0.047 percent in the UK and 0.015 percent in the US).

[13]Certainly the bounds in the area capturing the IRFs may mix the responses of different candidate models at different horizons. Yet, given that their patterns are generally supported by the exactly-identified recursive scheme, we think that they provide a good illustration of the overall dynamics of the IRFs. Further, using 90 percent coverage areas instead of 68 percent ones does not imply any major change in the conclusions (see Charnavoki and Dolado, 2012).

[14]The models which allow for a strong negative impact effect of the GC shock on global economic activity, $\mathbf{A}_0(1,2) < -0.1$, result in less positive (more negative) response of Canadian expenditure and output variables to a negative GC shock, shifting downwards the IRFs to this GC shock. However, relative IRFs (in particular Canada vs. US expenditures and sectoral output) are fairly robust to this impact restriction (see online appendix). In fact, Dutch disease and spending effects become even more pronounced after a negative GC shock, but we do not still observe such effects after a GD shock.

definition of the latter includes changes of the commodity prices. Note that the

Table 4—: Recursive identification

	GD Shock, $\epsilon^*_{D,t}$	GC Shock, $\epsilon^*_{C,t}$	GS Shock, $\epsilon^*_{S,t}$
Global Economic Activity, $u^*_{Y,t}$	$\times$	0	0
Real Commodity Price, $u^*_{C,t}$	$\times$	$\times$	0
Global Inflation, $u^*_{\pi,t}$	$\times$	$\times$	$\times$

chosen recursive identification is not without limitations. First, it imposes zero restrictions on some elements of the impact matrix which may not hold exactly with quarterly data. Secondly, as reported by Kilian (2009) and also found in this paper (see discussion in subsection II.A), the IRF of the extracted global economic activity factor to a negative GC shock is mildly anomalous since, albeit small, it is positive and significant within one year and it only declines later on.

II. Empirical Results

This section presents the main empirical results obtained from our SDFM. First, we present the estimates of the three global factors, illustrate their dynamic response to the global shocks and show historical decompositions of these factors in terms of the shocks on the basis of the two above-mentioned identification schemes. Next, using Canadian data, we report the main dynamic effects of global shocks on this SCEE. In particular, given that a positive GD shock and negative GC shock turn out to be the more important ones in explaining the volatility of real commodity prices, for brevity we restrict our attention to the role of these two shocks in checking whether they can replicate for Canada the different effects listed in the Introduction.[15]

[15]IRFs for the individual domestic variables are generated by Gibbs sampling algorithm. For each iteration, we sequentially draw the variance-covariance matrix of measurement errors from the conditional inverse Gamma distribution, the non-zero elements of loading matrix from the conditional Normal distribution, and the parameters of the restricted VAR from the Normal-Wishart (see Appendix A). These realizations of the parameters are then used to compute IRFs of the Canadian variables to structural shocks. The simulated data from each Gibbs iteration (after truncation of the first 10000 realizations) are used to approximate the posterior distribution of these IRFs.

A. Global common factors and shocks

Figure 1 plots the estimated PC for the real activity, inflation and real commodity prices data sets. These factors match closely the empirical evidence about international business cycles reported by Kose, Otrok and Whiteman (2003) and Mumtaz and Surico (2009), as well as the main developments in the world commodity markets summarized by Kilian (2006) and Hamilton (2011) in their application to oil markets.

In particular, the global economic activity factor captures the main global downturns between 1975q1 and 2010q4: the double-dip recession at the beginning of 1980s, the downturn in 1991-1993, the East Asian crisis in 1997-1998, the slowdown of the early 2000s after the Dot-com bubble collapse and 9/11 attacks, and finally the Great Recession of the late 2000s. Likewise, it captures the long expansion during the great moderation period. The real commodity price factor in turn reflects the more important events in commodity markets: the turbulence of the 1978-1981 period ignited by the Iranian revolution and outbreak of the Iran-Iraq war, the oil glut of 1980s, falling commodity prices during the East Asian crisis in 1997-1998, rising commodity demand in 2000s and the downturn in commodity markets in 2008-2009. Lastly, the global inflation factor encompasses the stagflation of the 1970s-early 1980s, the rising food and energy prices in 2000s as well as the deflation of the late 2000s.

Figure 2 plots the IRFs of the factors to the three global shocks based on the sign restrictions scheme (shaded area covering the conventional 68 percent credible set reported in most of the literature) and the recursive identification scheme (solid line together with 68 percent interval). In general, both schemes provide similar results. Thus, a positive GD shock generates a significant expansion in global economic activity, increases global inflation and pushes up real commodity prices, with the largest effect taking place within one year. A negative GS shock leads to a decline in real activity, accelerates inflation and depresses real commodity prices. Lastly, a negative GC shock gives rise to a temporary spike in global

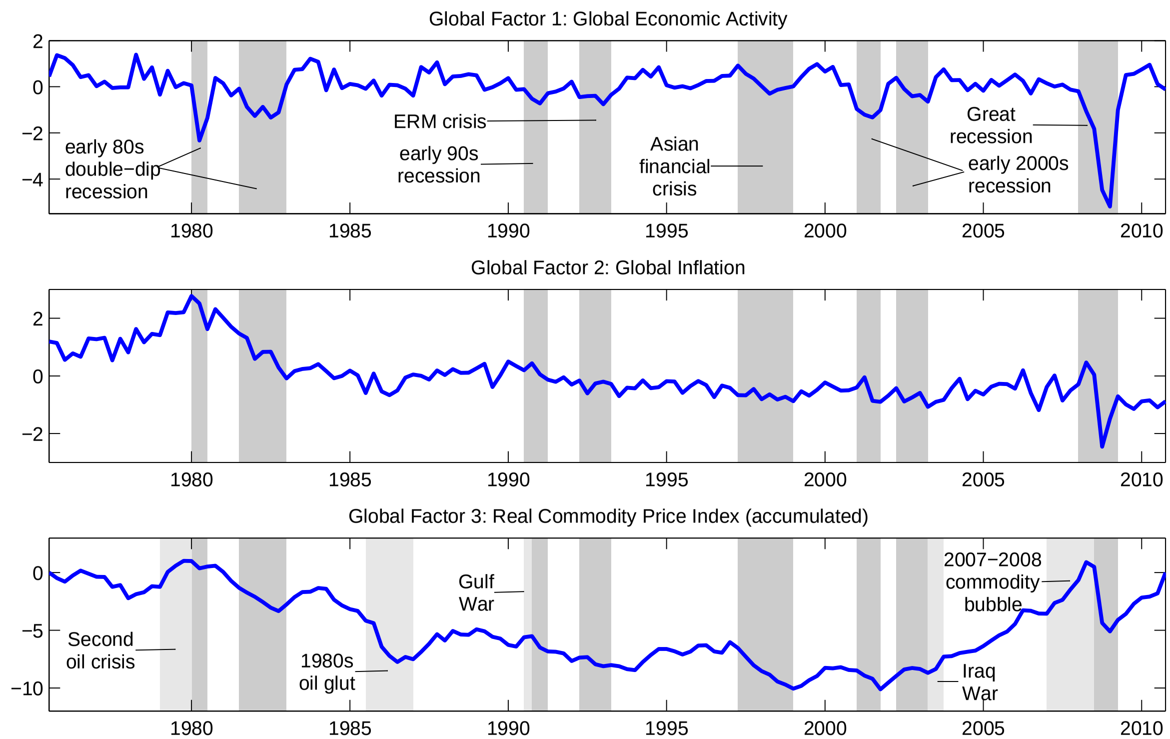


Figure 1. : Principal component estimates of international factors

Dark gray shaded regions represent the main global recessions; light gray shaded areas depict the main events in global commodities markets inflation and very strong increase in real commodity prices. As noticed earlier, the most important difference between the sign-restriction and recursive identification schemes is that, under the latter, the adverse effect of the GC shock on real activity is delayed for one year.[16] By imposing a negative accumulated response of the real activity to a GC shock after four quarters, the sign identification scheme avoids this puzzling short-run phenomenon, which is also documented in Kilian (2009).

Figure 3 plots historical decompositions of the global economic activity, global inflation and real commodity prices based on the sign-identified structural model. It shows the contribution of each of the three global shocks to the development of these global factors during the sample period. In this case, the results are virtually invariant to the method of identification. First, both schemes suggest that most of the volatility in the global real activity factor during this period has to be attributed to GD shocks, although a positive GS shock (possibly due to the raising productivity in emerging economies and larger trade liberalization) also seems to play an increasing role from the mid-1990s. Further, some GC shocks seem to have contributed to the economic slowdown at the beginning of 1980s, as well as to revival of global economy after the Asian financial crisis during 1997-1998. Secondly, to some extent all the three shocks played an important role in driving the global inflation. While the episode of high inflation in the late 1970s-early 1980s is mostly attributed to the negative GS shock under recursive identification, sign restrictions point out to a combination of positive GD and negative GC shocks.

Finally, from the viewpoint of our subsequent analysis, the most interesting finding is that a large part of the volatility in real commodity prices during this period is mainly attributed to a GC shock and, to a lesser extent, to a GD shock.[17]

[16]However, this delayed response of the real output to commodity shock conforms well to the results of Rotemberg and Woodford (1996) for United States, which show that one percent increase in oil prices leads to a reduction in output of about 0.25 percent after five-seven quarters (with statistically significant decline only from the third quarter onwards).

[17]Though not reported, but available upon request, the (median) variance decompositions for the three global factors point out that the GC shock explains most of the volatility in the real commodity prices

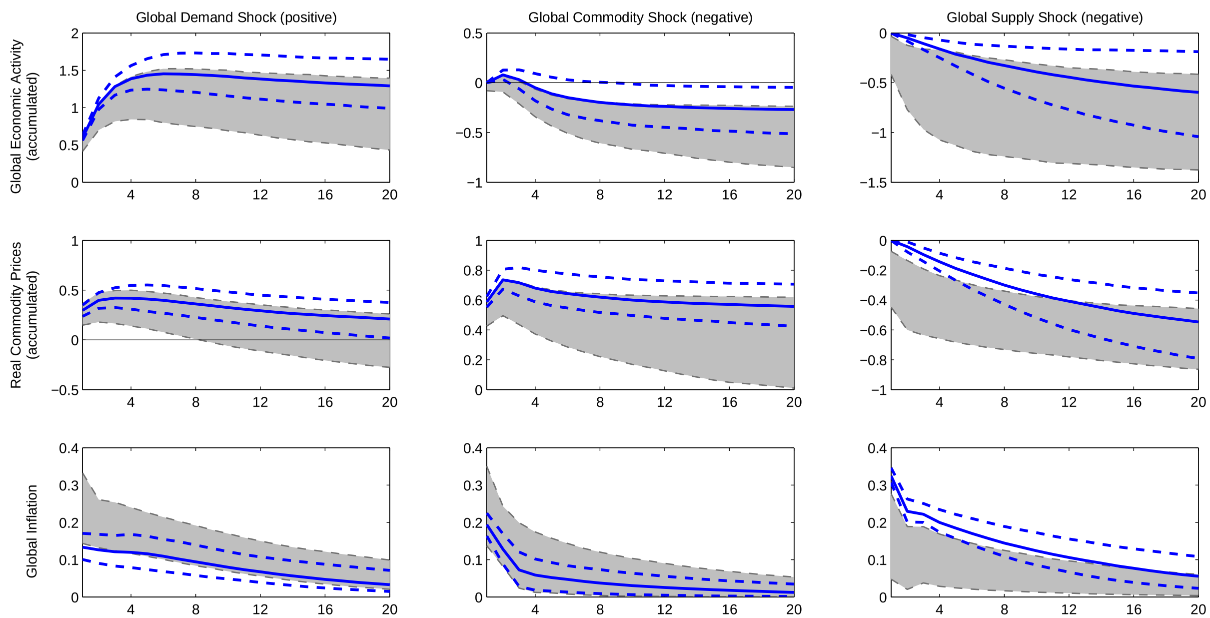


Figure 2. : Impulse responses of international factors to global shocks

Identification by sign restrictions - shaded area covering equally-tailed 68 percent credible set; recursive identification - median (solid line) together with equally-tailed 68 percent credible interval

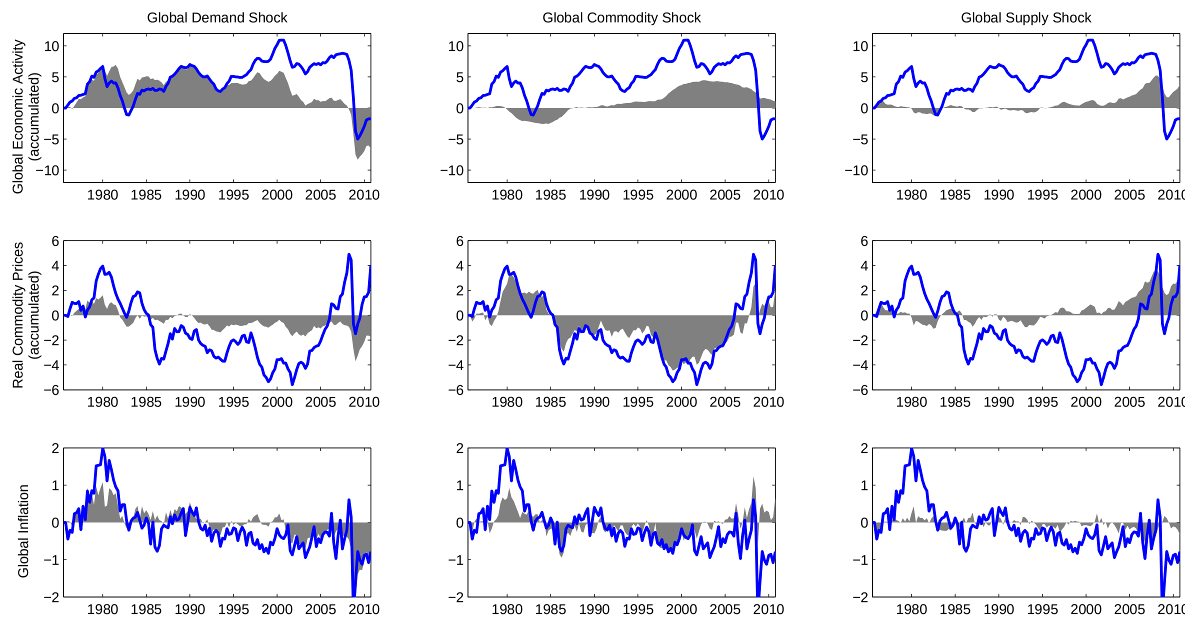


Figure 3. : Historical decompositions of the global factors: 1975q1-2010q4

Global factors - thick solid lines; identification by sign restrictions - shaded areas

The former captures the disruption of the oil supply in the late 1970s-early 1980s, the oil glut of the mid of 1980s, the region-specific downturn in 1997-1998 and the speculative episode in commodity prices at the beginning of 2008.[18] The latter indicates that the Great Recession of the late 2000s was behind the falling commodity prices during 2008-2009. Hence, in the sequel, we will concentrate on these two shocks (a negative GC shock and a positive GD shock) in analyzing their propagation mechanisms to the Canadian economy.[19]

B. *Transmission of international shocks to a SCEE*

In this section we analyze the effects of these two shocks on the Canadian economy at business-cycle frequencies. We divide our discussion into two parts. First, we illustrate that the sources of changes in real commodity prices are not specially important when studying external balances and commodity currency effects. Next, by contrast, we show that a negative GC shock and a positive GD shock imply very different effects on the aggregate expenditure components (spending effect) and sectoral output (Dutch disease effect) of the Canadian economy.

To report the IRFs of the Canadian variables, we convert them to the original units of the data using standard deviations computed in the first stage of the estimation procedure. Further, we standardize the shocks such that both the negative GC shock and the positive GD shock result in the same median level of increase in the real commodity price on impact. This level is chosen to be equal to one standard deviation of the real commodity price factor, which roughly

(about 80 percent in the recursive case and 60 percent in the model with sign restrictions), followed by the GD shock which accounts for approximately 20-25 percent. Hence, the GS shock explains practically nothing under the recursive identification scheme.

[18]Since the East Asian financial crisis during 1997-1998 did not generate a strong global recession, our measure of global economic activity fails to account for its effect on commodity markets. Moreover, the impact of this crisis was different across commodity groups. Oil prices recovered very quickly, and by the end of 1999 they reached their pre-crisis level. By contrast, prices of food, wood, base metals and fertilizers stagnated until the end of 2003. As a result, our measure of GC shocks differs slightly from the measure of oil-market specific demand shocks computed by Kilian (2009), especially after 1998.

[19]A positive GS shock has a very similar effect to a positive GD shock on most of the Canadian variables under the sign identification scheme. Two differences worth mentioning are that: i) this shock has a deflationary effect on the nominal prices (in contrast to an inflationary effect of a positive GD shock), and ii) its effect is very persistent in contrast to GD shock which has a maximum impact in 1-2 years. Under the recursive scheme the effects of GS shock are mostly statistically insignificant.

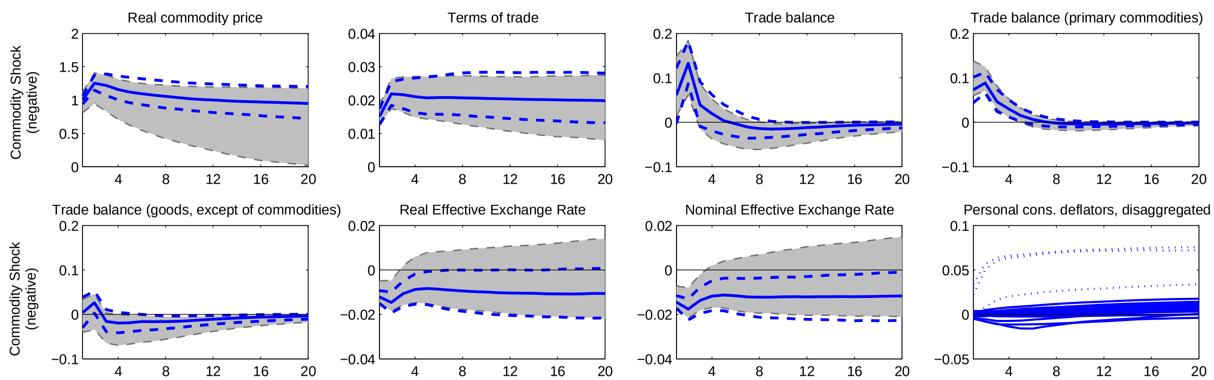
corresponds to an increase of 13 percent in the real energy price index. This procedure helps making compatible the results on the conditional central tendency and the coverage areas.

Features for which the source of commodity price changes does not matter much. —

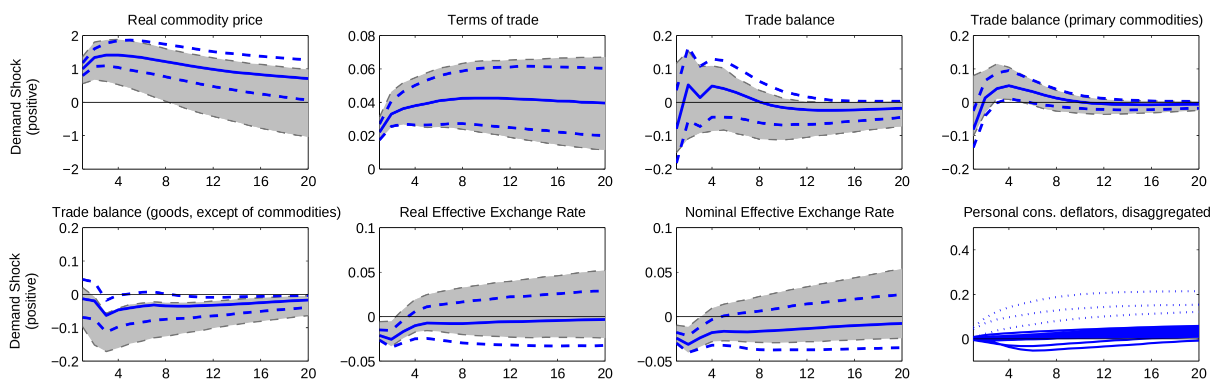
Terms of trade and external balances effects. — We begin by reporting the results concerning terms of trade and external balances effects (feature I). Recall that this effect first predicts that a rise in commodity prices improves Canadian terms of trade. Secondly, when commodity prices are high (low), the current account and trade balances tend to improve (worsen). Since so far the evidence for this effect is restricted to oil-exporting economies (see, Kilian, Rebucci and Spatafora, 2009), it is interesting to check its validity for other SCEEs.

Figure 4 plots the IRFs of the terms of trade and trade balances (as percent of GDP) to the two global shocks. Like in the graphs to be presented in the remaining subsections, the top panel (a) depicts IRFs of the relevant variables with respect to a negative GC shock, whereas the bottom panel (b) does the same for a positive GD shock. As can be observed, both shocks significantly increase real commodity prices and improve Canadian terms of trade. Their effects on external balances are however slightly different. While a negative GC shock improves the trade balance on impact, mainly through a sudden increase in the trade balance of primary commodities, a positive GD shock improves the trade balance of primary commodities more slowly and worsens the trade balance of non-commodity goods. Thus, the effect of a GD shock on the total trade balance (as percent of GDP) is not so strong as in the case of a negative GC shock.[20]

[20] A *positive* GD shock not only increases non-commodity exports and imports in Canada by stimulating inter- and intra-industry trade, but also appreciates the real exchange rate, which makes Canadian tradable goods more expensive than foreign tradable substitutes. Though the direct (foreign) income effect strongly dominates this price effect and hence real exports raise, real imports increase by even more.



(a) Negative commodity shock



(b) Positive demand shock

Figure 4. : Impulse responses: terms of trade, trade balance and commodity currency effect

Identification by sign restrictions - shaded area covering equally-tailed 68 percent credible set; recursive identification - median (solid line) together with equally-tailed 68 percent credible interval; medians of the disaggregated energy prices - solid lines, medians of the disaggregated non-energy prices - dotted lines

Commodity currency effect and relative prices. — Another empirical regularity frequently observed in this type of economies is a commodity currency effect (feature II) implying that their real exchange rates are strongly correlated with prices of the exported commodities. In particular, raising commodity prices result in appreciation of the real exchange rate. This effect is well documented in the literature. For example, Cashin, Cespedes and Sahay (2004) find a long-run cointegrating relationship between the real exchange rates and real prices of exported commodities for 19 out of 58 commodity-exporting economies, while Chen and Rogoff (2003) report similar findings for a few developed resource-rich economies.

Figure 4 illustrates how both shocks result in a short-run appreciation of Canada's real effective exchange rate.[21] Moreover, this real appreciation is almost fully due to the appreciation of the nominal exchange rates.[22] Finally, the last plot in each of the two panels in Figure 4 reports that there is quite a strong heterogeneity in the effect of the two global shocks on the implicit price deflators for disaggregated groups of personal consumption in Canada (as in Boivin, Giannoni and Mihov, 2009). Both shocks generate strong immediate increases on energy prices (dotted lines), whereas the remaining non-energy prices (solid lines) exhibit different dynamics. In the long run, however, prices of non-energy goods always go up, reflecting higher production costs in an environment of high commodity prices.

Features for which the source of commodity price changes does matter. —

The net effect is a deterioration of the trade balance of non-commodity tradable goods. By contrast, the commodity trade balance unambiguously improves due to the higher terms of trade, albeit not so strongly as after *negative* GC shock. As a result, the overall effect of the positive GD shock on the trade balance is not very clear.

[21] The real exchange rate is defined here as the price of foreign consumption in terms of consumption in Canada, i.e. $RER_{i,CAN,t} = NER_{i,CAN,t} \cdot P_{i,t}/P_{CAN,t}$, where $NER_{i,CAN,t}$ is a nominal exchange rate in terms of Canadian dollar per unit of country i currency, $P_{i,t}$ and $P_{CAN,t}$ are, respectively, foreign and Canadian consumer price indices. Thus, an appreciation of the real (nominal) exchange rate in Canada means a decrease in $RER_{i,CAN,t}$ ($NER_{i,CAN,t}$).

[22] In the online appendix of this paper we report that the ratio of US and Canadian consumer price indices, $P_{USA,t}/P_{CAN,t}$, barely changes after a negative GC shock and slightly increases in response to a positive GD shock, reflecting the increase in foreign inflation induced by raising global demand.

Spending effect. — As shown before, soaring commodity prices significantly improve the terms of trade in Canada, generating windfall revenues from its commodity exports. Their overall effect on the economy depends crucially on how this windfall income is spent. A favorable response of external balances in Canada to a negative GC shock (and to a lesser extent to positive GD shock) signals that at least a part of commodity revenues is saved abroad, leveling their effect on the domestic economy. However, the rest of this income is spent inside the country affecting its output and final expenditures (feature III).

In their application to a sample of oil-exporting developing countries, Spatafora and Warner (1999) find a strong positive effect of the terms of trade shocks on domestic spending components, i.e. consumption, investment and government expenditures. However, they do not control for developments in global economic activity (except for a debt crisis dummy, world real interest rate and linear growth trend). Consequently, their results may be affected by GD shocks which simultaneously improve the terms of trade and increase domestic income and expenditures in SCEEs, masking an immediate effect of windfall income spending. We illustrate here that the sources of the real commodity price fluctuations may indeed significantly matter when analyzing this spending effect.

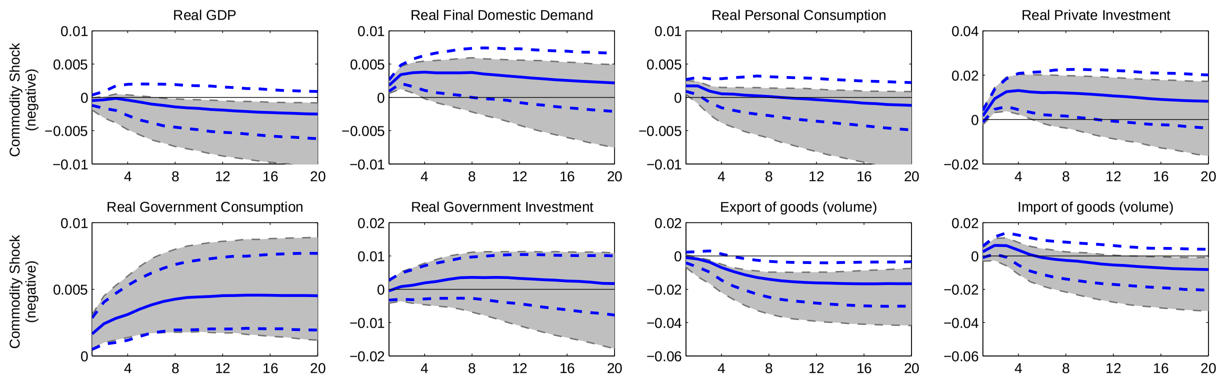
Figure 5 illustrates this effect for the different aggregate demand components in Canada. First, a negative GC shock (panel a) has a slightly negative (yet insignificant) effect on real GDP and a positive (significant) impact effect on final domestic expenditures, whose rise is mainly explained by both an increasing current government expenditure (due to a surge in tax revenues from the commodity sector) and a rise in real private investments.[23] Real personal consumption expenditures also raise but only on impact. Lastly, this adverse shock has a strong

[23]A *negative* GC shock generates windfall revenues from exports of primary commodities and drives real domestic demand. Hence, real consumption, real investment and real government expenditures all increase. However, a significant share of this higher demand falls on cheaper foreign goods, so that real imports slightly increase in the first year after shock. Furthermore, deteriorating foreign demand strongly decreases Canadian real exports. Consequently, real GDP falls as a result of the worsening of the trade balance at constant prices, $X - M$, despite an increase in the real final domestic demand. Notice, however, that the trade balance in current prices $P_X X - P_M M$ strongly improves due to the raising terms of trade P_X / P_M.

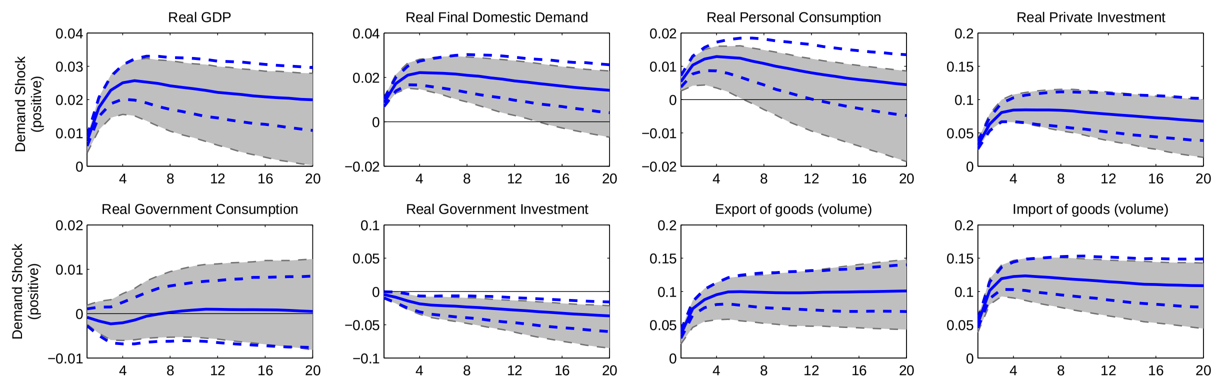
but protracted negative effect on real exports while the effect on real imports is not statistically significant.

By contrast, a positive GD shock (panel b) stimulates global economic activity and international trade, so both real exports and imports go up. As a result, it has a highly significant and unambiguous positive effect on real GDP and real final domestic expenditures, as well as on total employment and industrial capacity utilization (see online appendix). This strong expansionary effect is triggered mostly by higher foreign demand and somewhat hides the immediate effect of windfall income from commodity exports. Moreover, real current government expenditures do not change whereas real government investment gradually decreases, signaling the countercyclical character of fiscal policy.

The differences in the effects of the two shocks become even more evident in the comparison of the dynamic responses of the relative indicators of aggregate spending components in Canada vs. US. As can be observed in Figure 6 (panel a), a negative GC shock has a very different effects on the two countries, implying that windfall income from commodity exports in Canada is spent partly inside this economy. More concretely, this shock leads to increase in all domestic spending components in the Canadian economy (personal consumption, investment and government expenditures), whereas the corresponding U.S. variables experience a statistically significant decline. Thus, the relative indicators of these variables, as well as of GDP, in Canada vs. US (i.e., Canadian IRF minus the US IRF) significantly increase. Moreover, the largest increase of consumption in Canada is in terms of cheaper goods, which in a large extent are imported from abroad. As a result, the relative imports significantly increase, whereas relative exports significantly falls. By contrast, a positive GD shock (panel b) affects aggregate expenditures in both economies in a very similar way: real GDP, consumption, investment, export and import unambiguously increase. Furthermore, given that many GD shocks have their origin in the US, this shock is bound to have a stronger (positive) effect there (especially on real investment), so that the



(a) Negative commodity shock



(b) Positive demand shock

Figure 5. : Impulse responses: output and spending effect

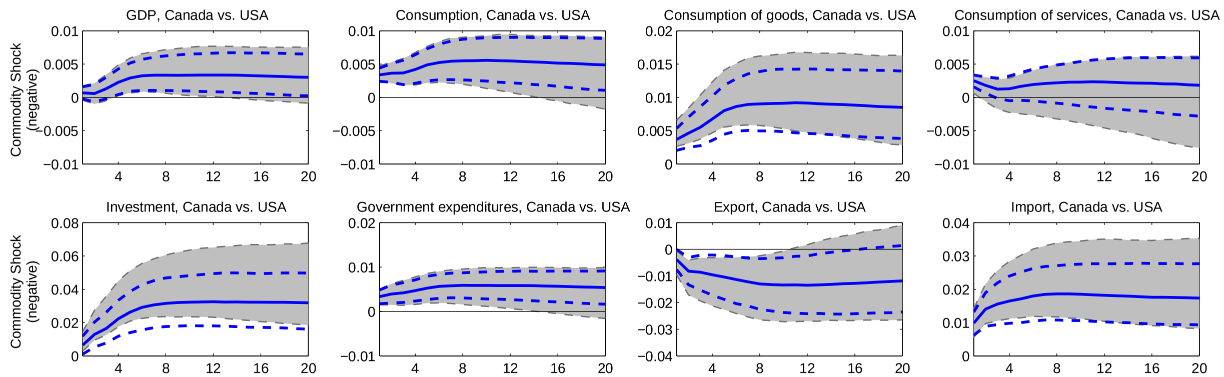
Identification by sign restrictions - shaded area covering equally-tailed 68 percent credible set; recursive identification - median (solid line) together with equally-tailed 68 percent credible interval

relative indicators of the corresponding expenditures components in Canada vs. US (except for imports) tend to decrease.[24]

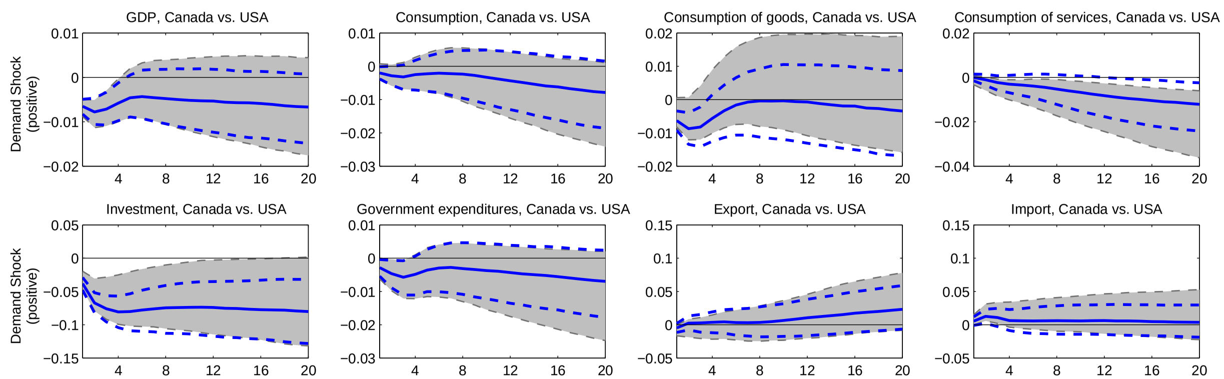
We finish this section with a brief summary of our main findings regarding a closer examination of the effects of these two shocks on several components of personal consumption, investment and their price deflators in Canada (see online appendix). As regards personal consumption (namely consumption on durable and non-durable goods, and services, as well as on their disaggregated series), the effects of a negative GC shock on the aggregate and disaggregate definitions of consumption are quite similar to those on total real consumption, namely hardly significant. Conversely, a positive GD shock has a uniform and strongly positive effect on all aggregated and disaggregated consumption items.

With regard to the effects of global shocks on real investment, we reported earlier that a substantial portion of the windfall revenues from commodity export in Canada is channeled into the real private investments in fixed capital. However, besides this direct spending effect, there is another indirect propagation mechanism of global shocks to private investment growth. More precisely, an appreciation of the real exchange rate associated with an increase in commodity prices, results in decreasing relative prices of investment goods, which are predominantly tradable. Hence, investment demand increases. As Spatafora and Warner (1999) have documented for oil-exporting countries, a large share of this investment boom goes into the nontradable and commodity-producing sectors of the economy. When looking at the different effects of the two shocks on the components of the business gross fixed capital formation, we find that a negative GC shock generates an increase in total real investment in Canada mostly via "machinery and equipment" and "non-residential structures". By contrast, a positive GD shock results in strong rise in all investment components, including residential investments.

[24]For example, during the recent Great Recession, the fall of quarterly real GDP from the peak in 2007:Q4 to the trough in 2009:Q2 was 5.1 percent in the US vs. 3.4 percent in Canada.



(a) Negative commodity shock



(b) Positive demand shock

Figure 6. : Impulse responses: spending and Dutch disease effects, Canada vs. USA

Identification by sign restrictions - shaded area covering equally-tailed 68 percent credible set; recursive identification - median (solid line) together with equally-tailed 68 percent credible interval

Lastly, as for price deflators, both shocks lead to an increase of the consumer price index, after a spike in commodity prices, while the investment price deflator initially decreases following the appreciation of the nominal exchange rate. Most of this deflation is explained by its tradable component ("machinery and equipment"), whereas the price deflators of the investments in residential and non-residential structures (produced by non-tradable construction) tend to increase.

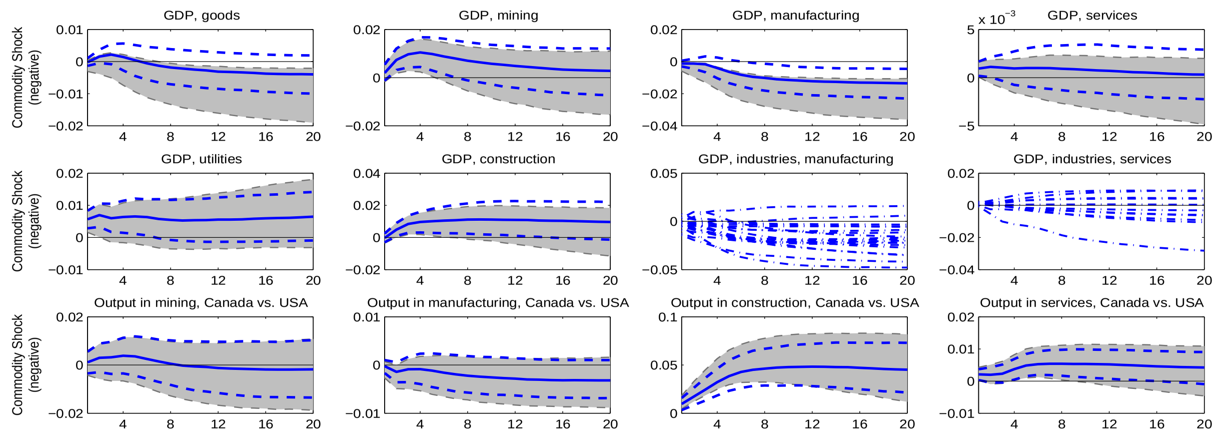
Dutch disease. — The so-called Dutch disease is perhaps the most famous phenomenon associated with SCEEs. It captures a negative relationship between an increase in export revenues from primary commodities and a decline in the output of the non-commodity tradable sector, mainly manufacturing (feature IV). The underlying mechanism is well known and goes as follows: an increase in primary commodities exports appreciates the real exchange rate, making non-commodity exports more expensive; as a result, the manufacturing sector becomes less competitive and its output declines while the output of nontradable and commodity sectors increases; labor and capital move simultaneously from manufacturing to the booming sectors of the economy .

Before discussing the results on this issue, it is worth recalling that the Dutch disease can take place in two different situations (see Corden, 1984). First, when a country sees a notable discovery of some natural resources or a significant technological improvement in the primary commodity sector. Second, when a country experiences an exogenous rise in the world prices of exported commodities. In this paper we concentrate exclusively on the second kind of the Dutch disease for two main reasons. First, because a large discovery of natural resources or a major breakthrough in the extraction technology are relatively rare events in a given country and have important long-run consequences on its economy. Secondly, because world commodity prices experience significant fluctuations at business-cycle frequencies which are quantitatively much more important than those of production in primary commodity sectors. The reason is that, in an environment where both short-run supply and demand of commodities are very inelastic, a small (realized or expected) reduction in the world supply or a small increase in the world demand will provoke very large increase in real commodity prices. In particular, the standard deviation of the quarterly growth of crude oil production in Canada over 1975-2010 equals 4.8 percent against 13.7 percent for the quarterly growth of the crude oil price.[25] Therefore, the lion's share of windfall income from commodity exports stems from the changes in the world commodity prices rather than from changes in the volume of commodity exports.

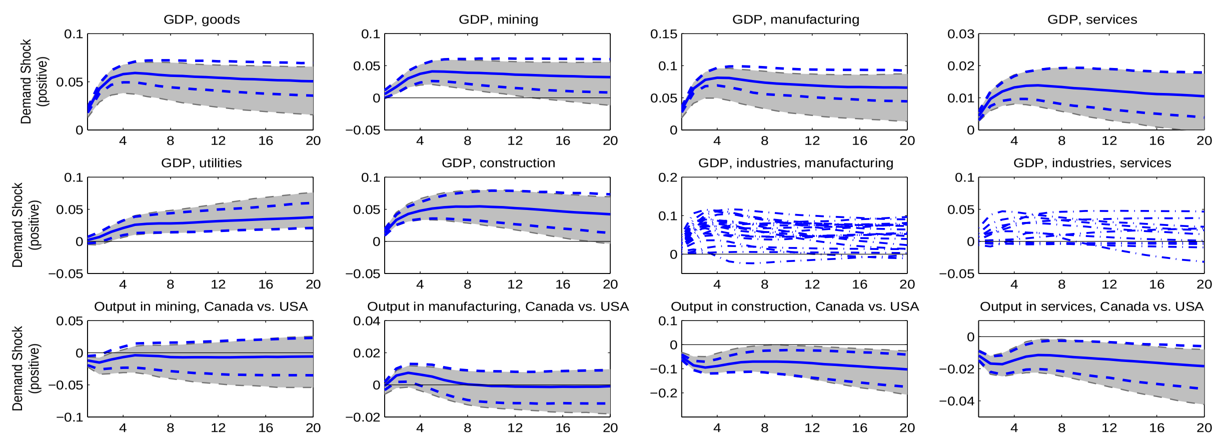
The Dutch disease effect has drawn a lot of attention in the literature (see Stijns, 2003, for good review). Yet, there is striking lack of unambiguous empirical evidence supporting this phenomenon. For example, Spatafora and Warner (1999) fail to detect a contraction in the manufacturing sector of a group of developing oil-exporting countries after an oil price shock. By contrast, using the gravity trade model and international trade data, Stijns (2003) reports that a one percent increase in world energy price is estimated to decrease real manufacturing exports from energy-exporting economy by almost half a percent. Our claim is that the main reasons for this disagreement could be, on the one hand, the difficulty in disentangling relative price effects of commodity price fluctuations from their impact on domestic and global macroeconomic conditions and, on the other, ignoring that fluctuations in commodity prices may be the result of changing global demand or supply.

Indeed, our empirical strategy illustrates well why these difficulties may arise. Figure 7 plots IRFs of real GDP in the main Canadian sectors (namely in mining, manufacturing, services, utilities and construction, as well as for disaggregated industries in manufacturing and services) to the two shocks. Strikingly, they imply completely different responses.

[25] During the more recent period of 1990-2010 this difference is even more pronounced: 3.2 percent for the Canadian oil production and 15.8 percent for the world crude oil price.



(a) Negative commodity shock



(b) Positive demand shock

Figure 7. : Impulse responses: GDP in industries and Dutch disease

Identification by sign restrictions - shaded area covering equally-tailed 68 percent credible set; recursive identification - median (solid line) together with equally-tailed 68 percent credible interval; medians of the output in the disaggregated industries - dash-dot lines

As shown before, a negative GC shock (panel a) does not significantly affect aggregate output. However, there are Dutch disease symptoms in the response of output in the different sectors to this shock. First, it has a significant positive effect on commodity-producing tradable sectors (e.g., mining), with the largest increase taking place after three quarters. Nontradable sectors reap the benefits too. For example, output in the services sector exhibits a statistically significant increase on impact, while the rise in construction and utilities is highly persistent. On the contrary, output in non-commodity tradable sectors (e.g., manufacturing) unambiguously falls following a decline in foreign demand, with the largest decrease in output happening after one year.[26]

Secondly, Table 5 shows that output in disaggregated manufacturing industries decreases over time. The strongest (and most significant) negative effect of a GC shock takes place in the largest manufacturing sector in Canada, namely transportation equipment, as well as on furniture and related products. Other durable manufacturing sectors also decline though less strongly. By contrast, the manufacturing industries performing primary processing of the rough materials (petroleum and coal product, wood product, primary metal and chemical manufacturing) are not significantly affected by a GC shock.[27] In turn, output in the different service-producing industries slightly increases on impact but the IRFs become quite disperse afterwards. In particular, windfall export revenues after a negative GC shock have a strong positive effect on the education, health and social assistance sectors (which are mostly publicly funded in Canada) as well as on professional services (which, among others, include construction-related services of architects, engineers, real estate brokers, etc.). At the same time, in line with the results of Kilian (2008), this shock has a strong negative effects on other services (including auto repairs).

We have seen before that a positive GD shock (panel b) also increases the real

[26]Recall from the Section II.B that real exports are declining too.
[27]Output in petroleum and coal product manufacturing even increase after a negative GC shock, though this effect is not statistically significant.

Table 5—: Impulse responses: GDP in selected manufacturing and services industries

	Negative Global Commodity Shock				Positive Global Demand Shock			
	0	4	8	16	0	4	8	16
Manufacturing	−0,27*	−1,23*	−1,78**	−2,12**	3,07**	7,59**	6,33*	5,37*
Food manufacturing	−0,26*	−0,54*	−0,57*	−0,57*	0,10	0,67	0,64	0,53
Clothing manufacturing	−1,24*	−2,01*	−2,23*	-2,10	2,09*	8,34**	8,26*	9,23*
Wood product manufacturing	0,57	-0,52	-0,91	-1,17	3,06**	6,09*	5,80*	6,56*
Paper manufacturing	-0,24	−1,57*	−1,81*	−1,88*	1,89*	6,06*	5,76*	6,12*
Petroleum and coal products	-0,06	1.13	1,53	1,57	0,50	-2,59	-2,53	-1,04
Chemical manufacturing	-0,14	-0,54	-0,81	-0,83	3,20**	7,11**	7,01**	7,75**
Plastics and rubber products	0,12	−1,44*	−2,08*	−2,16*	4,16**	8,67**	7,33*	7.79*
Primary metal manufacturing	0,39*	0,22	-0,74	-1,57	4,60**	10,20**	7,64*	5,79
Fabricated metal products	−0,49*	−1,47*	−2,29*	−3,07*	2,65**	9,06**	6,61*	2,92
Machinery manufacturing	-0,50	-0,73	−1,69*	−2,62*	2,82**	10,42**	8,06*	4,58
Computer and electronic products	−0,83*	−1,59*	−2,04*	−2,35*	3,66**	11,64**	10,00*	8,39*
Transportation equipment	-0,39	−3,23**	−4,37**	−4,79*	5,70**	11,03*	8,96*	8,23
Furniture and related products	−1,40**	−2,82**	−3,45**	−4,03**	3,30**	7,56*	5,39*	3,77
Services, business sector	0,11*	-0,04	-0,12	-0,25	0,65**	2,03**	1,89*	1,40*
Wholesale trade	0,24	-0,22	-0,47	-0,83	2,16**	4,59**	3,77*	2,84
Retail trade	0,20	-0,13	-0,31	-0,52	0,75*	1,16	0,75	0,01
Transportation and warehousing	0,27	-0,22	-0,62	-0,96	1,32**	3,91**	3,35*	2,25
Finance	0,05	-0,15	-0,19	-0,26	0,15	-0,09	-0,35	-0,73
Professional services	0,18	0,76*	0,93*	0,94	0,30	4,27**	5,16**	4,95**
Educational services	0,09	0,31*	0,39*	0,42*	-0,13	-0,51	-0,34	-0,17
Health care and social assistance	0,01	0,47*	0,72*	0,88*	-0,02	0,47	1,21*	2,00*
Other services (including auto repairs)	-0,01	−1,42*	−2,19*	−2,92*	-0,63	1,46	0,19	-2,63

Note: * and ** denote respectively significant at the 68 and 95 percent levels of confidence commodity prices and appreciates the real exchange rate. However, in contrast to a negative GC shock, it exhibits a uniform positive effect on output across the different industries, with largest increase in output taking place after 3-4 quarters. In view of the contrasting effects of these two shocks explaining most of the volatility of commodity prices and of the common factors capturing domestic and global economic activity, it is not all surprising that the Dutch disease has been so difficult to detect in the raw data.

The online appendix supports this conclusion by analyzing the IRFs of capacity utilization and employment to these two shocks. A negative GC shock leads to more intensive capacity utilization in mining, no significant response in construction and, foremost, more excess capacity in manufacturing. Yet, it has a negative, albeit insignificant, effect on employment in these industries, except in the construction sector where employment slightly increases after 2-3 quarters. In sharp contrast, a positive GD shock has a strong and uniformly positive effect on both variables across all industries.

Finally, as can be inspected in the last rows of the two panels in Figure 6, it is reassuring to check that the previous conclusions are strongly confirmed by the rather different responses of the relative indicators of sectoral output (Canada vs. US) to the two shocks. In effect, a negative GC shock (panel a) induces responses which have noticeable cross-industry and cross-country differences. Although there is a boom in the mining sector in both economies and a decline in manufacturing (with similar rates across countries, so that the ratios do not experience significant changes), the main finding is that this shock increases output in the Canadian non-tradable sectors (construction and services), whereas it declines in the corresponding US industries. This effect is especially evident and statistically significant in construction sector. Moreover, we have already seen in Figure 5 that exports (imports) of goods in Canada significantly falls (increases) relatively to the US after a negative GC shock, illustrating the deteriorating consequences of this shock on production of tradable goods in Canada. No such evidence exists after a positive GD shock (panel b) where the main finding is that output goes up in all Canadian and US industries (mining, manufacturing, services and construction). Moreover, as argued earlier, to the extent that this shock is likely to affect more strongly the US economy, its industries experience relatively higher growth than the Canadian ones.[28]

In sum, the Dutch disease effect can only be retrieved when a rise in commodity prices is due to a negative GC shock since a positive GD shock stimulates real output uniformly across industries and countries.

III. Robustness analysis

In this section we provide a sensitivity analysis of our results.

A. Structural breaks and subsample analysis

Since there have been important changes in the share of various commodity groups in Canada over the sample period, being the rise in the share of energy products since the late 1990s the most noticeable, it might be important to test for the stability of the SDFM and the FAVAR. To do so, we have performed the time invariance test of the factor loading proposed by Chen, Dolado and Gonzalo (2012) for the Canadian block of the SDFM model and found some indication of a structural break in the early 1990s.[29] Additionally, we analyzed possible breakpoints in the individual VAR regressions using the testing approach

[28]However, manufacturing output in Canada increases more strongly after a *positive* GD shock than in the US, despite an increase in its relative price due to real exchange rate appreciation. This larger response reflects the well-known fact that manufacturing output is more volatile in Canada than in the US (see, for example, Baldwin, 2009). In particular, during the period 1975q1-2010q4, one standard deviation of the quarterly (log) rate of growth of this sector in Canada was 2,2 percent vs. 1,7 percent in the US (for the more recent period 1990q1-2010q4 this difference is very similar, i.e., 2,2 percent vs. 1,6 percent). This higher Canadian volatility in turn may be linked to a general finding in the literature that the estimated income elasticities for US imports of goods (which are highly correlated with Canadian manufacturing exports and production) are significantly greater than the foreign income elasticities for US exports of goods (known as the Houthakker-Magee income elasticity asymmetry). There are different explanations of this asymmetry, such as demography, supply factors, production relocation, vertical integration, and improvements in global and regional market access (see Brook, Sedillot and Ollivaud, 2004, for review).

[29]This test is based on choosing the number of factors by means of Bai and Ng (2002) IC and estimate them by PC. Then, Chow tests (for known breaking date) and sup-type tests (for unknown breaking date) are used in (subsample) regressions where the first factor is regressed on the remaining ones.

developed by Bai and Perron (1998). These tests indicate that there may be structural breaks during two episodes of global recession, namely in 1990-93 and to a lesser extent in 2007-08, in the global block of VAR model. Yet, there is no evidence for such breaks in the Canadian VAR block.

To provide robustness checking we compare the results of the model for the full sample of 1975-2010 and for the more recent period of 1990-2010, which correspond to the breakpoint of the beginning of 1990s.[30] During this period, some important institutional and policy changes occurred in the Canadian economy. For example, in 1991 the Bank of Canada adopted inflation targeting regime, in 1994 the NAFTA trade agreement came into force, and at the beginning of 1995 the federal government introduced a number of tax and expenditure changes to reduce significantly the budget deficit.

The online appendix provides the IRFs of the selected variables to the shocks in these two samples using the sign identification scheme. In general, the results are qualitatively similar to those found with the whole sample. The most noticeable difference is that spending and Dutch disease effects are less strong after a negative GC shock for the most recent period. In particular, the rise in real personal consumption, real private investment and real imports in Canada relative to their U.S. counterparts are not so large as in the model using the whole sample, whereas relative exports do not exhibit any significant response. Additionally, output in the construction and services sectors of the Canadian economy relative to those in the US raises less than in the whole sample. Thus, although there are still Dutch disease symptoms in this subsample, they turn out to be less acute than in the whole sample.

[30]To check how important is the recent Great Recession episode for our results, we have also estimated the model for the pre-crisis sample of 1975-2007. The results are essentially the same after negative GC shock, but output and expenditure responses to a GD shock are weaker for this subsample, indicating that the Great Recession is identified in our model as an important negative GD shock.

B. Oil prices and Kilian's index of economic activity

We next check the sensitivity of the results to the use of alternative measures of the global factors by considering two modified variants of the model.

First, we replace the real commodity price factor by the real price of crude oil. The online appendix provides the IRFs of the selected variables to the shocks for this version of the model. Not surprisingly, the results are qualitatively similar to those reported above given that crude oil constitute an important fraction of Canadian commodity exports, especially since the late 1990s, and that our estimated commodity factor explain 54 percent of the variation in the real price of crude oil (see online appendix). Yet, the evidence in the whole sample for the Dutch disease effect, as well as for the different role played by the GD and GC shocks in explaining the spending effect, is weaker (less significant) than with the real commodity factor.

Secondly, we consider a variant of the model where our estimated global economic activity factor is replaced by Kilian (2009) global economic activity index which is based on dry cargo bulk freight rates. The variation in this leading indicator for economic activity is hardy explained (7 percent) by our global economic activity factor, which mainly relies upon output and trade statistics. Though Kilian's index may be more successful in capturing economic growth in South-East Asia than our factor, it suffers from several drawbacks. First, as stressed by Kilian (2009), crude oil price spikes may affect this index through increased costs of fuel for maritime transportation. Secondly, it is based on prices rather than on quantities produced. As a result, any changes in USD nominal exchange rates simultaneously affect commodity prices and dry cargo bulk freight rates, both denominated in this currency. These two features may lead to an overestimation of the positive effect of global demand on the real commodity prices and to an underestimation of the negative effect of a rise in commodity prices on global economic activity. In fact, the model based on this index attributes most the oil price spike of 1979-1980 (disruption of oil supply after Iranian revolution) to a large and positive GD shock. It may also predict a negative GD shock in 1986 (the oil glut episode), when falling petroleum prices significantly reduced freight rates, but there was no sign of recession in OECD countries (except for oil exporters). Finally, this index may overestimate the negative demand effect of the 1997-1998 Asian crisis on the US and Canadian economies.

The online appendix illustrates the IRFs of the selected variables to the shocks for this version of the model. Since some GC shocks now interpreted as being GD demand shocks (e.g., a positive oil supply shock in 1986), the spending and Dutch disease effects after a negative GC shock become less pronounced in this model while the evidence in favor of an spending effect after a positive GD shock becomes stronger.

IV. Conclusions

In this paper we have analyzed the sources and effects of internationally-driven shocks on a small commodity-exporting economy, using Canada as a representative case study. Combining structural dynamic factor modeling and VAR techniques, we quantify the dynamic responses of a wide variety of Canadian variables to several global structural shocks that drive changes in real commodity prices. We then illustrate how the use of a data-rich environment and an appropriate identification scheme of relevant shocks can jointly account for the main predictions in the literature dealing with the effects at business-cycle frequencies of unexpected fluctuations in real commodity prices on this type of economies.

Using a sign restriction as the benchmark identification scheme, our results support previous findings (see, e.g., Kilian, 2009; Kilian and Murphy, 2012, for the specific case of oil-exporting economies) about changes in commodity prices being driven by a variety of global structural shocks. In particular, we identify global demand, commodity-specific and global non-commodity supply shocks., with the first two shocks explaining most of the volatility in real commodity prices. Both positive global demand and negative commodity-specific shocks, which result in increasing commodity prices, generate a favorable effect on external balances and a commodity currency effect. However, only the latter shock leads to Dutch disease and spending effects. By contrast, a positive global demand shock stimulates real output and real expenditures uniformly across Canadian industries, without any clear indication of these two effects. Therefore, ignoring the different sources of shocks driving changes in commodity prices might explain why these effects are so strikingly absent in the data.

Several sensitivity checks (including a recursive identification scheme, subsample estimation and replacing our extracted factors by some other variables used in the literature) confirm somewhat these results, although we find evidence that, in some instances, the Dutch disease and spending effects are less pronounced that what we find with our methodology. Further investigation on why these differences arise remain high in our research agenda.

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Appendices

Estimation method

This appendix discusses the estimation of dynamic factor model by likelihood-based Gibbs sampling.

The measurement equation is written in the following general form:

$$\mathbf{X}_t = \mathbf{\Lambda}\mathbf{F}_t + \mathbf{e}_t \tag{A1}$$

where $\mathbf{X}_t$ is a $N \times 1$ vector of observed time series, $\mathbf{F}_t$ is a $K \times 1$ vector of unobserved factors, $\mathbf{\Lambda}$ denotes a $N \times K$ loading matrix with zero restrictions as discussed in the text and $\mathbf{e}_t$ is a $N \times 1$ error vector which is assumed to be normally distributed according to $\mathbf{e}_t \sim N(\mathbf{0}, \mathbf{R})$ with $\mathbf{e}_t$ independent across time and $\mathbf{R}$ diagonal.

The restricted VAR in our model has a different set of explanatory variables in each equation and may be estimated as a system of seemingly unrelated regression equations (SURE). In particular, we can write this system as

$$\mathbf{F}_t = \mathbf{G}_t\boldsymbol{\phi} + \mathbf{v}_t \tag{A2}$$

where $\mathbf{F}_t$ is a $K \times 1$ vector of factors, $\mathbf{G}_t$ is a $K \times M$ block-diagonal matrix with blocks $\mathbf{g}'_{kt}$ containing the current and lagged values of the factors relevant for the k-th variable, $\boldsymbol{\phi}$ is a $M \times 1$ vector of parameters, and $\mathbf{v}_t$ is an $K \times 1$ error vector with $\mathbf{v}_t \sim N(\mathbf{0}, \mathbf{\Sigma})$.

To estimate the system (A1-A2) we use Bayesian methods (see Koop, Poirier and Tobias, 2007), treating the model's parameters $\mathbf{\Lambda}$, $\mathbf{R}$, $\boldsymbol{\phi}$, $\mathbf{\Sigma}$ as random variables. Likelihood estimation by multi-move Gibbs sampling proceeds by alternately sampling these parameters from conditional posterior distributions.

The Gibbs sampling proceeds as follows. First, we choose a set of starting values for the parameters, say $\mathbf{\Lambda}^0$, $\mathbf{R}^0$, $\boldsymbol{\phi}^0$, $\mathbf{\Sigma}^0$, for example, as estimated from equation-by-equation OLS. Second, conditional on $\mathbf{R}^0$, $\mathbf{\Sigma}^0$ and the data, we draw $\mathbf{\Lambda}^1$ from the conditional posterior density $p(\mathbf{\Lambda}|\mathbf{X},\mathbf{F},\mathbf{R}^0)$ and $\boldsymbol{\phi}^1$ from $p(\boldsymbol{\phi}|\mathbf{F},\mathbf{G},\mathbf{\Sigma}^0)$. Third, conditional on generated $\mathbf{\Lambda}^1$, $\boldsymbol{\phi}^1$ and the data, we draw a set of values of the variance-covariance matrices $\mathbf{R}^1$ and $\mathbf{\Sigma}^1$, from the conditional distributions $p(\mathbf{R}|\mathbf{X},\mathbf{F},\mathbf{\Lambda}^1)$ and $p(\mathbf{\Sigma}|\mathbf{F},\mathbf{G},\boldsymbol{\phi}^1)$. The final two steps are repeated until the empirical distributions converge.

To be more specific, we impose conjugate Normal-Inverse-Gamma priors on the parameters of the measurement equation. Then, posterior conditional distribution of the coefficients $\mathbf{\Lambda}_i$ of the i-th measurement equation is Normal: $\mathbf{\Lambda}_i|\mathbf{X},\mathbf{F},\mathbf{R} \sim N(\overline{\mathbf{\Lambda}}_i, \mathbf{R}_{ii}\overline{\mathbf{M}}_i^{-1})$, where $\mathbf{R}_{ii}$ is the i-th diagonal element of $\mathbf{R}$, $\overline{\mathbf{\Lambda}}_i = \overline{\mathbf{M}}_i^{-1}(\underline{\mathbf{M}}_i\underline{\mathbf{\Lambda}}_i + \mathbf{F}^{(i)\prime}\mathbf{X}^{(i)})$, $\overline{\mathbf{M}}_i = \underline{\mathbf{M}}_i + \mathbf{F}^{(i)\prime}\mathbf{F}^{(i)}$, $\mathbf{F}^{(i)}$ and $\mathbf{X}^{(i)}$ are respectively the regressors and dependent variable of the i-th measurement equation, and $\underline{\mathbf{\Lambda}}_i$ and $\underline{\mathbf{M}}_i$ are prior parameters, which will be discussed later.

We assume that variance-covariance matrix $\mathbf{R}$ is diagonal, so its diagonal elements $\mathbf{R}_{ii}$ have conditional posterior Inverse-Gamma distribution: $\mathbf{R}_{ii}|\mathbf{X},\mathbf{F},\mathbf{\Lambda} \sim IG(\overline{\alpha}_i, \overline{\beta}_i)$, where $\overline{\alpha}_i = \underline{\alpha}_i + \frac{T}{2}$ is a shape parameter, $\overline{\beta}_i = \underline{\beta}_i + \frac{1}{2}(\mathbf{X}^{(i)} - \mathbf{F}^{(i)}\mathbf{\Lambda}_i)'(\mathbf{X}^{(i)} - \mathbf{F}^{(i)}\mathbf{\Lambda}_i)$ is a scale parameter, T is a number of time observations, $\underline{\alpha}_i$ and $\underline{\beta}_i$ are priors.

A commonly used distribution for the parameters of VAR equation is an independent Normal-Wishart distribution. The conditional posterior distribution of the restricted VAR coefficients is given by $\boldsymbol{\phi}|\mathbf{F},\mathbf{G},\mathbf{\Sigma}^{-1} \sim N(\overline{\boldsymbol{\phi}}, \overline{\mathbf{V}})$ where $\overline{\mathbf{V}} = \left(\underline{\mathbf{V}}^{-1} + \sum_{t=1}^{T} \mathbf{G}_t'\mathbf{\Sigma}^{-1}\mathbf{G}_t\right)^{-1}$, $\overline{\boldsymbol{\phi}} = \overline{\mathbf{V}}\left(\underline{\mathbf{V}}^{-1}\underline{\boldsymbol{\phi}} + \sum_{t=1}^{T} \mathbf{G}_t'\mathbf{\Sigma}^{-1}\mathbf{F}_t\right)$ and $\underline{\boldsymbol{\phi}}$ and $\underline{\mathbf{V}}$ are respectively prior mean and variance of the VAR coefficients.

The posterior for $\mathbf{\Sigma}^{-1}$ conditional on $\boldsymbol{\phi}$ has a Wishart distribution: $\mathbf{\Sigma}^{-1}|\mathbf{F},\mathbf{G},\boldsymbol{\phi} \sim W(\overline{\mathbf{H}}, \overline{v})$, where $\overline{\mathbf{H}} = \left(\underline{\mathbf{H}}^{-1} + \sum_{t=1}^{T}(\mathbf{F}_t - \mathbf{G}_t\boldsymbol{\phi})(\mathbf{F}_t - \mathbf{G}_t\boldsymbol{\phi})'\right)^{-1}$, $\overline{v} = T + \underline{v}$ and $\underline{\mathbf{H}}$ and $\underline{v}$ are respectively a scale matrix and degrees of freedom of the prior distribution.

We estimate the model using both informative and uninformative priors. To specify informative priors we loosely follow Sims and Zha (1998) and Bernanke, Boivin and Eliasz (2005). In particular, parameters of the conditional prior Normal distribution of the loading matrix coefficients are set to $\underline{\mathbf{\Lambda}}_i = \mathbf{0}$ and $\underline{\mathbf{M}}_i = \mathbf{I}_{K_i \times K_i}$. Given that all time series in $\mathbf{X}_t$ are normalized and standard deviations of the measurement errors cannot exceed one, we specify the shape and scale parameters of the prior Inverse-Gamma distribution of the $\mathbf{R}_{ii}$ to $\underline{\alpha}_i = 1.5$ and $\underline{\beta}_i = 0.5$, so the prior mean of $\mathbf{R}_{ii}$ is equal to one and prior distribution is pretty diffuse on the interval $[0, 1]$.

To specify the prior mean of the coefficients in the (reduced form) VAR equation we assume that $\underline{\boldsymbol{\phi}}$ has a AR(1) structure for each endogenous variable. Since all factors are assumed to be stationary (due to proper transformation of the time series in $\mathbf{X}_t$), we set the prior mean to the OLS estimates of the AR(1) coefficient for each variable. The variance of the prior distribution $\underline{\mathbf{V}}$ is specified by modification of the Minnesota prior (as in Sims and Zha, 1998), so the elements of $\boldsymbol{\phi}$ are independent and the conditional standard deviation of the coefficient on lag l of variable j in equation i is given by $\frac{\mu_0 \mu_1}{\sigma_j l^{\mu_3}}$, where μ_0, μ_1 and μ_3 are hyperparameters and σ_j are standard deviations of residuals from AR(1) fit to the individual factors. Following Sims and Zha (1998) we set these hyperparameters to $\mu_0 = 1$, $\mu_1 = 0.3$ and $\mu_3 = 1$. We do not specify intercept in the VAR model, given that all factors are demeaned. Finally, as in Bernanke, Boivin and Eliasz (2005), a scale matrix and degrees of freedom of the conditional prior Wishart distribution of the matrix $\mathbf{\Sigma}^{-1}$ are set to $\underline{\mathbf{H}}^{-1} = diag\{\sigma_1^2, \sigma_2^2, \ldots, \sigma_K^2\}$ and $\underline{v} = K + 2$, where σ_j are standard deviations of residuals from AR(1).

The model with uninformative priors is estimated by setting $\underline{\mathbf{\Lambda}}_i = \mathbf{0}$, $\underline{\mathbf{M}}_i = \mathbf{0}$, $\underline{\beta}_i = 0$, $\underline{\boldsymbol{\phi}} = \mathbf{0}$, $\underline{\mathbf{V}}^{-1} = \mathbf{0}$ and $\underline{\mathbf{H}}^{-1} = \mathbf{0}$. Both specifications provide similar results.

Inference is based on the empirical distribution of parameters $\mathbf{\Lambda}$, $\mathbf{R}$, $\boldsymbol{\phi}$, $\mathbf{\Sigma}$, for iterations $s > B$, with B large enough to guarantee convergence of the algorithm (we set $B = 10000$). The distribution from the sampling procedure should well approximate the joint posterior. Calculating medians and quantiles of $\mathbf{\Lambda}$, $\mathbf{R}$, $\boldsymbol{\phi}$, $\mathbf{\Sigma}$, as well as impulse responses (which are nonlinear functions of these parameters), for $s = B, \ldots, S$, where S is a number of iterations, provides estimates of these parameters and the associated Bayesian probability regions. Notice, that to avoid an explosive behavior of the IRFs we retain only iterations with stable draws.

Identification using sign and bound restrictions

The sign restrictions are imposed using the procedure proposed by Rubio-Ramirez, Waggoner and Zha (2010). Let $\mathbf{B}_0$ be a structural impact matrix computed using the Cholesky decomposition of the reduced form variance-covariance matrix $\mathbf{\Omega}$ with the global factors ordered first, i.e. $\mathbf{\Omega} = \mathbf{B}_0\mathbf{B}_0'$. Let $\tilde{\mathbf{Q}}$ be identity matrix with the foreign (upper-left) block substituted by any (rotational) orthogonal 3×3 matrix, such that $\tilde{\mathbf{Q}}\tilde{\mathbf{Q}}' = \mathbf{I}$. Then, multiplying the impact matrix $\mathbf{B}_0$ by $\tilde{\mathbf{Q}}$ yields a new structural impact matrix $\tilde{\mathbf{B}}_0 = \mathbf{B}_0\tilde{\mathbf{Q}}$ (with the global factors again ordered first). Notice, that $\tilde{\mathbf{B}}_0\tilde{\mathbf{B}}_0' = \mathbf{\Omega}$. Drawing repeatedly from the set of orthogonal rotational matrices one can generate a wide range of possible choices for the structural model.

The algorithm consists of the following steps:

1) Compute the Cholesky decomposition $\mathbf{B}_0^k$ of the posterior draw k of the reduced form variance-covariance matrix $\mathbf{\Omega}^k$ with the global factors ordered first.

2) Draw an independent standard normal 3×3 matrix $\mathbf{X}$ and let $\mathbf{X} = \mathbf{QR}$ be the QR decomposition of $\mathbf{X}$ with the diagonal of $\mathbf{R}$ normalized to be positive. Then $\mathbf{Q}$ is a rotational orthogonal matrix and has the uniform (or Haar) distribution. Substitute the upper-left diagonal block of the identity matrix $\tilde{\mathbf{Q}}$ by $\mathbf{Q}$.

3) Compute $\mathbf{A}_0^k = \mathbf{B}_0^k\tilde{\mathbf{Q}}$. If this model satisfies the sign and bound restrictions, keep it. Otherwise, move to the next Gibbs iteration.