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The dynamic response of the Current Account to Commodity Prices shocks in Mining and Non-mining exporting economies

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The dynamic response of the Current Account to Commodity Prices shocks in Mining and Non-mining exporting economies *

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Abstract

The boom and bust of Commodity Prices have had a significant macroeconomic impact on commodity-exporter economies. This paper assesses the dynamic impact of Commodity Prices on the Current Account surplus for several commodity-exporter economies. Because these economies share several economic features, and since they are subject to the same external shocks, it is necessary to estimate their behavior simultaneously. Moreover, the impact of these shocks might be different along the sample of analysis. Thus, we estimate a Panel VAR model with dynamic inter-dependencies and time varying parameters. Within this framework, we have computed an average current account indicator and studied the responses of individual current account balances to shocks in fuel and metal prices. We have found that our common indicator for the current account follows closely the dynamic pattern of the commodity price index i.e. surpluses (deficit) are usually associated with increases (decreases) in commodity prices, and this indicator is statistically significant across the sample of analysis. At the country level, by comparing the impulse response functions, we found that commodity price shocks have a similar effect across countries, although their magnitude differ. In general, our results suggest that the impact on the current account balances have increased since 2002. In the case of a fuel shock, we do not found significant current account responses. However, the evidence for a metal shock is more robust, with higher responses in the case of the metal-exporting countries.

JEL Classification: C11, C33, E32, F42

Key words: Commodity Prices, Current Account, Panel Vector Autoregressions, Bayesian Methods

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1 Introduction

By the beginning of the last decade, the global economy began to experience the positive effects of an expansionary phase of the business cycle. The latter triggered a significant increase in the terms of trade of many commodity-exporting economies. In fact, according to the World Bank, commodity prices increased by 135 percent from 2003 to 2007. This was the largest increase recorded in a single five-year period since 1960s decade. Overall, this improvement in prices have had a significant impact in the current account and the aggregate GDP of commodity exporting economies.

Among the commodities that experienced a significant increase in prices, the case of metals deserves a particular attention. As a result, the current account dynamics of countries such as Australia, Canada, Chile, Peru and South Africa (economies that export mainly metals like copper and gold) was mainly associated with the behavior of metals prices. Fornero et al. (2016) show that in these countries, the current account deficits or reversals are associated with the response of investment, mainly in the mining sector, which is highly correlated with the price of metals. Moreover, this investment reaction depends on the temporal nature of the price shocks, i.e. transitory shocks do not generate a huge increase in commodity sectors investment, whereas permanent shocks produce a significant impact. Therefore, the transitory shocks tend to be associated with current account surpluses, while persistent shocks are highly correlated with significant current account deficits.

In order to assess the impact of commodity prices fluctuation, in this paper we use quarterly data for a group of commodity exporting countries (Australia, Brazil, Canada, Chile, Colombia, Mexico, New Zealand, Norway, Peru and South Africa). In particular, we evaluate the individual responses of the current account surplus to a global commodity prices shock, where we focus our attention to metal prices. The sample of analysis goes from 1996 to 2015 in order to include the latest episode of price increases. Unlike Fornero et al. (2016), who estimate individual VARs for each country, we employ a Panel VAR approach in the spirit of Canova and Ciccarelli (2009)[1]. The latter methodology allows us to capture cross-country lagged inter-dependencies

[1] See also Canova and Ciccarelli (2013).

and incorporate common, country-specific and variable-specific indicators summarizing spillover effects across countries and variables. In addition, we allow for time variation in order to explore the impulse responses in different dates, making the distinction between periods before and after the commodity boom. Additionally, by comparing the effects on mining countries against non-mining ones, it may be possible to extract the differentiated effect of commodity price shocks.

Within this framework, we have computed an average current account indicator and studied the responses of individual current account balances to shocks in fuel and metal prices. We have found that our common indicator for the current account follows closely the dynamic pattern of the commodity price index i.e. surpluses (deficit) are usually associated with increases (decreases) in commodity prices, and this indicator is statistically significant across the sample of analysis. At the country level, by comparing the impulse response functions, we found that commodity price shocks have a similar effect across countries, although their magnitude differ. In general, our results suggest that the impact on the current account balances have increased since 2002. In the case of a fuel shock, we do not found significant current account responses. However, the evidence for a metal shock is more robust, with higher responses in the case of the metal-exporting countries.

The document is organized as follows: section 2 describes the econometric model, section 3 describes the estimation procedure, section 4 discusses the main results, and section 5 concludes.

2 The Multi-Country Panel VAR model

This section closely follows Canova and Ciccarelli (2009). We specify a Multi-Country model with lagged inter-dependencies and time varying parameters. We abstract from the possible presence of Stochastic Volatility, since the current setup is already computationally demanding.[2]

[2]See also Canova et al. (2007), Canova and Ciccarelli (2012) and Canova et al. (2012).

2.1 The setup

The statistical model employed in this paper has the form:

$$y_{it} = D_{it}(L) Y_{t-1} + F_{it}(L) Z_t + c_{it} + e_{it} \tag{1}$$

where $i = 1, \ldots, N$ refers to countries and $t = 1, \ldots, T$ refers to time periods. In addition, y_{it} is a $M \times 1$ vector of endogenous variables for each country i and $Y_t = (y'_{1t}, y'_{2t}, \ldots, y'_{Nt})'$.

We define the polynomials

$$D_{it}(L) = D_{it,1} + D_{it,2}L + \cdots + D_{it,p}L^{p-1}$$

$$F_{it}(L) = F_{it,0} + F_{it,1}L + \cdots + F_{it,q}L^{q}$$

where $D_{it,j}$ are $M \times NM$ matrices for each lag $j = 1, \ldots, p$. Moreover, Z_t is a $M_2 \times 1$ vector of exogenous variables common to all countries and $F_{it,j}$ are $M \times M_2$ matrices for each lag $j = 0, \ldots, q$, c_{it} is a $M \times 1$ vector of intercepts and e_{it} is a $M \times 1$ vector of random disturbances.

Notice that cross-unit lagged inter-dependencies are allowed whenever the $NM \times NM$ matrix $D_t(L) = [D_{1t}(L), D_{2t}(L), \ldots, D_{Nt}(L)]'$ is not block diagonal. Notice also that coefficients in (1) are allowed to vary over time and that dynamic relationships are unit-specific. All these features add realism to the econometric model. However, this comes at the cost of having an extremely large number of parameters to estimate (we have $k = NMp + M_2(1+q) + 1$ parameters per equation). For that reason, we specify a more parsimonious representation of the latter model in order to proceed to the estimation.

Equation (1) can be rewritten in a compact form as

$$Y_t = W_t \delta_t + E_t, \qquad E_t \sim N(0, \Omega) \tag{2}$$

where $W_t = I_{NM} \otimes X'_t$; $X'_t = \left(Y'_{t-1}, Y'_{t-2}, \ldots, Y'_{t-p}, Z'_t, Z'_{t-1}, \ldots, Z'_{t-q}, 1\right)$; $\delta_t = \left(\delta'_{1,t}, \delta'_{2,t}, \ldots, \delta'_{N,t}\right)'$ and δ_{it} are $Mk \times 1$ vectors containing, stacked, the M rows of matrix D_{it} and F_{it}, while Y_t and E_t are $NM \times 1$ vectors. Notice that since δ_t varies with cross-sectional units in different time periods, it is impossible to estimate it using classical methods. Even in the case of constant coefficients, the amount of degrees of freedom needed to conduct proper inference is tremendously large. For that reason, Canova and Ciccarelli (2009) suggest to reduce the dimensionality of this problem as follows:

$$\delta_t = \Xi_1 \theta_{1t} + \Xi_2 \theta_{2t} + \Xi_3 \theta_{3t} + \Xi_4 \theta_{4t} + u_t \tag{3}$$

where Ξ_1, Ξ_2, Ξ_3, Ξ_4 are matrices of dimensions $NMk \times 1$, $NMk \times N$, $NMk \times M$, $NMk \times 1$ respectively. θ_{1t} captures movements in coefficients that are common across countries and variables; θ_{2t} captures movements in coefficients which are common across countries; θ_{3t} captures movements in coefficients which are common across variables; θ_{4t} captures movements in coefficients which are common across exogenous variables. Finally, u_t captures all the un-modeled features of the coefficient vector[3].

The factorization (3) significantly reduces the number of parameters to be estimated. In other words, it transforms an over-parametrized panel VAR into a parsimonious SUR model, where the regressors are averages of certain right-hand side variables. In fact, substituting (3) in (2) we have

$$Y_t = \sum_{i=1}^{4} \mathcal{W}_{it} \theta_{it} + \upsilon_t$$

where $\mathcal{W}_{it} = W_t \Xi_i$ capture respectively, common, country-specific, variable-specific and exogenous-specific information present in the data, and $\upsilon_t = E_t + W_t u_t$.

To complete the model, we specify $\theta_t = [\theta'_{1t}, \theta'_{2t}, \theta'_{3t}, \theta'_{4t}]'$ so that we have the law of motion:

$$\theta_t = \theta_{t-1} + \eta_t, \qquad \eta_t \sim N(0, B_t)$$

where B_t is block-diagonal with:

$$B_t = \gamma_1 B_{t-1} + \gamma_2 \overline{B}$$

where γ_1 and γ_2 are scalars and a $\overline{B}$ is block-diagonal matrix.

[3]See details in Canova and Ciccarelli (2009).

To summarize, the empirical model has the state-space form:

$$Y_t = (W_t \Xi)\,\theta_t + \upsilon_t \tag{4}$$

$$\theta_t = \theta_{t-1} + \eta_t \tag{5}$$

where $\upsilon_t \sim N(0, \sigma_t)$; $\sigma_t = \left(1 + \sigma^2 X_t' X_t\right)$ and $\eta_t \sim N(0, B_t)$. To compute the posterior distributions, we need prior densities for the parameters $\left(\Omega, \sigma^2, \overline{B}, \theta_0\right)$.

2.2 Priors

Following the references we set conjugated priors, i.e. such that the posterior distribution has the same shape as the likelihood function. In particular, given the normality assumption for the shocks, the variance and covariance parameters have an Inverse Gamma distribution [4] or Inverse Wishart distribution for the multivariate case. In addition, since we are going to use the Kalman filter and smoother for simulating the posterior distribution of latent factors, it is reasonable to assume the initial point as normally distributed.

$$p\left(\Omega^{-1}\right) = Wi\left(z_1, Q_1\right)$$

$$p\left(\sigma^2\right) = IG\left(\frac{\zeta}{2}, \frac{\zeta s^2}{2}\right)$$

$$p\left(b_i\right) = IG\left(\frac{\varpi_0}{2}, \frac{\delta_0}{2}\right), \qquad i = 1, \ldots, 4$$

$$p\left(\theta_0\right) = N\left(\overline{\theta}_0, \overline{R}_0\right)$$

where the latter implies a prior for $\theta_t = N\left(\theta_{t-1|t-1}, R_{t-1|t-1} + B_t\right)$.

[4] See e.g. Zellner (1971) and Koop (2003).

2.3 Posterior Distribution

The posterior distribution of model parameters is the efficient combination of prior information with the observed data. Denote the parameter vector as

$$\psi = \left(\Omega^{-1}, \{b_i\}_{i=1}^{4}, \sigma^2, \{\theta_t\}_{t=1}^{T}\right) \tag{6}$$

Given the normality assumption of the error term υ_t, the likelihood function of the Multi-Country Panel VAR model (4) is equal to

$$L\left(Y^T \mid \psi\right) \propto \left(\prod_{t=1}^{T} \sigma_t^{-NM/2}\right) |\Omega|^{-T/2} \exp\left[-\frac{1}{2}\sum_{t=1}^{T} \left(Y_t - W_t \Xi \theta_t\right) \left(\sigma_t \Omega\right)^{-1} \left(Y_t - W_t \Xi \theta_t\right)'\right] \tag{7}$$

where $Y^T = (Y_1, Y_2, \ldots, Y_T)$ denotes the data, and $\sigma_t = \left(1 + \sigma^2 X_t' X_t\right)$.

Using the Bayes' rule, we have the posterior distribution

$$p\left(\psi \mid Y^T\right) \propto L\left(Y^T \mid \psi\right) p\left(\psi\right) \tag{8}$$

In the next section we will explain how to obtain the optimal estimates of model parameters in a tractable way. So far, we have identified our object of interest, and the next step is to proceed to the estimation.

3 Bayesian Estimation

3.1 A Gibbs Sampling routine

Analytical computation of the posterior distribution (8) is impossible. However, we can factorize $p\left(\psi \mid Y^T\right)$ into different parameter blocks according to (6). The latter allows us to specify the cycle:

1. Simulate $\{\theta_t\}_{t=1}^{T}$ from $p\left(\theta_t \mid Y^T, \psi_{-\theta_t}\right)$ such that

$$\theta_t \mid Y^T, \psi_{-\theta_t} \sim N\left(\overline{\theta}_{t|T}, \overline{R}_{t|T}\right),\ t \leq T \tag{9}$$

2. Simulate Ω^{-1} from $p\left(\Omega^{-1} \mid Y^T, \psi_{-\Omega}\right)$ such that

$$\Omega^{-1} \mid Y^T, \psi_{-\Omega} \sim Wi\left(z_1 + T, \left[\frac{\sum_t \left(Y_t - W_t \Xi \theta_t\right)\left(Y_t - W_t \Xi \theta_t\right)'}{\sigma_t} + Q_1^{-1}\right]^{-1}\right) \tag{10}$$

3. Simulate b_i from $p\left(b_i \mid Y^T, \psi_{-b_i}\right)$ such that

$$b_i \mid Y^T, \psi_{-b_i} \sim IG\left(\frac{\varpi^i}{2}, \frac{\sum_t \left(\theta_t^i - \theta_{t-1}^i\right)'\left(\theta_t^i - \theta_{t-1}^i\right) + \delta_0}{2\xi_t}\right) \tag{11}$$

   where $\xi_t = \gamma_1^t + \gamma_2 \frac{1-\gamma_1^t}{1-\gamma_1}$.

4. Simulate σ^2 from $p\left(\sigma^2 \mid Y^T, \psi_{-\sigma^2}\right)$ such that

$$\sigma^2 \mid Y^T, \psi_{-\sigma^2} \propto L\left(Y^T \mid \psi\right) p\left(\sigma^2\right) \tag{12}$$

where $\overline{\theta}_{t|T}$ and $\overline{R}_{t|T}$ are the one-period ahead forecasts of θ_t and the variance-covariance matrix of the forecast error, respectively, calculated through the Kalman Smoother, as described in Chib and Greenberg (1995). We also have $\varpi^1 = T + \varpi_0$, $\varpi^2 = TM + \varpi_0$, $\varpi^3 = TN + \varpi_0$, $\varpi^4 = T + \varpi_0$.

The posterior of σ^2 is simulated using a Random-Walk Metropolis-Hastings step, since it is non-standard. That is, at each iteration l we draw a candidate $\left(\sigma^2\right)^*$ according to

$$\left(\sigma^2\right)^* = \exp\left[\ln\left(\sigma^2\right)^{l-1} + c_\sigma \varepsilon\right]$$

with $\varepsilon \sim N(0,1)$ and c_σ is a parameter for scaling the variance of the proposal distribution. In particular, this is chosen such that the acceptance rate is between $0.2 - 0.4$. Moreover, the acceptance probability at each draw l is given by:

$$\alpha = \min\left\{\frac{L\left(\left(\sigma^2\right)^*, \psi_{-\sigma^2}^l \mid Y^T\right) p\left(\left(\sigma^2\right)^*\right) \varrho\left(\left(\sigma^2\right)^{l-1} \mid \left(\sigma^2\right)^*\right)}{L\left(\left(\sigma^2\right)^{l-1}, \psi_{-\sigma^2}^l \mid Y^T\right) p\left(\left(\sigma^2\right)^{l-1}\right) \varrho\left(\left(\sigma^2\right)^* \mid \left(\sigma^2\right)^{l-1}\right)}, 1\right\}$$

where we take into account the fact that the proposal distribution is not symmetric.

Under regularity conditions, cycling through the conditional distributions (9) – (10) – (11) – (12) will produce draws from the limiting ergodic distribution.

3.2 Estimation setup

We run the presented Gibbs sampler for $K = 150,000$ draws and discard the first $100,000$ in order to minimize the effect of initial values. Moreover, in order to reduce the serial correlation across draws, we set a thinning factor of 10, i.e. given the remaining $50,000$ draws, we take 1 every 10 and discard the remaining ones. As a result, we have $5,000$ draws for conducting inference. Priors are calibrated using a training sample based on the first five years of data. Specific details about the Data Description and how we conduct inference and assess convergence can be found in Appendices A and B respectively. We set $\varpi_0 = 10^6$, $\delta_0 = 1$, $z_1 = NM + 5$, $Q_1 = diag\left(Q_{11}, \ldots, Q_{1N}\right)$ where Q_{1i} is the residual covariance matrix of the time invariant VAR for the i-th country, $\zeta = 1$, $s^2 = \hat{\sigma}^2$ where $\hat{\sigma}^2$ is the average of the estimated variances of NM independent $AR(p)$ models. Moreover, $\overline{\theta}_0 = \hat{\theta}_0$ is the OLS estimation of the time-invariant version of the model and $\overline{R}_0 = I_{dim(\theta_t)}$. Given the calibrated value of c_σ, the acceptance rate of the metropolis-step is around 0.38. Finally, we set $\gamma_1 = 0$ and $\gamma_2 = 1$, meaning that η_t has a constant variance.

3.3 Impulse responses computation

In this section we explain how we compute the dynamic responses at different points in time using the presented model. We define the Impulse Responses as follows: let the expression

$$IR_Y^j\left(t,h\right) = E\left(Y_{t+h} \mid F_t^1\right) - E\left(Y_{t+h} \mid F_t^2\right), \quad h = 1, 2, \ldots$$

be the response of vector Y_t to a shock in variable j of size δ at date t. Where

$$F_t^1 = \left\{Y^t, \theta_{t+1}^{t+h}, S_t, J_t, \xi_{j,t}^{\delta}, \xi_{-j,t}, \xi_{t+1}^{t+h}\right\}$$

$$F_t^2 = \left\{Y^t, \theta_{t+1}^{t+h}, S_t, J_t, \xi_t, \xi_{t+1}^{t+h}\right\}$$

$$S_t = (\Omega, B_t)\,; \quad \Omega = J_t J_t'$$

and where

$$\theta_{t+1}^{t+h} = \left[\theta_{t+1}', \theta_{t+2}', \ldots, \theta_{t+h}'\right]'$$

$$Y_{t+1}^{t+h} = \left[Y_{t+1}', Y_{t+2}', \ldots, Y_{t+h}'\right]'$$

In order to forecast Y_{t+h} and θ_{t+h}, we use the equations (4) and (5), respectively. We repeat this procedure for a subset of random draws from the posterior distribution, and for different dates. Then we collect the draws and compute the median value and relevant percentiles.

4 Results

4.1 Data and variables selection

For each country we use year-to-year growth rates of GDP, Consumer Price Index, Terms of Trade and Exchange Rates. As in Canova et al. (2012), we include domestic price indexes in order to control for variation in nominal variables. We also include the Current Account Surplus (as percentage of GDP) and the domestic interbank rate. As exogenous variables, we include the annual growth rate of US's GDP, the growth rate of WTI Oil prices and a Commodity Price Index, the growth rate of prices of only metals, fuel and non-fuel commodity prices. It is important to mention that we assume that all the commodity exporting economies take the international commodity prices as given. Our main data sources are the International Financial Statistics (IFS) from the International Monetary Fund (IMF) and the Databases of FRED, IDB, OECD and domestic Central Banks. The sample of analysis covers the period 1997Q1-2015Q4. Following the references, data is demeaned and standardized.

4.2 Model Comparison

Our Baseline specification considers one lag for domestic and exogenous variables, i.e. $p = 1$ and $q = 1$. We also include a common component, a country-specific component, a variable-specific component and an exogenous component. The purpose of this section is to compare this

Baseline specification with alternative ones. To do so, a good practice in Bayesian Econometrics is to compute the Marginal Likelihood for each model. That is, we need to integrate out the posterior distribution across the parameter space, and the see to what extent a given model is a good representation of the data, i.e. the model with a higher marginal likelihood will be the best one. The marginal likelihood for each model M_i is

$$f\left(Y^T \mid M_i\right) = \int L\left(\psi_j \mid Y^T, M_i\right) P\left(\psi_j \mid M_i\right) dj$$

Given the scales, it is better to compute the log-marginal likelihood $\ln f\left(Y^T \mid M_i\right)$, and this is estimated using a standard harmonic mean estimator. Results are shown in Table 1. In particular, we select the Baseline specification for conducting inference in the next subsection.

Model	Description	$\ln f\left(Y^T \mid M_i\right)$
M_1	Baseline Model $(p = 1, q = 1)$	-4068.6
M_2	No Country Component	-4072.4
M_3	No Variable Component	-4132.8
M_4	Alternative model $(p = 2, q = 2)$	-4461.7
M_5	Alternative model $(p = 2, q = 1)$	-4300.3

Table 1: Log-Marginal Likelihood of Different models

4.3 Analysis of Commodity exporting Current Account

Based in our methodology we are able to construct a common current account indicator for the whole sample of countries. This indicator, following Canova et al. (2012), corresponds to the posterior distribution of $\mathcal{W}_{3t}$ multiplied by the estimated θ_{3t},it is depicted in Figure 1, and this indicator is statistically significant across the sample of analysis.

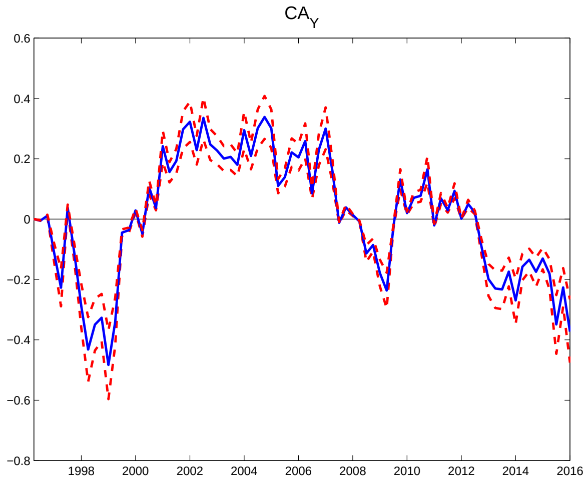


Figure 1: Posterior distribution of Current Account Indicator

One important thing to notice is that our indicator shows the average ups and downs of current account balances for the countries in our sample, which should be correlated with the dynamic behavior of the commodity price index. In fact, between 2000 and 2008 we see a current account surplus and this period coincides with one of high increase in the commodity price index (commodity prices increased 106.6%). In addition, after 2008 commodity prices experienced a sharp and persistent decline, which is also reflected in our current account indicator.

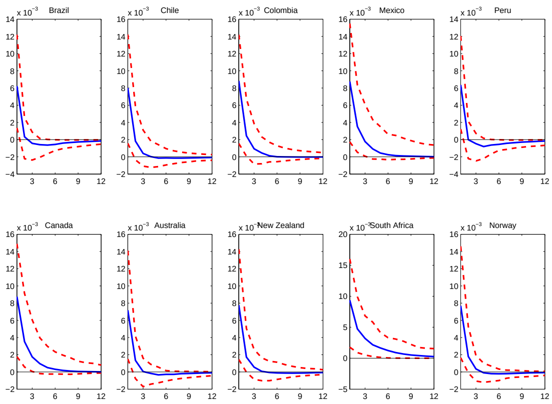
Finally, since the second quarter of 2011 commodity prices began a downturn trend i.e. commodity prices declined almost 52% up to the end of 2015. As a consequence, current account balances deteriorated, which in most countries meant an increase of its deficit (Figure 1 shows a common current account deficit for the same period)

4.4 The transmission of distinct Commodity Price shocks across commodity exporting countries

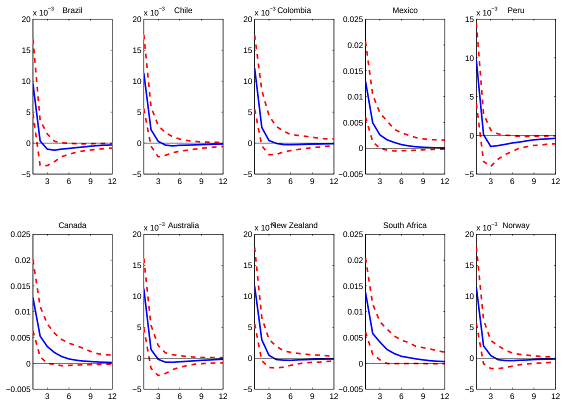
The previous section gave an overall picture of the impact of commodity price changes on current account balances. Although the commodity price index we are using is a good starting point, some commodities deserve special attention. In particular, we focus our analysis on fuel and metal prices.

We compute the impulse response functions for a fuel and metal unit shock so we can analyze the heterogeneity in responses across countries and for different time periods, which is one of the most important outputs that can be obtained through the Panel VAR methodology. It is important to remark that we could also add more persistence to the shock in order to be in line with actual data. However, given that the purpose of this exercise is only to capture the dynamic effects after an isolated shock, it is not necessary to add these features to the model. Since our target is to analyze the current account dynamics, we only report the responses of this variable.

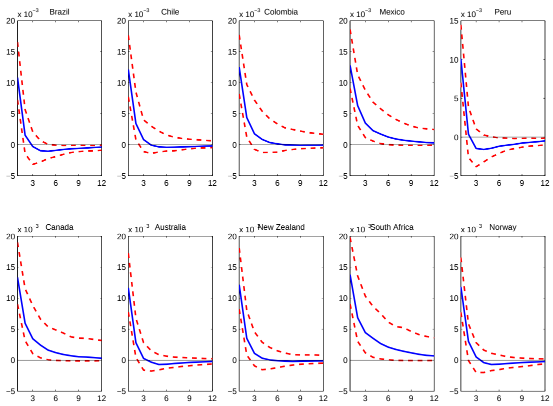
We first present the results for a fuel price shock in Figure2. Although we found a positive impact across countries and in different time periods for the first quarters, most impulse response functions turn to be not significant. Nonetheless, it is worth mention that for Peru, we found a significant negative impact after three or four quarters in line with the expected behavior for a oil-importing economy.



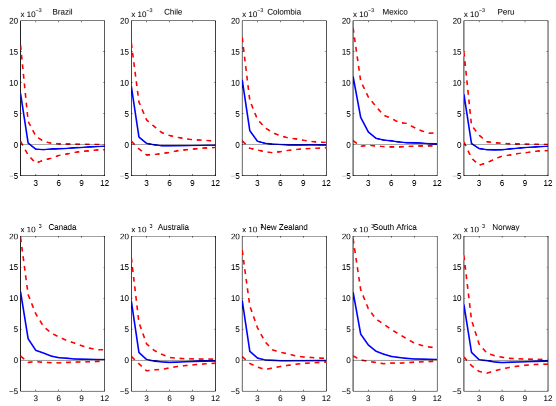
(a) 2002



(b) 2006



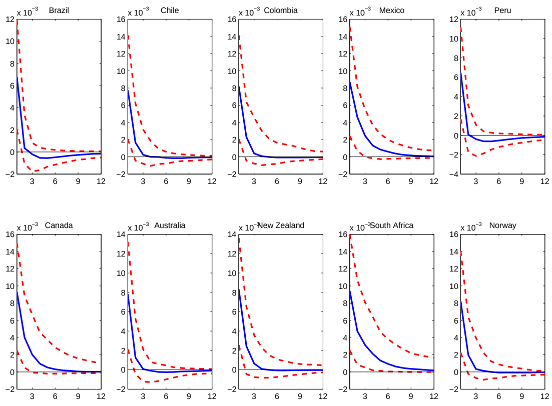
(c) 2010



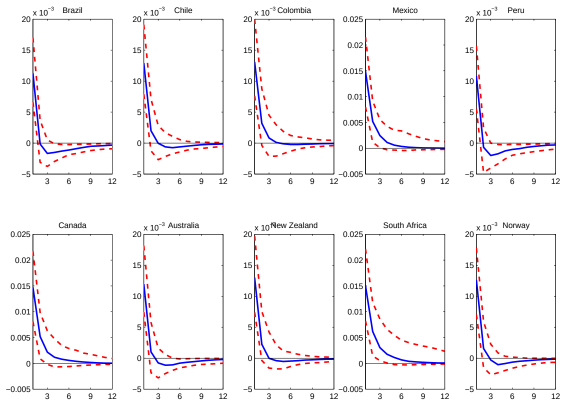
(d) 2014

Figure 2: Response of Current Account to a unit shock on Fuel Prices; median value and 68% bands

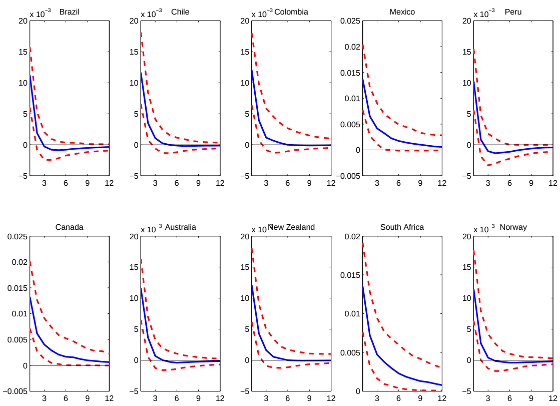
The results for the metal price shock are showed in Figure3. This analysis allows us to reach two important conclusions. First, the dynamic response of current accounts have changed along the sample. For all countries, metal price shocks had, quantitatively, a more important impact in 2014 compared to 2002. Second, the higher impact had been experienced by metal-exporting countries like Australia, Chile, Peru and South Africa. However, the impact in the case of Peru seems to be less persistent and it last, on average, less than three quarters.



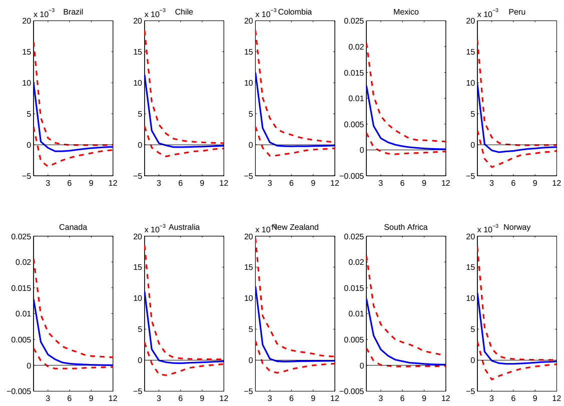
(a) 2002



(b) 2006



(c) 2010



(d) 2014

Figure 3: Response of Current Account to a unit shock on Metal Prices; median value and 68% bands

5 Concluding Remarks

We have estimated a Panel VAR with dynamic inter-dependencies and time varying parameters for ten commodity-exporting countries (Brazil, Chile, Colombia, Mexico, Peru, Canada, Australia, New Zealand, South Africa and Norway). Within this framework, we have computed an average current account indicator and studied the responses of individual current account balances to shocks in fuel and metal prices. We have found that our common indicator for the current account follows closely the dynamic pattern of the commodity price index i.e. surpluses (deficit) are usually associated with increases (decreases) in commodity prices, and this indicator is statistically significant across the sample of analysis. At the country level, by comparing the impulse response functions, we found that commodity price shocks have a similar effect across countries, although their magnitude differ. In general, our results suggest that the impact on the current account balances have increased since 2002. In the case of a fuel shock, we do not found significant current account responses. However, the evidence for a metal shock is more robust, with higher responses in the case of the metal-exporting countries.

Although we have included domestic interest rates, most of the literature have emphasized the effect of commodity prices on credit and other financial variables. In this regard, the future research agenda should include the response of financial variables to a external shock as the commodity price shock.

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A The posterior distribution of hyper-parameters

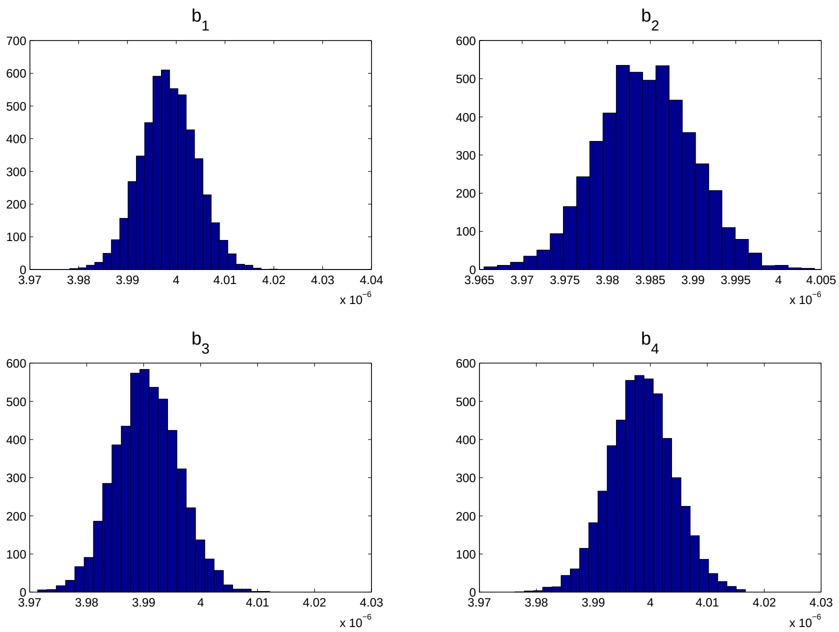

Figure 4: Posterior Distribution of b

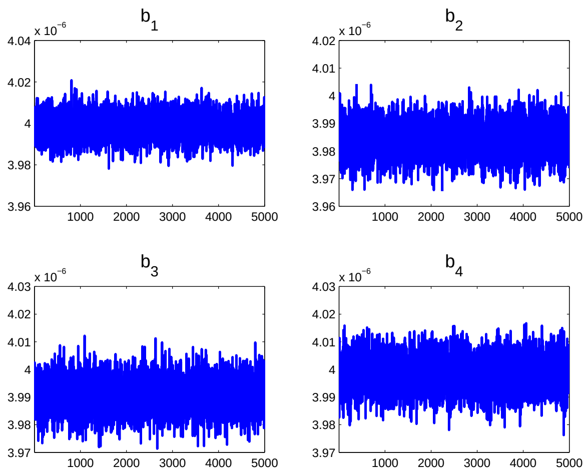

Figure 5: Posterior Draws of b

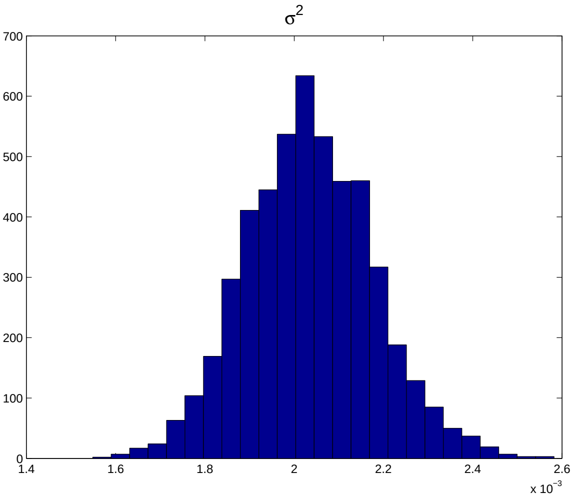

Figure 6: Posterior Distribution of σ^2

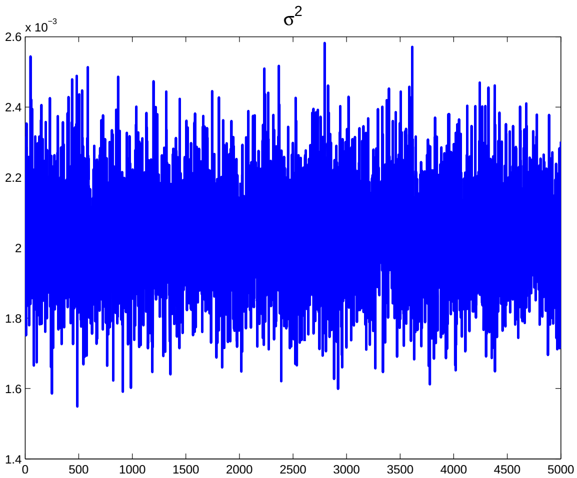

Figure 7: Posterior Draws of σ^2

B Data Description

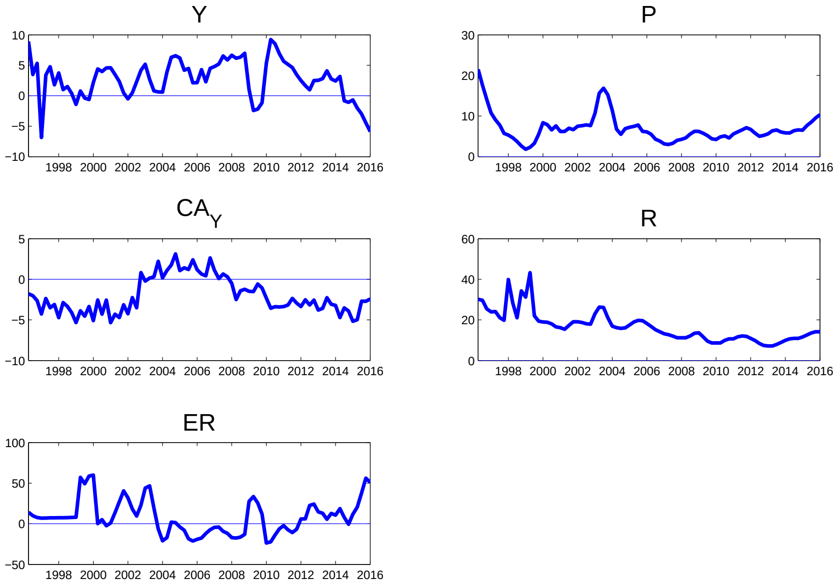

Figure 8: Brazilian Data

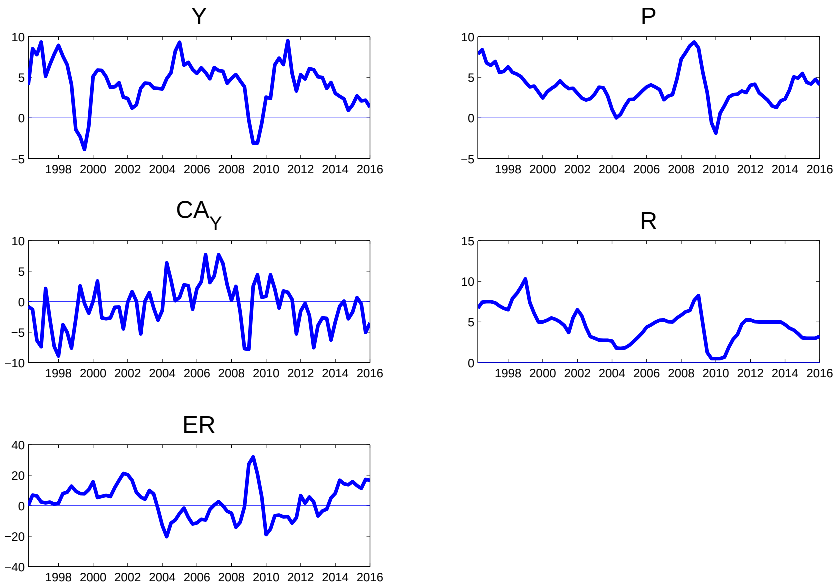

Figure 9: Chilean Data

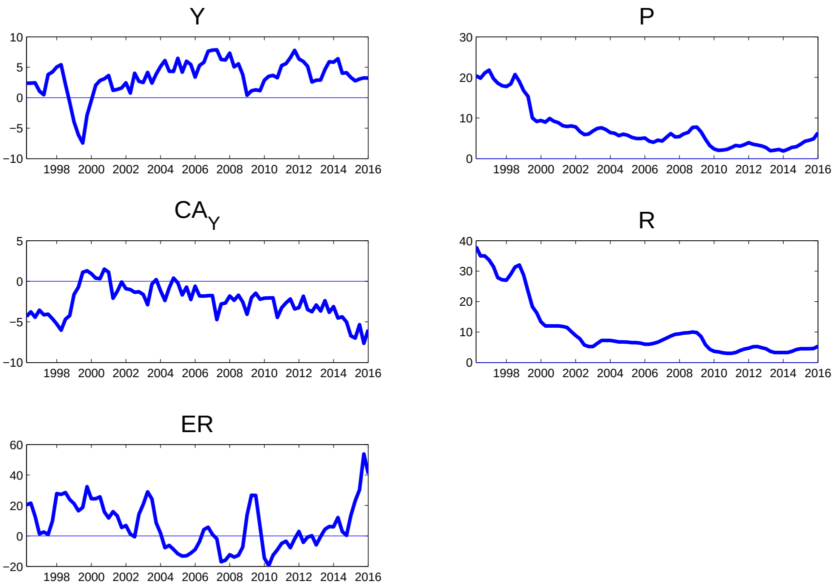

Figure 10: Colombian Data

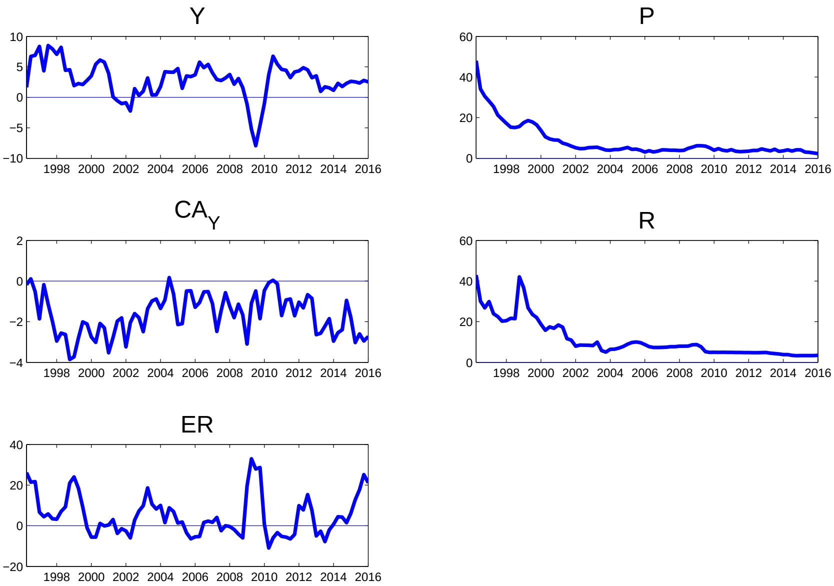

Figure 11: Mexican Data

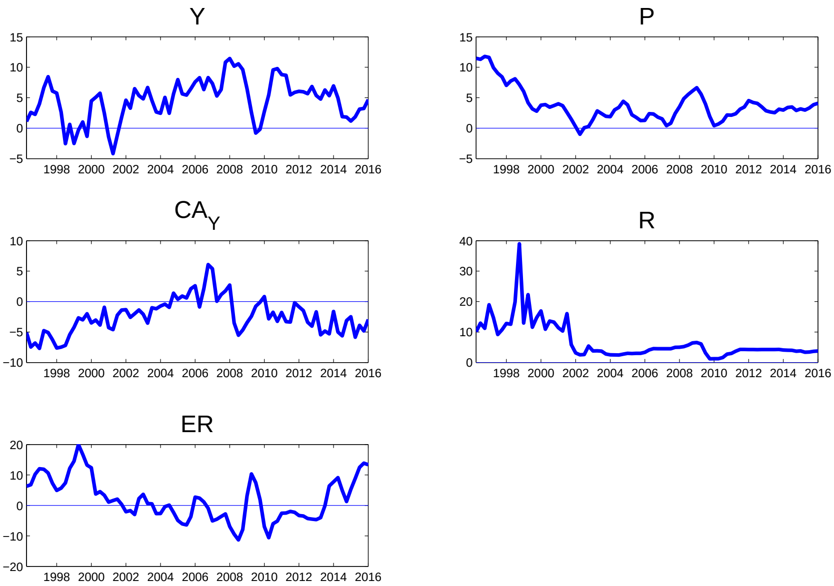

Figure 12: Peruvian Data

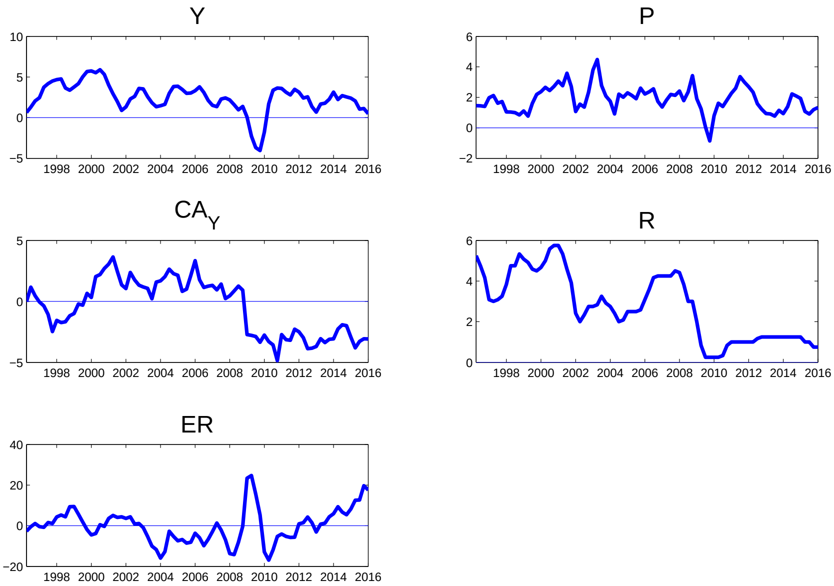

Figure 13: Canadian Data

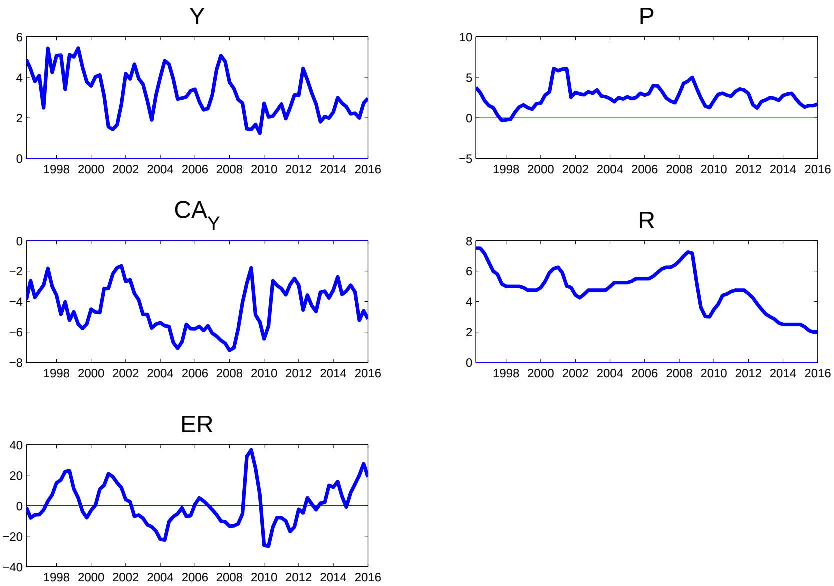

Figure 14: Australian Data

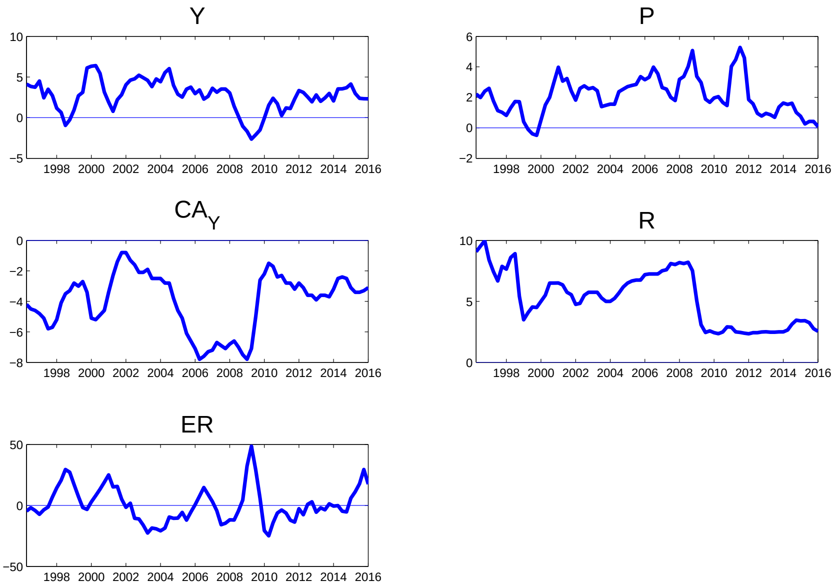

Figure 15: New Zealand Data

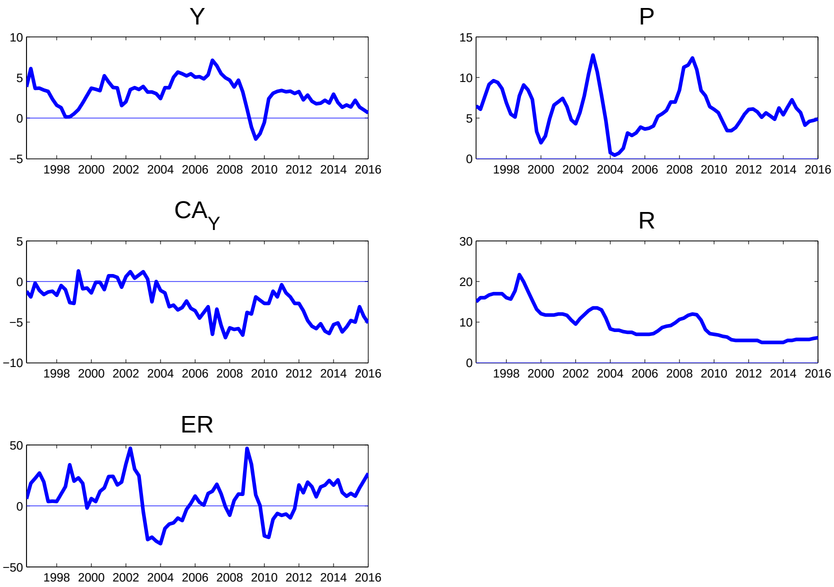

Figure 16: South African Data

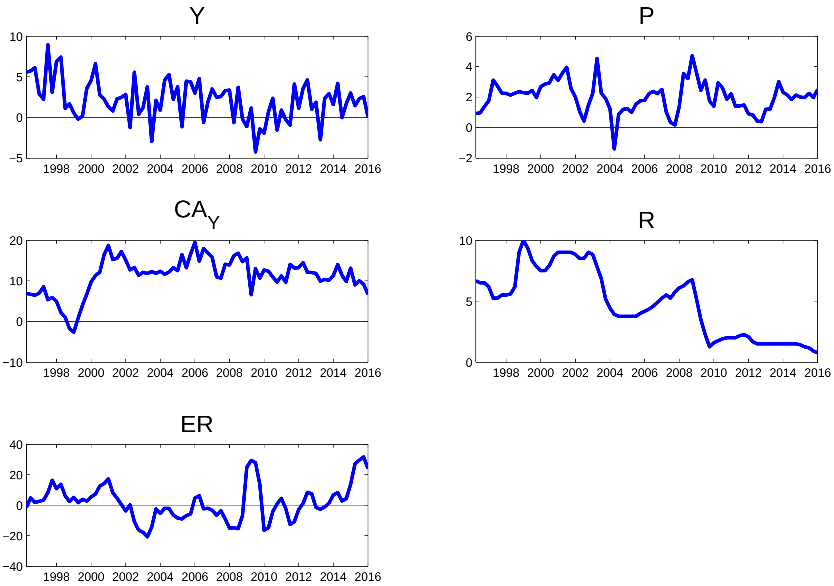

Figure 17: Norwegian Data

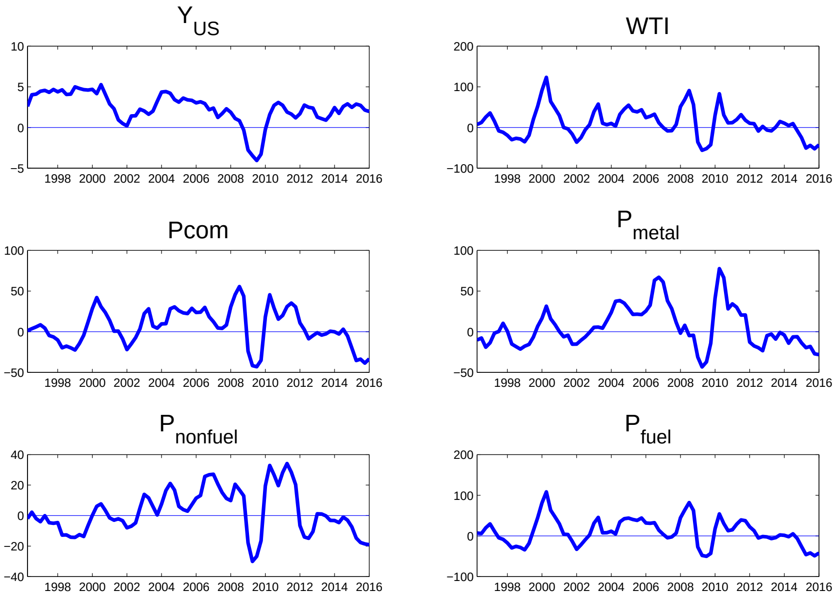

Figure 18: Exogenous Data