Deniz Igan | Emanuel Kohlscheen | Gabriela Nodari | Daniel Rees
Deniz.Igan@bis.org | *Emanuel.kohlscheen@bis.org* | *Gabriela.Nodari@bis.org* | *Daniel.Rees@bis.org*

Annex: Commodity market disruptions, growth and inflation

This appendix describes the econometric approach we use to assess the macroeconomic implications of commodity price shocks.

Identifying commodity price shocks

Following Kilian (2009), we use a structural vector autoregression (SVAR) model of the global crude oil market to identify demand- and supply-driven oil price shocks. The model is the following:

$$\boldsymbol{A_0 z_t} = \boldsymbol{\alpha} + \sum_{p=1}^{12} \boldsymbol{A_p z_{t-p}} + \boldsymbol{\varepsilon_t}$$

with the vector $\boldsymbol{z_t} = (\Delta prod_t, \Delta y_t, \Delta rwti_t)$, where $\Delta prod_t$ denotes global crude oil production growth (the data are from the US Energy Information Administration and expressed in thousands of barrels)[1], Δy_t denotes global industrial production growth (from the OECD database) and $\Delta rwti_t$ refers to percentage changes in the real price of oil, ie the nominal West Texas Intermediate (WTI) oil price deflated by the US consumer price index. All variables are monthly. We estimate the model over a sample spanning January 1972–December 2019.

We apply a recursive identification scheme, using the ordering above, to identify structural shocks. This allows us to distinguish three types of shock: shocks to the physical availability of crude oil (oil supply shocks), shocks to the current demand for crude oil driven by fluctuations in the global business cycle (aggregate demand shocks) and shocks driven by shifts in the demand for oil (oil market-specific demand shocks). The oil market-specific demand shock could, in principle, capture any number of omitted factors. However, the model ensures that it is orthogonal to crude oil supply shocks and to world demand for industrial commodities. Importantly, this shock will capture fluctuations in oil prices driven by rising geopolitical tensions (to the extent that these are not already captured through their impact on oil supply or global aggregate demand). In our analysis, we consider only oil supply and oil market-specific demand shocks, as aggregate demand shocks are less relevant in the current environment.

We adopt a similar approach to identify agricultural commodity price shocks. In this case, the vector is $\boldsymbol{z_t} = (\Delta y_t, \Delta rer, \Delta rag_t)$, where Δrer denotes changes in the US real exchange rate and Δrag_t is the World Bank index of agricultural commodity prices, which includes food and beverage components as well as raw materials such as cotton and rubber. The lack of a timely measure of agricultural commodities production prevents us from separately identifying agricultural commodity supply shocks. Thus, we identify only two types of shock for the agricultural commodities market: shocks to the current demand for agricultural commodities driven by fluctuations in the global business cycle (aggregate demand shocks) and shocks driven by shifts in the demand for agricultural commodities (agricultural commodities market-specific demand shocks). Again, the latter will capture fluctuations in agricultural prices driven by rising geopolitical tensions and it is the shock that we employ in our analysis.

[1] See www.eia.gov.

Estimating the macroeconomic effects of commodity price shocks

We use a panel SVAR model to analyse the implications of commodity prices shocks on key macroeconomic variables. The countries considered are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, New Zealand, Norway, South Africa, Spain, Sweden, Switzerland, the United Kingdom and the United States. We restrict our analysis to these economies due to data availability, ie quarterly data on income flows to households and firms are available for relatively few emerging market economies over a long sample. The model is:

$$\boldsymbol{B_{i0}x_{it}} = \boldsymbol{\alpha_i} + \sum_{p=1}^{P} \boldsymbol{B_{ip}x_{it-p}} + \boldsymbol{u_{it}}$$

The identification strategy we applied in the first step ensures that our commodity price shocks are structural. Thus, given degrees of freedom considerations, we estimate bivariate country-specific VARs and use the mean group estimator to calculate the average impulse responses of each macroeconomic variable of interest. In particular, the vector $\boldsymbol{x_{it}} = (shock_t, macro\_variable_{it})$ where $shock_t$ is, in turn, one of the three shocks we identified (ie oil supply, oil market-specific demand shocks and agricultural commodities market-specific demand shocks) and $macro\_variable_{it}$ is one of the following country-specific variables: GDP, consumption, investment, headline inflation, core inflation, wage income, profits.[2] We use quarterly data and four lags for the SVAR models featuring GDP, expenditure or income components and monthly data with 12 lags for the models featuring inflation measures. The sample period is the same used in the first step, ie 1972 to 2019.

For each estimated VAR, we compute the response of the macro variable of interest to a structural commodity price shock that raises the price of the given commodity by 10%. We then calculate mean group estimates for each variable by averaging the responses across groups of countries. The energy exporter economies in our sample are Australia, Canada, Norway and South Africa, with Canada and Norway being oil-specific exporters. The agricultural commodity exporter economies are Australia, Canada, Denmark, the Netherlands, New Zealand, Norway and Spain. The remaining countries are classified as importers.[3]

Finally, we calculate confidence intervals using 10,000 replications of a bootstrap procedure that accounts for possible correlation of the SVAR residuals across countries.

SVAR impulse responses

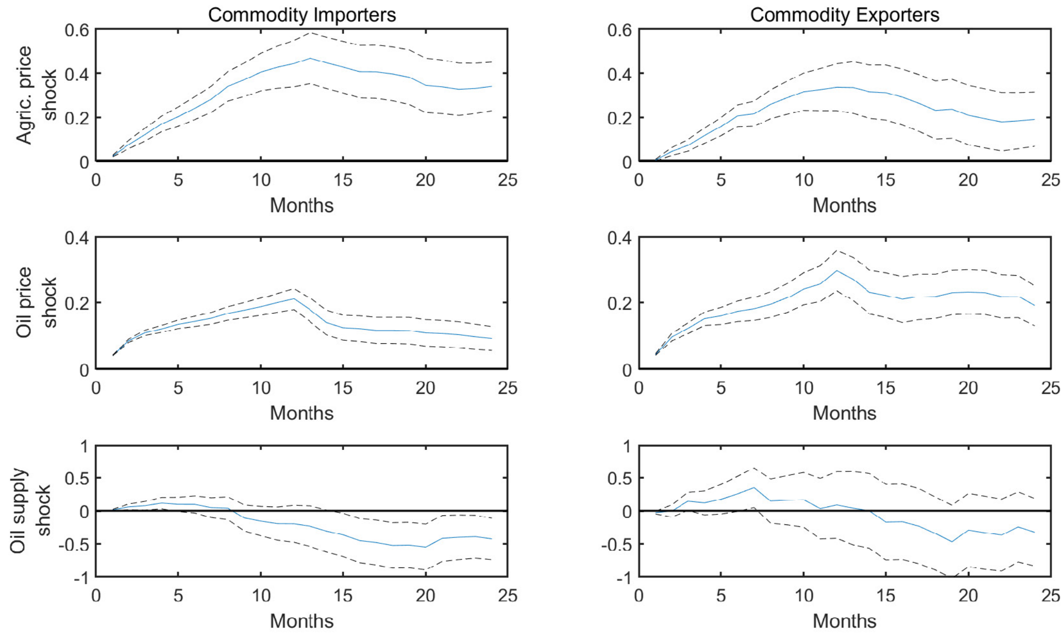
The figures below show the impulse response functions from our SVAR models alongside the one-standard deviation confidence intervals.

[2] Plagborg-Møllerand Wolf (2021) show that the "internal instrument" strategy of ordering a previously identified shock first in a VAR yields valid impulse responses.

[3] The set of oil importer economies differs from that of agricultural commodity importers based on the respective exporters' classification.

Headline inflation responses to a 10% commodity price increase

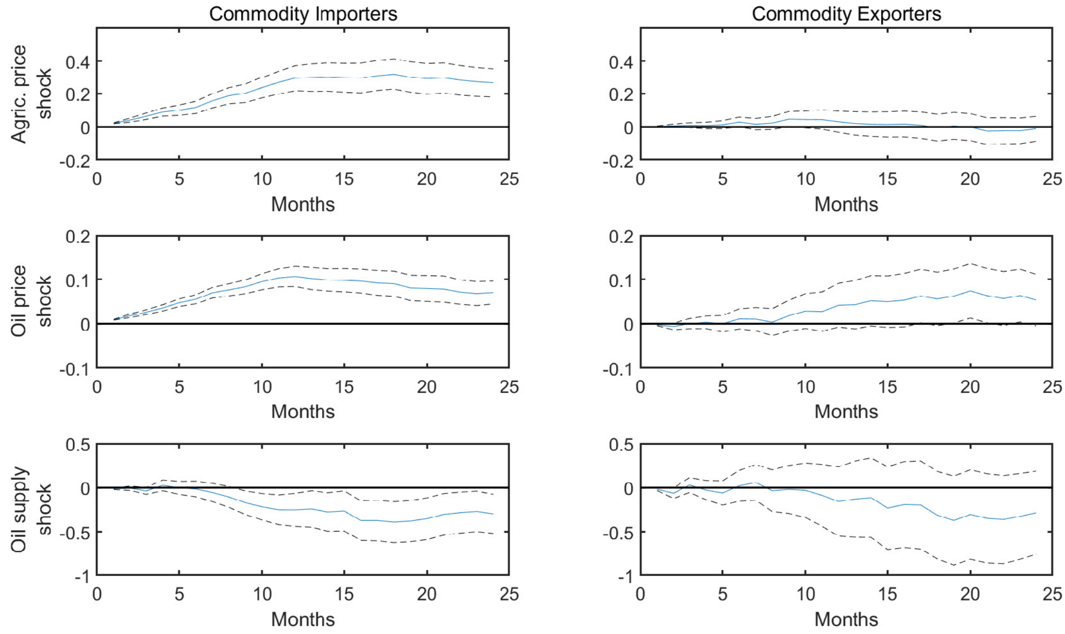
Graph A1



Source: Authors' calculations.

Core inflation responses to a 10% commodity price increase

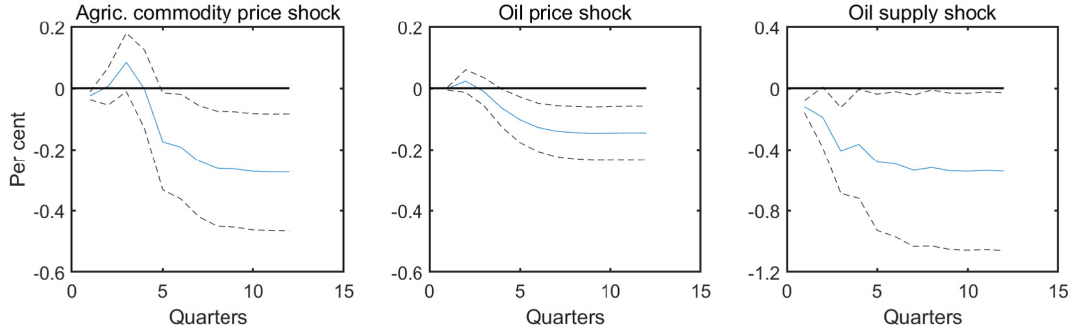
Graph A2



Source: Authors' calculations.

Aggregate GDP responses to a 10% commodity price increase

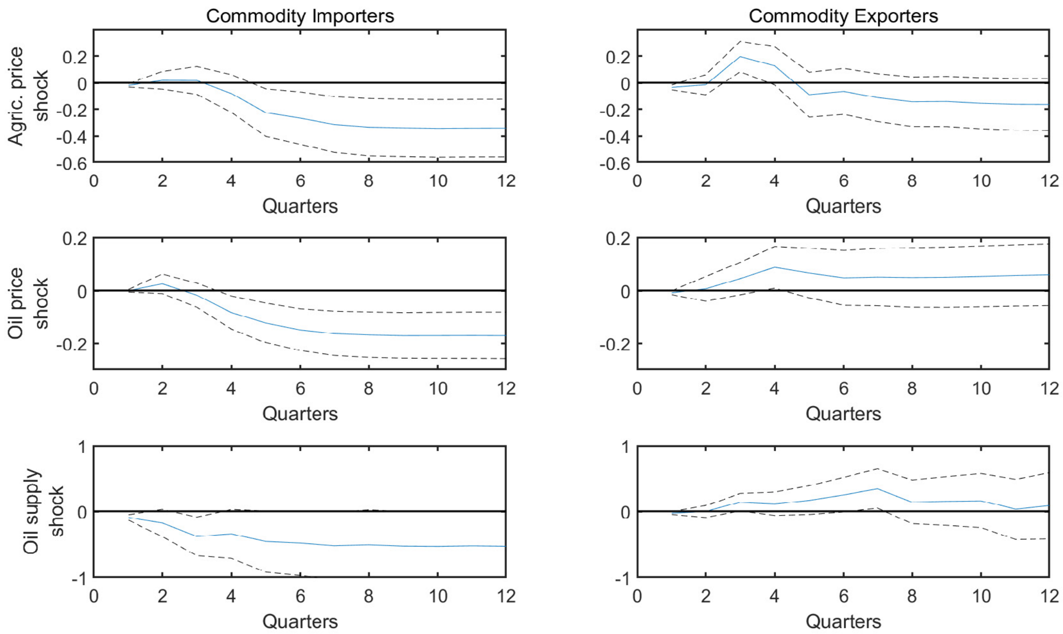
Graph A3



Source: Authors' calculations.

GDP responses to a 10% commodity price increase

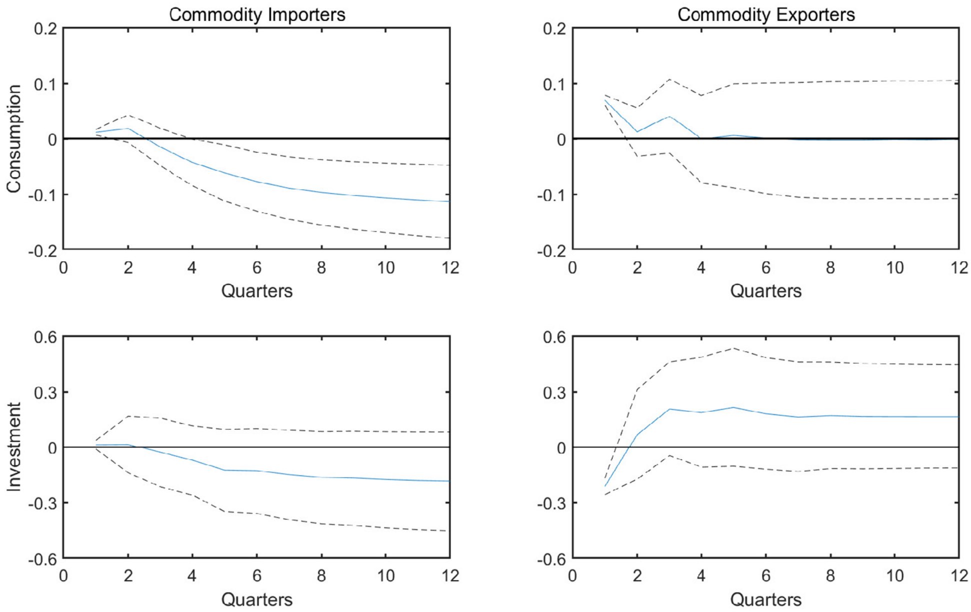
Graph A4



Source: Authors' calculations.

Expenditure responses to a 10% oil price increase

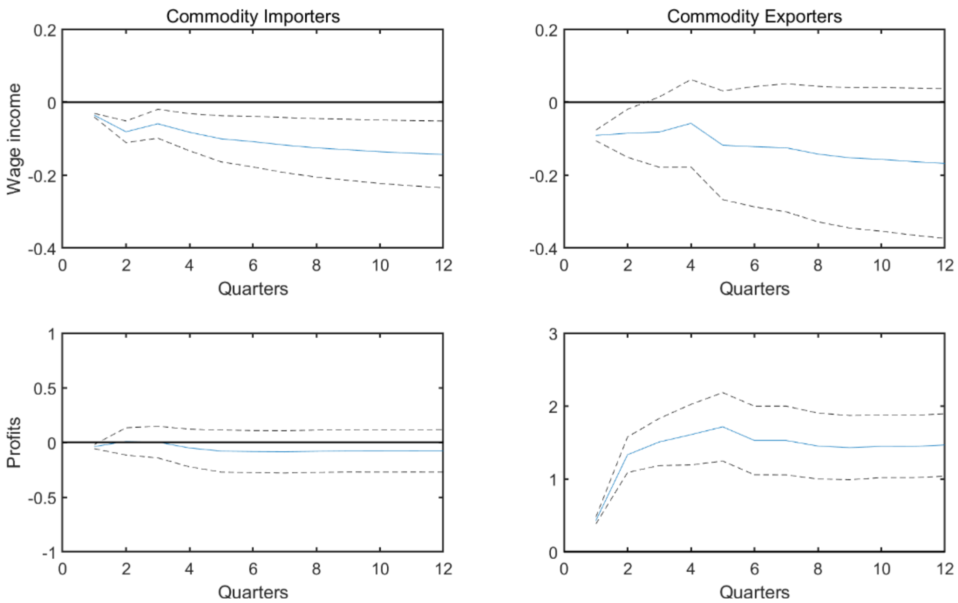
Graph A5



Source: Authors' calculations.

Income responses to a 10% oil price increase

Graph A6



Source: Authors' calculations.

References

Kilian, L (2009): "Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market", *The American Economic Review*, vol 99, no 3, pp 1053–69.

Plagborg-Møller, M and C Wolf (2021): "Local projections and VARs estimate the same impulse responses", *Econometrica*, vol 89, no 2, pp 955–80.