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# WORKING PAPER

## AGRICULTURAL PRICE SHOCKS AND BUSINESS CYCLES: A GLOBAL WARNING FOR ADVANCED ECONOMIES

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# Agricultural Price Shocks and Business Cycles*

## A Global Warning for Advanced Economies

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**Abstract**

For a panel of 75 countries, we find that increases in global agricultural commodity prices that are caused by unfavorable harvest shocks in other regions of the world significantly curtail domestic economic activity. The effects are much larger than for average global agricultural price shifts. The impact is also considerably stronger in high-income countries, despite the lower shares of food in household expenditures these countries have compared to low-income countries. On the other hand, we find weaker effects in countries that are net exporters of agricultural products, have higher shares of agriculture in GDP or lower shares of non-agricultural trade in GDP; that is, characteristics that typically apply to low-income countries. When we control for these country characteristics, we find indeed that the effects on economic activity become smaller when income per capita is higher. Overall, our findings imply that the consequences of climate change on advanced economies are likely larger than previously thought.

*JEL classification:* E32, F44, O13, O44, Q11, Q54

*Keywords:* Agricultural commodity prices, economic activity, climate change

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# 1 Introduction

There is growing evidence that climatic changes have increased the mean and variance of weather conditions around the globe (e.g. Munasinghe et al. 2012). The Intergovernmental Panel on Climate Change projects also for the coming century a further rise in the variability and frequency of extreme weather events such as droughts, tropical cyclones and heavy rainfall (IPCC 2014). Since temperature and precipitation are direct inputs in agricultural production, the economic consequences of climate change are considered to be most important for agriculture (Auffhammer and Schlenker 2014; Carleton and Hsiang 2016). Especially developing countries are projected to suffer a lot because poorer countries already have hotter climates, as well as higher shares of agricultural sectors in economic activity (Nordhaus 2006; Mendelsohn 2008). For example, Jones and Olken (2010) and Dell et al. (2012) show that higher temperatures in a given year reduce the growth rate of exports and real GDP significantly, but only in poor countries.

An element that has not been considered so far is the possible impact of climate change on economic performance of countries through a rise in the volatility of global agricultural (food) commodity prices. More specifically, disruptions in agricultural markets around the globe that are the result of severe weather conditions could lead to substantial changes in the prices of agricultural commodities. For example, the extreme droughts in Russia and Eastern Europe were the primary reason for the rise in global real agricultural commodity prices by almost 30% in the summer of 2010 (De Winne and Peersman 2016, henceforth DWP 2016). These changes in agricultural prices could, in turn, curtail economic activity of countries that are not directly exposed to the extreme weather conditions, for example, through an impact on consumer spending. Given the high proportion of food consumption in household expenditures, this could augment the costs of global climate change for poor countries. Moreover, these indirect effects may as well affect rich economies, which also have non-negligible shares of food expenditures. DWP (2016) demonstrate that this is the case for the United States, where the macroeconomic effects of shifts in global food commodity prices turn out to be a multiple of the share of food commodities in household consumption.[1]

[1] Between 1960 and 2015, food commodity expenditures per capita per year measured in constant 2015 dollar values amounted to approximately $900 in the United States (DWP 2016). As a reference, crude oil expenditures over this period were on average roughly $750 per capita per year. DWP (2016) find that the effects of a rise in global food commodity prices on U.S. real GDP are approximately twice as large as a rise in global crude oil prices. The stronger impact of food commodity price shocks can mainly be explained by the larger share in household expenditures and a more aggressive monetary policy response to the inflationary consequences. We are not aware of other studies that have estimated the effects of changes in agricultural prices on economic activity of advanced economies.

In this paper we provide empirical evidence on the impact of (non-domestic) fluctuations in global agricultural markets on economic activity of 75 advanced and developing countries. In particular, we (i) estimate the effects of changes in global agricultural commodity prices on real GDP, (ii) examine whether there are differences between high and low-income countries, and (iii) explore the correlation with other relevant country characteristics. Such evidence is not only useful for evaluating possible indirect consequences of climate change. As can be observed in Figure 1, variation in global agricultural commodity prices can be substantial. Given the relevance of food in household expenditures, swings in agricultural prices may also be a significant driver of business cycles in many countries. This matters for the construction of business cycle models and it is relevant for fiscal and monetary policymakers who want to stabilize economic fluctuations. In addition, the results should help to assess the consequences of policies that may influence agricultural prices, such as agricultural trade policies, ethanol subsidies or food security programs.

Since reverse causality between economic activity and agricultural prices is likely present, the key challenge of our analysis is the identification of shifts in prices of agricultural commodities that are exogenous rather than endogenous responses to global economic conditions. For example, popular explanations that have been postulated for the considerable rise of agricultural commodity prices at the beginning of the century are strong income growth in the BRIC countries and an increase in the demand for biofuels as a consequence of soaring crude oil prices (e.g. Zhang and Law 2010; Abbott et al. 2011). Even for small economies that do not affect global demand this distinction is presumably important.[2] To address this problem, we construct two instrumental variables for each country that reflect non-domestic exogenous shocks to global agricultural markets.

The first instrument is a quarterly series of unanticipated foreign harvest shocks. The shocks are estimated as prediction errors of composite production indices that aggregate the harvests of the world's four most important staple food commodities: corn, wheat, rice and soybeans. Overall, these commodities, which are storable and traded in integrated global markets, make up approximately 75% of the caloric content of food production worldwide (Roberts and Schlenker 2013). We use harvest data of 192 countries, and systematically exclude the harvests of the country itself, the entire sub-region in which the country is located and the harvests in the neighboring sub-regions. We also orthogonalize the shocks to domestic weather conditions. As a second instrument, we use the 13 episodes of major

[2] If shifts in global agricultural prices are caused by a rise in global economic activity, individual countries could, for example, be part of the expansion or benefit from trade with other countries. This is not the same as shocks at the supply side of global agricultural markets, which could depress output of trade partners.

global agricultural commodity market disruptions that have been identified with narrative methods in DWP (2016). The episodes that did not directly affect the harvests of a country are converted to an instrumental variable series for that country. In the next step, we use both instruments to estimate the dynamic effects of a rise in global agricultural commodity prices on real GDP. We apply two methods that are popular in empirical macroeconomics. As the baseline, we estimate panel (and individual-country) structural vector autoregression models with external instruments (SVAR-IV). As an alternative, we conduct direct panel IV regressions of the effects with local projection methods (LP-IV).

According to the SVAR-IV estimations, an exogenous rise in global agricultural commodity prices by 1% on impact (which further increases to 1.5% after one quarter) ultimately reduces average real GDP across countries by 0.11%. The effects are statistically significant, but also economically important if one considers that the quarterly standard deviation of changes in the commodity price index that we use for the estimations has been 7.3% over the past five decades, and 8.7% since the start of the millennium (see Figure 1). The results of the LP-IV estimations turn out to be similar. Furthermore, we show that the use of external instruments matters. In particular, when we estimate the effects of "average" global agricultural commodity price innovations (that is, a recursively identified SVAR with commodity prices ordered first), we find much milder effects on economic activity. Notably, the latter also applies to small economies.

The estimation of panel SVAR-IVs for country groups reveals that the effects are significantly larger in high-income countries; that is, the decline of real GDP is 0.12% for the top income-tertile of the countries, compared to only 0.03% for the lowest income-tertile. This difference is surprising given the fact that high-income economies have much lower shares of food in household expenditures. Moreover, high-income countries usually have more advanced government institutions and better developed financial markets to absorb food price volatility.

We then explore the effects according to alternative country groupings. We find that the macroeconomic consequences are on average significantly smaller in countries that are net exporters of agricultural products or that have higher shares of agriculture in GDP. In contrast, the effects are larger in countries that have higher overall shares of trade in GDP (non-agricultural trade integration). Finally, we find no robust relationship between the extent of agricultural tariffs and the impact of global agricultural price shocks on local activity. Since high-income countries have on average lower shares of agriculture in GDP, higher shares of trade in GDP and are typically net importers of agricultural products, this could be an explanation for the counterintuitive stronger effects on high-income countries. Indeed, when we control for these country features by considering all characteristics simultaneously in the

LP-IV model, the effects on real GDP become smaller when income per capita increases.

A caveat that comes with our analysis is that we document correlations between a selection of country characteristics and the effects of global agricultural commodity price shocks on economic activity. This does not imply causation nor does it reflect transmission channels. There may be several channels that vary across countries that are not captured in the analysis, such as the pass-through of global prices to local prices, the composition of food consumption and production, the monetary policy response or the presence of government food security programs. A detailed investigation of the transmission mechanisms is left for future research. Furthermore, since the methods that we use require sufficiently long quarterly time series, our analysis does not include extreme poor countries, which could behave differently.

Notwithstanding these caveats, there are several conclusions that are relevant for policymakers. First, swings in global agricultural prices appear to be important for economic activity in many countries, including advanced economies. This should be taken into account for the analysis of business cycles and policies that may affect agricultural prices. Second, it is often argued that poor countries have to bear the bulk of the climate change burden, which acts as a disincentive for rich countries to mitigate their greenhouse gas emissions (e.g. Althor et al. 2016). However, our results suggest that the repercussions of climate change on rich countries are probably larger than previously thought. Consider the severe droughts in Russia and Eastern Europe in the summer of 2010. According to our estimates, this lowered real GDP growth in high-income countries by roughly 1% during two years. Such events may happen more frequently and become more profound as a result of climatic changes. Finally, our results suggest that soaring food prices are not necessarily detrimental for low-income countries. In this context, our macro evidence complements several microeconomic studies, which conclude that we need a nuanced debate on the welfare effects of changes in food prices in low-income countries (e.g. Headey and Fan 2008; Swinnen and Squicciarini 2012).

In section 2, we discuss the baseline methodology and construction of external instruments to identify agricultural commodity price shocks. The panel results are reported in section 3. In section 4 we examine cross-country heterogeneity, while section 5 concludes.

## 2 Methodology

To examine the dynamic effects of disruptions in global agricultural markets on economic performance of countries, we estimate the consequences of exogenous shifts in global agricultural commodity prices on real GDP for a panel of 75 industrialized and developing countries. The selection of the countries is determined by the availability of sufficiently long time series of quarterly macroeconomic data. An overview of the countries can be found in the appendix of the paper (Table A1). The baseline methodology that we use are SVAR models in the spirit of Sims (1980). The advantage of an SVAR approach is that it requires us to impose only a limited structure on the data. It captures the dynamic relationships between a set of macroeconomic variables within a linear system and allows to measure the dynamic causal effects of structural shocks on all the variables in the model controlling for other developments in the economy that may also influence the variables.

The key challenge when estimating SVAR models is the identification of the structural shocks. To do this, an increasing number of studies use information from variables that are not included in the VAR system, for example high frequency data or series based on narrative evidence. The idea is that these external series are noisy measures of the true shocks and can be used as instruments in conjunction with the VAR model to identify impulse response functions. These are not the full shock series, but rather reflect an exogenous component of the shock. This method has also been described as "external instrument SVAR" (Stock and Watson 2012) or "proxy SVAR" (Mertens and Ravn 2013). In this study, we adopt such an approach in a panel setting. Specifically, we estimate VAR models identified with external instruments for each individual country, as well as Mean Group panel VARs for all (or a subset of) countries simultaneously. In section 2.1, we first discuss the baseline individual-country and panel SVAR model with external instruments and the data that we use to estimate the effects of disruptions in global agricultural markets. In section 2.2 and 2.3, we then describe two sets of external instruments that are used to achieve identification. The estimation results will be discussed and compared with LP-IV methods in section 3.

## 2.1 Baseline SVAR Model with External Instruments

For each country $i$, we assume that macroeconomic dynamics can be described by the following reduced form VAR-system of linear simultaneous equations:

$$Y_{i,t} = \alpha_i + A_i(L)Y_{i,t-1} + u_{i,t} \tag{1}$$

$Y_{i,t}$ is a vector of endogenous variables representing the global and individual country's economy in quarter $t$, $\alpha_i$ is a vector of constants and $A_i(L)$ is a polynomial in the lag operator $L$. $u_{i,t}$ is a vector of reduced form residuals, which are related to the structural shocks by

$$u_{i,t} = B_i\varepsilon_{i,t} \tag{2}$$

where $B_i$ is a nonsingular (invertible) matrix. For the baseline estimations, the vector of endogenous variables $Y_{i,t}$ contains three variables: global real agricultural commodity prices, global economic activity and the country's real GDP. All variables are measured in natural logarithms and seasonally adjusted. The first two variables are common for all countries.[3]

Global agricultural commodity prices is an index that is calculated as the weighted average of the benchmark prices in U.S. dollars of the four most important staples: corn, wheat, rice and soybeans. The benchmark prices, which are collected from IMF Statistics Data, are determined by the largest exporter of each commodity and should be representative of global markets. The weights are based on the trend production volumes of the four commodities. The nominal price index has been deflated by the U.S. CPI to retrieve real prices. We choose this index to portray price fluctuations in global agricultural markets because these four food commodities closely resemble with the instruments that will be used to identify exogenous agricultural commodity price shocks. Moreover, the four commodities are storable and traded in integrated global markets, which is important in the context of our analysis. Together, the four staples account for approximately 75 percent of the caloric content of food production worldwide, while the prices of other food commodities are also typically linked to these staple food items (Roberts and Schlenker 2013). In section 3.1, we will also use a broader price index of the IMF to assess the robustness of the results. To proxy global economic activity, we follow Baumeister and Peersman (2013) and use the world industrial production index from the Netherlands Bureau for Economic Policy Analysis. We include this variable in the VAR-model to capture changes in global income that may affect the demand for food commodities. In addition, it could capture transmission and spillover channels of agricultural shocks to individual countries via the global business cycle. Finally, to measure economic activity of the individual countries, the vector of endogenous variables includes real GDP. For details of all these series, we refer to the data appendix.

The coefficients of $\alpha_i$ and $A_i(L)$ in equation (1) can simply be estimated by OLS. Also the variance-covariance matrix of the reduced form VAR can be estimated; that is, $E\left[u_{i,t}u_{i,t}^{\prime}\right] = B_iB_i^{\prime}$, which provides six independent identifying restrictions to obtain the coefficients of $B_i$. Because we are only interested in one of the structural shocks; that is, exogenous shifts in real agricultural commodity prices, we do not have to identify all the coefficients of $B_i$. Only the elements of the first column of $B_i$ have to be identified, which nevertheless requires additional restrictions. To do this, we follow Stock and Watson (2012) and Mertens and Ravn (2013) by

[3]Because the third variable of $Y_{i,t}$ varies across countries, the reduced form VAR for the two common variables also varies across countries. Notice, however, that the results are very similar when we do not allow for feedback of the individual country's real GDP on the common variables; that is, when we estimate so-called near-VAR models. These results are available upon request.

using external instruments. Specifically, let $Z_{i,t}$ be a vector of external instrumental variables for country $i$. These variables can be used for identification of the first column of $B_i$ if the following conditions are satisfied:

$$E\left[Z_{i,t}\varepsilon_{i,t}^{1'}\right] \neq 0 \tag{3}$$

$$E\left[Z_{i,t}\varepsilon_{i,t}^{2'}\right] = 0 \tag{4}$$

where $\varepsilon_{i,t}^{1}$ is an exogenous shock to real agricultural prices and $\varepsilon_{i,t}^{2}$ a vector of all other structural shocks. Equation (3) postulates that the instruments are correlated with shocks to real agricultural prices (instrument relevance condition), while equation (4) requires that the instruments are uncorrelated with all other shocks (exogeneity condition). These are the key identifying assumptions to obtain the first column of $B_i$ up to scale and sign. The scale and sign are set by normalizing the shock to have a one percent impact on real agricultural commodity prices. For more technical details and implementation in practice, we refer to Stock and Watson (2012), Mertens and Ravn (2013) or Ramey (2016). In the next subsections, we propose two instruments that fulfill these conditions, i.e. unanticipated harvest shocks and a series of narratively identified major agricultural commodity market disruptions.

## 2.2 Unanticipated Foreign Harvest Shocks

As a first possible external instrument that could shift global prices of agricultural commodities in a way that is plausibly unrelated to economic conditions, we consider unanticipated "foreign" harvest shocks. The underlying idea is that unexpected variations in harvests that are sufficiently large to affect global supply of food commodities likely trigger significant shifts in global agricultural commodity prices, which should fulfill the instrument relevance condition in equation (3). On the other hand, harvest volumes can in principle not (endogenously) respond to changes in the state of the economy within one quarter, which accomplishes the exogeneity condition in equation (4). More specifically, for the staple food commodities that we consider, there is a time lag of at least one quarter between the planting and harvesting seasons. Farmers could thus adjust their planting volumes in response to changing economic conditions within one quarter, but this cannot (yet) have an impact on the harvest volumes of that quarter. Furthermore, one could realistically argue that a possible influence of food producers on the volumes during the quarter of the harvest itself is meager relative to variation induced by other factors such as weather conditions, pests or diseases affecting crops. For example, it is not realistic to postulate that farmers increase food production by raising fertilization activity during the harvesting quarter in response to an improvement of economic conditions. In particular, several studies have shown that in-season fertilization strategies are inefficient and often even counterproductive for the staples that we consider.[4]

To derive the instruments, in a first step, we construct a quarterly index of foreign harvest volumes for all countries in our panel. To do so, we elaborate on DWP (2016). More precisely, the Food and Agriculture Organization (FAO) of the United Nations publishes annual harvest data for each of the four major staples for 192 countries over the period 1961-2014.[5] DWP (2016) combine the annual harvest data of each individual country with that country's planting and harvesting calendars for each of the four crops, in order to allocate the harvest volumes to a specific quarter. Harvests are only allocated if the planting season was at least one quarter earlier. Since most countries have only one relatively short harvest season for each crop; that is, a few months, and the delay between planting and harvesting varies between 3 and 10 months, DWP (2016) can assign two-thirds of world harvests to a specific quarter. The four crops of all countries are then aggregated on a caloric-weighted basis to construct a quarterly composite global agricultural commodity production index.

In the present study, we use the same principium to construct foreign harvest volumes for each individual country. More precisely, for each country, we aggregate the harvest volumes of all other countries in the world, except the harvests of the country itself, the entire sub-region in which the country is located and the harvests in the neighboring sub-regions.[6] For example, for Italy, we exclude the harvests of all countries in South-Europe, West-Europe, East-Europe and North-Africa. The reason why we exclude domestic harvests is that we do not want to capture possible direct effects of the shocks on the domestic economy, in particular on the domestic agricultural sector, which could distort the analysis.[7] For an individual country, such shocks to agricultural commodity prices are not truly exogenous. The harvests of the other countries in the region are also excluded because weather variation might be correlated

[4]See, for example, Mallarino (2010), Schmitt et al. (2001), Fanning (2012) and Scharf et al. (2002). The reason is that fertilization enhances vegetative growth of the plant before the ripening phase. The best timing is hence before or shortly after planting, while fertilization programs should be completed before the jointing phase. Applying such strategies after the vegetative phase implies that the plant can spend less energy on ripening, resulting in lower grain yields. Notice, however, that food producers could always destroy crops or treat diseases insufficiently in response to a decline in economic activity, but that is not likely to happen at a global scale. Overall, DWP (2016) show that global food production does not convey relevant endogenous responses to macroeconomic conditions within (at least) one quarter.

[5]This database is available at http://faostat3.fao.org/.

[6]We use the United Nations definitions of sub-regions, which can be found at http://unstats.un.org/unsd/methods/m49/m49regin.htm.

[7]Given that harvest shocks are typically the consequence of weather variation, changes in weather conditions could potentially also directly affect economic activity; that is, beyond the agricultural sector. For example, storms may affect harvests and economic activity simultaneously. There are also studies that find negative effects of hotter temperatures on labor productivity and labor supply at the spatial level for poor countries (Dell et al. 2014).

across neighboring countries. After aggregating, the series are seasonally adjusted using the Census X-13 ARIMA-SEATS Seasonal Adjustment Program (method X-11). The result of this exercise are 75 indicators of foreign harvest volumes.

In a next step, we use the aggregated harvest volumes to obtain unanticipated foreign harvest shocks. In essence, the shocks are prediction errors of the harvest volumes conditional on past harvests and a set of relevant information variables that may influence harvests. Specifically, we estimate the following agricultural commodity production (harvest) equations:

$$q_{i,t} = c_{i,t} + \Theta_{i,t} + C_i(L)X_{t-1} + D_i(L)q_{i,t-1} + \nu_{i,t} \tag{5}$$

where $q_{i,t}$ is the natural logarithm of the foreign harvest volume of country $i$. $X_t$ is a vector of control variables that may affect global food commodity markets and hence also harvest volumes with a lag of one or more quarters; that is, the natural logarithms of respectively real agricultural commodity prices, global economic activity and real crude oil prices. The former two variables are evident. We also include the real price of crude oil because food commodities can be considered as a substitute for crude oil to produce refined energy products, while oil is used in the production, processing and distribution of food commodities. $\Theta_{i,t}$ is a vector of weather variables to minimize possible correlation of the estimated foreign shocks with domestic weather conditions and harvests of the countries.[8] Specifically, this vector includes the Multivariate El Niño Southern Oscillation Index and the Oceanic Niño Index to control for global weather phenomena that may also affect the countries. In addition, for each country $i$ we include the European Drought Observatory index of domestic precipitation (rain anomaly) and an index of temperature anomaly, as well as the corresponding squared values. $c_{i,t}$ is a constant, while $C_i(L)$ and $D_i(L)$ are polynomials in the lag operator ($L = 5$). Notice that the results are robust when we also include a deterministic trend in the production equation or choose an alternative number of lags.

For all 75 countries, we estimate equation (5) over the sample period 1975Q1-2015Q4. The sample period is determined by the availability of the precipitation (from 75Q1 onward) and temperature (until 15Q4) series. If we assume that the information sets of local farmers are no greater than equation (5), the residuals $\nu_{i,t}$ of this equation can be considered as unanticipated harvest shocks. Notice that anticipated harvest innovations before the harvesting quarter should be reflected in the control variables, in particular agricultural commodity prices, because an arbitrage condition ensures that changes in futures prices also shift sport

[8]Ideally, we directly control for domestic harvest volumes. Unfortunately, the harvest volumes are not available for all countries at a quarterly frequency.

prices of storable commodities (Pindyck 1993).[9]

In sum, due to the time lag between the planting and harvesting season, the foreign harvest shocks are uncorrelated with other macroeconomic shocks. Hence, if the shocks have a relevant impact on agricultural commodity prices, the series fulfill the conditions specified in equations (3) and (4). The instrument relevance condition will be evaluated based on the F-statistics. Notice also that the standard errors of the VAR estimations are not distorted by generated regressor issues, because the generated regressors are used as instrumental variables and are not directly included in the VAR model. In particular, as shown by Pagan (1984), any instrumental variable estimation with generated regressors yields a consistent estimator of the true standard errors.

### 2.3 Narrative Global Agricultural Market Shocks

As a second external instrument, we use the series of major exogenous global agricultural commodity market disruptions that have been identified with narrative methods in DWP (2016). More precisely, DWP (2016) rely on newspaper articles, FAO reports, disaster databases and other online sources to identify 13 historical episodes of substantial movements in food commodity prices that are unambiguously caused by disturbances in global agricultural markets and unrelated to the state of the economy. An overview and brief description of these episodes is reported in Table 1. For more details, we refer to the online appendix of DWP (2016). Six episodes are unfavorable shocks that have augmented food prices, while seven episodes have been characterized by a meaningful decline in food commodity prices. These episodes are converted to a dummy variable series, which is equal to 1 and -1 for unfavorable and favorable shocks respectively, and can be used as an external instrument to identify the VAR. However, to minimize correlation of the shocks with domestic agricultural conditions, for each individual country, we exclude the episodes when domestic annual agricultural production growth deviated more than one standard deviation from its mean over the period 1965-2016. Accordingly, about 30 percent of the episodes are excluded.

## 3 Effects of Global Agricultural Market Shocks

The VAR models in this study are estimated in log levels, which gives consistent estimates while allowing for possible cointegration relationships between the variables (Sims et al. 1990).

[9] Futures prices of agricultural commodities are not available over the whole sample period.

The VARs are estimated for all 75 individual countries. To obtain Mean Group panel VAR estimates, we average the impulse response functions of the individual countries. In contrast to Fixed Effects panel estimations, a Mean Group estimator allows for cross-country heterogeneity and does not require that the dynamics of the economies in the VAR are the same.[10] In the estimations, we include five lags of the endogenous variables, which is the maximum number of lags suggested by the Akaike information criterion across all individual country VARs. The results are, however, not sensitive to the lag order choice. The first column of Table A1 in the appendix reports the sample periods of each country. Notice that the start of the sample, which is 1965Q1 the earliest, varies a lot across countries. This can be explained by data availability and obvious historical reasons. For example, the samples of the Russian Federation and several Eastern European countries only start in the 1990s. The end of the sample period is mostly 2017Q2, but for some countries earlier due to data availability. The sample period of the VAR and of the estimation of the external instruments are thus often different.[11]

To check the validity and strength of the instruments for the baseline estimations, Table A1 shows the first-stage F-statistics and robust F-statistics allowing for heteroskedasticity. With very few exceptions, the values for each country turn out to be much higher than the threshold suggested by Stock and Yogo (2005) for having possible weak instrument problems. The F-statistic of the instruments at the panel level (based on a Mean Group estimation of the first stage) that is robust for clustering by time is 36.7, while the corresponding clustered t-statistics of the harvest and narrative shocks are 5.1 and 6.5, respectively. Put differently, our instruments can be considered as strong, which fulfills the relevance condition posited in equation (3).

In the figures, we always show the estimated impulse responses for a global agricultural market shock that raises real agricultural commodity prices by 1% on impact. We construct one- and two-standard error confidence intervals using a recursive-design wild bootstrap procedure. Specifically, following Mertens and Ravn (2013), we generate bootstrap draws of $Y_{i,t}^{b}$ recursively by using the estimated coefficients of the VAR denoted in equation (1), where

[10] Pesaran and Smith (1995) show that the Fixed Effects panel estimator is biased in dynamic panels when the coefficients of the lagged endogenous variables differ across cross-sectional units, which is usually the case in panel VARs. As an alternative, they propose a Mean Group panel estimator, where separate regressions are estimated for each cross-sectional unit, and the panel estimates are obtained by taking cross-sectional averages of the estimated coefficients. For panel VARs, this is typically done by calculating the averages of the estimated impulse responses (e.g. Gambacorta et al., 2014).

[11] This is not a problem because the instruments are only used to estimate the elements (of the first column) of $B_i$. See also Gertler and Karadi (2015) for a similar discrepancy between the VAR sample and the sample period that is used to estimate the instruments. Overall, we explore the maximum data available for the estimations, which should improve efficiency.

the residuals of all countries are (simultaneously) multiplied by a random variable $e_t^b$ taking on values of -1 or 1 with probability 0.5. We also generate a draw for the instruments $Z_{i,t}^b = Z_{i,t}e_t^b$. The reduced form VAR is then re-estimated for $Y_{i,t}^b$, and the shocks are identified using the instruments $Z_{i,t}^b$. We use 5,000 replications to calculate the confidence intervals. To obtain the confidence intervals of the panel VARs, we also calculate the average impulse responses of the individual countries for each replication. Notice that this procedure requires symmetric distributions for the residuals and instruments, but it is robust to conditional heteroskedasticity of unknown form and takes into account uncertainty about identification and measurement (Mertens and Ravn 2013). Furthermore, because $e_t^b$ is the same for all countries, the procedure takes into account the correlation of the VAR residuals across countries to construct the confidence bands of the panel VARs.[12] In section 3.1, we report the baseline panel VAR results. Section 3.2 discusses a battery of sensitivity checks. In section 3.3, we compare the results with an LP-IV approach that directly estimates the dynamic effects at different horizons, whereas the effects on individual countries are presented in section 3.4.

### 3.1 Baseline Panel VAR Results

The estimated impulse responses of the panel VAR are shown in Figure 2. An exogenous shock to global agricultural markets that raises real agricultural commodity prices by 1% on impact reaches a peak of approximately 1.5% after one quarter, in order to gradually decline to roughly 0.3% at longer horizons. The rise in commodity prices leads to a fall in the global economic activity index, as well as average real GDP of the 75 countries in our panel. The decline in output is sluggish and very persistent. In particular, the effects on real GDP are only statistically significant after 3-4 quarters and reach a maximal decline of approximately 0.11% after more than 3 years.[13] Beyond this horizon, output remains permanently lower at this level.

The macroeconomic effects of changes in agricultural prices are not only statistically significant, but also economically important. Notice, for example, that the standard deviation of quarterly changes in real agricultural commodity prices has been 7.3% since the 1960s,

[12]Notice that the standard bootstrap based on a random reshuffle of the residuals with replacement would be problematic because the reshuffle has to be same across countries to account for cross-country correlation of the residuals, while the panel is unbalanced. In addition, given that the narrative instrument series contains many zero observations, a drawing procedure with replacement would produce zero vectors with positive probability. It is therefore more convenient to apply the Rademacher bootstrapping procedure.

[13]In the VAR literature, the significance of the results is typically based on one standard error bands. Two standard error bands are mostly not even reported. In this context, the impulse responses of agricultural commodity price shocks are quite precisely estimated. When we compare the panel results with the individual country results, also the use of a panel dataset appears to increase the precision of the estimates.

and even 8.7% since the start of the millennium. Furthermore, as shown in Figure 1, swings in agricultural prices can be very persistent. For example, global prices increased by 112% between 2002 and 2011, followed by a collapse of 83% afterwards. These fluctuations are obviously only partly driven by agricultural supply disruptions; that is, the consequences of endogenous shifts in agricultural prices may be different, but the magnitudes suggest that developments in agricultural markets matter for business cycle fluctuations.

An alternative way to assess the economic relevance of our estimates are the extreme events that have been documented in Table 1. In the summer of 2010, real cereal prices increased for example by 29%, which was predominantly the consequence of the worst heatwave and drought in more than a century in Russia and Eastern Europe (DWP 2016). According to our estimates (that is, a peak rise of 1.5% after one quarter leads to a decline of real GDP per capita by 0.1% after approximately two years), this global agricultural shock has lowered average real GDP per capita growth across countries by roughly 1% during two years. Similarly, the unfavorable shocks that occurred in 2002Q3 and 2012Q3 have likely reduced real GDP growth in two subsequent years by 0.6% and 0.4%, respectively. On the other hand, the two most recent favorable agricultural market shocks (1996Q3 and 2004Q3) should have boosted economic activity in the following two years by respectively 0.8% and 0.6%. In sum, global agricultural shocks matter for countries' business cycle fluctuations.

### 3.2 Sensitivity of Panel VAR Results

Figure 3 and 4 show a number of sensitivity checks of the panel VAR results. For brevity reasons, we only report the impulse responses of real GDP. We first assess the influence of using instrumental variables to identify the shocks. More specifically, Figure 3 compares the baseline SVAR-IV results with an estimation of the panel SVAR that does not use external instruments to identify the shocks. Instead, we use a standard recursive (Cholesky) decomposition of the variance-covariance matrix of the reduced form VAR, where the agricultural commodity price index is ordered first. In essence, this identification strategy assumes that all reduced form innovations to real agricultural commodity prices are exogenous price shocks for the individual countries. This assumption is often made to identify commodity price shocks more generally, in particular to estimate the effects on small economies.[14]

[14] For example, Dreschel and Tenreyro (2017) assume that Argentina is a relatively small country, which does not drive global commodity prices. Addison et al. (2016) use this premise to estimate the effects of agricultural commodity price shocks on growth in Sub-Saharan Africa. Similar assumptions have, for example, been made in the literature examining the impact of food prices on conflict (e.g. Brückner and Ciccone 2010; Dube and Vargas 2013; Bazzi and Blattman 2014).

As can be observed in Figure 3, the effects on real GDP are much smaller for the recursive identification. The impact is even significantly positive in the short run, while the long-run decline is approximately 0.07%, compared to 0.11% in the benchmark estimations. As shown in the right panel of the figure, the difference between both impulse response functions is also statistically significant. Since both identification methods rely on the same reduced form VAR system, this can formally be tested by calculating the difference between the impulse responses for each replication of the bootstrapping procedure. This finding suggests that the reduced form innovations to agricultural prices are a mixture of exogenous agricultural market shocks and endogenous responses to other macroeconomic shocks (e.g. global demand shocks), which could bias the estimated effects considerably. A rise in agricultural prices caused by a disruption in global agricultural markets is clearly different from a surge that is consequence of increased worldwide economic activity. In fact, we find that this also applies to most small countries that could not influence global agricultural prices. It is hence important to isolate shifts in commodity prices that are truly exogenous to estimate the macroeconomic effects properly.

The results do not seem to depend on one of the instruments that we have used. This is shown in panels (A) and (B) of Figure 4. Specifically, panel (A) shows the impulse responses when we only use the unanticipated foreign harvest shocks as an external instrument, while panel (B) shows the results for an estimation solely based on the narrative shocks. The panels also show the baseline point impulse responses (dotted red lines) to compare with the benchmark results. The effects on real GDP turn out to be very similar.[15]

In panels (C) and (D), we show the results of two extended VAR models. The panels show the results of a VAR-IV that also includes respectively the inflation rate and the real (bilateral) USD exchange rate of the individual countries in the vector of endogenous variables $Y_{i,t}$, which could enrich the dynamics of the VAR model. A caveat of these extensions is that exchange rate regimes have varied over time, while inflation has been very unstable in some countries during the sample period, which may imply possible structural breaks in the VAR dynamics. We find a positive impact of the shocks on inflation and a temporary depreciation of the USD real bilateral exchange rates.[16] The results of both extensions for real GDP per

[15]The clustered panel VAR F-statistic of both instruments independently are 29.7 and 59.2 for the foreign harvest and narrative shocks, respectively. Notice, however, that the robust F-statistics are below 10 for 19 countries if only the foreign harvest shocks are used for the identification of the shocks. For the narrative shocks, this is only the case for 3 countries. For this reason, we excluded Mexico, Jamaica, Belize, Costa Rica and Guatemala from the estimations that are solely based on the foreign harvest shocks. The first-stage robust F-statistics for these countries are less than 1, resulting in explosive error bands of the panel VARs. The exclusion of these countries, however, has a negligible influence on the point estimates of the impulse responses.

[16]The impulse responses of inflation and the exchange rate are not shown, but available upon request. The

capita turn out to be quite similar to the baseline results.

Panel (E) shows the results when we estimate the panel VAR only from 1990 onward. A shorter sample period can be motivated by the reduced share of food in household expenditures over time, and the fact that the series of several countries only start in the 1990s. However, as can be observed in the figure, the results are again very similar. In fact, we find that this is also the case for alternative (shorter and longer) sample periods.

Finally, panel (F) shows the estimated impulse responses when we use the broad food commodity price index of the IMF instead of the weighted average of the four major staple food items, which was also shown in Figure 1. In addition to the four staples, this index also includes the prices of vegetable oils, meat, seafood, sugar, bananas and oranges. Panel (F) reveals that the effects of a rise in food commodity prices by 1% are stronger than an equal rise in the prices of the four staples. In particular, real GDP decreases by 0.15% in the long run. This finding is not very surprising since this index covers a larger share of food commodities. Overall, we can conclude that the panel VAR results are generally robust to several perturbations of the VAR model.

### 3.3 Comparison with a Panel LP-IV Approach

If the SVAR model adequately captures the data generating process, this method is most efficient to estimate the dynamic effects of agricultural shocks at all horizons. However, if the SVAR is not a correct representation of the dynamics of the variables in the system, the specification errors will be compounded at each horizon resulting in impulse responses that are potentially biased (Ramey 2016). To further check the robustness of the results, we therefore also estimate the impulse responses directly with panel LP-IV methods. The advantage compared to VARs is that LP methods are more robust to misspecification (Jordà 2005; Stock and Watson 2017).[17] Another advantage is that it will be able to estimate the relationship between the dynamic effects and several country characteristics simultaneously in section 4, which is not possible with panel VARs. A disadvantage of this method, however, is a loss of efficiency and hence less precisely estimated effects that are often quite erratic at longer horizons.

temporary depreciation of the real USD exchange rate may be the consequence of the relative strong decline of US real GDP compared to the majority of the other countries, which is shown in Figure A1.

[17]The baseline SVAR-IV assumes invertibility of $B_i$, i.e. the space of the VAR innovations spans the space of the structural shocks, which can be interpreted that there are no omitted variables in the VAR. Under invertibility, SVAR-IV and LP-IV are both consistent, but SVAR-IV is more efficient. However, if invertibility fails, the SVAR-IV estimates are not consistent, while LP-IV estimates are. LP-IV methods can hence be a solution to omitted variables bias. See Stock and Watson (2017) for more details.

For each horizon $h$ we estimate the following panel LP-IV model:

$$y_{i,t+h} = \alpha_{i,h} + \delta_{i,h}(L)\, y_{i,t-1} + \rho_{i,h}(L)\, X_{i,t-1} + \gamma_h RACP_t + \varepsilon_{i,t+h} \tag{6}$$

where $y_{i,t+h}$ is real GDP per capita of country $i$ at horizon $h$. $\alpha_{i,h}$ are country fixed effects, while $\delta_{i,h}(L)$ and $\rho_{i,h}(L)$ are polynomials in the lag operator ($L = 5$) that could vary across countries. $X_{i,t-1}$ is a set of control variables determined before date $t$. In line with the VAR estimations, this vector includes the lags of global real agricultural commodity prices, global economic activity, as well as lags of the instruments. Accordingly, $\gamma_h$ represents the dynamic response of real GDP per capita at horizon $h$ to a change in real agricultural commodity prices ($RACP_t$) at time $t$, which we estimate with the two instrumental variables that we have described in section 2.2 and 2.3.

Figure 5 shows the estimation results for $\gamma_h$ when we estimate equation (6) with respectively the Pooled Mean Group (PMG) and Mean Group (MG) estimator as described in Pesaran et al. (1999). Specifically, the PMG estimator allows all coefficients and error variances to differ across countries, but constrains the effects of agricultural shocks on real GDP per capita ($\gamma_h$) to be the same across countries. This specification is most closely related to the extended LP-IV model that we will estimate in section 4, i.e. when we allow $\gamma_h$ to vary according to a set of country characteristics. The MG estimator, in contrast, is most closely related to the panel SVAR estimations, by also allowing the effects of agricultural shocks to be different across countries, i.e. $\gamma_{i,h}$. The standard errors of the estimates are adjusted for correlations between the residuals across countries, as well as serial correlation between the residuals over time. These are calculated as discussed in Thompson (2011).

As expected, the precision of the LP-IV estimates is less accurate than the SVAR-IV results due to the loss of efficiency. The effects on real GDP are, however, still significant at 5% level for several horizons. For both estimators, we find a peak decline of real GDP by 0.16%, which is somewhat larger than the SVAR-IV estimates. Overall, we can conclude that the panel results are robust to the estimation method.

### 3.4 Individual Country Results

The individual-country SVAR-IV results are shown in Figure A1 of the appendix. For each country, we show the effects of a 1% increase in agricultural commodity prices on real GDP. The figure reveals that there is considerable cross-country heterogeneity. Several countries experience substantial declines in real GDP following a rise in cereal prices, e.g. Belize, Bulgaria, Chile, Denmark, Estonia, Finland, Greece, Luxembourg, Portugal, Spain and the Russian Federation. On the other hand, a large number of countries, e.g. Argentina, India, Indonesia, Jamaica, Korea, Kyrgyzstan, Macedonia, Morocco, Peru, the Philippines and South Africa, experience a temporary increase in real GDP. Also the shapes are different across countries. In the next section, we explore in more detail whether there is cross-country heterogeneity depending on a set of country characteristics.

## 4 Exploring Cross-Country Heterogeneity

So far, we have documented that exogenous agricultural price increases significantly reduce average real GDP, while the effects are very different across individual countries. The aim of this section is to examine whether (i) rich and poor countries are on average differently affected by fluctuations in global agricultural markets, and (ii) there is a relationship between the magnitude of the effects and some key country characteristics. Notice that the results in this section reflect correlations, which does not imply causation nor does it reflect transmission mechanisms. Nevertheless, it could improve our understanding of the pass-through of global agricultural market shocks to economic activity. At the same time, it provides stylized facts that could serve as a benchmark for the construction of theoretical business cycle models that incorporate agricultural markets.

The analysis in this section is mainly based on the effects of global agricultural shocks across country groups. The composition of the groups is based on the averages of a selection of country characteristics over the period 2000-2015 (annual data). More precisely, we use the baseline panel SVAR-IV model and calculate the Mean Group impulse responses of respectively the top and bottom tertile of the countries according to a specific country characteristic, as well as the differences between both tertiles.[18] The groups hence always contain respectively the 25 highest and lowest ranked countries for a characteristic. The period to compose the groups overlaps but does not correspond one-to-one with the SVAR-IV sample periods of the countries due to the unbalanced nature and availability of the data. However, since we use the underlying data only to compose the groups and the middle tertile is excluded from the analysis, this should have little or no impact on the results. Notice also that the results are qualitatively robust to alternative sizes of the groups, e.g. top/bottom half or quintiles of the countries. As a special case, in section 4.3 we will also estimate an LP-IV specification

[18] Since the bootstrapping procedure is done for all countries simultaneously and takes into account the correlation of the residuals, it is also possible to calculate confidence bands for the differences between country groups.

that is based on the country averages directly. Details about the data sources can be found in the appendix. Table A1 reports for each country the averages of the characteristics between 2000 and 2015, as well as the country's rankings that have been used to construct the groups between parentheses.

### 4.1 Are the Effects Different between Rich and Poor Countries?

There is large agreement in the literature that poor countries suffer more from climate change because the economic repercussions are considered to be most severe for agricultural production, while the share of agricultural production in total GDP is usually larger in these countries. Moreover, poor countries typically already have hotter climates, which increases the likelihood of extreme weather events. Dell et al. (2012), for example, find that a 1°C rise in temperature in a given year reduces economic growth by about 1.3% in poor countries. On the other hand, changes in temperature appear not to have a meaningful impact on growth in rich countries. To assess whether this is also the case for the indirect effects of climatic changes as a result of a rise in the volatility of global harvest volumes and more frequent surges in global agricultural commodity prices, we first estimate the Mean Group impulse responses of the top versus the bottom tertile of the countries according to income (PPP-adjusted real GDP) per capita. All countries in the top tertile are advanced economies according to the IMF's 2015 World Economic Outlook country classification, while the low-income countries are all classified as emerging market or developing economies.

The results are shown in Figure 6. A remarkable observation is that high-income countries appear to be much more affected by exogenous global agricultural price shocks. For the group of high-income countries, a rise in global cereal prices induces a gradual and persistent decline in economic activity; that is, real GDP per capita declines by 0.12% in the long run. In contrast, low-income countries experience a temporary increase of real GDP during the first year after the shock, which reaches a statistically significant peak of 0.07% after two quarters. Subsequently, the effects on real GDP start to decrease and become negative after one year. The peak decline, however, is only 0.03% and statistically insignificant. Furthermore, as shown in the right panel of the figure, the differences between the impulse responses of both country groups are clearly significant at all horizons.

The stronger output effects in rich countries turn out to be very robust. Figure 7 summarizes a battery of robustness checks. We only show the estimated differences between both groups. First, the results do not depend on the way the groups are constructed. As shown in panels (A) and (B), we also find significant differences between the top and bottom half or quintiles of the countries. We also find it when we estimate the SVAR-IV model solely for the post 1990 sample period, which implies that this result is e.g. not driven by the longer sample periods that most high-income countries have (panel (C)). Furthermore, the results are similar when we estimate the effects of changes in global agricultural prices measured in domestic currency. The results are thus also not the consequence of exchange rate movements that are different between high and low-income countries (panel (D)).[19] Finally, as can be observed in panels (E) and (F), we find stronger effects when we estimate the difference between both groups with panel LP-IV techniques or when we identify average agricultural price shocks using a simple recursive (Cholesky) decomposition of the variance-covariance matrix of the VAR residuals.[20]

The finding of significantly larger effects on economic activity of high-income countries is surprising. In fact, there are several reasons why real GDP of high-income countries is expected to be less affected by changes in global agricultural commodity prices. First, the share of food (commodities) consumption in total household expenditures is much lower compared to low-income countries. For example, the share of food and non-alcoholic beverages consumed at home in total household expenditures over the period 2000-2015 has been respectively 12% and 33% for the top and bottom income-tertile, while the elementary correlation with average income per capita across all countries has been -0.76. Although such data does not exist, this is likely also the case for the share of (raw) food commodities in household expenditures. Second, high-income countries typically have more effective government institutions. It is hence less likely that increases in food prices trigger conflicts such as food riots which, in turn, could have an impact on real GDP. Finally, high-income countries are financially more developed than low-income countries, which should allow households to smooth consumption and firms to smooth production when they experience income shocks.[21] In sum, there must be other important mechanisms that explain why rich countries are more vulnerable to exogenous changes in global agricultural prices.

[19]This estimation has been done by simply converting global USD agricultural prices in domestic currency using bilateral USD exchange rates. Ideally, we should use direct measures of domestic prices for this check, but unfortunately such data is not available for a sufficiently long era and number of countries.

[20]The panel LP-IV model that we have used to do this, will be discussed in section 4.3.

[21]The correlation between real GDP per capita and the World Bank indicator of government effectiveness is 0.88, while the correlation with the percentage of persons that have a credit card is 0.85. When we split the country-groups according to these two characteristics, we also find counter-intuitive stronger effects in "rich" countries.

## 4.2 Alternative Country Characteristics

We now discuss a number of alternative characteristics that might explain why real GDP of advanced economies declines more in response to increases in global agricultural prices. We discuss four possible country characteristics. The correlations of these characteristics with income per capita are reported in Table 2, as well as the overlap between the top and bottom tertiles of the groups. In section 4.3, we will show the relationships between the characteristics and the dynamic effects of global agricultural shocks on real GDP.

**Net exports of primary food and beverages** A first possible explanation for the counterintuitive stronger effects on high-income countries is that rich countries are typically net importers of agricultural products. If a country is net importer of food commodities, a rise in global food commodity prices deteriorates its terms of trade. In contrast, net food commodity exporters should benefit from higher agricultural prices. We therefore split the countries according to their net export position of primary food and beverages as a percentage of GDP. As shown in Table 2, the cross-country correlation of income per capita and net exports of primary food and beverages is negative (-0.32). Twelve of the high-income countries belong to the bottom tertile of net food exports and fourteen low-income countries to the top tertile of food exporters.

**Value added agricultural sector** As can be observed in Table 2, there is a strong negative correlation between income per capita and the share of agriculture in GDP. There are several reasons why a larger share of the agricultural sector in GDP may be associated with more subdued macroeconomic repercussions of changes in global agricultural prices in low-income countries, in addition to net export benefits. Specifically, in countries that have relatively large agricultural sectors, more households are likely self-sufficiency farmers, while a lot of agricultural commodities are typically traded on local markets only, which isolates them from changes in global agricultural prices. In addition, when food prices increase, countries with large agricultural sectors may have more scope to increase food production at longer horizons after the shock.

Furthermore, agricultural commodity price increases do not only affect the terms of trade, it also involves redistribution of income within countries, which could magnify or dampen the consequences on economic activity if food producers have different propensities to consume (or invest) out of changes in disposable income than food consumers.[22] Since low-income

[22]Browning and Crossley (2009) show that households that experience transitory income shocks can signif-

households usually have higher marginal propensities to consume, such effects may be different between rich and poor countries. In particular, the revenues of higher food prices in rich countries are typically concentrated to a relatively small group of people, e.g. industrial food producers, while the bulk of poor people are urban with limited access to land that spend large portions of their income on food. For example, households belonging to the lowest income quintile in the United States spend 35.8% of their income after taxes on food consumption. For the highest quintile, this is only 9.1%.[23] Since low-income households have no access to capital markets to smooth consumption and food is a basic necessity, they have no other options than reducing their non-food expenditures. For example, DWP (2016) find that changes in food prices in the United States trigger a significant decline in durable consumption of households, which magnifies the repercussions on economic activity considerably.

On the other hand, food consumers typically have higher average incomes than food sellers in low developed countries (Aksoy and Isik-Dikmelik 2008), while many impoverished people in low-income countries depend upon food production for their livelihood (Headey and Fan 2008). Although poor households in these countries spend higher shares of their budgets on food, their incomes are likely more responsive to agricultural prices. Poor countries may thus also benefit from higher agricultural prices as a result of redistribution of income that, in turn, stimulates aggregate spending.[24] Overall, favorable redistribution effects are likely greater when the share of agriculture in the economy is larger; that is, more households benefit from higher food prices. For example, Jacoby (2016) constructs a simple general equilibrium model and finds that countries with large shares of agricultural employment could ultimately benefit from higher food prices because this has a positive impact on rural wages.[25]

**Trade openness** Varies studies have shown that enhanced trade integration increases the correlation of business cycles among countries (e.g. Frankel and Rose 1998; Clark and Van Wincoop 2001; Calderón et al. 2007). There also exist a number of studies that find a

icantly reduce their expenditures with little loss in welfare if they concentrate their budget cuts on durables purchases and continue to consume their existing stock of durables. Although the losses of this behavior might be modest for individual households, the macroeconomic effects could be substantial. The consequences on economic activity of this change in the composition of spending can be further magnified if this involves costly reallocation of capital and labor across sectors within a country, see e.g. Hamilton (1988).

[23]Authors' calculations based on the U.S. Bureau of Labor Statistics' Consumer Expenditure Survey for 2014. These percentages include both food at home, food away from home and alcoholic beverages.

[24]In this context, Headey (2014) and Ivanic and Martin (2014) find that in the long run higher food prices typically reduce poverty in low-income countries. However, other studies have found that higher food prices increase poverty. See Headey and Fan (2010) for a review.

[25]We find very similar results when we use the share of agricultural employment in total employment to construct the groups. The correlation between the share of agriculture value added in GDP and agricultural employments in total employment across the countries in our sample is 0.85.

positive link between trade and volatility of economic activity (e.g. Rodrik 1998; di Giovanni and Levchenko 2009; Newbery and Stiglitz 1984). Since global agricultural shocks have a significant impact on worldwide economic activity, countries that are more integrated with the rest of the world via trade are probably also more affected by the shocks. We consider the ratio of total exports plus imports to GDP as a measure of trade integration. As can be seen in Table 2, there is a positive correlation between income per capita and the trade-to-GDP ratio (0.35).

**Trade tariffs for agricultural goods** Finally, agricultural import barriers may mitigate the consequences of global agricultural shocks on the domestic economy because retail prices might be more decoupled from international prices. Anderson and Nelgen (2012) find that the pass-through of changes in global cereal prices to domestic prices is on average only about 0.5. Gouel (2014) argues that the incomplete transmission is likely the result of trade policies.[26] To evaluate whether countries that have tighter import barriers are differently affected by global agricultural shocks, we group the countries according to the effectively applied rate for agricultural goods calculated with the UNCTAD method based on Trade Analysis Information System (TRAINS) data. There seems to be a moderate positive correlation between import barriers and the wealth of nations (see Table 2).

### 4.3 Estimation Results

**Panel SVAR-IV for country groups** Figure 8 shows the impulse responses estimated with the panel SVAR-IV approach for the top and bottom tertiles of the countries according to each characteristic. The results confirm several hypotheses that have been postulated in section 4.2. More specifically, we find weaker average effects of unfavorable global agricultural price shocks on the economies of countries that are large net exporters of primary food and beverages, as well as countries that have a higher share of agriculture in GDP. Both features may thus be a possible explanation for the stronger effects on high-income countries. This also applies to the degree of trade integration. Figure 8 reveals that the decline in real GDP is on average greater in countries with higher shares of trade in GDP. Specifically, real GDP decreases by 0.15% in the top-tertile of the countries, compared to only 0.08% in the lowest

[26] The price transmission elasticity is higher for soybeans (0.72) than for wheat (0.47) and rice (0.52), because the former is traded more heavily (30% of total soybeans production, versus 8% of rice and 20% of wheat production) and the rate of protection for soybeans is not significantly negatively correlated with the world price, unlike for other commodities.

tertile. Finally, we do not find a relationship between the extent of trade tariffs for agricultural goods and the consequences of swings in global cereal prices.

**Simultaneous analysis of country characteristics** Panel SVARs do not allow to examine the country features simultaneously. To do this, we estimate an extended version of the LP-IV model introduced in section 3.3, which allows for an influence of the country characteristics on the effects of changes in real agricultural commodity prices on real GDP:

$$\begin{aligned} y_{i,t+h} = \alpha_{i,h} + \textstyle\sum_k \phi_{k,h} char(k)_i + \delta_{i,h}\left(L\right) y_{i,t-1} + \rho_{i,h}\left(L\right) X_{i,t-1} \\ + \left[\gamma_{0,h} + \textstyle\sum_k \gamma_{k,h} char(k)_i\right] RACP_t + \varepsilon_{i,t+h} \end{aligned} \tag{7}$$

where $char(k)_i$ is a vector of five $(k = 5)$ country characteristics; that is, income per capita and the four country features that have been discussed in section 4.2. All other variables are the same as in section 3.3. We estimate two versions of equation (7) using the PMG estimator. In the first, $char(k)_i$ is a vector of five dummy variables that are equal to 1 if the country belongs to the top-tertile of characteristic $k$. As an alternative, we estimate a specification where $char(k)_i$ contains the underlying data series that we have used to compose the country groups; that is, the average values of the country characteristics over the period 2000-2015. Since the latter period does not fully overlap with the LP-IV sample period, these results should be interpreted with more than the usual degree of caution. In contrast to the simple grouping of countries (excluding the mid-tertile), endogeneity issues might also be at play. We will therefore only provide a qualitative interpretation of the estimates with the sole aim to improve our understanding of cross-country differences.

The results of both specifications are shown in panels (A) and (B) of Figure 9, respectively. Although the standard errors are quite large, there are some clear patterns. First, there is a negative relationship between the net agricultural export position of a country and the effects of global agricultural shocks on domestic economic activity. Hence, net exporters suffer less from the shocks. Conversely, countries that have a higher overall share of trade in GDP are more vulnerable to the shocks. Notice, however, that both characteristics are statistically only significant for the dummy variables specification.

For both specifications, we find that countries are significantly less affected by the shocks when they have a higher share of agriculture in GDP. It seems that countries that have relatively large agricultural sectors are better insulated to global agricultural shocks. Furthermore, the extent of trade tariffs for agricultural goods turns out to be positively correlated with the effects on real GDP, but the uncertainty of the estimates is relatively high to make robust conclusions. A possible explanation of the positive correlation is endogeneity. In particular, countries that are more vulnerable to agricultural shocks may, for example, impose more trade barriers.

Interestingly, once we control for these four alternative country characteristics, we find that the effects on real GDP are more subdued when countries are richer; that is, when income per capita is higher. For both specifications, the relationship turns out to be statistically significant. This suggests that the stronger average effects on high-income countries that we have documented in this paper are likely related to the other country characteristics. More specifically, high-income countries are typically net importers of primary food and beverages, and have a relatively small share of agriculture in GDP, a large share of trade in GDP and higher trade tariffs for agricultural goods, which seems to make them more vulnerable to global agricultural shocks.

# 5 Conclusions

In this study, we have estimated the consequences of exogenous shifts in global agricultural commodity prices on real GDP per capita for a panel of 75 advanced and developing countries. Isolating exogenous shifts in agricultural prices is challenging because the prices of food commodities typically respond quickly to changes in the state of the economy, implying that reverse causality effects from macroeconomic aggregates to agricultural prices are also present. To address this problem, for each country we construct two instrumental variables that reflect disturbances to global agricultural markets, which shift prices in a way that is plausibly unrelated to economic conditions: unanticipated foreign harvest shocks and a series of exogenous global agricultural shocks identified with narrative methods. These instruments are then used to estimate the dynamic effects on economic activity with panel SVAR-IV and LP-IV methods.

The results reveal that swings in global agricultural prices appear to be important for economic activity; that is, a rise in agricultural commodity prices significantly reduces average real GDP. Scholars that study business cycle fluctuations should hence consider to accommodate agricultural markets in their models. This also applies to the analysis of policies that may affect agricultural prices, such as public food security programs, agricultural export bans, import tariffs, ethanol subsidies or carbon offset programs.

The macroeconomic consequences turn out to be very different across countries. A striking result is that we find much larger effects in high-income countries. Additionally, we document stronger effects on countries that have a high share of trade in GDP. On the other hand, countries that are net food commodity exporters and/or have a high share of agriculture in GDP appear to be less affected by disruptions in global agricultural markets. These findings are interesting in the context of the literature on climate change. Specifically, several studies find that poor countries with higher shares of agriculture suffer more from climatic changes than rich countries or countries with less agricultural activities because they have relatively large agricultural sectors (e.g. Nordhaus 2006; Jones and Olken 2010; Dell et al. 2014; Althor et al. 2016). While this might be the case for the direct effects of a rise in the mean and variance of global weather conditions on the economies of poor and rich countries, it appears to be the opposite for the indirect effects of changes in weather conditions in other countries around the globe. The consequences of climate change on advanced economies may hence be much larger than previously thought.

The weaker effects on countries that are net exporters of food commodities and/or have large agricultural sectors is also in line with the skepticism of several scholars about the idea that higher food prices are unambiguously harmful for the poor (e.g. Headey and Fan 2008; Swinnen and Squicciarini 2012). In particular, the world's poor are highly dependent on farming or are employed in sectors that are related to agricultural production. Soaring food prices could thus result in redistribution of income in favor of the poor. Accordingly, our macro evidence complements microeconomic welfare studies of changes in food prices in low-income countries (e.g. Deaton 1989; de Hoyos and Medvedev 2011; Ivanic and Martin 2008; Ivanic and Martin 2014;Verpoorten et al. 2013).

As a final remark, it should be mentioned that we have only provided a first set of stylized facts on the relationship between the effects of global agricultural price shocks and some country characteristics. There are, however, a range of other factors that could influence the vulnerability of economies to rising food prices. Examples are the degree of the pass-through of global price shifts to local price changes or the composition of food production and consumption. Furthermore, the monetary policy response to the inflationary consequences or the presence of government policies aimed at mitigating price increases are likely also important for the effects on economic activity. The exact transmission mechanisms need to be further addressed in future research.

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# Appendix: Data

### Baseline SVAR-model

- **Global real agricultural commodity prices**: The global cereal price index is a production-weighted aggregate of the price series of corn (U.S. No.2 Yellow, FOB Gulf of Mexico), wheat (No.1 Hard Red Winter, ordinary protein, FOB Gulf of Mexico), rice (5 percent broken milled white rice, Thailand) and soybeans (U.S. soybeans, Chicago Soybean futures contract No. 2 yellow and par) made available by the IMF. These benchmark prices are representative for the global market and determined by the largest exporter of each commodity. The price series (in U.S. dollar per metric ton) are weighted with trend production volumes (in metric ton) of the four commodities. The trend production volumes are obtained by applying a Hodrick-Prescott filter to annual global production data (with smoothing parameter = 100). Note that for rice, the paddy production volumes are converted to a milled rice equivalent using a conversion ratio of 0.7, since the price series is expressed in U.S. dollar per metric ton of milled rice. The agricultural price index has been seasonally adjusted using Census X-13 (X-11 option). The nominal price index has been deflated by U.S. CPI.

- **Global economic activity**: Seasonally adjusted world industrial production index from the Netherlands Bureau for Economic Policy Analysis, backcasted for the period before 1991 using the growth rate of industrial production from the United Nations Monthly Bulletin of Statistics.

- **Real GDP** (country-specific): As the preferred source we use the seasonally adjusted real GDP index from the OECD Main Economic Indicators database. This series is available for 38 countries for varying sample periods. For Greece this series still contains seasonality, so we perform additional seasonal adjustment. For the remaining countries we download real GDP from the IMF International Financial Statistics (IFS) database. In order to obtain longer time series we backcast the OECD and IMF series using various other sources: 1) We use GDP series from the Bank for International Settlements (BIS) for Argentina, Brazil, China, Chile, Colombia, Czech Republic, Estonia, Hungary, Indonesia, India, Latvia, Poland and Hong Kong. 2) We use GDP series from Oxford Economics (downloaded via Datastream) for Argentina, Bulgaria, China, Croatia, Malaysia, Romania, Russia and Thailand. 3) We use GDP series provided by the respective national statistical office for Belize, Iran, Morocco and Uruguay. 4) For Iceland we backcast using a GDP series from the OECD Quarterly National Accounts database. 5) For Kyrgyzstan we use the GDP series from the World Development Indicators Database (quarterly series, downloaded via Datastream). 6) For Colombia, Cyprus, Hungary, Indonesia, Israel, Macedonia, Malaysia, Poland, Slovakia we backcast using annual GDP, Chow-Lin interpolated with quarterly industrial production from the IMF IFS database. Additional details are available on request.

**Unanticipated foreign harvest shocks**

- **Foreign harvest volume** (country-specific): These indices are based on annual food production data downloaded from the Food and Agriculture Organization (FAO). For a more detailed description of the construction of the index, see main text.

- **Real crude oil prices**: The refiner acquisition cost of imported crude oil, deflated by the U.S. CPI.

- **Multivariate El Niño Southern Oscillation Index**: Index provided by the Earth System Research Laboratory (https://www.esrl.noaa.gov/psd/enso/mei/, accessed August 2016). The index is based on six different variables in order to measure El Niño/Southern Oscillation (ENSO).

- **Oceanic Niño Index**: Index made available by the Earth System Research Laboratory (https://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Data/nino34.long.anom.data, accessed August 2016). This index is calculated by averaging sea surface temperature anomalies in an area of the east-central equatorial Pacific Ocean (the Nino-3.4 region).

- **European Drought Observatory (EDO) index of domestic precipitation** (country-specific): The Standardized Precipitation Index 3 (SPI 3) measures the observed rainfall in mm. over 3 months minus the average over 3 months divided by the standard deviation of 3 months. The country average of half minute cells is made available by the European Drought Observatory (EDO).
  Data downloaded from http://edo.jrc.ec.europa.eu/edov2/php/index.php?id=1140 in March 2017.

- **Temperature anomaly index** (country-specific): This index measures quarterly averages of monthly deviations from long-term (1901-2015) average national temperatures. Data was downloaded from the World Bank Climate Change Data Portal (http://sdwebx.worldbank.org/climateportal, accessed September 2017). The underlying dataset was produced by the Climatic Research Unit (CRU) of University of East

Anglia (UEA).) Missing values for Romania and Hong Kong were replaced by anomaly data from Berkeley Earth (http://berkeleyearth.lbl.gov/country-list/, accessed September 2017).

### Sensitivity of SVAR-Model

- **Inflation rate** (country-specific): As the preferred source we use the not seasonally adjusted Consumer Price index (CPI), from the OECD Main Economic Indicators database. This series is available for 45 countries for varying sample periods. For the remaining countries we use the CPI series from the IMF International Statistics Database. There are a few exceptions: for Argentina we use CPI from the MIT project (http://www.inflacionverdadera.com/?page_id=362), for Bulgaria we obtain CPI from Oxford Economics (via Datastream). For Colombia we backcast the OECD CPI series with CPI from The National Administrative Department of Statistics (DANE) (downloaded via Datastream). For Chile, China, Denmark, Ireland, Mexico, Hong Kong we backcast the series using BIS data. If not already done so by the source, all series are seasonally adjusted using Census X-13 (X-11 option). We calculate the inflation rate by taking log differences.
- **Real (bilateral) USD exchange rate** (country-specific): Based on nominal exchange rates (quarterly average) downloaded from the IFS database. For euro area countries, the legacy currency is converted to euro based on fixed conversion rates. The nominal exchange rates are converted to real exchange rates using U.S. and domestic CPI.
- **Broader commodity price index**: Food commodity index calculated by the IMF. The index is a trade-weighted average of different benchmark food prices in US dollars for cereals, vegetable oils, meat, seafood, sugar, bananas and oranges. These benchmark prices are representative for the global market and determined by the largest exporter of each commodity. Seasonally adjusted using Census X-13 (X-11 option). The nominal price index has been deflated by U.S. CPI.

### Cross-country heterogeneity

- **Income per capita** (country-specific, annual frequency): Real GDP per capita, calculated by dividing output-side real GDP at current PPPs (in mil. 2011 U.S. dollar) by population (both series obtained from Penn World Table, version 9.0).

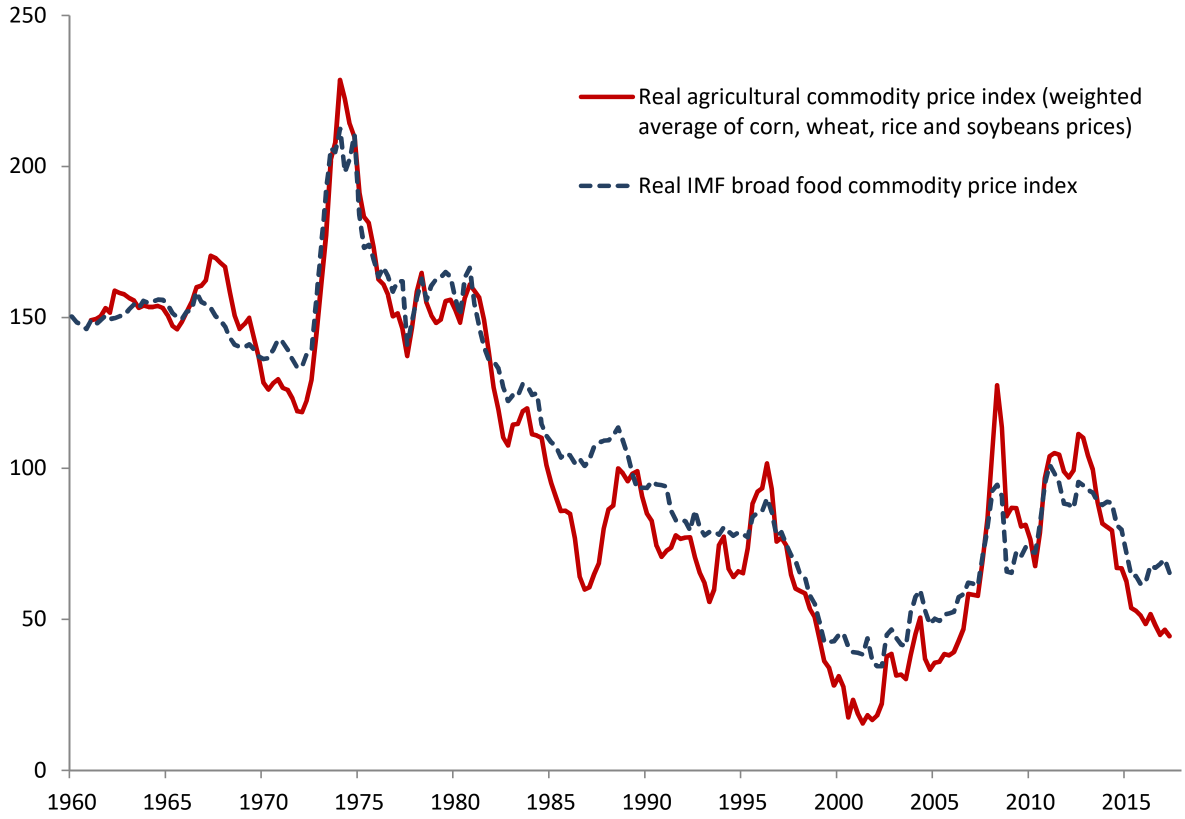
- **Net exports of primary food and beverages** (country-specific, annual frequency): Share in GDP of primary food and beverages net exports. Trade data in U.S. dollar downloaded from the UN Comtrade database. Primary food and beverages corresponds with Broad Economic Categories (BEC) Classification 11 and includes primary food and beverages both for industry and household consumption. Nominal annual GDP in U.S. dollar was downloaded from the World Bank (NY.GDP.MKTP.CD).

- **Value added agriculture** (country-specific, annual frequency): We use the value added of agriculture (% of GDP) provided by the World Bank (code: NV.AGR.TOTL.ZS) as the primary source. We backcast these series with data from various other sources. For Austria, Australia, Belgium, Switzerland, Czech Republic, Germany, Estonia, Finland, United Kingdom, Hungary, Iceland, Italy, Lithuania, Latvia, Poland, Portugal, Slovenia, Slovakia and the U.S. we use data from AMECO (the annual macro-economic database of the European Commission's Directorate General for Economic and Financial Affairs). For Canada, Spain, Hong Kong and Ireland we use data from the respective national statistical offices. For Israel and Luxembourg we use OECD data. For Croatia, Latvia and Poland we use data from Trading Economics.

- **Trade openness** (country-specific, annual frequency): Trade (% of GDP), provided by the World Bank (code: NE.TRD.GNFS.ZS). Trade is the sum of exports and imports of goods and services measured as a share of GDP.

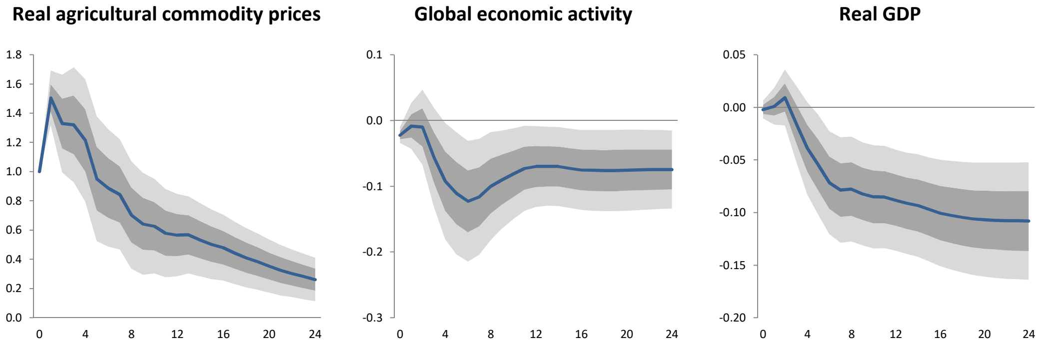
- **Trade tariffs for agricultural goods** (country-specific, annual frequency): Effectively Applied Rate for Agricultural Goods (HS classification), including ad-valorem-equivalents (AVEs) calculated with UNCTAD method based on Trade Analysis Information System (TRAINS) data. Downloaded using World Integrated Trade Solutions (WITS).

**Figure 1 - Evolution of agricultural commodity prices over time**



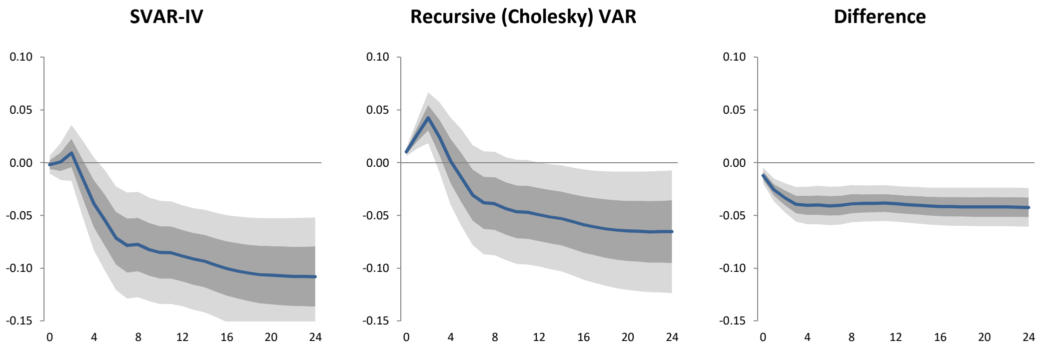

Note: variables are measured as 100*log of index deflated by US CPI. The agricultural commodity price index aggregates the prices of corn, wheat, rice and soybeans on a (trend) production-weighted basis (source: IMF). The IMF broad food commodity price index is a trade-weighted average of benchmark food prices in US dollars for cereals, vegetable oils, meat, seafood, sugar, bananas and oranges.

**Figure 2 - Effects of 1% increase in global real agricultural commodity prices: panel SVAR-IV estimations**



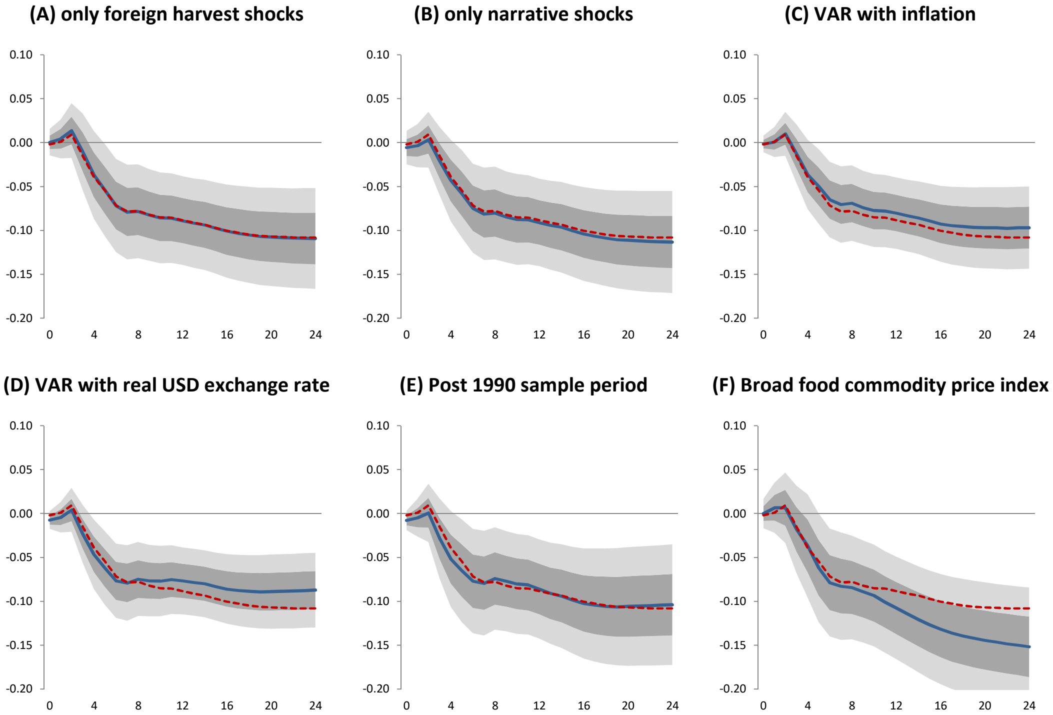

Note: Mean Group impulse responses with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly

**Figure 3 - Assessing the role of the instruments for the output effects: comparison with a recursively identified VAR**



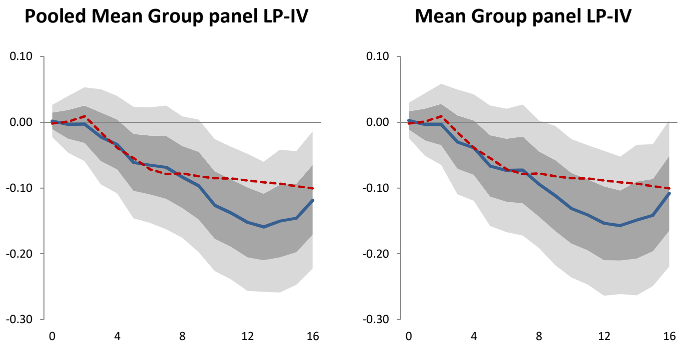

Note: Mean Group impulse responses with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly

**Figure 4 - Effects of 1% increase in global real agricultural commodity prices on real GDP: alternative SVAR-IV estimations**



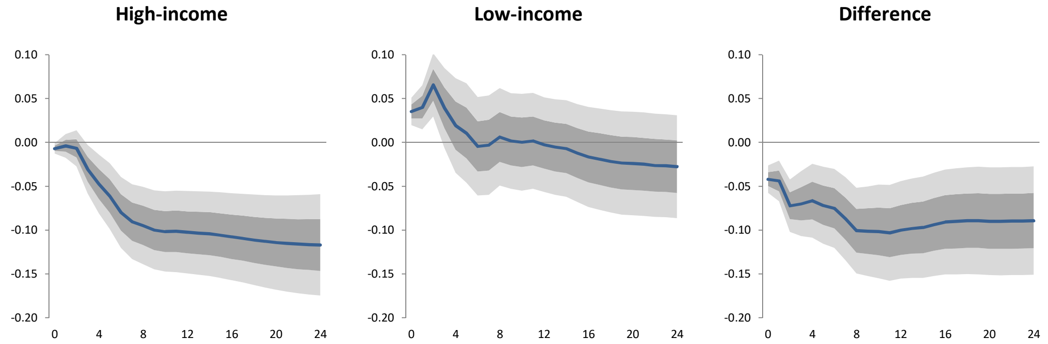

Note: Mean Group impulse responses with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly; red dashed lines are the responses of the benchmark panel SVAR-IV

**Figure 5 - Effects of 1% increase in global real agricultural commodity prices: panel LP-IV estimations**



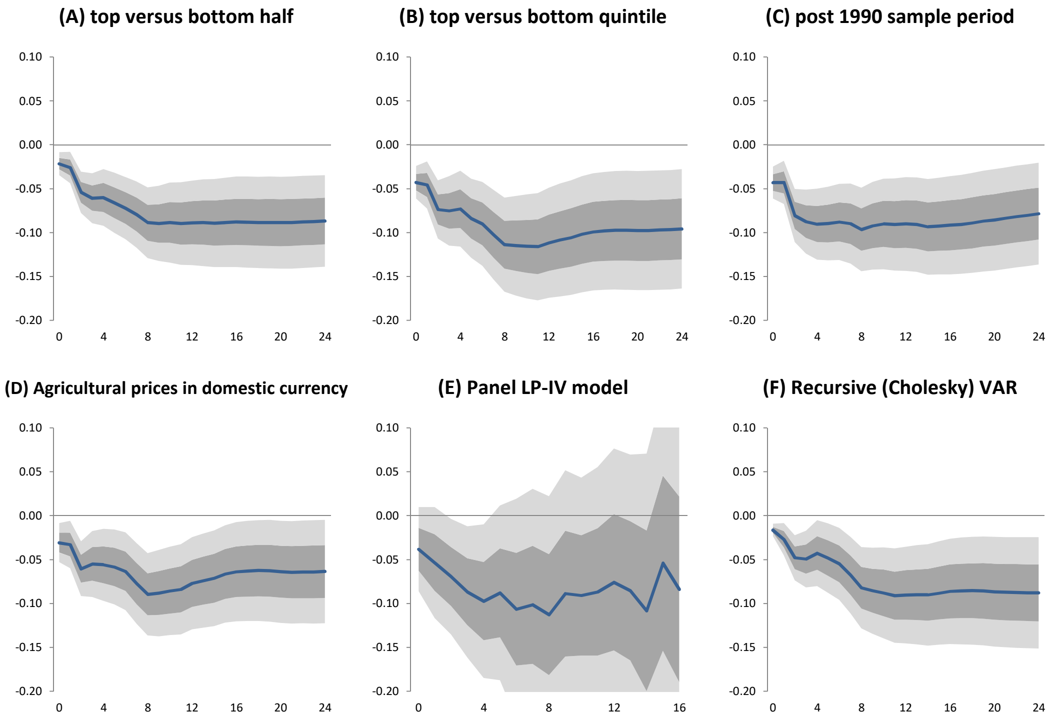

Note: Impulse responses with one- and two-standard error bands; the confidence intervals are adjusted for correlations between the residuals across countries, as well as serial correlation between the residuals over time; horizon is quarterly red dashed lines are the responses of the benchmark panel SVAR-IV

**Figure 6 - Effects of 1% increase in global real agricultural commodity prices on high-income versus low-income countries**



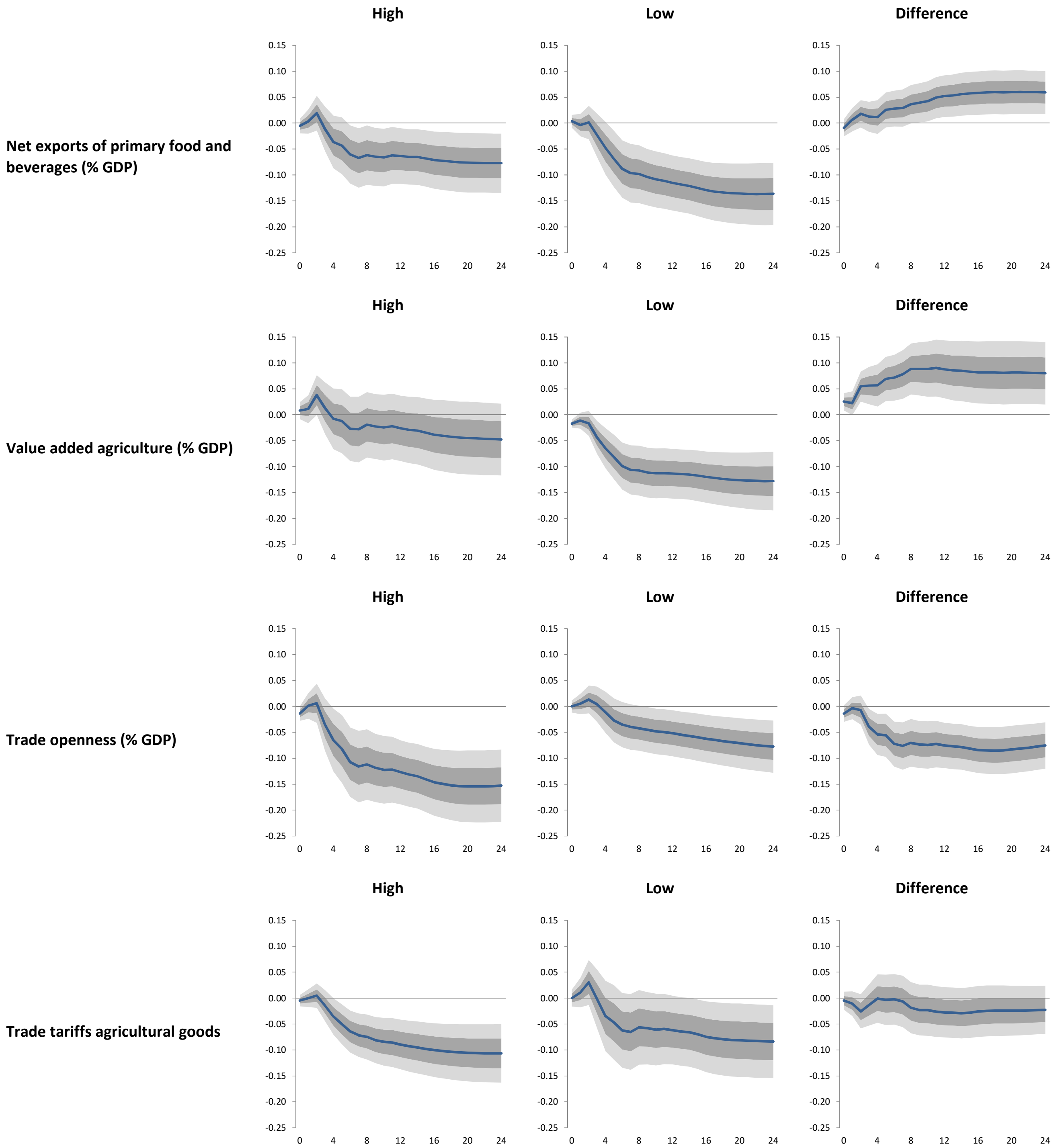

Note: Mean Group impulse responses for top and bottom tertiles of the countries with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly

**Figure 7 - Difference between high-income and low-income countries: robustness checks**




Note: Differences between impulse responses of high-income versus low-income countries with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly

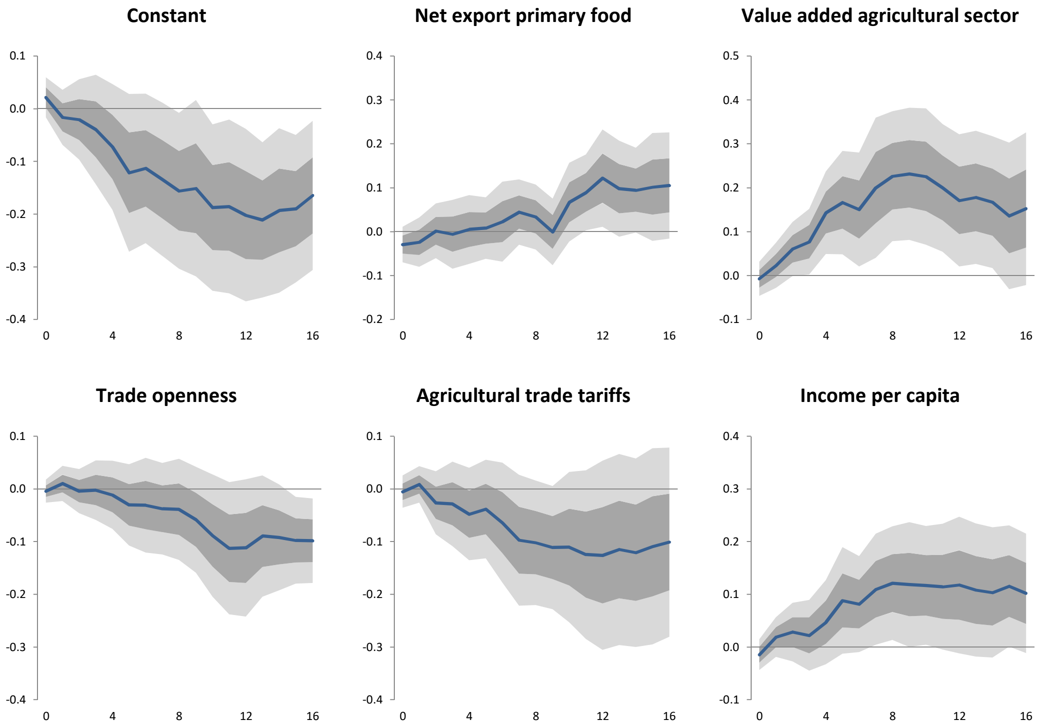
**Figure 8 - Effects of 1% increase in global real agricultural commodity prices on country groups: alternative characteristics**



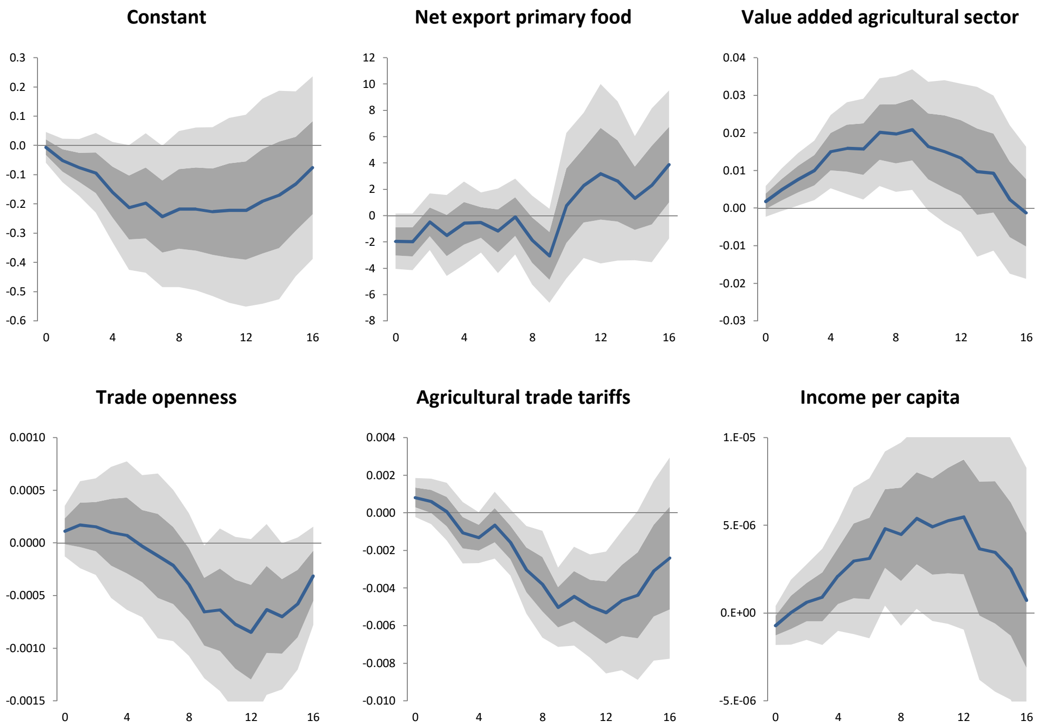

Note: Mean Group impulse responses for top and bottom tertiles of the countries with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly

**Figure 9 - Country characteristics and the effects of global agricultural price shocks on real GDP: simultaneous analysis**

**(A) Panel LP-IV with dummy variables**



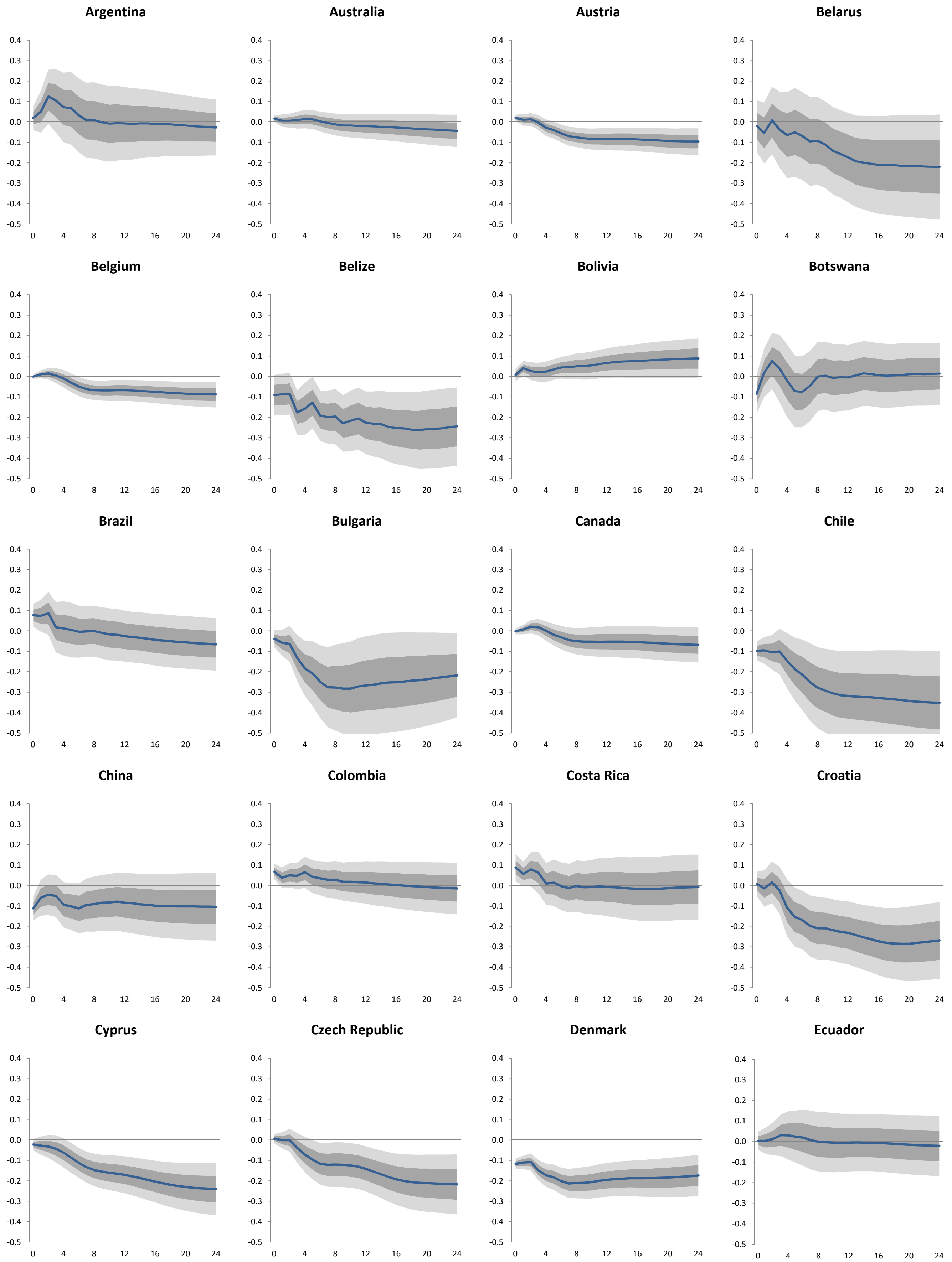

**(B) Panel LP-IV with continues variables**




Note: Impulse responses with one- and two-standard error bands; the confidence intervals are adjusted for correlations between the residuals across countries, as well as serial correlation between the residuals over time; horizon is quarterly

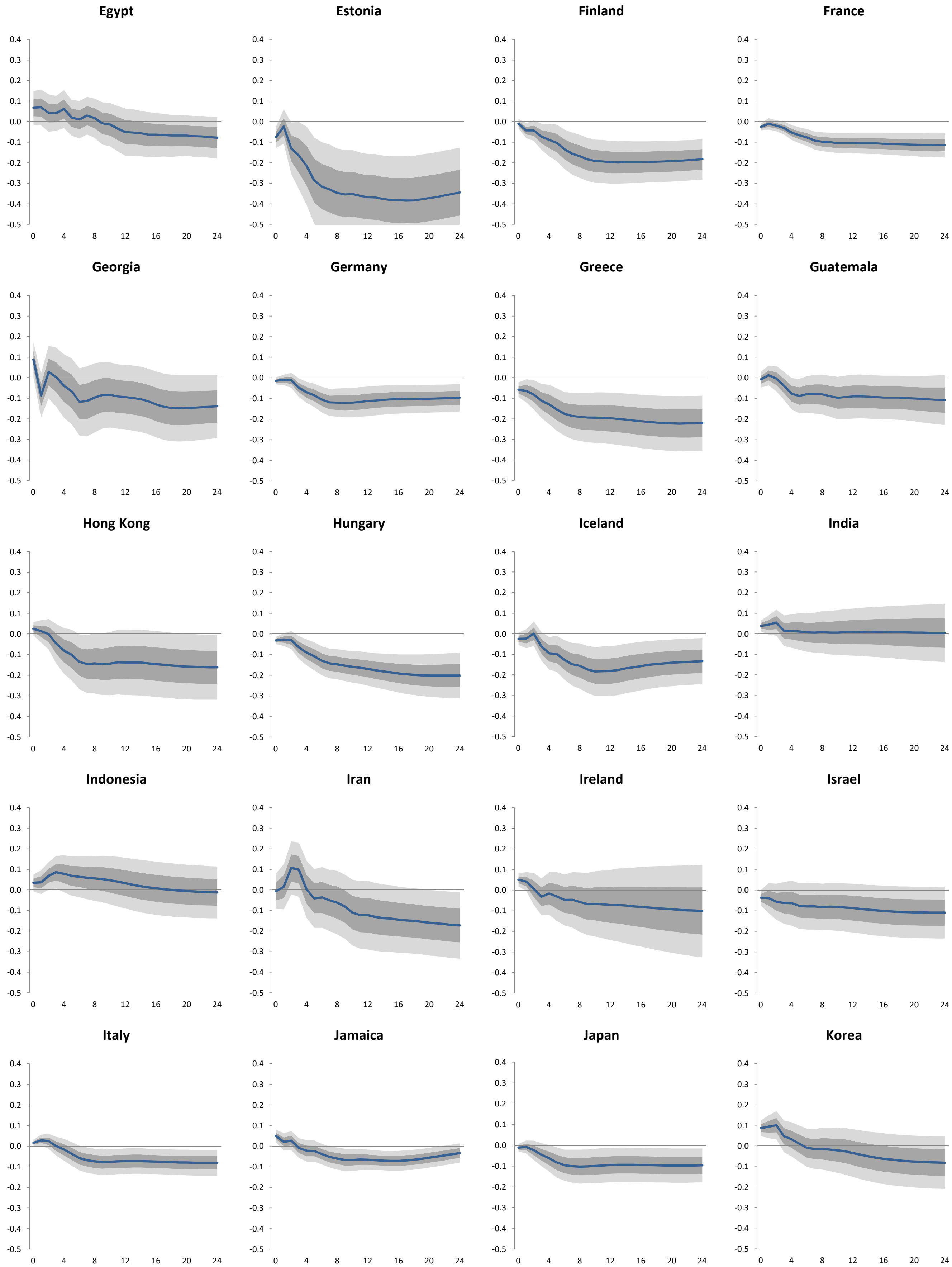
(A) dummy variables if countries belong to top-tertile of characteristics; (B) based on average values of characteristics over period 2000-2015

**Figure A1 - Effects of 1% increase in global real agricultural commodity prices on real GDP: individual countries**



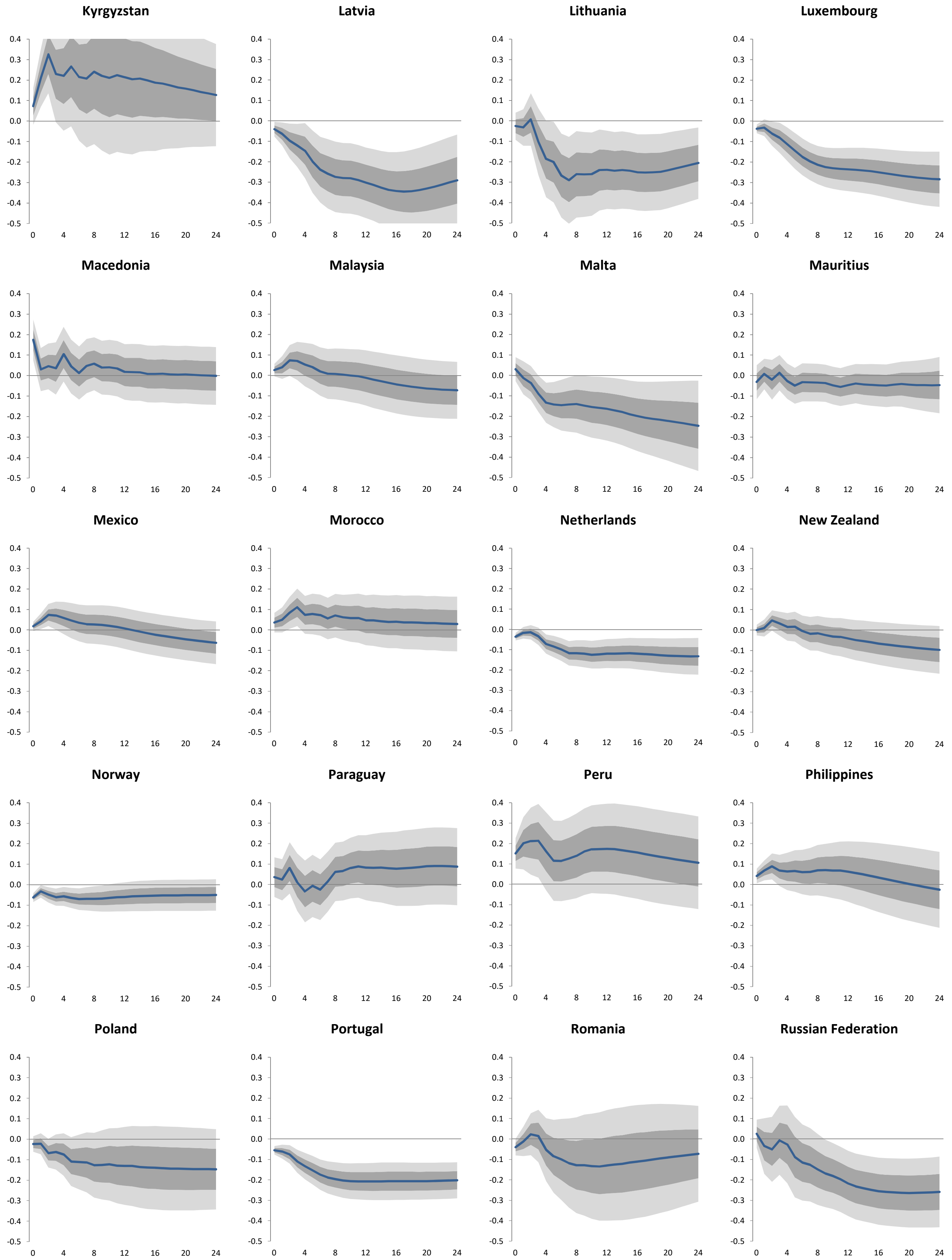

Note: Impulse responses with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap; horizon is quarterly

**Figure A1 (continued) - Effects of 1% increase in global real agricultural commodity prices on real GDP: individual countries**



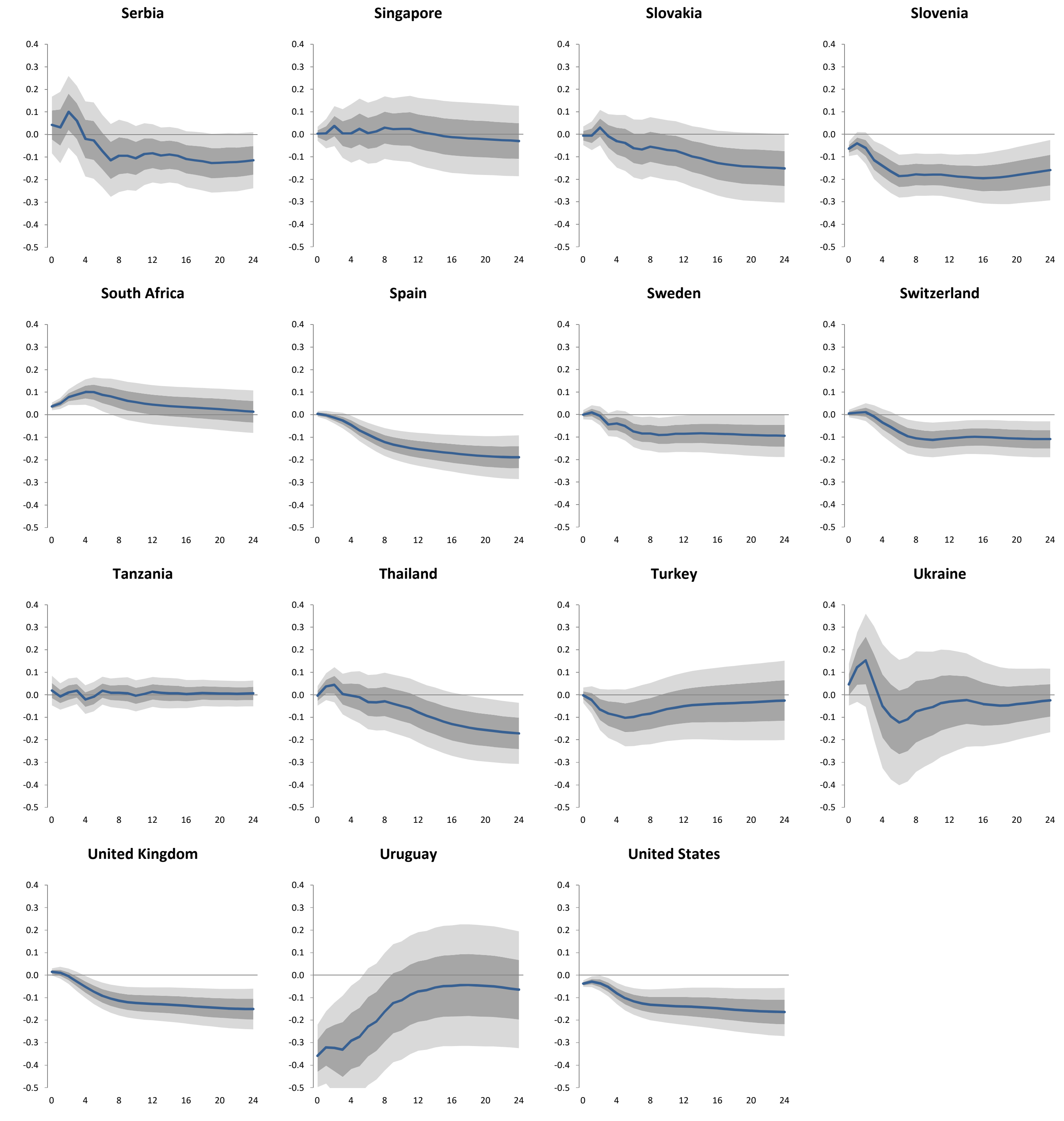

Note: Impulse responses with one- and two-standard error bands; the confidence intervals are constructed using  a recursive-design wil bootstrap; horizon is quarterly

**Figure A1 (continued) - Effects of 1% increase in global real agricultural commodity prices on real GDP: individual countries**




Note: Impulse responses with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap; horizon is quarterly

**Figure A1 (continued) - Effects of 1% increase in global real agricultural commodity prices on real GDP: individual countries**




Note: Impulse responses with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap; horizon is quarterly

## Table 1 - Overview of narrative global agricultural commodity market shocks

| Date | Type | (Cumulative) change in agricultural commodity prices Impact | After 1Q | Food commodity market event |
|---|---|---|---|---|
| 1972Q3 | Unfavorable | 1.4% | 18.3% | **Russian Wheat Deal and failed monsoon in Southeast Asia**<br>Wheat production in the USSR declined by 13% due to disastrous weather conditions. This resulted in purchases on an unprecedented scale by the Soviet Union on the world market, leading to large price increases from July and August 1972 onwards. The negative consequences of the bad weather conditions in the USSR were only known very late, and were percieved as a considerable shock worldwide since only a few months earlier there were reports of heavy surplus stocks building. The sales involved a series of subsidized transactions following an agreement whereby the US made available credit to the USSR for the purchases (Russian Wheat Deal). The rise in wheat prices was further accelerated by a decision of the US to suspend the subsidies normally paid on exports.<br>At the same time, the global agricultural sector was severely affected by monsoon failure in most of southeast Asia during summer, followed by extremely dry weather throughout autumn and early winter. Rice production decreased in Cambodia, India, Malaysia and Thailand by respectively 29%, 9%, 13% and 10%.<br>Overall, annual global cereal production declined by 1.6% in 1972, compared to a rise of respectively 9.2% and 7.4% in 1971 and 1973. |
| 1975Q2 | Favorable | -10.9% | -9.9% | **Significant improved estimate of world grain production**<br>In April 1975, the USDA predicted a significant increase in world grain production (the previous forecast was in December 1974), indicating an easing of the tight supply-demand balance of the previous two years. Furthermore, in May 1975, the USDA increased its US wheat production estimate for 1975 because of favorable May field conditions. A record wheat harvest was expected. In retrospect, annual global cereal production increased by 6.9% relative to the previous year. |
| 1975Q4 | Favorable | -4.7% | -10.7% | **Optimistic rice forecast because of very favorable monsoon season**<br>In September 1975, there were expectations of a record rice crop because of a favorable monsoon season. As a consequence, rice prices started to decrease from October 1975 onwards, which is the start of the harvesting season. Real cereal prices fell by 19% over two subsequent quarters. Ex post, 1975 proved indeed to be a very favorable rice year for India, Japan and Thailand, with an acceleration of production yields relatively to 1974 by respectively 23%, 7% and 14%. |
| 1977Q3 | Favorable | -20.9% | -12.9% | **Predictions of record US and Soviet harvests**<br>Several favorable and/or increased food production forecasts were published throughout July and August: predictions of record US corn crops (July 1977), increased forecasts of world wheat and feed grains production (July 1977), news on record Soviet wheat harvest (August 1977), and predictions of record US soybeans crops (August 1977). |
| 1977Q4 | Unfavorable | 8.0% | 15.6% | **Record grain harvests did not materialize**<br>Despite expectations of record harvests in the previous quarter, global grain production turned out to be below trend in 1977 as a result of unfavorable weather conditions in the major producing areas. In November 1977, the Financial Times announced that the Soviet crop would be roughly 10% below the latest estimate predicted by the USDA. In addition, the International Wheat Council lowered its estimate of world wheat output by 2%-3%. In retrospect, Soviet wheat production decreased by 5% compared to the previous year. Chinese wheat production declined by 18% and in the US wheat production shrunk by 5%. It is clear that this came as an unexpected shock in 1977Q4, given the extreme optimistic forecasts in 1977Q3. |
| 1984Q3 | Favorable | -10.4% | -14.1% | **Favorable weather in North America and exceptionally good cereal harvest in Western Europe**<br>In July 1984, the USDA improved its June estimate for US wheat production, and predicted record grain production worldwide. Much of this increase was a consequence of the North American recovery from the sharp decline of 1983 as a consequence of increased planting, as well as favorable weather. Western Europe also had exceptionally good harvests of cereals. In retrospect, US maize production rose considerably, i.e. 84%. Furthermore, wheat production increased in China, India and France by respectively 8%, 33% and 6%. Overall, global cereal production increased by 11.4% in 1984, which was the largest annual rise since the 1960s. |
| 1988Q4 | Favorable | -4.5% | -9.4% | **Expectations of global surge in wheat production**<br>In December 1988, it was announced by the International Wheat Council that worldwide wheat production was expected to rise considerably in 1989, amongst others because of a reduction in the requirement for US set-aside of arable land, from 27.5% to only 10% of the wheat acreage in the next year, which was a farm policy response to the 1988 drought in the US (The Disaster Relief Act of 1988). In response to drought-shortened crop inventories, the 1989 version of the farm bill was expected to encourage larger crop planting. Wheat production in 1989 increased indeed in all large wheat producing countries (China 6%; France 10%; India 17%; US 12%; USSR 11%). Ex post, annual global cereal production increased by more than 10% in 1989. |

| | | | | |
|---|---|---|---|---|
| 1995Q3 | Unfavorable | 6.6% | 7.8% | **Significant downward revised world cereal estimates**<br>In 1995Q3, there were large downward revisions of 1995 world cereal production. This was especially the case for wheat and coarse grains production in the US (poor weather conditions, predominantly hot and dry weather during early September) and the Commonwealth of Independent States, and for wheat production in Argentina and China. In Central America, a below-normal coarse grain crop was in prospect in Mexico due to a combination of reduced plantings and dry weather in parts. In retrospect, wheat production declined in the US and Russia by 6%, and in Argentina by 16%. Mexican maize production stagnated in 1995, but US maize production decreased by 26%. Annual global production of the four major staples ultimately declined by 2.6% in 1995. |
| 1996Q3 | Favorable | -4.5% | -12.5% | **Expectations of excellent global cereal harvest**<br>The FAO issued a first provisional favorable forecast for world 1996 cereal output (6.5% up from the previous year) in June 1996. The largest increase was expected in coarse grains output, mostly in the developed countries. Additionally, wheat output was forecast to increase significantly, and rice production to rise marginally. In September 1996, the International Grains Council increased its forecast (compared to a month earlier) for 1996-97 global wheat production in response to a confirmation of favorable harvests in the Northern Hemisphere and excellent prospects in the Southern Hemisphere. |
| 2002Q3 | Unfavorable | 9.4% | 10.7% | **Significant downward revised global cereal estimates**<br>The FAO's July forecast pointed to a global cereal output which is considerably less than the previous forecast in May. It would be the smallest wheat crop since 1995. The downward revision was mostly a result of a deterioration of production prospects for several of the major wheat crops around the globe because of adverse weather in the northern hemisphere or for planting in the southern hemisphere. The forecast for global coarse grain output was also revised downwards since the last report mainly because of dry weather conditions in the Russian Federation. In September, the Australian Bureau of Agricultural and Resource Economics announced that drought will slash the country's winter grain production. Australia is one of the big five wheat exporters. In retrospect, US wheat production decreased by 18% in 2002 and Australian wheat production by 60%. |
| 2004Q3 | Favorable | -6.9% | -10.9% | **Significant improved forecast of world cereal output**<br>Favorable weather conditions triggered expectations of significant higher cereal production in Europe, China, Brazil and the US. In July 2004, the International Grains Council announced an expected rise in the global volume of coarse grain. In september 2004, the FAO's raised its forecast for world cereal output since the previous report in June. Annual global cereal production increased by more than 9% in 2004. |
| 2010Q3 | Unfavorable | 8.6% | 22.1% | **Droughts in Russia and Eastern Europe**<br>The 2010 cereal output in the Republic of Moldova, Russian Federation, Kazakhstan and Ukraine was seriously affected by adverse weather conditions. Russian Federation, Kazakhstan and Ukraine (all three amongst the world's top-10 wheat exporters) suffered the worst heatwave and drought in more than a century, while the Republic of Moldova was struck by floods and hail storms. In the Russian Federation, the most severely affected by adverse conditions, the 2010 cereal crop was 33% lower than the previous year. In Ukraine the wheat harvest decreased 19%. Accordingly, in July 2010, wheat prices have seen the biggest one-month jump in more than three decades, i.e. a rise of nearly 50% since late June. In September, wheat prices were even 60% to 80% higher due to a decision by the Russian Federation to ban exports. |
| 2012Q3 | Unfavorable | 7.9% | 6.9% | **Droughts around the globe**<br>Due to droughts in Russia, Eastern Europe, Asia and the US, there was a signifcant decline in global cereal production. In retrospect, annual global cereal production contracted by 2.4%. In July, the USDA decreased its previous (June) estimate for US corn by 12% because of the worst Midwest drought in a quarter century. Heatwaves in southern Europe added serious concern about global food supplies later that month, as well as below-average rainfall in Australia. In August, there was news about a late monsoon affecting the rice harvest in Asia negatively. According to the International Food Policy Institute, production of food grains in the South Asia region was expected to decline by 12% compared to a year earlier. Also in August, the Russian grain harvest forecasts were reduced because of drought. In October 2012, wheat output in the Russian Federation was estimated some 30% down from 2011, in Ukraine, a decrease of about 33% was expected, while in Kazakhstan, output was reported to be just half of last year's good level. Wheat harvest indeed declined in 2012, respectively by 33%, 29%, 57% in Russia, Ukraine and Kazakhstan. |

Note: a detailed motivation and description of the episodes can be found in the online appendix of De Winne and Peersman (2016).
The (cumulative) change in agricultural commodity prices in De Winne and Peersman (2016) is based on the IMF broad food commodity price index.

**Table 2 - Overlap of country groups and correlation of country characteristics**

| | | Income per capita | | Net export primary food & beverages | | Share agriculture in GDP | | Trade openness | | Agricultural tariffs | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | high | low | high | low | high | low | high | low | high | low |
| Income per capita | high | | | 5 | 12 | 0 | 20 | 7 | 8 | 7 | 4 |
| | low | | | 14 | 4 | 19 | 1 | 5 | 10 | 9 | 12 |
| Net export primary food & beverages | high | -0.32 | | | | 12 | 2 | 6 | 10 | 8 | 13 |
| | low | | | | | 4 | 15 | 12 | 5 | 7 | 8 |
| Share agriculture in GDP | high | -0.71 | | 0.40 | | | | 6 | 9 | 10 | 11 |
| | low | | | | | | | 11 | 5 | 5 | 5 |
| Trade openness | high | 0.35 | | -0.25 | | -0.25 | | | | 6 | 10 |
| | low | | | | | | | | | 9 | 8 |
| Agricultural tariffs | high | 0.10 | | -0.07 | | 0.04 | | -0.16 | | | |
| | low | | | | | | | | | | |

Note: numbers above diagonal are number of countries that overlap across groups (maximum is 25), numbers below diagonal are correlations of underlying variables, values are based on the period 2000-2015. See data appendix.

## Table A1 - Country characteristics

| | Sample period | F-statistics instruments | Robust F-statistics instruments | Country characteristics: average values 2000-2015 (ranking between brackets) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Income per capita | | Net export primary food & beverages (%GDP) | | Value added agriculture (%GDP) | | Trade (%GDP) | | Agricultural tariffs (%) | |
| Argentina | 1968Q1-2017Q1 | 13.2 | 13.7 | 16031 | (41) | 2.16 | (6) | 8.0 | (25) | 34 | (72) | 5.1 | (66) |
| Australia | 1965Q1-2017Q2 | 16.0 | 21.1 | 41353 | (9) | 0.77 | (18) | 2.9 | (48) | 41 | (70) | 2.9 | (72) |
| Austria | 1965Q1-2017Q2 | 15.5 | 19.6 | 39429 | (13) | -0.28 | (50) | 1.6 | (65) | 96 | (26) | 10.3 | (43) |
| Belarus | 1992Q1-2015Q4 | 10.8 | 18.7 | 13327 | (48) | -0.73 | (67) | 10.1 | (18) | 131 | (12) | 6.4 | (60) |
| Belgium | 1965Q1-2017Q2 | 16.2 | 19.5 | 36218 | (18) | -0.58 | (66) | 0.9 | (69) | 149 | (8) | 10.3 | (35) |
| Belize | 1994Q1-2015Q4 | 8.8 | 11.7 | 6952 | (64) | 4.84 | (3) | 14.8 | (5) | 125 | (16) | 13.4 | (18) |
| Bolivia | 1990Q1-2016Q4 | 10.4 | 30.2 | 4182 | (72) | 0.72 | (19) | 13.9 | (9) | 69 | (47) | 5.6 | (65) |
| Botswana | 1994Q1-2016Q4 | 14.0 | 36.3 | 11940 | (51) | -1.27 | (74) | 2.7 | (52) | 97 | (25) | 0.6 | (74) |
| Brazil | 1980Q1-2017Q2 | 10.9 | 15.0 | 11018 | (52) | 0.84 | (15) | 5.5 | (33) | 26 | (75) | 6.9 | (58) |
| Bulgaria | 1980Q1-2017Q2 | 15.5 | 32.5 | 12983 | (50) | 1.43 | (11) | 7.5 | (29) | 106 | (22) | 14.1 | (17) |
| Canada | 1965Q1-2017Q2 | 11.8 | 18.8 | 40379 | (10) | 0.60 | (22) | 1.7 | (61) | 68 | (49) | 11.1 | (25) |
| Chile | 1965Q1-2017Q2 | 14.9 | 13.9 | 15523 | (42) | 2.07 | (8) | 4.2 | (40) | 68 | (48) | 3.6 | (70) |
| China | 1980Q1-2016Q1 | 19.9 | 31.3 | 7771 | (61) | -0.20 | (48) | 11.0 | (16) | 50 | (64) | 16.6 | (12) |
| Colombia | 1980Q1-2017Q1 | 10.7 | 14.0 | 9263 | (58) | 0.80 | (16) | 7.7 | (27) | 36 | (71) | 11.1 | (26) |
| Costa Rica | 1991Q1-2017Q1 | 3.1 | 4.3 | 10951 | (53) | 4.87 | (2) | 8.0 | (24) | 78 | (38) | 7.9 | (54) |
| Croatia | 1991Q1-2017Q2 | 11.7 | 31.1 | 17788 | (35) | -0.49 | (63) | 5.1 | (35) | 84 | (35) | 7.2 | (56) |
| Cyprus | 1988Q1-2017Q2 | 16.8 | 53.1 | 26383 | (26) | -0.32 | (52) | 2.9 | (49) | 116 | (19) | 15.6 | (15) |
| Czech Republic | 1988Q3-2017Q2 | 12.3 | 15.6 | 24538 | (29) | -0.07 | (45) | 2.5 | (54) | 125 | (15) | 9.4 | (48) |
| Denmark | 1965Q1-2017Q2 | 16.5 | 21.0 | 40161 | (11) | 0.00 | (38) | 1.6 | (62) | 93 | (29) | 10.3 | (40) |
| Ecuador | 1991Q1-2017Q2 | 7.2 | 47.9 | 8035 | (59) | 4.62 | (4) | 10.7 | (17) | 57 | (55) | 9.8 | (45) |
| Egypt | 2002Q1-2017Q2 | 7.7 | 15.3 | 7502 | (63) | -1.17 | (73) | 14.0 | (8) | 49 | (65) | 13.4 | (19) |
| Estonia | 1988Q3-2017Q2 | 13.7 | 14.5 | 18690 | (34) | -0.21 | (49) | 3.6 | (43) | 141 | (10) | 8.7 | (51) |
| Finland | 1965Q1-2017Q2 | 14.5 | 17.4 | 36705 | (16) | -0.41 | (58) | 2.8 | (51) | 76 | (40) | 10.3 | (29) |
| France | 1965Q1-2017Q2 | 15.7 | 19.7 | 34735 | (19) | 0.08 | (34) | 1.9 | (60) | 55 | (58) | 10.3 | (36) |
| Georgia | 1996Q1-2016Q4 | 10.8 | 52.9 | 6388 | (66) | -0.30 | (51) | 13.5 | (10) | 86 | (31) | 7.0 | (57) |
| Germany | 1965Q1-2017Q2 | 12.0 | 17.8 | 39353 | (14) | -0.44 | (61) | 0.9 | (71) | 75 | (42) | 10.3 | (41) |
| Greece | 1965Q1-2017Q2 | 16.2 | 18.0 | 25916 | (27) | 0.01 | (37) | 4.2 | (39) | 56 | (56) | 10.3 | (32) |
| Guatemala | 2001Q1-2016Q4 | 6.0 | 11.3 | 5887 | (69) | 3.27 | (5) | 12.6 | (11) | 62 | (50) | 6.4 | (61) |
| Hong Kong | 1966Q1-2017Q2 | 20.4 | 33.7 | 45664 | (7) | -1.67 | (75) | 0.1 | (74) | 381 | (1) | 0.0 | (75) |
| Hungary | 1979Q1-2017Q2 | 14.4 | 26.0 | 18842 | (33) | 0.78 | (17) | 4.5 | (37) | 148 | (9) | 12.9 | (21) |
| Iceland | 1965Q1-2017Q2 | 17.9 | 23.4 | 37044 | (15) | 1.86 | (9) | 7.1 | (30) | 85 | (32) | 19.2 | (9) |
| India | 1965Q1-2017Q2 | 18.7 | 26.3 | 3519 | (73) | 0.28 | (28) | 19.2 | (4) | 43 | (69) | 46.2 | (2) |
| Indonesia | 1970Q1-2017Q2 | 20.0 | 24.0 | 5891 | (68) | 0.18 | (33) | 14.2 | (6) | 55 | (59) | 4.4 | (67) |
| Iran | 1988Q1-2012Q4 | 15.2 | 28.6 | 13893 | (45) | 0.26 | (30) | 7.6 | (28) | 48 | (66) | 17.5 | (10) |
| Ireland | 1965Q1-2017Q2 | 12.4 | 12.2 | 48326 | (6) | -0.20 | (47) | 1.4 | (66) | 174 | (6) | 10.3 | (42) |
| Israel | 1965Q1-2017Q2 | 17.8 | 22.1 | 29501 | (24) | -0.16 | (46) | 1.9 | (58) | 71 | (44) | 11.9 | (22) |
| Italy | 1965Q1-2017Q2 | 13.0 | 17.1 | 34094 | (21) | -0.42 | (59) | 2.3 | (56) | 52 | (61) | 10.3 | (34) |

| | Sample period | F-statistics instruments | Robust F-statistics instruments | Country characteristics: average values 2000-2015 (ranking between brackets) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Income per capita | | Net export primary food & beverages (%GDP) | | Value added agriculture (%GDP) | | Trade (%GDP) | | Agriculture tariffs (%) | |
| Jamaica | 1996Q1-2016Q3 | 7.6 | 14.4 | 6432 | (65) | -0.54 | (65) | 6.4 | (32) | 88 | (30) | 16.1 | (13) |
| Japan | 1965Q1-2017Q2 | 18.6 | 30.2 | 34659 | (20) | -0.33 | (54) | 1.2 | (67) | 28 | (73) | 22.8 | (6) |
| Korea | 1965Q1-2017Q2 | 11.7 | 25.0 | 29413 | (25) | -0.36 | (55) | 3.0 | (46) | 84 | (34) | 96.1 | (1) |
| Kyrgyzstan | 1986Q2-2016Q2 | 18.1 | 35.5 | 3093 | (74) | -0.04 | (43) | 27.1 | (2) | 115 | (20) | 4.0 | (69) |
| Latvia | 1988Q3-2017Q2 | 17.6 | 39.7 | 16240 | (39) | -0.03 | (41) | 4.1 | (41) | 102 | (24) | 9.6 | (47) |
| Lithuania | 1995Q1-2017Q2 | 9.5 | 33.6 | 17310 | (37) | 0.51 | (25) | 4.3 | (38) | 124 | (17) | 7.9 | (53) |
| Luxembourg | 1965Q1-2017Q2 | 17.9 | 59.3 | 57796 | (2) | -0.42 | (60) | 0.4 | (73) | 318 | (3) | 10.3 | (37) |
| Macedonia | 1993Q1-2017Q2 | 10.5 | 90.6 | 9966 | (57) | 0.02 | (36) | 11.7 | (14) | 95 | (28) | 10.9 | (27) |
| Malaysia | 1970Q1-2017Q1 | 16.0 | 15.1 | 16233 | (40) | -0.78 | (68) | 9.2 | (21) | 178 | (5) | 10.5 | (28) |
| Malta | 2000Q1-2017Q2 | 9.8 | 17.2 | 22973 | (31) | -0.95 | (70) | 1.9 | (59) | 265 | (4) | 8.1 | (52) |
| Mauritius | 2000Q1-2014Q4 | 5.2 | 11.5 | 14932 | (43) | -1.08 | (71) | 5.1 | (34) | 117 | (18) | 5.7 | (64) |
| Mexico | 1965Q1-2017Q2 | 16.4 | 27.8 | 13587 | (46) | 0.27 | (29) | 3.5 | (44) | 58 | (53) | 15.2 | (16) |
| Morocco | 1966Q2-2014Q4 | 11.9 | 12.6 | 5681 | (70) | 0.32 | (26) | 14.1 | (7) | 72 | (43) | 25.9 | (5) |
| Netherlands | 1965Q1-2017Q2 | 19.2 | 24.8 | 43794 | (8) | -0.02 | (40) | 2.0 | (57) | 133 | (11) | 10.3 | (39) |
| New Zealand | 1965Q1-2017Q2 | 18.9 | 23.1 | 29511 | (23) | 1.22 | (12) | 6.4 | (31) | 60 | (51) | 8.7 | (50) |
| Norway | 1965Q1-2017Q2 | 16.8 | 18.5 | 69450 | (1) | 0.61 | (21) | 1.6 | (63) | 70 | (45) | 40.4 | (3) |
| Paraguay | 1994Q1-2016Q4 | 9.3 | 21.7 | 5976 | (67) | 7.27 | (1) | 19.4 | (3) | 96 | (27) | 6.0 | (63) |
| Peru | 1979Q1-2017Q1 | 10.1 | 15.6 | 7645 | (62) | 0.93 | (14) | 7.8 | (26) | 47 | (67) | 6.5 | (59) |
| Philippines | 1981Q1-2017Q1 | 15.7 | 18.5 | 4919 | (71) | -0.04 | (42) | 12.5 | (12) | 83 | (36) | 11.3 | (24) |
| Poland | 1982Q1-2017Q2 | 15.8 | 34.5 | 17712 | (36) | -0.05 | (44) | 3.1 | (45) | 78 | (37) | 13.4 | (20) |
| Portugal | 1965Q1-2017Q2 | 14.6 | 14.5 | 23873 | (30) | -1.12 | (72) | 2.6 | (53) | 69 | (46) | 10.3 | (31) |
| Romania | 1980Q1-2017Q2 | 11.6 | 28.9 | 13484 | (47) | 0.22 | (32) | 8.6 | (23) | 75 | (41) | 15.9 | (14) |
| Russian Federation | 1990Q1-2017Q2 | 12.4 | 23.7 | 16493 | (38) | -0.32 | (53) | 4.9 | (36) | 54 | (60) | 11.6 | (23) |
| Serbia | 1995Q1-2017Q2 | 7.5 | 9.7 | 10478 | (56) | 0.57 | (23) | 12.0 | (13) | 76 | (39) | 10.3 | (30) |
| Singapore | 1975Q1-2017Q2 | 20.3 | 25.8 | 51756 | (3) | -0.78 | (69) | 0.1 | (75) | 380 | (2) | 1.5 | (73) |
| Slovakia | 1992Q1-2017Q2 | 14.1 | 47.3 | 19373 | (32) | -0.02 | (39) | 4.0 | (42) | 154 | (7) | 8.8 | (49) |
| Slovenia | 1992Q1-2017Q2 | 8.8 | 31.4 | 24864 | (28) | -0.49 | (64) | 2.4 | (55) | 125 | (14) | 9.6 | (46) |
| South Africa | 1965Q1-2017Q2 | 15.5 | 15.8 | 10674 | (54) | 0.52 | (24) | 2.9 | (50) | 59 | (52) | 6.1 | (62) |
| Spain | 1965Q1-2017Q2 | 14.4 | 12.8 | 30484 | (22) | 0.24 | (31) | 3.0 | (47) | 57 | (54) | 10.3 | (33) |
| Sweden | 1965Q1-2017Q2 | 17.5 | 19.8 | 39603 | (12) | -0.41 | (57) | 1.6 | (64) | 85 | (33) | 10.3 | (38) |
| Switzerland | 1965Q1-2017Q2 | 14.5 | 22.8 | 51248 | (4) | -0.47 | (62) | 0.9 | (70) | 109 | (21) | 31.4 | (4) |
| Tanzania | 2001Q1-2013Q3 | 4.4 | 8.8 | 1722 | (75) | 1.05 | (13) | 31.9 | (1) | 45 | (68) | 20.1 | (8) |
| Thailand | 1980Q1-2017Q2 | 18.3 | 25.8 | 10615 | (55) | 0.62 | (20) | 9.8 | (19) | 129 | (13) | 16.6 | (11) |
| Turkey | 1965Q1-2017Q2 | 21.9 | 34.5 | 14466 | (44) | 0.32 | (27) | 9.6 | (20) | 52 | (63) | 20.6 | (7) |
| Ukraine | 2000Q1-2016Q4 | 13.7 | 19.0 | 7963 | (60) | 1.45 | (10) | 11.1 | (15) | 103 | (23) | 7.5 | (55) |
| United Kingdom | 1965Q1-2017Q2 | 15.5 | 16.5 | 36294 | (17) | -0.37 | (56) | 0.7 | (72) | 55 | (57) | 10.3 | (44) |
| Uruguay | 1988Q1-2016Q4 | 5.2 | 10.6 | 13216 | (49) | 2.16 | (7) | 9.2 | (22) | 52 | (62) | 4.3 | (68) |
| United States | 1965Q1-2017Q2 | 13.8 | 26.5 | 49020 | (5) | 0.03 | (35) | 1.2 | (68) | 27 | (74) | 2.9 | (71) |

Note: rankings of country characteristics are based on the period 2000-2015. See data appendix for more details.