The Adverse Consequences of Global Harvest and Weather Disruptions on Economic Activity

SUPPLEMENTARY APPENDIX

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Appendix A: Data

A1. Unanticipated harvest disruptions in other regions of the world

- **Harvest volumes in other regions of the world** (country-specific variable): These indices are based on annual food production data downloaded from the Food and Agriculture Organization (FAO).[1] 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 1961-2016; that is, corn, wheat, rice and soybeans. The production data, which are measured in ton, are first converted into edible calories. De Winne and Peersman (2016a) 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, it is possible to assign two-thirds of world harvests to a specific quarter. The four crops of all countries are

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

then aggregated on a caloric-weighted basis to construct a quarterly composite global agricultural commodity production index. We use the same principium to construct harvest volumes "in other regions of the world" for each individual country. Specifically, 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 neighbouring sub-regions.[2] For example, for Italy, we exclude the harvests of all countries in South-Europe, West-Europe, East-Europe and North-Africa. 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 harvest volumes in other regions of the world. Notice that, since we systematically exclude the harvests of the whole sub-region and neighbouring sub-regions, all countries in a sub-region have the same harvest indicator. Overall, there are 20 sub-regions in the world.

- **Global real agricultural commodity prices**: The global agricultural price index is a trade-weighted aggregate of the price series of corn (US 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 (US 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 are measured in US dollar per metric ton. The IMF trade-weights are 22.8%, 36.6%, 13.8% and 26.8% for corn, wheat, rice and soybeans, respectively. The agricultural price index has been seasonally adjusted using Census X-13 (X-11 option). The nominal price index has been deflated by US CPI.

- **OECD Composite Leading Indicator:** downloaded from the OECD online database. The (amplitude adjusted) indicator is designed to provide early signals of turning points in business cycles showing fluctuation of the economic activity around its long

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

term potential level.

- **MSCI World Real Equity Price Index:** downloaded from Datastream. Observations are end-of-quarter and are measured in US dollar. The nominal price index has been deflated by US CPI.
- **Real crude oil prices**: The refiner acquisition cost of imported crude oil, deflated by the US CPI.

The time series of the estimated global harvest disruptions when we do **not** exclude the harvests of own and neighbouring sub-regions is shown in Figure A1 for illustrative purposes. The shocks are measured in percentage points of the projected quarterly global harvest volumes, as specified in equation 6 of the paper. The correlations with the estimated "harvest shocks in other regions of the world" that are used as an instrumental variable (i.e., excluding own and neighbouring sub-regions) are reported in Table A2.

A2. Narrative Global Agricultural Market Disruptions

The shocks are collected from De Winne and Peersman (2016a), who 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 were unambiguously caused by disturbances in global agricultural markets and were unrelated to the state of the economy. An overview and brief description of these episodes are reported in Table A1. For a detailed discussion and motivation of the events, we refer to De Winne and Peersman (2016b). The episodes are converted to a dummy variable, which is equal to 1 and -1 for unfavourable and favourable disruptions, respectively. Six episodes are unfavourable shocks, while seven episodes have been characterized as favourable. The full series is shown in Figure A1. 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.

A3. Weather Shocks

We construct quarterly global agricultural-weighted weather shocks for a quadratic in average temperature as well as total precipitation. The underlying idea is similar to Roberts and Schlenker (2013), who use annual agricultural-output-weighted temperature (precipitation) and squared temperature (precipitation) shocks over the growing season as instrumental variables for changes in agricultural supply. Also Mendelsohn et al. (1994) use quadratic specifications of temperature en precipitation to capture non-linear (concave) relationships between weather conditions and crop yields. As a robustness check, we also report results when we allow for more non-linearities.

- **Weather data:** we use the global gridded weather dataset of the Climate Research Unit at the University of East Anglia (Harris et al. 2020), which provides monthly estimates of average temperature and total precipitation on a 0.5 degree grid (i.e., roughly 55 km across at the equator) for the entire world covering the period 1901-2019. As a robustness check, we use the University of Delaware gridded weather data. This dataset is also monthly on a 0.5 degree grid, and covers the period 1900-2017 (version 5.01) and available at https://psl.noaa.gov/data/gridded/data.UDel_AirT_Precip.html.

- **Crop-specific area weights:** The fraction of each 5 minute grid that is used for the four major staple food items (corn, wheat, rice and soybeans) are obtained from Monfreda et al. (2008), and reported in the database constructed by Sacks et al. (2010). The harvested areas depict circa the year 2000. We assume that these fractions have been constant over the sample period. The variable $AREA$ used in the equation below represents the ratio of the harvest area in the grid cell to the total harvest area of the country. Hence, we assume that productivity (average yields) is the same *within* countries.

- **Growing season:** the start and end date (day of the year) of the planting and harvesting season are collected from Sacks et al. (2010) (https://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/index.php). The authors provide this information on a 5 minute grid for each of the four crops. Overall, the dataset covers 95 percent of the FAO global production volumes of the four crops, and also 95 percent of global export volumes of the crops. Again, we assume that the growing season has been constant over the sample period. Furthermore, we assume a linear evolution of planting and harvesting over the season. For example, if the harvest season is between day 70 and 100 of the year, we assume that half of the harvest has been realized at day 85, while the other half is exposed to the weather conditions on that day. The same principum is applied to the planting season. Accordingly, the way that crops in the grid are exposed to the monthly weather outcomes are 0.0 before planting and after harvesting, 1.0 between last day of planting and first day of harvesting, and varies between 0.0 and 1.0 during the planting and harvesting seasons. This indicator is *CALENDAR* in the equation below. As a robustness check, we also report results where *CALENDAR* is equal to 1.0 from first day of planting until last day of harvesting, and 0.0 outside the growing season.

- **Export shares:** share of each country in global agricultural export for each of the four crops, which is *EXPORT* in the equation below. This information is collected from the FAO and covers 192 countries (http://www.fao.org/faostat/en/#data, downloaded on 12/10/2020). Shares are averages over the period 1992-2016 and based on volumes in tonnes. The start in 1992 is motivated by the availability of data for former USSR countries (which are also included in the databases of crop-specific area weights and the crop calendars discussed above). Accordingly, whereas we assume that average agricultural productivity is the same across grids within a country, we allow for differences across countries. Note that we use export shares to construct the shocks because this is most closely related to the (trade-weighted) agricultural price index that is used in the estimations. As a robustness check, we also report results that are based on the production share of each country in global production.

- **Crop weights:** To aggregate the four crops into a single variable, we use the same weights as those that have been used to obtain the global agricultural price index (see above). The IMF trade-weights are 22.8%, 36.6%, 13.8% and 26.8% for corn, wheat, rice and soybeans, respectively, and represent *CROP* in the equation below.

For example, we obtain global temperature as follows:

$$TEMP_t = \sum CROP_j * EXPORT_{c,j} * AREA_{i,j} * CALENDAR_{i,j,t} * temp_{i,j,t}$$

where $temp_{i,j,t}$ is average temperature in month t for crop j in grid cell i, $CALENDAR_{i,j,t}$ is the share of crop j in grid cell i that is exposed to the weather conditions in month t (varying between 0.0 and 1.0 over the growing season), $AREA_{i,j}$ is the share of harvest area in grid cell i relative to the harvest area of the whole country for crop j, $EXPORT_{c,j}$ the share of the country's export in global export for crop j and $CROP_j$ the share of crop j in the agricultural price index. The same way, we calculate global squared temperature (i.e., $temp^2_{i,j,t}$ instead of $temp_{i,j,t}$ in the above equation), and global (squared) total precipitation. In line with the harvest shocks, for each of the 75 countries, we construct global weather indicators excluding the weather conditions of the entire sub-region in which the country is located and the neighbouring sub-regions.

In the next step, we regress the weighted global weather variables over the period 1901-2019 on 12 monthly dummies, as well as a linear, quadratic and cubic time trend to capture climatic trends. The quarterly averages of the monthly residuals of this estimation are the weather shocks that are used as instrumental variables. The weather shocks when we do not exclude own and neighbouring regions are shown in Figure A1 for illustrative purposes. We scale the shocks by the standard deviation of the shock series over the sample period. The correlations with the "weather shocks in other regions of the world" that are used as instrumental variables are reported in Table A2.

A4. Baseline SVAR-IV model

- **Real GDP** (country-specific variable): As the preferred source we use the seasonally adjusted chain-weighted real GDP index (volume, national currency, base year 2010) 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 chain-weighted 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. All sample periods are reported in Table A3.

- **Global real agricultural commodity prices**: see above.
- **OECD Composite Leading Indicator:** see above.
- **MSCI World Equity Price Index:** see above.
- **Us dollar nominal effective exchange rate:** collected from the FRED database.

A5. Sensitivity of SVAR-IV Analysis

Note that the results of the sensitivity analysis are reported below (Appendix B). We have used the following additional data series:

- **Consumer prices** (country-specific variable): 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).

- **Bilateral USD exchange rate** (country-specific variable): 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 US and domestic CPI.

- **Broad real food 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 US CPI.

- **Global economic activity**: Following Baumeister and Peersman (2013), global economic activity is the 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. The index is a weighted average of industrial production of a large set of individual countries, including for instance China and India.

- **US export and import deflator:** downloaded from the FRED database. The data are seasonally adjusted, national accounts basis and represent export/import of goods and services. The base year is 2012.

- **US manufacturing prices:** downloaded from the FRED database. Domestic Producer Prices Index: Manufacturing for the United States, Index 2015=100, Quarterly, Not Seasonally Adjusted. Seasonally adjusted using Census X-13 (X-11 option).

- **Population:** used to calculate real GDP per capita. The data are collected from Penn World Table, version 9.0. The annual figures are applied to each quarter of the year.

- **Stock-to-use ratio of agricultural commodities:** The stocks and consumption (use) data are from the Production, Supply, and Distribution (PSD) Online of the US Department of Agriculture. We use ending stocks to construct the ratio. The data is available at annual frequency based on the "marketing" year, which ends in April. We apply this value from Q2 onwards, until Q1 of the following year.

A5. Cross-country heterogeneity

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

- **Net exports of agricultural commodities** (country-specific variable, annual frequency): Share in GDP of food and live animals net exports. Trade data in US dollar downloaded from the UN Comtrade database. Food and live animals corresponds with SITC REV.1 Classification: 0. Nominal annual GDP in US dollar was downloaded from the World Bank (NY.GDP.MKTP.CD). We include live animals since the prices of meat commodities are typically influenced by the four major staple food items because the latter are used to feed animals.

- **Value added agricultural sector** (country-specific variable, 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. For Austria, Australia, Belgium, Switzerland, Czech Republic, Germany, Estonia, Finland, United Kingdom, Hungary, Iceland, Italy, Lithuania, Latvia, Poland, Portugal, Slovenia, Slovakia and the US 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 variable, 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.

For all four variables, we calculate the average values for each country over the period 2000-2015. The average values are used for the panel LP-IV estimations. The composition of the country groups (SVAR-IV estimations) are based on the average values; that is, by ranking the countries. The average values for each country, as well as the ranking (between parentheses), are reported in Table A3.

Appendix B: SVAR-IV Results

The sample period for each individual country, which is determined by the availability of real GDP data, is reported in Table A3. Table A4 shows the first-stage F-statistics and robust F-statistics allowing for heteroskedasticity, the corresponding p-values as well as the adjusted R-squares for the harvest disruptions and weather shocks, respectively. The two series of harvest disruptions turn out to be strong instrumental variables for the bulk of the countries. The weather shocks also have a significant impact on agricultural commodity prices in the first stage of the estimations for most countries, but are less efficient instruments, in particular for North and Central American countries.

At the panel level (i.e., the first-stage of the LP-IV estimations), the F-statistic for joint significance of the harvest disruptions is 35.4 (p-value 0.00). The t-statistics for the harvest and narrative shocks are 6.46 and 3.97, respectively. These statistics are adjusted for correlations between the residuals across countries and time. On average, the 13 narrative shocks trigger a shift in agricultural commodity prices of 8.5 percent, while a one-standard deviation harvest disruption (at the quarterly frequency) augments agricultural commodity prices by roughly 2.3 percent. The latter corresponds to a shift in the quarterly harvest volume of roughly 4.8 percent.

For the four series of weather shocks, the joint F-statistic at the panel level is 3.5 (p-value 0.01). The coefficients (t-statistics) for temperature, squared temperature, precipitation and squared precipitation are -3.97 (1.72), 6.07 (2.45), -5.48 (2.50) and 4.98 (2.22), respectively. Since these four shock series have a different scale (i.e., its standard deviation over the sample period), and are based on nonlinear variables due to the quadratic specification, we also did some back-of-the-envelope simulations to interpret the magnitudes. Specifically, a one-standard deviation quarterly temperature shock turns out to be the equivalent of a rise in average temperature by 0.6° C in food production regions. At the same time, such a rise in temperature (uniformly across the crop areas) by one-standard deviation relative to the baseline; that is, relative to the monthly average and its trend, leads to a rise in squared temperature by 1.01 standard deviations. Accordingly, there is an overall rise in global real agricultural commodity prices by 2.16 percent. Furthermore, if there is a uniform rise in temperature by two or three standard deviations from the historical mean and trend, agricultural prices increase by 4.45 and 7.03 percent, respectively. Similarly, a one-standard deviation decline in total precipitation corresponds to 10.5 mm per month. Such a decline below its historical mean and trend leads to a rise of global agricultural prices by 1.55 percent. A reduction by two and three standard deviations, in turn, leads to a rise of agricultural prices by 2.64 and 3.28 percent, respectively.

The relevance of weather conditions for fluctuations in agricultural commodity prices can also be illustrated by the historical evolution of the shock series. For example, based on the above coefficients, a simple calculation reveals that unfavourable weather conditions in subsequent quarters augmented global real agricultural commodity prices by 14.3 percent in the period 88Q2-89Q1, 11.9 percent in 95Q3-96Q2, 9.9 percent in 02Q2-03Q1, 17.3 percent in 05Q2-07Q4 and 28.6 percent in 09Q4-12Q3.

Furthermore, Figure A2 shows all the panel impulse responses of the baseline SVAR-IV model for the estimations based on the harvest disruptions, weather shocks and average agricultural price shifts (i.e., Cholesky decomposition with agricultural prices ordered first), respectively. The SVAR-IV results for individual countries are shown in Figure A3. For each country, we show the effects of a ten percent increase in global agricultural commodity prices caused by global harvest disruptions and weather shocks, respectively. The figure reveals that there is considerable cross-country heterogeneity. Several countries experience substantial and statistical significant declines in real GDP following a rise in agricultural prices. On the other hand, a large number of countries experience a temporary increase in real GDP. Also the shapes are different across countries.

Appendix C: Sensitivity of Panel SVAR-IV Results

Figure A4, A5 and A6 show a number of sensitivity checks of the panel SVAR-IV results for real GDP. The panels also show the baseline point impulse responses (dashed red lines) to compare with the corresponding benchmark results.

C1. Choice and Construction of the Instrumental Variables

The results do not seem to depend on the choice of the instruments that we have used, as can be observed in figure A4.

- Panel A shows the impulse responses when we only use the harvest disruptions in other regions of the world as an external instrument, while panel B shows the results for an estimation solely based on the narrative shocks. The peak effects are slightly lower for the harvest shocks and somewhat stronger for the narrative shock relative to the baseline effects, but the latter fall within the 68% confidence bands. Notice, however, that the robust F-statistics are below 10 for 18 countries if only the harvest shocks are used for the identification of the shocks. For this reason, we excluded Jamaica, Belize, Canada, Costa Rica, Guatemala and the United States from the estimations that are solely based on the foreign harvest shocks. The first-stage robust F-statistics for these countries are less than 3, resulting in explosive confidence intervals of the panel VARs. The exclusion of these countries, however, has a negligible influence on the point estimates of the impulse responses. For the narrative shocks, the robust F-statistics are below 10 for 11 countries. Overall, the F-statistics suggest that it is optimal to combine both instruments to estimate the macroeconomic repercussions of food commodity market disruptions across countries, as have been done in the paper. Furthermore, as shown in panel C, the results are very similar when we do not exclude own and neighbouring regions from the global harvest volume, and we also use all the narrative agricultural market shocks as the second instrument.

- Panel D, E and F show the results when we only use the temperature and squared temperature shocks as instrumental variables, precipitation and squared precipitation, and the results when we do not exclude weather outcomes in the own and neighbouring regions to construct the instruments.

- As documented in panel G, the results are very similar when we use the University of Delaware gridded weather data. It appears that the t-statistics for temperature are larger for the Delaware dataset, but the t-statistics for precipitation are lower compared to the weather dataset of the Climate Research Unit at the University of East Anglia that we have used for the baseline estimations. Overall, the F-stats are slightly higher for the baseline dataset.

- Finally, the results are similar when we use the share of individual-country agricultural production in global production rather than the export share to construct the global weather outcomes (panel H), and when we set *CALENDAR* equal to 1.0 from first of planting until last day of harvesting, and 0.0 outside the growing season (panel I). For both alternative specifications, the first-stage F-stats are somewhat lower than the baseline results.

C2. Alternative SVAR-IV Specifications

Figure A5 reports the sensitivity of the results for several alternative SVAR-IV specifications.

- The baseline SVAR-IV model is estimated in (log) levels, which gives consistent estimates when the variables have stochastic trends and are cointegrated (Sims et al. 1990). A drawback of such a specification is that the results could be distorted because initial conditions explain an implausibly large share of the variation in the data to a deterministic component (Sims 2000). Panel A therefore shows the results when the SVAR-IV model is estimated in first differences. Differencing the data does not account for cointegrating relationships in the data, but it is less likely that the estimates are distorted by the initial conditions. As can be observed, the peak decline in economic activity is similar to the specification in levels. However, the decline in real GDP turns out to be more persistent, while the confidence intervals are larger than the baseline results. This is likely due to the fact that cointegration in the data is not captured by a specification in first differences.

- In the baseline, we have used US CPI as the deflator, which is most common in the literature. A caveat is that the CPI is heavily weighted by US prices for non-traded goods, which most commodity producers do not face. Panel B and C show the sensitivity of the results when we use alternative deflators to calculate real agricultural commodity prices; that is, the average of the US import and export deflator, and US manufacturing prices, respectively. The results turn out to be not sensitive to the choice of the deflator.

- Panel D shows the results when we use real GDP per capita in the estimations. A caveat of this estimation is that population data is only available at annual frequency. The results are, however, nearly identical to the baseline results reported in the paper.

- Panel E shows the impulse response of real GDP when we use the broad food commodity price index of the IMF (also shown in Figure 1) instead of the weighted average of the four major staple food items. In addition to the four staples, this index also includes the prices of vegetable oils, meat, seafood, sugar, bananas and oranges. Panel E reveals that the effects of a rise in the broad food commodity price index by 10 percent are stronger than an equal rise in the prices of the four staples. In particular, real GDP decreases by 0.73 percent at its peak. This finding is consistent with the fact that this index covers a larger share of food commodities. A caveat of these estimations is that the harvest and narrative shocks are weaker instruments for the broad price index, in contrast to the price index that directly corresponds to shocks used in the paper.

- Panel F shows the results when we estimate the panel SVAR-IV model 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. As can be observed in the figure, the effects are slightly stronger; that is, the peak decline in real GDP is 0.67 percent, compared to 0.53 percent for the whole sample period.

The remaining panels (G, H, I and J) of Figure A5 report the results for specifications where we allow for non-linearities in the first-stage of the estimations. Specifically, in the paper we assume that the impact of the harvest disruptions and weather shocks on agricultural commodity prices in the first-stage of the regressions is linear. There exist, however, studies that have documented that the impact of an agricultural output shock on prices is conditional on the amount of stocks, and that positive and negative production shocks have a different impact on agricultural prices (e.g. Deaton and Laroque 1992, Wright 2014). Accordingly, the question is i) whether such nonlinearities are present in the first-stage of our regressions and ii) whether this matters for the results in the second stage.

- In panel G, we allow for asymmetries between favourable and unfavourable harvest disruptions. This is implemented by using four instruments in the first-stage; that is, a separate series for positive and negative values of the instruments. At the panel level, we find indeed somewhat larger coefficients for unfavourable shocks in the first-stage: 9.48 versus 7.47 for the narrative shocks and -2.58 versus -1.92 for the harvest shocks. The differences are, however, statistically insignificant (p-values are 0.69 and 0.40, respectively). In addition, as can be observed in panel G, there is no influence on the results in the second-stage of the SVAR-IV estimations. The same applies for the estimations based on the weather shocks, which are reported in panel H.

- Panel I shows the results when we estimate a specification that allows for an influence of stocks in the first-stage of the estimations. More precisely, for each country, the first-stage of the estimations becomes:

$$u_{1,t} = \alpha_1 Z_{1,t} + \alpha_2 Z_{2,t} + \lambda_1 stocks_{t-1}\, Z_{1,t} + \lambda_2 stocks_t\, Z_{2,t}$$

where $u_{1,t}$ are the reduced-form residuals of real global agricultural commodity prices of the SVAR-IV, $Z_{1,t}$ and $Z_{2,t}$ are the instrumental variables (i.e., harvest shocks and narrative shocks), whereas $stocks_t$ is the stocks-to-use ratio of agricultural commodities (i.e., for the four staple food items that we consider), which is included with a lag to avoid endogeneity problems. The stocks-to-use ratio is measured as standard deviations from the sample mean. Hence, α_1 and α_2 represent the average impact of the instruments on agricultural commodity prices over the full sample period, while λ_1 and λ_2 capture the additional effect when stocks are one standard-deviation above (or below) the sample average. For the narrative shocks, it turns out that the impact does not depend on the volume of stocks. The coefficient for the additional effects has the wrong sign and is statistically insignificant (t-stats 0.48). However, for the harvest shocks, we find a stronger impact on agricultural commodity prices when stocks are below the sample average that is statistically significant. Specifically, whereas the average impact of a (one-standard deviation) unfavourable harvest shock on agricultural prices is 2.53, there is an additional impact of 0.95 when the stock-to-use ratio is one standard deviation below its average over the sample. The t-statistic of this coefficient is 2.75. Nevertheless, as can be observed in panel I, it appears that this does not affect the results in the second-stage of the estimations.

- For the weather shocks, we do not find evidence of non-linearities in the first stage depending on the amount of stocks. The p-value for a joint test on the four instruments is 0.38. This might be somewhat surprising since previous studies have argued that the relationship between weather and agricultural output might be highly asymmetric, whereas a quadratic function assumes symmetry around the optimum (Auffhammer et al. 2013). We only find some weak additional effects for precipitation and squared precipitation (p-values are 0.10 and 0.14). As shown in panel J, the effects on real GDP are very similar when we allow for such non-linearities in the first stage of the regressions.

- Finally, for the harvest shocks, we have also explored the possibility of a quadratic relationship between the harvest shocks and agricultural commodity prices in the first-stage of the regressions (akin to the weather shocks). It turns out that there is no significant quadratic relationship between harvest shocks and changes in agricultural commodity prices; that is, the p-value is 0.98 at the panel level. Accordingly, allowing for such a relationship does also not affect the macroeconomic consequences, as shown in panel (K) of Figure A5.

C3. Extensions with Additional Variables

To have sufficient degrees of freedom for countries with a relatively short sample period, the number of variables in the benchmark SVAR-IV model are limited to five. We now examine the sensitivity of the results when we include additional variables in the vector of endogenous variables $Y_{i,t}$, which could further enrich the dynamics of the VAR model. The impulse responses for real GDP are reported in Figure A6, while the effects on the extra variables are shown in Figure A7.

- In panels A and B of Figure A6, we show the results of two VAR models with an additional country-specific variable. The panels show the results of an SVAR-IV that also includes respectively the domestic consumer price index and the real (bilateral) US dollar exchange rate of the individual countries. 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 an insignificant response of the USD real bilateral exchange rates. Both results are reported in the paper (Figure 3). As shown in Figure A6, the effects on real GDP are quite similar to the baseline results.

- Panel C shows the results when we extend the baseline VAR model with an additional global variable; that is, world industrial production (panel C). This does not affect the dynamic effects.

- Finally, panel E and F show that the effects on real GDP when we include the global food production index of De Winne and Peersman (2016a) as an additional variable in the baseline VAR.

Overall, we can conclude that the panel SVAR-IV results are robust to several perturbations of the baseline model.

Appendix D: Rich versus Poor Countries - Sensitivity Analysis

Figure A8 shows the impulse responses when we split the countries in six groups according to income per capita; that is, when each tertile is divided in two subgroups.

Figure A9 reports several sensitivity checks:

- Estimations based on the weather shocks. Results are similar to the baseline results.

- When we estimate the SVAR-IV model solely for the post 1990 sample period; that is, the results are not driven by the longer sample periods that most high-income countries have

- The results are similar when we estimate the effects of changes in global agricultural prices measured in domestic currency. This estimation has been done by converting global USD agricultural prices in domestic currency using bilateral USD exchange rates. The results are thus also not the consequence of exchange rate movements that are different between high and low-income countries.

- We also find stronger effects in advanced countries when we identify average agricultural price shocks using a simple recursive (Cholesky) decomposition of the variance-covariance matrix of the VAR residuals. Note that the results are also very similar when we include the additional variables of Appendix C in the baseline VAR model (results not shown but available upon request).

Appendix E: Other Country Characteristics

Figure A10 are the results for weather shocks that correspond to Figure 5 in the paper, which reports the effects across country groups depending on the alternative country characteristics. As can be observed in the figure, the results are very similar.

Figure A11 shows the impact of the harvest shocks in other regions of the world on domestic consumer prices across country groups. A relevant finding is that consumer prices appear not to rise in countries with a high share of agriculture in GDP, in contrast to the two other groups of countries. This suggest that the former countries are more isolated for global agricultural market shocks (in other regions of the world).

Figure A12 depicts the effects on the bilateral US dollar exchange rate across country groups. As can be observed in the figure, there are no meaningful differences depending on the country characteristics.

Appendix F: Panel LP-IV Estimations - Robustness Analysis

Figure A13 documents the robustness of the panel LP-IV results:

- Panel A shows the results for the weather shocks. The magnitudes of the average effects (i.e., the constant) are somewhat larger than the baseline results. But the uncertainty is quite large and the main conclusions are similar to the baseline results.
- Panel B and C show the effects when the harvest and the narrative shocks, respectively, are used as the sole instrumental variable. Results are qualitatively the same for both shocks.
- Panel D shows the results when we allow for a different impact of harvest disruptions on agricultural commodity prices in the first stage of the regressions depending on the amount of stocks that are available prior to the disruptions (see above). As can be observed, the results are very similar to the baseline results reported in the paper.
- Panel E are the results when we limit the sample period to the post-1990 era.
- Finally, panel F evaluates the robustness when we include time fixed-effects in the LP-IV model. Note that, since the time fixed-effects absorb the common effects of food commodity price changes, it is not possible to report the average effects for this specification (i.e., the constant changes every t). The results are indeed robust for this extension.

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Table A1 - Overview of narrative global agricultural commodity market shocks

Date	Type	Food commodity market event
1972Q3	Unfavorable	**Russian Wheat Deal and failed monsoon in Southeast Asia** 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, while only a few months earlier there were reports of heavy surplus stocks building. Moreover, it was a suprise that the Soviet Union was willing to buy wheat, which was an attempt to boost its sinking popularity in the era, since previous production declines did not result in purchases. The agents for the USSR operated simultaneously and quietly so the extent of the stock draw down was a surprise when revealed. 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. 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%. 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	**Significant improved estimate of world grain production** 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	**Optimistic rice forecast because of very favorable monsoon season** 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	**Predictions of record US and Soviet harvests** 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	**Record grain harvests did not materialize** 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	**Favorable weather in North America and exceptionally good cereal harvest in Western Europe** 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	**Expectations of global surge in wheat production** 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	**Significant downward revised world cereal estimates** 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	**Expectations of excellent global cereal harvest** 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	**Significant downward revised global cereal estimates** 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	**Significant improved forecast of world cereal output** 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	**Droughts in Russia and Eastern Europe** 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	**Droughts around the globe** 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.

A detailed motivation and description of the episodes can be found in De Winne and Peersman (2016b).

Table A2 - Correlation of global shocks and shocks that exclude own and neighbouring regions

	Harvest	Temperature	Temp squared	Precipitation	Precip squared
World	1.00	1.00	1.00	1.00	1.00
Northern America	0.71	0.59	0.52	0.63	0.74
Central America	0.55	0.58	0.49	0.32	0.25
South America	0.83	0.97	0.95	0.85	0.74
Caribbean	0.55	0.58	0.49	0.32	0.25
Northern Europe	0.76	0.85	0.95	0.95	0.98
Southern Europe	0.75	0.88	0.95	0.96	0.99
Western Europe	0.74	0.85	0.94	0.95	0.98
Eastern Europe	0.72	0.84	0.94	0.95	0.98
Eastern Africa	0.88	1.00	1.00	1.00	1.00
Middle Africa	NA	1.00	1.00	1.00	1.00
Northern Africa	0.95	1.00	1.00	1.00	1.00
Southern Africa	0.94	1.00	1.00	1.00	1.00
Western Africa	NA	1.00	1.00	1.00	1.00
Central Asia	0.75	0.97	0.98	0.99	0.98
Eastern Asia	0.75	0.97	0.98	0.99	0.98
Southern Asia	0.85	1.00	1.00	0.99	0.98
South-Eastern Asia	1.00	0.99	0.99	0.98	0.96
Western Asia	0.66	0.97	0.98	0.99	0.98
Oceania	1.00	0.99	0.99	0.99	0.98

Table A3 - Country characteristics

	Sample period	Income per capita		Net export agricultural commodities (%GDP)		Value added agriculture (%GDP)		Trade (%GDP)	
		Country characteristics: average values 2000-2015 (ranking between brackets)							
Argentina	1970Q1-2016Q4	16031	(41)	4.35	(11)	8.0	(25)	34	(72)
Australia	1970Q1-2016Q4	41353	(9)	2.49	(16)	2.9	(48)	41	(70)
Austria	1970Q1-2016Q4	39429	(13)	-0.76	(46)	1.6	(65)	96	(26)
Belarus	1992Q1-2016Q4	13327	(48)	0.03	(40)	10.1	(18)	131	(12)
Belgium	1970Q1-2016Q4	36218	(18)	-0.10	(41)	0.9	(69)	149	(8)
Belize	1994Q1-2016Q4	6952	(64)	10.50	(3)	14.8	(5)	125	(16)
Bolivia	1990Q1-2016Q4	4182	(72)	-0.24	(42)	13.9	(9)	69	(47)
Botswana	1994Q1-2016Q4	11940	(51)	-3.16	(68)	2.7	(52)	97	(25)
Brazil	1980Q1-2016Q4	11018	(52)	1.71	(21)	5.5	(33)	26	(75)
Bulgaria	1980Q1-2016Q4	12983	(50)	0.36	(34)	7.5	(29)	106	(22)
Canada	1970Q1-2016Q4	40379	(10)	0.72	(28)	1.7	(61)	68	(49)
Chile	1970Q1-2016Q4	15523	(42)	2.05	(18)	4.2	(40)	68	(48)
China	1980Q1-2016Q4	7771	(61)	0.59	(31)	11.0	(16)	50	(64)
Colombia	1980Q1-2016Q4	9263	(58)	3.84	(13)	7.7	(27)	36	(71)
Costa Rica	1991Q1-2016Q4	10951	(53)	11.05	(2)	8.0	(24)	78	(38)
Croatia	1991Q1-2016Q4	17788	(35)	-1.52	(60)	5.1	(35)	84	(35)
Cyprus	1988Q1-2016Q4	26383	(26)	-1.53	(61)	2.9	(49)	116	(19)
Czech Republic	1988Q3-2016Q4	24538	(29)	-0.74	(45)	2.5	(54)	125	(15)
Denmark	1970Q1-2016Q4	40161	(11)	3.98	(12)	1.6	(62)	93	(29)
Ecuador	1991Q1-2016Q4	8035	(59)	6.16	(5)	10.7	(17)	57	(55)
Egypt	2002Q1-2016Q4	7502	(63)	-3.47	(70)	14.0	(8)	49	(65)
Estonia	1988Q3-2016Q4	18690	(34)	-1.43	(58)	3.6	(43)	141	(10)
Finland	1970Q1-2016Q4	36705	(16)	-0.81	(48)	2.8	(51)	76	(40)
France	1970Q1-2016Q4	34735	(19)	0.16	(37)	1.9	(60)	55	(58)
Georgia	1996Q1-2016Q4	6388	(66)	-3.63	(72)	13.5	(10)	86	(31)
Germany	1970Q1-2016Q4	39353	(14)	-0.78	(47)	0.9	(71)	75	(42)
Greece	1970Q1-2016Q4	25916	(27)	-0.58	(44)	4.2	(39)	56	(56)
Guatemala	2001Q1-2016Q4	5887	(69)	5.62	(7)	12.6	(11)	62	(50)
Hong Kong	1970Q1-2016Q4	45664	(7)	-6.25	(74)	0.1	(74)	381	(1)
Hungary	1979Q1-2016Q4	18842	(33)	2.16	(17)	4.5	(37)	148	(9)
Iceland	1970Q1-2016Q4	37044	(15)	14.38	(1)	7.1	(30)	85	(32)
India	1970Q1-2016Q4	3519	(73)	0.60	(30)	19.2	(4)	43	(69)
Indonesia	1970Q1-2016Q4	5891	(68)	0.27	(36)	14.2	(6)	55	(59)
Iran	1988Q1-2016Q4	13893	(45)	-1.03	(53)	7.6	(28)	48	(66)
Ireland	1970Q1-2016Q4	48326	(6)	5.25	(9)	1.4	(66)	174	(6)
Israel	1970Q1-2016Q4	29501	(24)	-0.37	(43)	1.9	(58)	71	(44)
Italy	1970Q1-2016Q4	34094	(21)	-0.99	(52)	2.3	(56)	52	(61)
Jamaica	1996Q1-2016Q4	6432	(65)	-1.72	(63)	6.4	(32)	88	(30)
Japan	1970Q1-2016Q4	34659	(20)	-0.98	(50)	1.2	(67)	28	(73)
Korea	1970Q1-2016Q4	29413	(25)	-1.04	(54)	3.0	(46)	84	(34)
Kyrgyzstan	1986Q2-2016Q4	3093	(74)	-3.35	(69)	27.1	(2)	115	(20)
Latvia	1988Q3-2016Q4	16240	(39)	-1.35	(57)	4.1	(41)	102	(24)
Lithuania	1995Q1-2016Q4	17310	(37)	1.06	(25)	4.3	(38)	124	(17)
Luxembourg	1970Q1-2016Q4	57796	(2)	-1.62	(62)	0.4	(73)	318	(3)

		Country characteristics: average values 2000-2015 (ranking between brackets)							
	Sample period	**Income per capita**		**Net export agricultural commodities (%GDP)**		**Value added agriculture (%GDP)**		**Trade (%GDP)**	
Macedonia	1993Q1-2016Q4	9966	(57)	-3.52	(71)	11.7	(14)	95	(28)
Malaysia	1970Q1-2016Q4	16233	(40)	-2.36	(67)	9.2	(21)	178	(5)
Malta	2000Q1-2016Q4	22973	(31)	-7.32	(75)	1.9	(59)	265	(4)
Mauritius	2000Q1-2014Q4	14932	(43)	5.38	(8)	5.1	(34)	117	(18)
Mexico	1970Q1-2016Q4	13587	(46)	0.38	(33)	3.5	(44)	58	(53)
Morocco	1970Q1-2016Q4	5681	(70)	0.84	(27)	14.1	(7)	72	(43)
Netherlands	1970Q1-2016Q4	43794	(8)	2.92	(15)	2.0	(57)	133	(11)
New Zealand	1970Q1-2016Q4	29511	(23)	8.59	(4)	6.4	(31)	60	(51)
Norway	1970Q1-2016Q4	69450	(1)	0.68	(29)	1.6	(63)	70	(45)
Paraguay	1994Q1-2016Q4	5976	(67)	2.97	(14)	19.4	(3)	96	(27)
Peru	1979Q1-2016Q4	7645	(62)	1.57	(22)	7.8	(26)	47	(67)
Philippines	1981Q1-2016Q4	4919	(71)	0.32	(35)	12.5	(12)	83	(36)
Poland	1982Q1-2016Q4	17712	(36)	0.44	(32)	3.1	(45)	78	(37)
Portugal	1970Q1-2016Q4	23873	(30)	-1.95	(66)	2.6	(53)	69	(46)
Romania	1980Q1-2016Q4	13484	(47)	-1.07	(55)	8.6	(23)	75	(41)
Russian Federation	1990Q1-2016Q4	16493	(38)	-1.45	(59)	4.9	(36)	54	(60)
Serbia	1995Q1-2016Q4	10478	(56)	1.80	(20)	12.0	(13)	76	(39)
Singapore	1975Q1-2016Q4	51756	(3)	-3.67	(73)	0.1	(75)	380	(2)
Slovakia	1992Q1-2016Q4	19373	(32)	-0.90	(49)	4.0	(42)	154	(7)
Slovenia	1992Q1-2016Q4	24864	(28)	-1.81	(65)	2.4	(55)	125	(14)
South Africa	1970Q1-2016Q4	10674	(54)	0.85	(26)	2.9	(50)	59	(52)
Spain	1970Q1-2016Q4	30484	(22)	0.13	(38)	3.0	(47)	57	(54)
Sweden	1970Q1-2016Q4	39603	(12)	-0.98	(51)	1.6	(64)	85	(33)
Switzerland	1970Q1-2016Q4	51248	(4)	-1.13	(56)	0.9	(70)	109	(21)
Tanzania	2001Q1-2016Q4	1722	(75)	1.15	(24)	31.9	(1)	45	(68)
Thailand	1980Q1-2016Q4	10615	(55)	6.12	(6)	9.8	(19)	129	(13)
Turkey	1970Q1-2016Q4	14466	(44)	1.25	(23)	9.6	(20)	52	(63)
Ukraine	2000Q1-2016Q4	7963	(60)	1.89	(19)	11.1	(15)	103	(23)
United Kingdom	1970Q1-2016Q4	36294	(17)	-1.75	(64)	0.7	(72)	55	(57)
Uruguay	1988Q1-2016Q4	13216	(49)	5.03	(10)	9.2	(22)	52	(62)
United States	1970Q1-2016Q4	49020	(5)	0.09	(39)	1.2	(68)	27	(74)

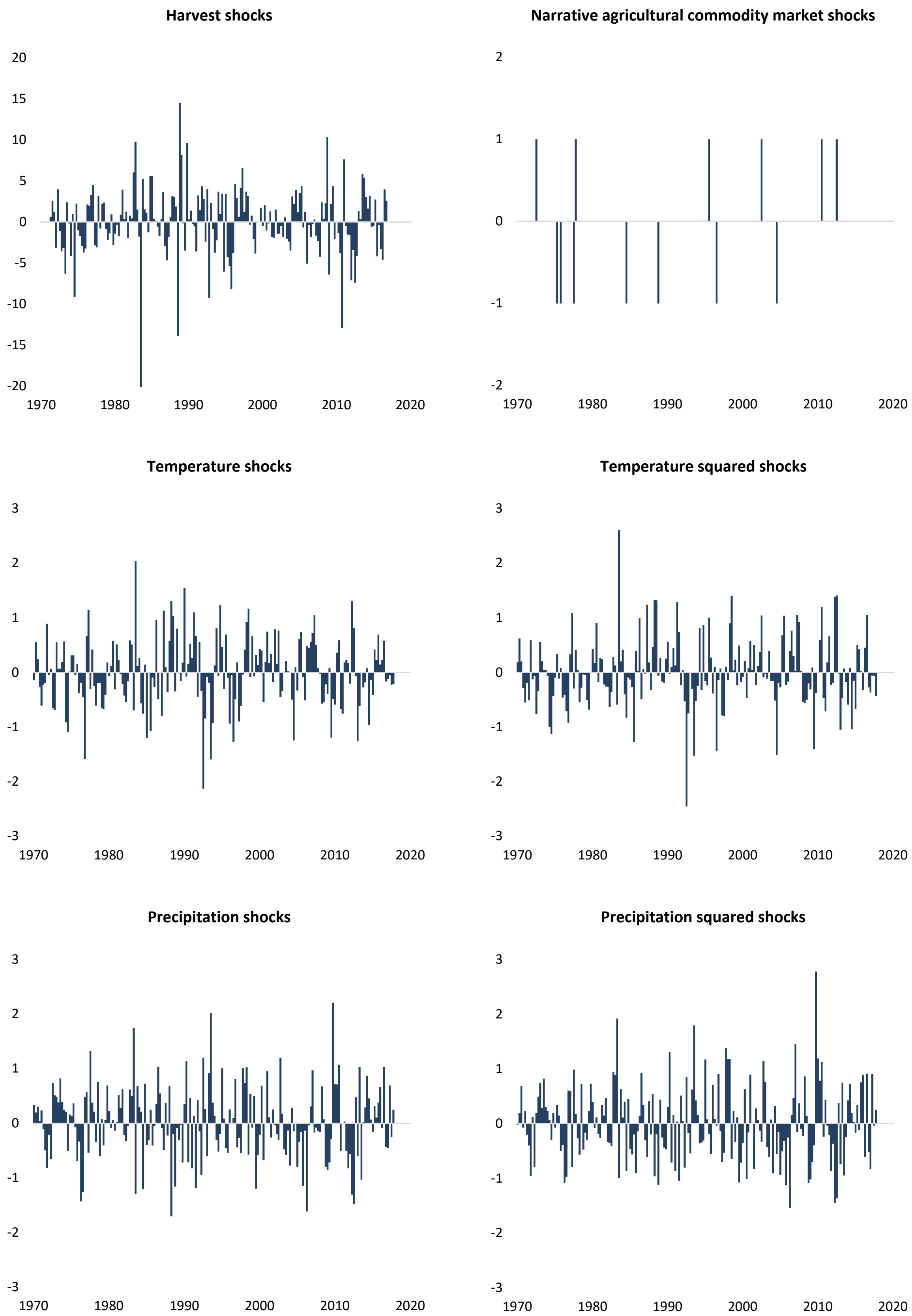
Rankings of country characteristics are based on the period 2000-2015. See data explanation for more details.

Table A4 - First-stage regression results for individual countries

	Harvest shocks and narrative agricultural market disruptions in other regions of the world					Weather shocks in other regions of the world (temperature, temperature squared, precipitation, precipitation squared)				
	Adj. R2	F-Stats (*,2)	P-value	Robust F-Stats (*,2)	P-value	Adj. R2	F-Stats (*,4)	P-value	Robust F-Stats (*,4)	P-value
Argentina	0.22	26.5	0.0000	19.7	0.0000	0.14	8.0	0.0000	9.3	0.0000
Australia	0.23	28.4	0.0000	25.6	0.0000	0.11	6.2	0.0001	6.5	0.0000
Austria	0.25	30.7	0.0000	33.1	0.0000	0.10	6.1	0.0001	6.1	0.0001
Belarus	0.16	9.3	0.0002	11.1	0.0000	0.12	3.9	0.0054	4.8	0.0007
Belgium	0.27	34.4	0.0000	35.6	0.0000	0.10	6.0	0.0001	7.0	0.0000
Belize	0.13	6.8	0.0019	9.3	0.0001	0.02	1.2	0.3107	1.2	0.2970
Bolivia	0.16	10.5	0.0001	9.5	0.0001	0.17	6.0	0.0002	6.1	0.0001
Botswana	0.22	12.4	0.0000	14.0	0.0000	0.07	2.4	0.0598	3.0	0.0174
Brazil	0.14	11.6	0.0000	10.0	0.0000	0.19	9.3	0.0000	9.7	0.0000
Bulgaria	0.21	19.1	0.0000	25.5	0.0000	0.11	5.0	0.0009	4.7	0.0008
Canada	0.13	14.4	0.0000	11.8	0.0000	0.01	1.3	0.2798	1.8	0.1256
Chile	0.18	21.1	0.0000	15.6	0.0000	0.14	8.1	0.0000	8.5	0.0000
China	0.22	20.0	0.0000	19.3	0.0000	0.12	5.5	0.0004	5.6	0.0002
Colombia	0.17	15.0	0.0000	9.1	0.0001	0.18	8.5	0.0000	8.2	0.0000
Costa Rica	0.15	9.3	0.0002	16.0	0.0000	0.01	0.9	0.4615	0.9	0.4732
Croatia	0.19	12.0	0.0000	14.0	0.0000	0.09	3.2	0.0152	3.7	0.0051
Cyprus	0.22	16.5	0.0000	17.2	0.0000	0.04	2.0	0.1052	1.5	0.2010
Czech Republic	0.16	10.6	0.0001	9.1	0.0001	0.08	3.1	0.0197	3.5	0.0070
Denmark	0.24	29.3	0.0000	32.1	0.0000	0.10	6.1	0.0001	6.5	0.0000
Ecuador	0.13	7.7	0.0008	7.3	0.0007	0.12	4.2	0.0034	5.7	0.0001
Egypt	0.24	9.0	0.0004	45.9	0.0000	0.01	0.9	0.4546	1.2	0.3031
Estonia	0.16	11.1	0.0000	7.7	0.0005	0.11	4.1	0.0040	4.2	0.0022
Finland	0.27	34.2	0.0000	34.9	0.0000	0.10	5.9	0.0002	6.1	0.0001
France	0.23	27.2	0.0000	33.7	0.0000	0.12	7.3	0.0000	7.4	0.0000
Georgia	0.25	13.6	0.0000	98.5	0.0000	0.07	2.3	0.0708	1.7	0.1367
Germany	0.22	26.3	0.0000	30.9	0.0000	0.09	5.4	0.0004	4.9	0.0006
Greece	0.25	30.6	0.0000	35.4	0.0000	0.09	5.0	0.0007	5.2	0.0003
Guatemala	0.15	5.8	0.0053	5.1	0.0061	0.06	1.6	0.1850	1.6	0.1696
Hong Kong	0.21	24.7	0.0000	18.0	0.0000	0.09	5.1	0.0006	5.2	0.0003
Hungary	0.18	16.5	0.0000	25.7	0.0000	0.16	7.9	0.0000	8.2	0.0000
Iceland	0.29	36.9	0.0000	40.6	0.0000	0.11	6.2	0.0001	6.8	0.0000
India	0.13	14.7	0.0000	17.1	0.0000	0.09	5.2	0.0006	4.9	0.0006
Indonesia	0.25	30.2	0.0000	19.4	0.0000	0.09	5.5	0.0003	5.7	0.0001
Iran	0.24	17.7	0.0000	18.7	0.0000	0.08	3.2	0.0148	2.7	0.0289
Ireland	0.24	28.7	0.0000	32.0	0.0000	0.10	5.9	0.0002	6.4	0.0000
Israel	0.24	28.5	0.0000	22.3	0.0000	0.09	5.3	0.0004	5.3	0.0003
Italy	0.23	27.7	0.0000	32.4	0.0000	0.12	6.9	0.0000	6.4	0.0000
Jamaica	0.13	6.3	0.0030	15.5	0.0000	0.02	1.1	0.3459	1.0	0.3812
Japan	0.19	21.6	0.0000	18.3	0.0000	0.08	4.7	0.0013	4.4	0.0015
Korea	0.15	17.0	0.0000	12.8	0.0000	0.10	5.9	0.0002	6.5	0.0000
Kyrgyzstan	0.22	16.7	0.0000	14.4	0.0000	0.08	3.4	0.0118	2.7	0.0268
Latvia	0.26	19.7	0.0000	28.9	0.0000	0.09	3.5	0.0104	3.7	0.0053
Lithuania	0.18	9.7	0.0002	35.2	0.0000	0.07	2.4	0.0573	2.8	0.0235
Luxembourg	0.32	43.6	0.0000	44.0	0.0000	0.11	6.6	0.0001	6.9	0.0000

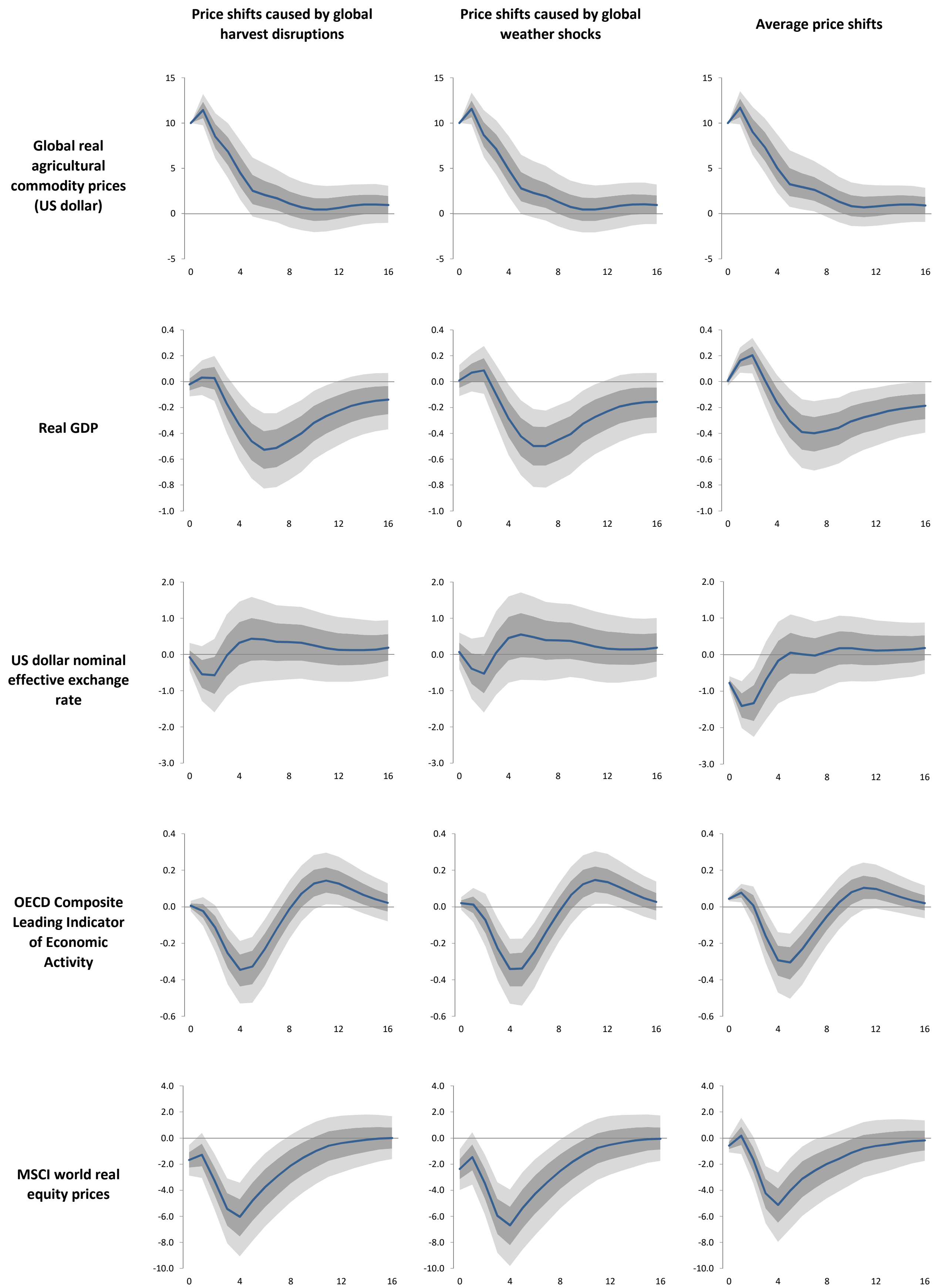
	Harvest shocks and narrative agricultural market disruptions in other regions of the world					Weather shocks in other regions of the world (temperature, temperature squared, precipitation, precipitation squared)				
	Adj. R2	F-Stats (*,2)	P-value	Robust F-Stats (*,2)	P-value	Adj. R2	F-Stats (*,4)	P-value	Robust F-Stats (*,4)	P-value
Macedonia	0.16	8.8	0.0003	11.1	0.0000	0.09	2.9	0.0262	3.4	0.0081
Malaysia	0.23	28.2	0.0000	18.4	0.0000	0.09	5.2	0.0006	5.1	0.0004
Malta	0.24	10.3	0.0001	16.0	0.0000	0.11	2.6	0.0421	2.8	0.0239
Mauritius	0.11	4.3	0.0179	5.0	0.0069	0.12	2.8	0.0339	2.4	0.0503
Mexico	0.14	15.3	0.0000	8.5	0.0002	0.05	2.9	0.0222	2.2	0.0705
Morocco	0.18	19.3	0.0000	11.6	0.0000	0.12	6.7	0.0000	6.8	0.0000
Netherlands	0.31	40.9	0.0000	44.6	0.0000	0.11	6.2	0.0001	6.3	0.0000
New Zealand	0.25	30.4	0.0000	18.8	0.0000	0.11	6.7	0.0001	6.7	0.0000
Norway	0.22	26.4	0.0000	29.5	0.0000	0.11	6.3	0.0001	6.9	0.0000
Paraguay	0.16	8.7	0.0004	9.4	0.0001	0.16	4.8	0.0016	6.3	0.0000
Peru	0.20	18.9	0.0000	15.0	0.0000	0.17	8.5	0.0000	8.3	0.0000
Philippines	0.22	20.4	0.0000	11.9	0.0000	0.13	5.7	0.0003	5.8	0.0001
Poland	0.21	18.2	0.0000	26.0	0.0000	0.12	5.3	0.0006	5.2	0.0004
Portugal	0.25	31.1	0.0000	32.7	0.0000	0.10	5.7	0.0002	6.2	0.0001
Romania	0.21	18.9	0.0000	24.0	0.0000	0.14	6.3	0.0001	5.9	0.0001
Russian Federation	0.19	12.1	0.0000	11.2	0.0000	0.09	3.3	0.0134	3.4	0.0086
Serbia	0.15	7.5	0.0010	7.7	0.0005	0.08	2.5	0.0509	3.1	0.0156
Singapore	0.25	27.9	0.0000	16.3	0.0000	0.13	6.5	0.0001	6.7	0.0000
Slovakia	0.16	9.1	0.0002	12.1	0.0000	0.07	2.6	0.0429	2.9	0.0214
Slovenia	0.15	9.0	0.0003	13.7	0.0000	0.08	2.7	0.0352	2.8	0.0237
South Africa	0.24	29.4	0.0000	20.9	0.0000	0.10	5.7	0.0002	5.3	0.0003
Spain	0.29	37.5	0.0000	34.1	0.0000	0.09	5.3	0.0005	5.4	0.0003
Sweden	0.29	38.0	0.0000	38.7	0.0000	0.09	5.5	0.0003	5.9	0.0001
Switzerland	0.24	30.0	0.0000	35.2	0.0000	0.12	6.9	0.0000	7.7	0.0000
Tanzania	0.27	11.4	0.0001	403.9	0.0000	0.13	2.9	0.0305	2.9	0.0208
Thailand	0.25	23.5	0.0000	17.7	0.0000	0.12	5.6	0.0003	5.5	0.0002
Turkey	0.27	34.9	0.0000	27.4	0.0000	0.09	5.4	0.0004	5.2	0.0004
Ukraine	0.17	6.9	0.0019	36.8	0.0000	0.10	2.4	0.0604	4.5	0.0013
United Kingdom	0.26	32.8	0.0000	35.0	0.0000	0.12	7.0	0.0000	6.8	0.0000
Uruguay	0.09	6.0	0.0035	5.0	0.0065	0.12	4.5	0.0022	4.5	0.0012
United States	0.18	20.2	0.0000	14.4	0.0000	0.00	0.8	0.5326	1.1	0.3689

Figure A1 - Global instrumental variables



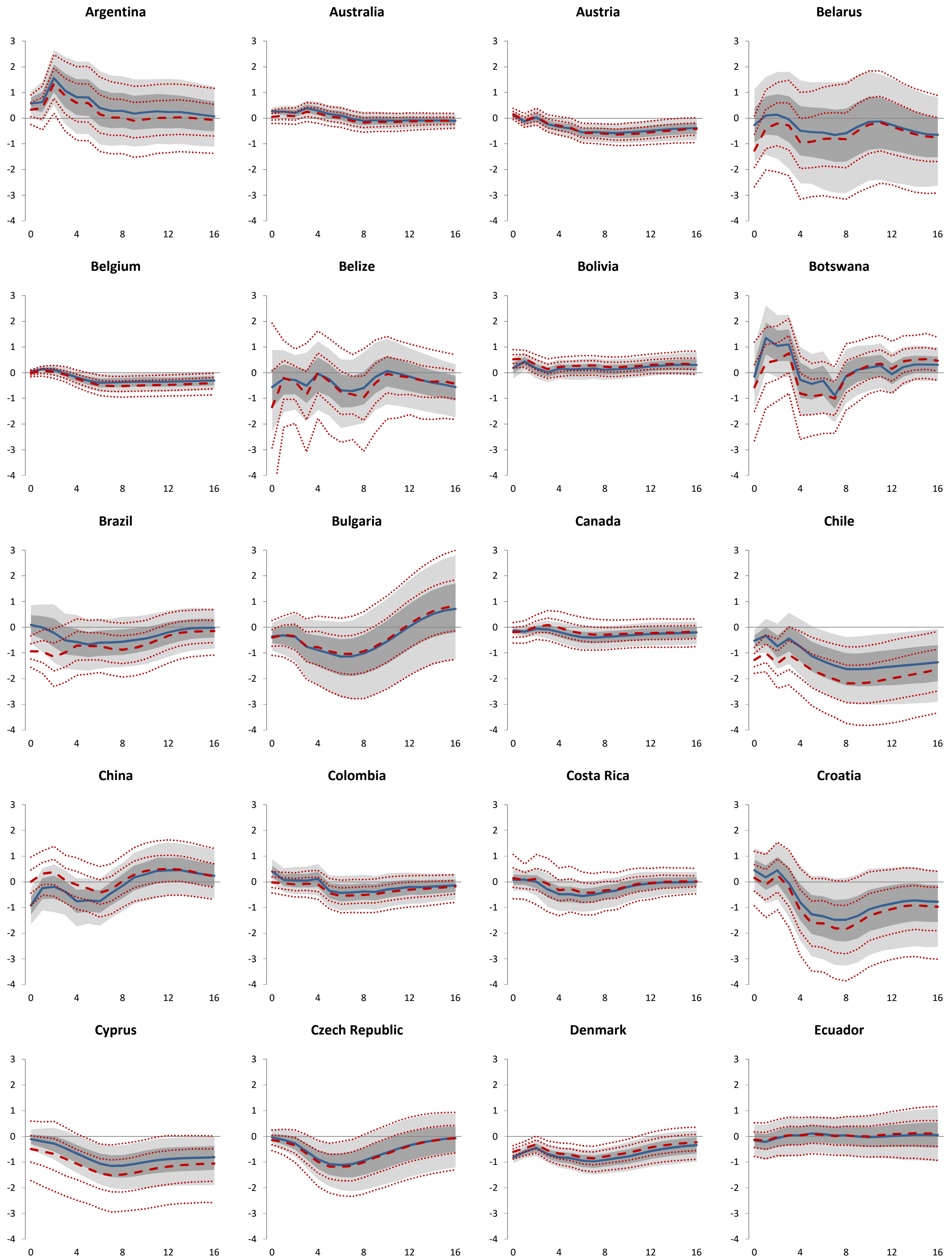
Time series of shocks when we do not exclude harvests/weather of own and neighbouring regions for illustrative purposes. Correlations with the instruments that are used in the estimations (i.e. excluding own and neighbouring regions) are reported in Table A2. Harvest shocks are measured as percentage points of harvest volumes, the narrative shock series is a dummy variable, and weather shocks are measured as standard deviations.

Figure A2 - Effects of 10% increase in global real agricultural commodity prices: full panel results



Impulse responses (mean group panel SVAR estimator) to a 10% increase in global agricultural commodity prices triggered by the shocks, with 68% and 95% confidence intervals. Horizon is quarterly. Results are based on 75 advanced and developing countries, covering the period 1970Q1-2016Q4.

Figure A3 - Effects of 10% increase in global agricultural commodity prices on real GDP: individual countries



Effects of price shifts caused by global harvest disruptions, with 68% and 95% confidence intervals.

Effects of price shifts caused by global weather shocks, with 68% and 95% confidence intervals.

Figure A3 (continued) - Effects of 10% increase in global agricultural commodity prices on real GDP: individual countries

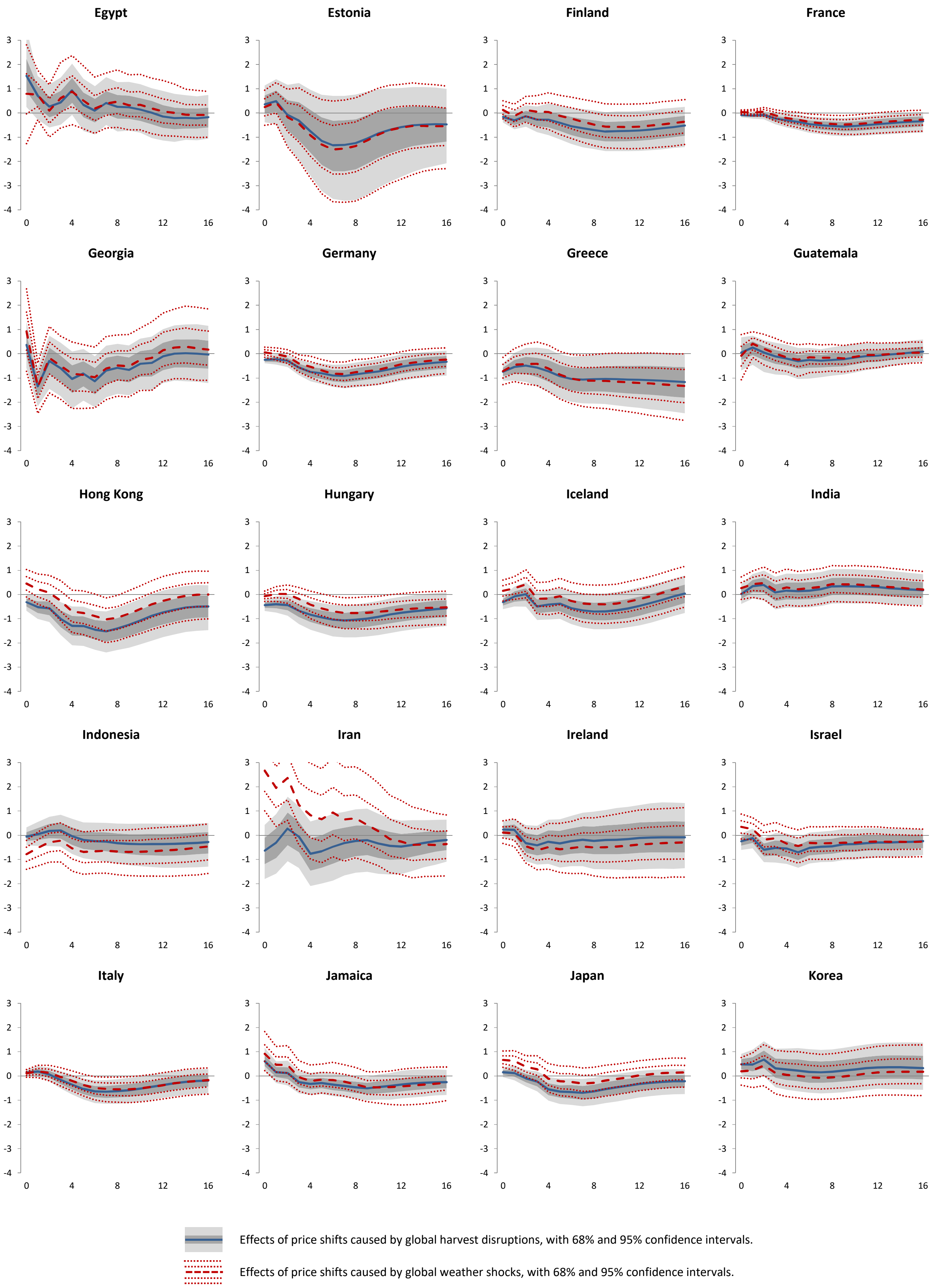


Figure A3 (continued) - Effects of 10% increase in global agricultural commodity prices on real GDP: individual countries

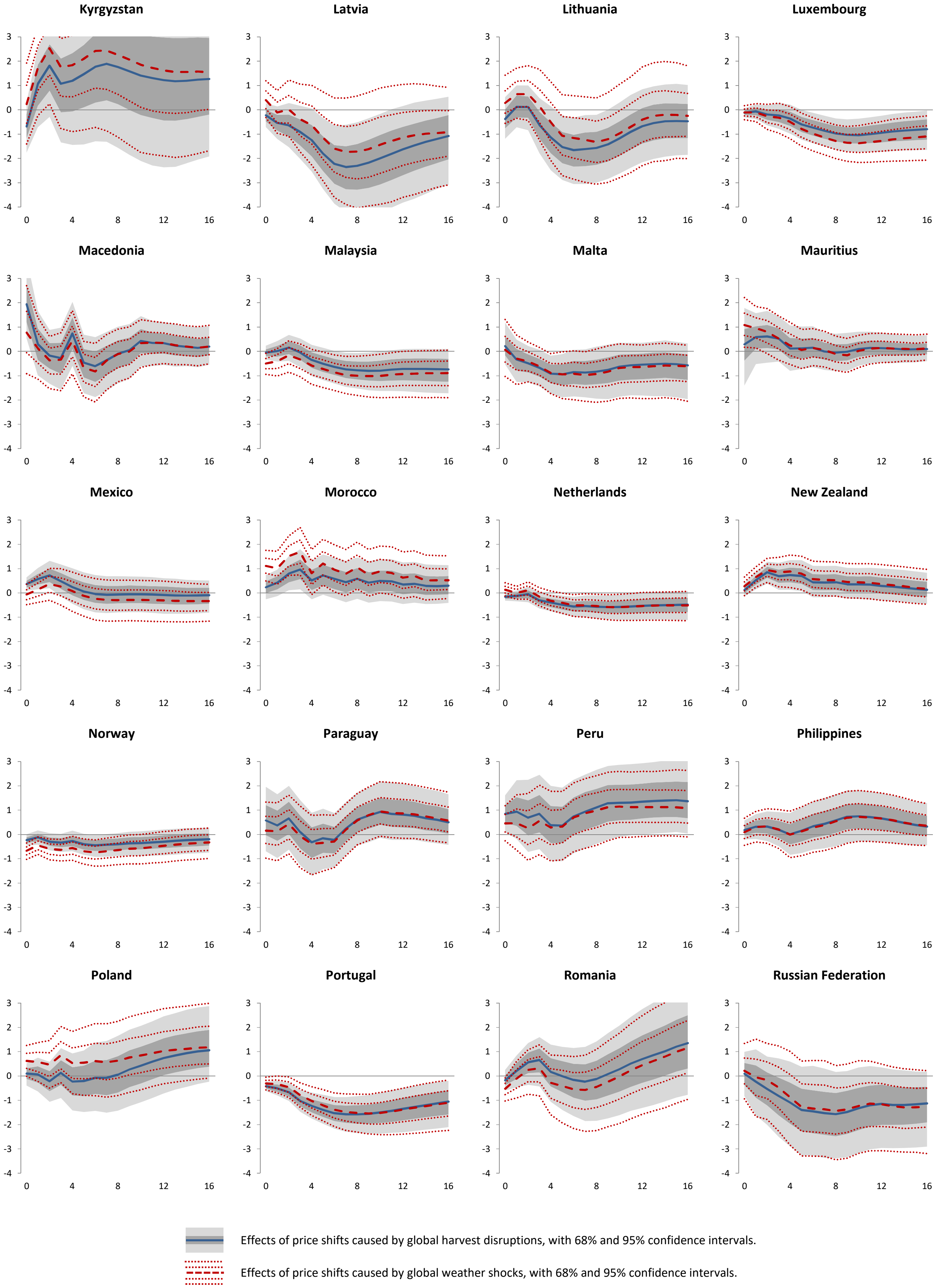
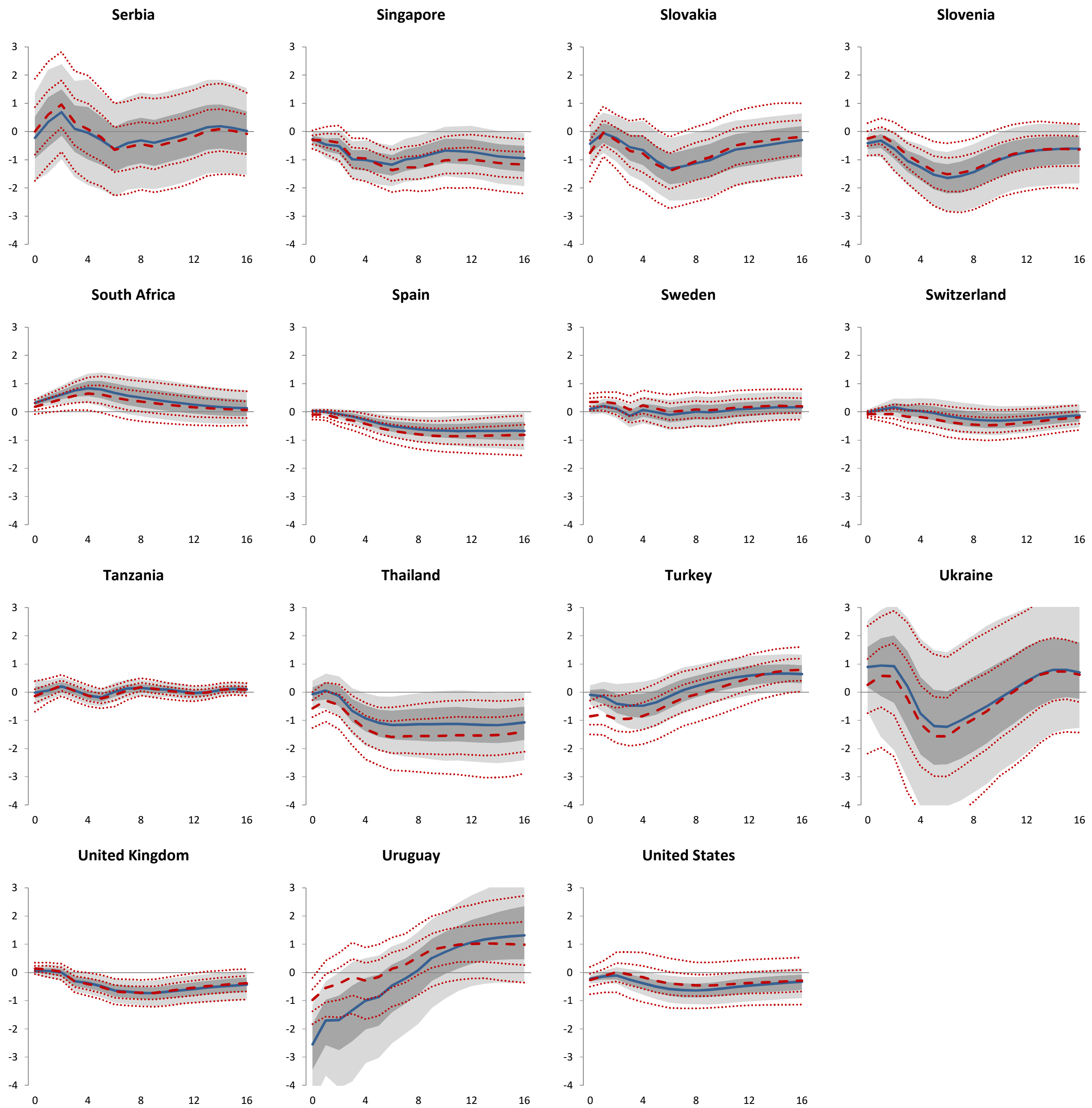


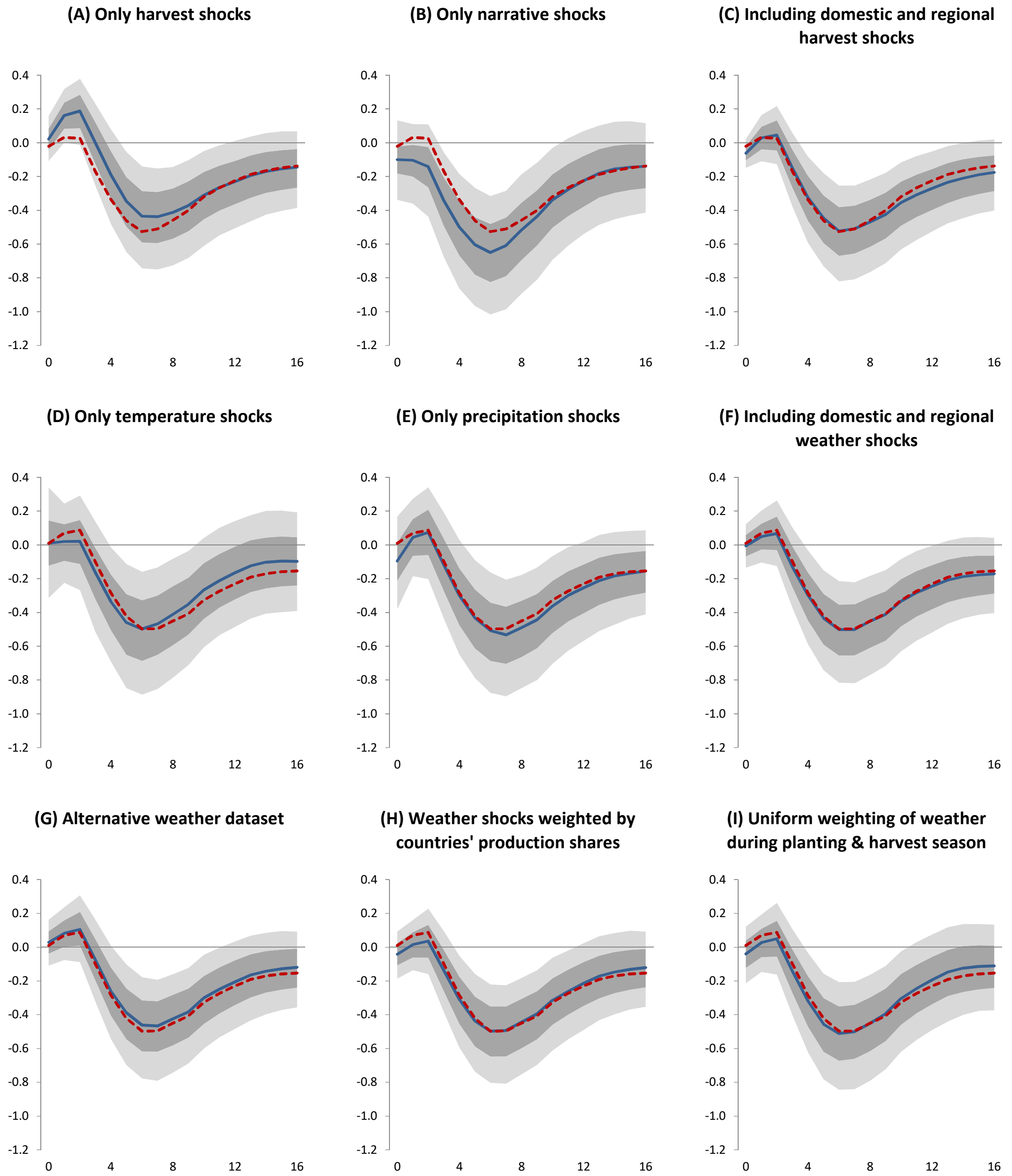
Figure A3 (continued) - Effects of 10% increase in global agricultural commodity prices on real GDP: individual countries



Effects of price shifts caused by global harvest disruptions, with 68% and 95% confidence intervals.

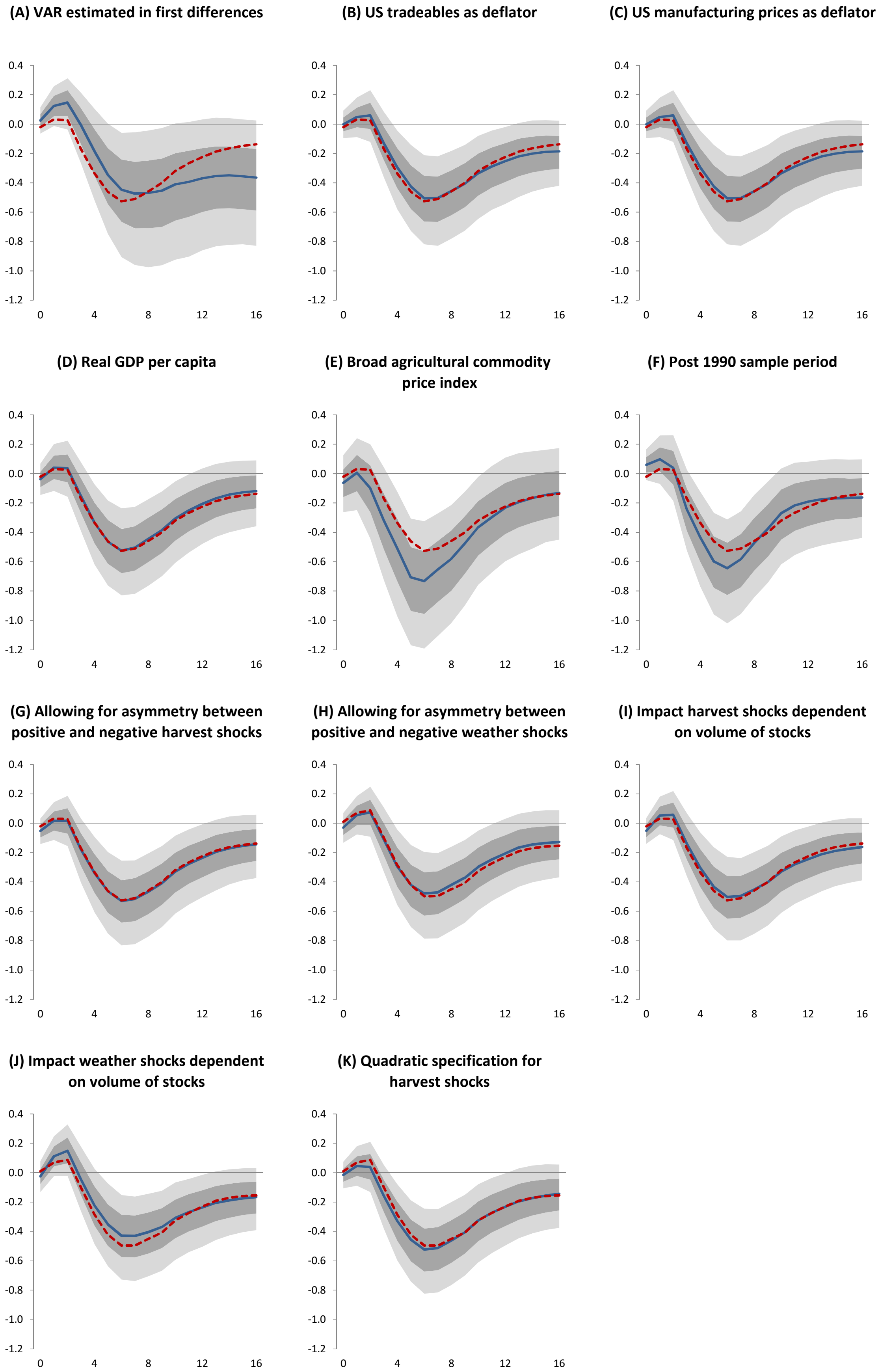
Effects of price shifts caused by global weather shocks, with 68% and 95% confidence intervals.

Figure A4 - Sensitivity analysis: choice and construction of the instrumental variables



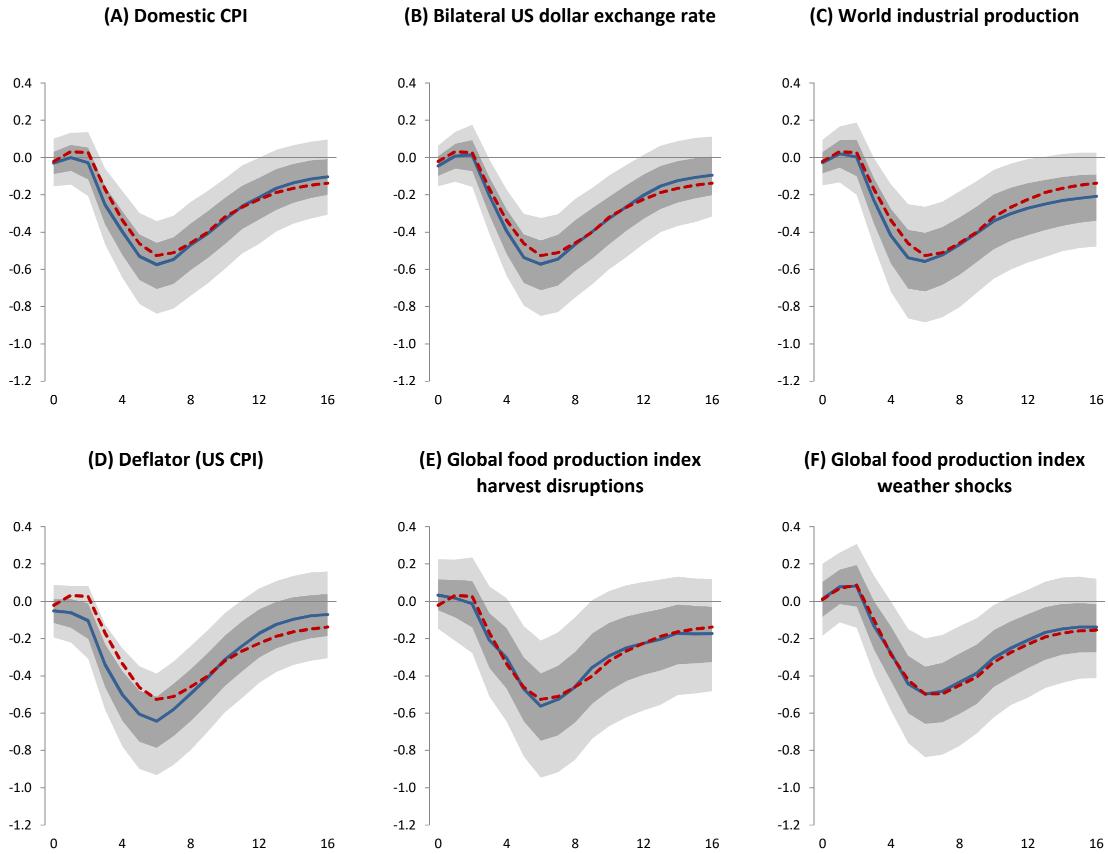
Impulse responses to a 10% increase in global agricultural commodity prices triggered by the shocks, with 68% and 95% confidence intervals. Horizon is quarterly. Results are based on 75 countries. Red dashed lines are the responses of the corresponding benchmark panel SVAR-IV.

Figure A5 - Sensitivity analysis: alternative SVAR-IV specifications



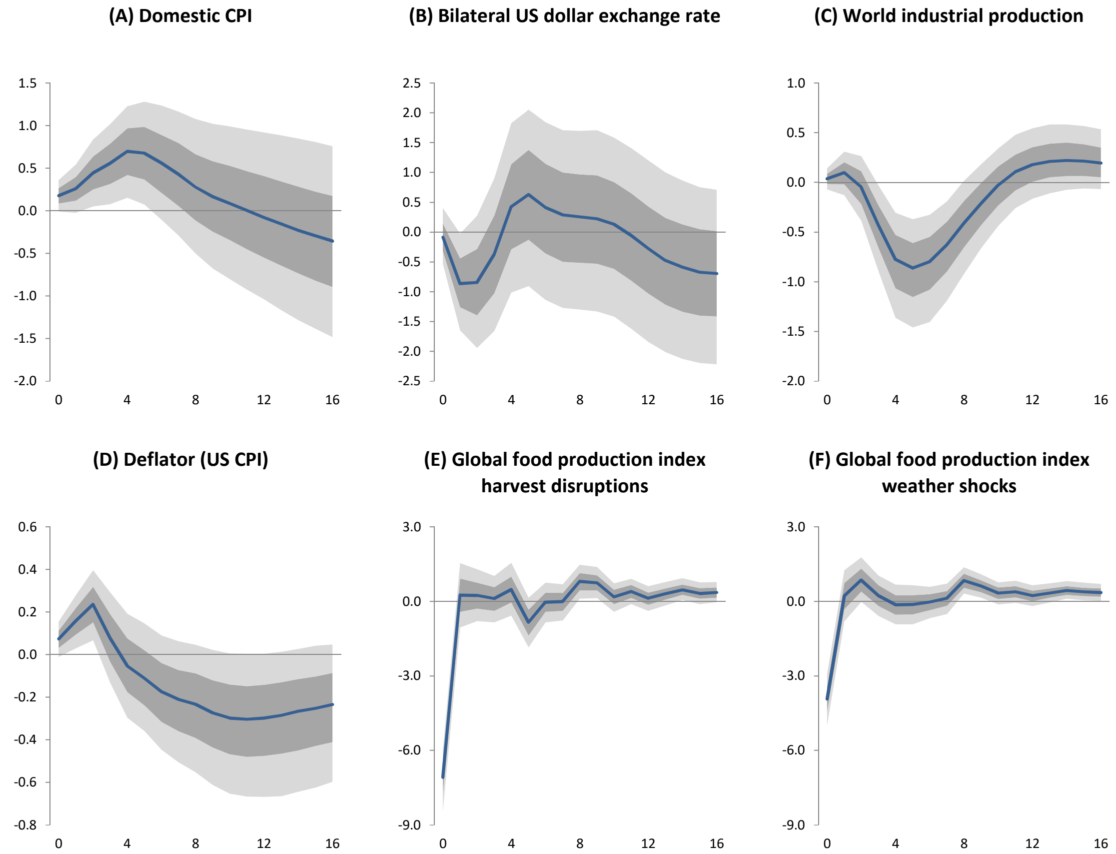
Impulse responses to a 10% increase in global agricultural commodity prices caused by harvest disruptions. 68% and 95% confidence intervals. Horizon is quarterly. Results are based on 75 countries. Red dashed lines are the responses of the corresponding benchmark panel SVAR-IV.

Figure A6 - Sensitivity analysis: benchmark SVAR-IV specification with additional variable



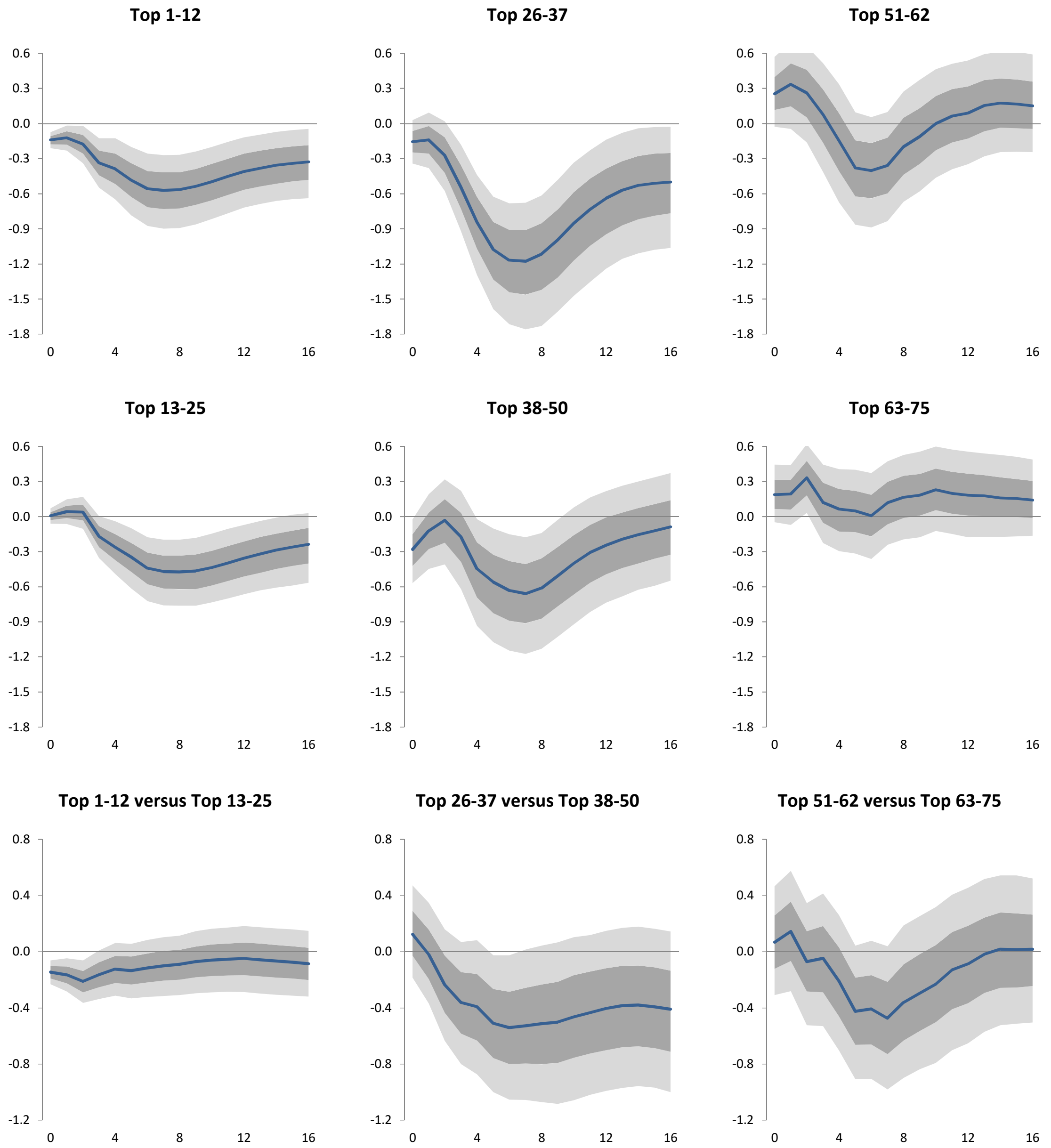
Impulse responses to a 10% increase in global agricultural commodity prices caused by harvest disruptions. 68% and 95% confidence intervals. Horizon is quarterly. Results are based on 75 countries. Red dashed lines are the responses of the corresponding benchmark panel SVAR-IV.

Figure A7 - Benchmark SVAR-IV specification with additional variable: impact on additional variable



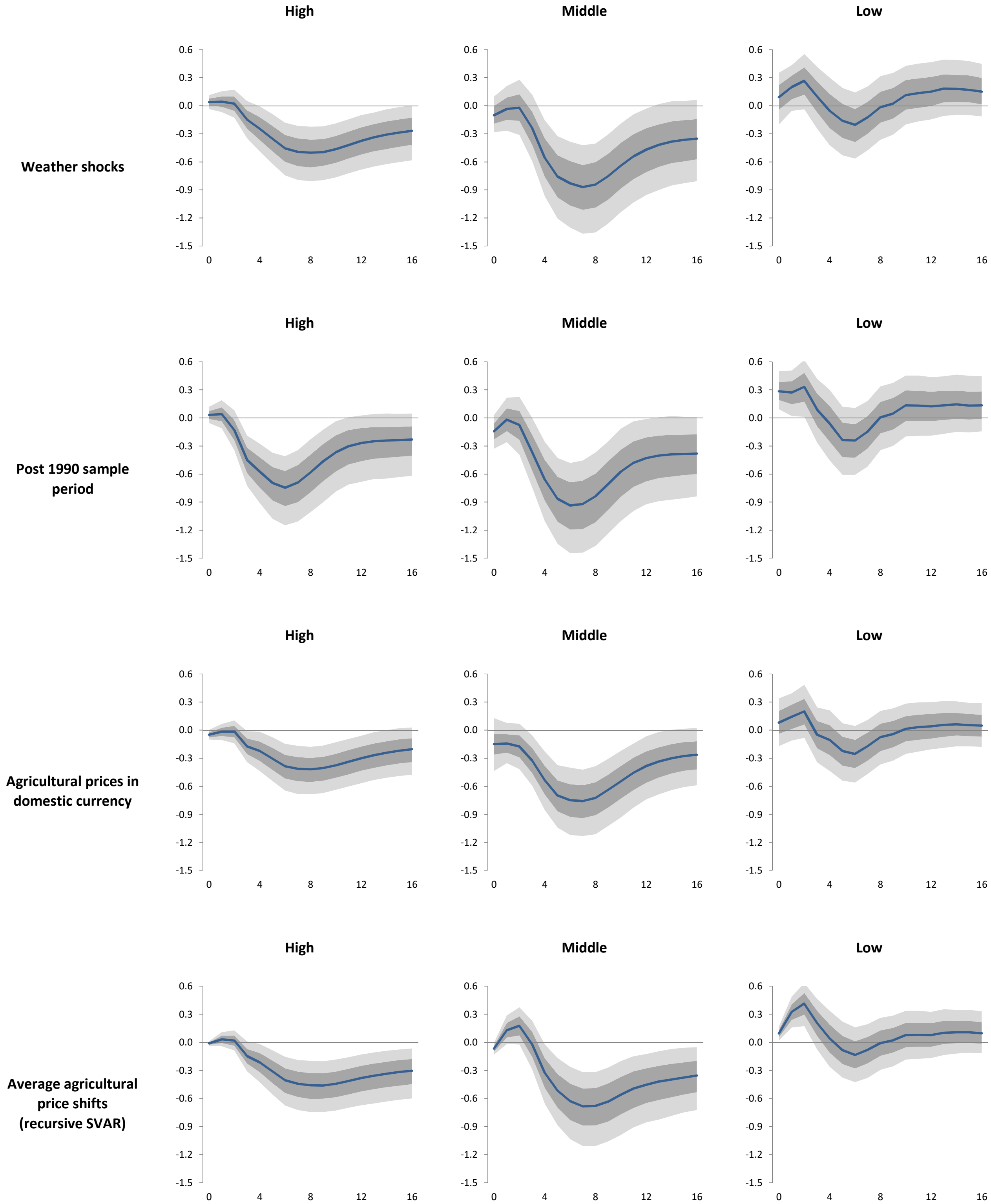
Impulse responses to a 10% increase in global agricultural commodity prices caused by harvest disruptions. 68% and 95% confidence intervals. Horizon is quarterly. Results are based on 75 countries.

Figure A8 - Effects in advanced versus poor countries: six country groups



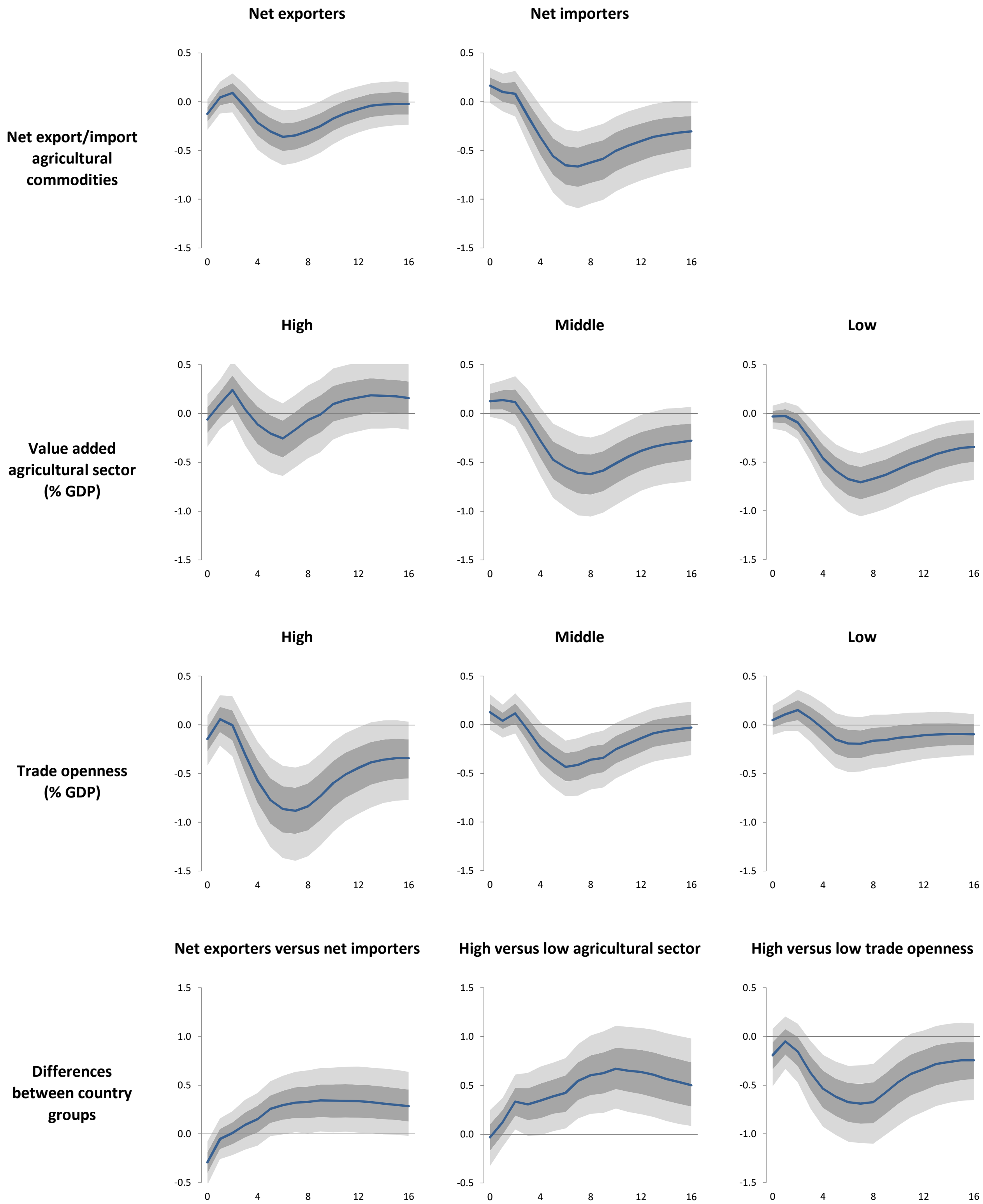
Impulse responses to a 10% increase in global agricultural commodity prices caused by harvest disruptions. 68% and 95% confidence intervals. Horizon is quarterly. Results are based on 75 countries.

Figure A9 - Effects in advanced versus poor countries: sensitivity analysis



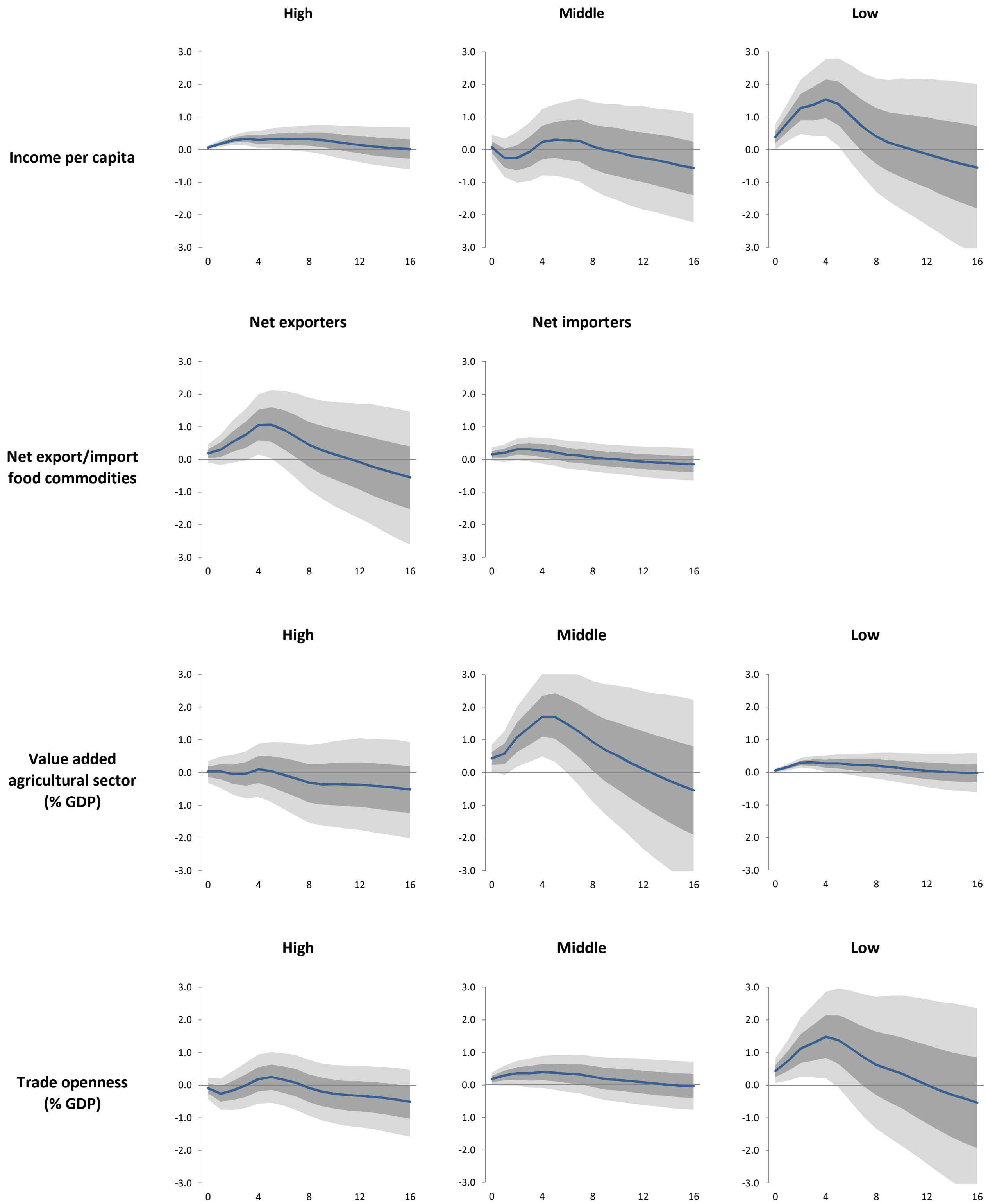
Impulse responses to a 10% increase in global agricultural commodity prices caused by harvest disruptions. 68% and 95% confidence intervals.
Horizon is quarterly. Results are based on 75 countries.

Figure A10 - Effects of agriculural price shifts caused by weather shocks: other characteristics



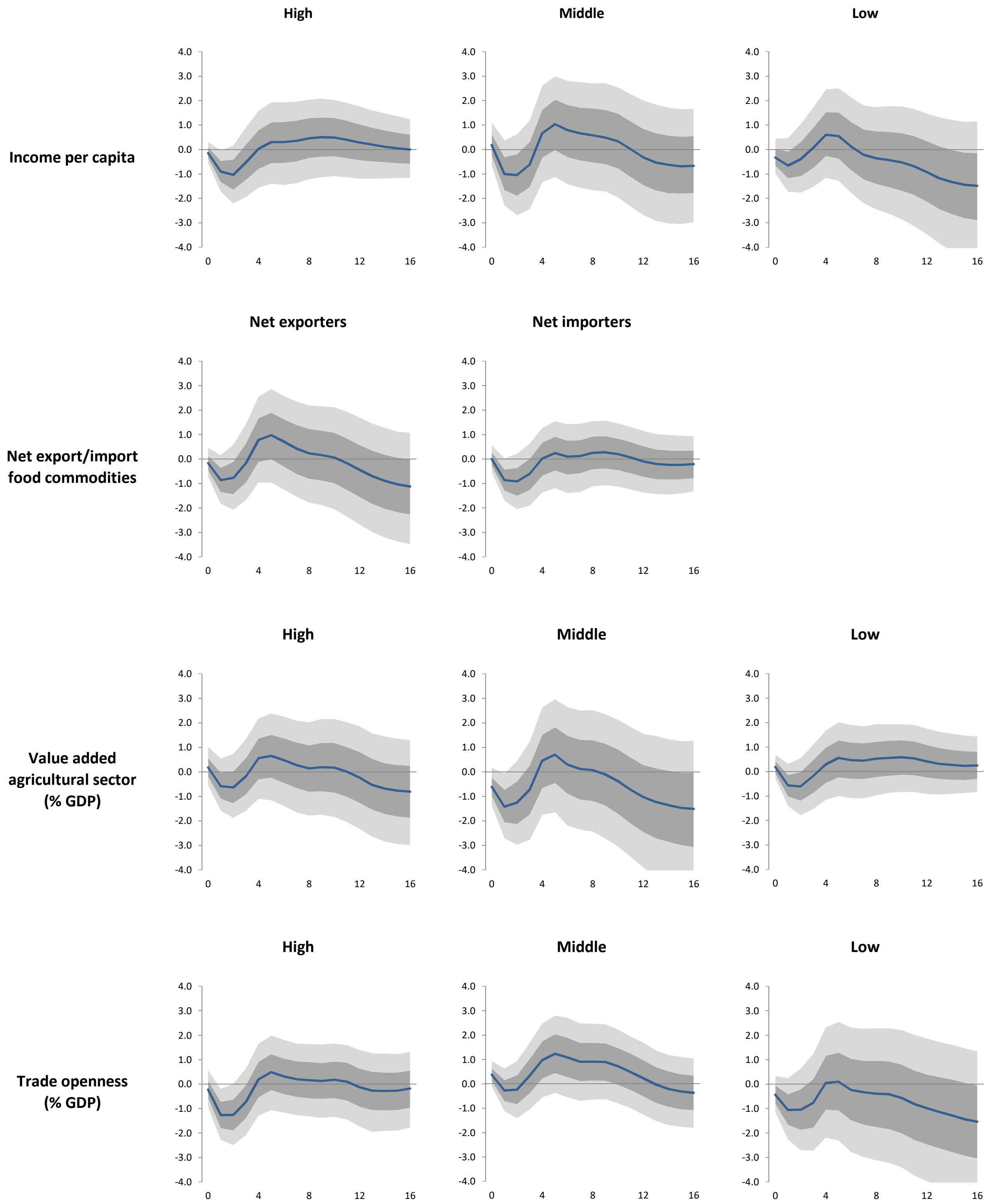
Impulse responses to a 10% increase in global agricultural commodity prices caused by weather shocks. 68% and 95% confidence intervals.
Horizon is quarterly. Results are based on 75 countries.

Figure A11 - Effects on domestic consumer prices



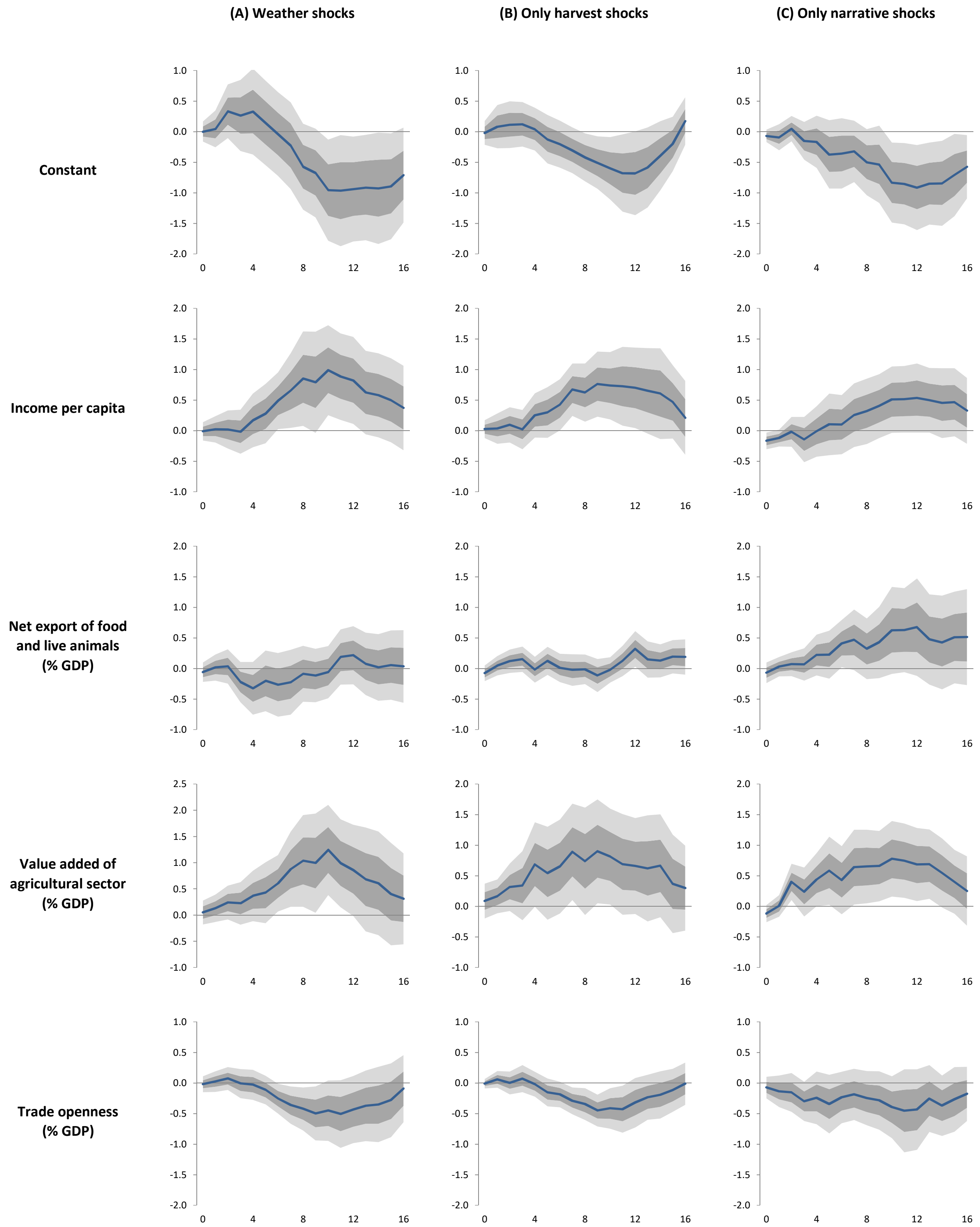
Impulse responses to a 10% increase in global agricultural commodity prices caused by harvest disruptions. 68% and 95% confidence intervals.
Horizon is quarterly. Results are based on 75 countries.

Figure A12 - Effects on bilateral US dollar exchange rates



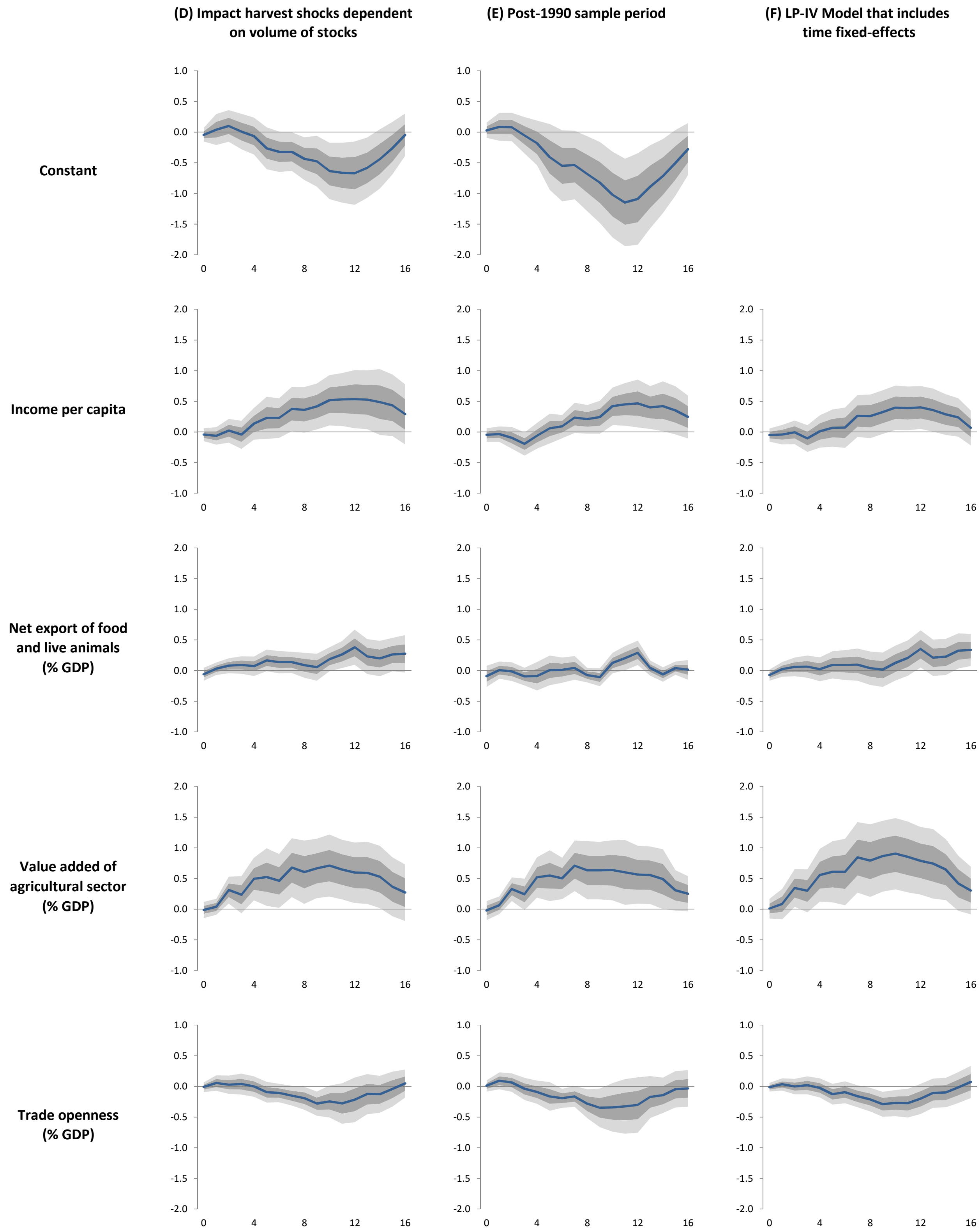
Impulse responses to a 10% increase in global agricultural commodity prices caused by harvest disruptions. 68% and 95% confidence intervals. Horizon is quarterly. Results are based on 75 countries.

Figure A13 - LP-IV estimations: sensitivity analysis



Impulse responses to a 10% increase in global agricultural commodity prices caused by global harvest disruptions. 68% and 95% confidence intervals that are adjusted for correlations between residuals across countries and serial correlation over time. The constant reflects the average effects for all countries, while the other panels show the additional impact on real GDP when a country characteristic deviates one-standard deviation from the sample mean.

Figure A13 (continued) - LP-IV estimations: sensitivity analysis



Impulse responses to a 10% increase in global agricultural commodity prices caused by global harvest disruptions. 68% and 95% confidence intervals that are adjusted for correlations between residuals across countries and serial correlation over time. The constant reflects the average effects for all countries, while the other panels show the additional impact on real GDP when a country characteristic deviates one-standard deviation from the sample mean.