International Food Commodity Prices and Missing (Dis)Inflation in the Euro Area

SUPPLEMENTARY APPENDIX

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Appendix A: Data

A1. Benchmark SVAR model data series

The euro/USD bilateral exchange rate, real GDP, real personal consumption, the short-term nominal interest rate and the HICP are collected from the ECB's Area-Wide Model dataset (awm19up17). The food commodity price index is collected from 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. The OECD Composite Leading Indicator has been 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 term potential level. Finally, the crude oil price index is the refiner acquisition cost of imported crude oil of the US Energy Information Administration.

A2. Unanticipated harvest shocks

The composite global food production index is constructed based on annual food production data from the Food and Agriculture Organization (FAO). For each of the four commodities (corn, wheat, rice and soybeans), the FAO publishes production volumes for 192 countries, which are available for the period 1961-2016. The production data, which are measured in ton, are first converted into edible calories. Relying on the country-specific planting and

harvesting calendars for each crop, De Winne and Peersman (2016) manage to assign two-thirds of world annual food production to a specific quarter, fulfilling the condition that the decision to produce (planting) did occur in an earlier quarter. For a more detailed description, see De Winne and Peersman (2016). In the present study, for each quarter, I aggregate the calories of all non-European countries and crops to obtain a quarterly global food production index excluding European harvests. After aggregating the quarterly production data across crops and countries, the quarterly global food production index is seasonally adjusted using the Census X-13 ARIMA-SEATS Seasonal Adjustment Program (method X-11).

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. Global oil production is obtained from the *Oil & Gas Journal* for the period before 1973, and from the U.S. Energy Information Administration afterwards (see also Baumeister and Peersman 2013). The OECD Composite Leading Indicator has been downloaded from the OECD online database, and the MSCI World Equity Price Index from Datastream. Before 1970, the equity price index has been backcasted based on the US S&P Composite Index (collected from Datastream).

The international cereal commodity price index is a production-weighted aggregate of the price series of corn, wheat, rice and soybeans, which are made available by the IMF. These benchmark prices are representative for the global market and determined by the largest exporter of each commodity. As in De Winne and Peersman (2016), the price series (in USD 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). Notice 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 USD per metric ton of milled rice. The food commodity price index has been seasonally adjusted using Census X-13 (X-11 option).

The Multivariate El Niño Southern Oscillation Index and the Oceanic Niño Index are provided by the Earth System Research Laboratory (https://www.esrl.noaa.gov/psd/enso/mei/, accessed August 2016). The former index is based on six different variables in order to measure El Niño/Southern Oscillation (ENSO), while the latter index is calculated by averaging sea surface temperature anomalies in an area of the east-central equatorial Pacific Ocean (the Nino-3.4 region).

A3. Robustness and sensitivity analysis

Aggregate real GDP of OECD countries is collected from the OECD database, the implied stock market volatility (VIX) from the Federal Reserve Bank of St-Louis (Fred) database and the Baker et al. (2016) Economic Policy Uncertainty Index from www.PolicyUncertainty.com. The narrative food commodity price shocks are from De Winne and Peersman (2016). The trade-weighted global price index and long-term interest rate are from the ECB Statistical Data Warehouse.

A4. Additional variables

The HICP-components are from Eurostat and downloaded from the ECB Statistical Data Warehouse. Before 1996, the components are a weighted average of the eleven initial euro area members states and Greece. Inflation expectations (SPF) are also collected from the ECB Statistical Data Warehouse. For each quarter, I use one-year-ahead inflation expectations. The qualitative measure of price expectations is collected from Eurostat. The nominal effective exchange rate, import deflator, export deflator, GDP deflator, unit labor costs, unit profits, unit taxes and nominal wage per head are from the Area-wide Model dataset. The price-wage ratio is the (log) difference between the GDP-deflator and unit labor costs. Finally, the individual country data are collected from the OECD Main Economic Indicators database.

A5. Share of Food Commodities in Household Expenditures

The share of food commodities in total household consumption expenditures (4.8%) is based on the Eurostat economic accounts for agriculture, Eurostat's external trade statistics and the European Market Observatory for Fisheries and Aquaculture Products. Data are available for the period 2005-2018. The share has been calculated as follows:

Consumption of agricultural commodities = agricultural goods output (sum of crop and animal output) - feedingstuffs used as intermediate consumption (own and obtained from agricultural sector) - seeds and planting used as intermediate consumption (own and obtained from agricultural sector) + net import of agricultural goods (sum of crops and animals).

The share of food commodities in total household consumption expenditures is the sum of agricultural commodities and fisheries & aquaculture products, divided by total household consumption expenditures, where:

Consumption of fishery and aquaculture commodities = fish production + net import of fish and other fishing products.

Notice that *net* imports of *processed* food, fish and beverages (which is not included in the calculation of the share since it requires assumptions about the share of food commodities in processed food) is on average close to zero.

The share of imported food commodities in household expenditures (1.1%) is calculated as follows:

Imported food commodities = import of agricultural goods (sum of crops and animals) + import of fish and other fishing products + import of processed food and fish.

For *processed* food and fish imports, I assume that 75% of the imported values are commodities. This percentage is a bit arbitrary (due to lack of data), but corresponds to estimates of the USDA for the US. When I lower this share to 50%, the share of imported commodities in household expenditures decreases to 0.9%.

A6. EU food commodity price index

The construction of the index of domestic (EU) food commodity prices is based on data from DG AGRI of the European Commission. The dataset puts together series of farm-gate and wholesale market prices from 1991 onward. The index is a weighted average of cereals (23.4%), animals (46.2%) and animal products (30.4%) commodity prices. The weights are based on the period 1999-2019 and collected from the Eurostat economic accounts for agriculture. Together, these components cover 57% of EU agricultural goods output. The main components of agricultural goods output that are missing due to lack of data are vegetables, wine and fruit.

Cereal commodity prices are, in turn, an unweighted average of the price series (i.e. an index of the price series normalized to the same base year) of bread wheat, feed wheat, feed barley, malting barley, durum wheat, bread rye, feed rye, feed maize and feed oats. Similarly, animal commodity prices are an unweighted average of beef (cows), pork (piglets) and chicken prices, while animal products commodity prices are an unweighted average of the prices of (raw) milk, butter, cheese (cheddar) and eggs. The reason why the prices are unweighted is lack of data for the volumes.

Appendix B: Food Production Index and Harvest Shocks

Panel A of Figure A1 shows the time series of the global food production index, which excludes European harvests. Panel B shows the time series of the unanticipated harvest shocks, which is used as an external instrument to identify exogenous international food commodity price shocks.

Appendix C: Historical Contributions for Full Sample Period

Figure A2 shows the historical contribution of international food commodity price shocks on international food commodity prices, (year-on-year) HICP inflation and (year-on-year) real GDP growth for the full sample period, together with confidence intervals. The latter are constructed based on different realizations of the VAR coefficients from the bootstrap exercise, which are used to compute alternative historical decompositions.

Appendix D: Sensitivity and Robustness of Benchmark Results

D1. The Use of an External Instrument

To investigate whether the use of an external instrument to identify food commodity price shocks matters, Figure A3 compares the baseline impulse responses with those that are obtained by assuming a lower triangular contemporaneous impact matrix B in equation (2), which corresponds to a Cholesky decomposition of the variance-covariance matrix of the reduced-form residuals. This is the recursive identification strategy that is usually used in the literature. It implicitly assumes that all (reduced-form) food commodity price innovations are exogenous shocks. Such estimates likely represent a mixture of exogenous food market disturbances and endogenous responses to other shocks in the economy. In essence, the estimated impulse responses reflect the dynamics of the variables included in the VAR after an "average" shift in food commodity prices over the sample period.

Figure A3 compares the impulse responses of some key variables for both identification strategies. The figure also shows the difference between the impulse response functions, together with confidence intervals. The latter can be constructed because both identification methods are based on the same reduced-form VAR. Hence, for each bootstrap replication, it is possible to calculate the difference between both responses. As can be observed in the figure,

the use of an external instrument indeed matters for the results. More specifically, the impact on the HICP of an exogenous food commodity price shock that is identified with the external instrument turns out to be twice as large as the impact of an average food commodity price innovation. In contrast to the benchmark results, a recursively identified food commodity price innovation is associated with an appreciation of the euro against the US dollar, and a significant rise of oil prices on impact.

D2. Construction and choice of the Instrumental Variable

Figure A4 summarizes the sensitivity of the results for the construction and choice of the instrumental variable, in particular (i) when I include European harvests in the global food production index, (ii) when I include the global economic policy uncertainty index of Baker et al. (2016) and the VIX as additional control variables in equation (5), (iii) when I allow for an immediate effect of all the control variables (except food commodity prices, for obvious reasons) on harvest volumes, (iv) when I use the narrative food commodity price shocks of De Winne and Peersman (2016) as an alternative instrumental variable, and (v) when I use both the harvest and narrative shocks as external instruments.

The magnitudes of the effects, contribution to the forecast error variance and historical contribution to the HICP are very similar to the benchmark results. The impact on the HICP and variance decomposition appears to be less persistent for the narrative shocks.[1] A caveat of this robustness check is that the first-stage F-statistic and robust F-statistic of the instrument are only 5.3 and 2.9, respectively, which could imply that the results are distorted due to weak instrument issues. This is reflected in the (90%) confidence intervals.

Finally, it is important to mention that the results are also not sensitive to the choice of the control variables, number of lags or sample period that is used to estimate equation (5).

D3. Alternative SVAR-IV Specifications

Figure A5 shows the robustness of the results for several perturbations to the benchmark VAR model. First, the benchmark VAR model is estimated in (log) levels. Sims et al. (1990)

[1] De Winne and Peersman (2016) rely on FAO reports, newspaper articles and several other sources to identify historical episodes in which major changes in food commodity prices were mainly caused by exogenous food commodity market disruptions. By converting the episodes to a dummy variable series, which is equal to 1 and -1 for respectively positive and negative shocks, these episodes can be used as an external instrument. In line with the construction of the harvest shocks, extreme weather events that could have had a direct influence on the European economy are excluded.

demonstrate that a log levels specification gives consistent estimates when the variables have stochastic trends and are cointegrated.[2] A caveat of a specification in levels is that the results could be distorted because initial conditions explain an implausibly large share of the low-frequency variation in the variables; that is, the VAR could attribute an unreasonably large share of the variation in the data to a deterministic component (Sims 2000). Notice that this is probably not the case for the benchmark results because, as shown in Figure 4, there is very little variation in the baseline (deterministic) projection of the variables implied by the VAR. To further address this issue, the first row of Figure A5 shows the results when the benchmark VAR 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. The results reveal that the impact on the HICP is stronger when the VAR is estimated in first differences, whereas the contribution to the variance is more subdued than the benchmark results. There is also a larger contribution of food commodity price shocks to the missing disinflation in the period 2009-2012; that is, more than 1%.

The second row shows the results when I use a narrow food commodity price index; that is, a weighted average of the prices of corn, wheat, rice and soybeans. This index of cereal prices corresponds directly to the instrumental variable. The instrumental variable is again strong (F-statistic and robust F-statistic of 19.3 and 28.9, respectively). The impact of a one-percent rise in the cereal price index has a more subdued impact on the HICP, while the shocks explain less of the forecast error variance of the HICP. This is not surprising since the shocks capture only a sub-component of the IMF broad food commodity price index. Nevertheless, exogenous changes in cereal prices seem to have been very important for the missing (dis)inflation puzzles.

The third row shows the results when I include actual real GDP of OECD countries instead of the CLI in the benchmark VAR model. The decline of real GDP and personal consumption turns out to be more sluggish (not shown in the figure), while the inflationary effects are stronger. In addition, food commodity price shocks explain 40%-45% of inflation volatility over the medium term. It appears that the OECD CLI contains information about changes in (future) aggregate demand that is not captured by crude oil price innovations, actual real GDP or the other variables in the VAR. In particular, when the CLI is not included in the VAR model, these changes seem to be partly absorbed by food commodity price shocks.

The fourth row shows the results when the benchmark VAR model is estimated over the sample period 1990Q1-2016Q4. The effects on the HICP are less persistent and become

[2]Elliott (1998) shows that explicitly imposing the unit root and cointegration relationships could lead to large distortions in the results. The estimation of the VAR in log levels is thus the safest approach.

statistically insignificant in the long run. On the other hand, the contribution of international food commodity market shocks to the HICP forecast error variance is much higher (even more than 60%). The larger contribution to the variance can be explained by the fact that the total variance of the HICP has declined over time, as well as the effects of all other macroeconomic shocks on the HICP. Accordingly, the relative contribution of the shocks increases.

Finally, the bottom row of Figure A5 shows the effects when the harvest shocks are directly included in the VAR model; that is, a Cholesky identification with the external instrument ordered first in the VAR. Plagborg-Moller and Wolf (2019) show that, under some regularity conditions, the shapes of the impulse responses are asymptotically the same. Indeed, Figure A5 reveals that the effects on the HICP are very similar. The contribution of the shocks to euro area inflation volatility is, however, substantially lower (i.e. less than 10%). The reason is that the harvest shocks represent only a subset of food market disturbances. Hence, when the instrument is included in the VAR, only this subset is taken into account for the variance and historical decompositions. In contrast, when the harvest shocks are used as an external instrument, the target shocks capture all exogenous food commodity market shocks. This illustrates that it is important to use the shocks as an external instrument to measure the relevance of food commodity price disturbances for inflation dynamics. On the other hand, the harvest shocks still explain a lot of the missing (dis)inflation puzzles, which suggests that the rise and fall in food commodity prices in this period was predominantly caused by the unexpected harvest shocks.

D4. Benchmark VAR with Additional Variables

Figure A6 shows the results when the benchmark VAR model is re-estimated with an additional variable. These additional variables are (i) the global economic policy uncertainty index of Baker et al. (2016), (ii) the MSCI global equity price index, (iii) a trade-weighted index of global real GDP, (iv) the global industrial production index (v) a global (trade-weighted) price index , and (vi) euro area long-term nominal interest rates. In general, the results are robust for these extensions. Figure A6 also depicts the effects of international food commodity price shocks on the additional variables. The results reveal that there is a rise in the economic policy uncertainty index, a significant fall in the MSCI world equity price index, a decline in trade-weighted global real GDP, a rise in global inflation, a temporary rise of nominal long-term interest rates, while the impact on global industrial production is

statistically insignificant for the first 12 quarters.[3]

Appendix E: Effects of Oil Price Shocks

Figure A7-A9 summarize the results of the effects of oil price shocks that are identified with an external instrument within the same VAR model; that is, simultaneously with the food commodity price shocks. The external instrument is obtained from Kanzig (2018), who uses variation in futures prices around OPEC announcements as an instrument for oil supply news shocks. The F-statistic and robust F-statistic are 78.2 and 53.7, respectively. The correlation between the target oil and food commodity price shocks is 0.05, which confirms that the identified food shocks are unrelated to oil price innovations. The correlation between both instruments is also 0.05. As can be observed in Figure A7, an oil price shock triggers a significant rise in global food commodity prices. In contrast to food commodity price shocks, the oil price shock triggers an appreciation of the euro against the USD, which is consistent with the depreciation of the nominal effective USD documented in Kanzig (2018). There is a persistent decline of real GDP.

The effect of a one-percent rise in crude oil prices on the HICP turns out to be much more subdued than a rise in international food commodity prices; that is, 0.02% at its peak, while oil price shocks explain a lower share of HICP volatility; that is ±20% in the medium term (see Figure A8). Notably, oil price shocks also made a relevant contribution to the missing disinflation in 2009-2012, and particularly the missing inflation since 2015. This is shown in the left panel of Figure A9. Overall, as can be observed in the right panel of Figure A9, both shocks together made a substantial contribution to the twin puzzle of inflation in the era after the Great Recession. In particular, inflation would have been below target in the period 2009-2012 without the shocks, and even temporarily above target in 2015.

Finally, when I use the effects of an oil price shock to "switch-off" the oil price increase after a food commodity price shock, the impact of food commodity price shocks on the HICP is 0.01% lower at the peak, as well as in the long run. Put differently, the contribution of the oil price increase to the HICP response is at most 0.01%.

[3]The impact on global industrial production becomes significantly positive after three years, which is a bit surprising and difficult to explain.

Appendix F: Relative Effects versus the US

To shed more light on the depreciation of the euro against the USD, Figure A10 shows the results when I re-estimate the baseline VAR model for relative variables. Specifically, I replace (log) real GDP, real personal consumption, nominal interest rate and HICP in the benchmark VAR model by the (log) differences of the variables relative to the US. As shown in the figure, the nominal interest rate increases 7 basis points more in the US. Furthermore, whereas the impact of food commodity price shocks on consumer prices is initially quite similar (even slightly stronger in the US), the effects in the euro area are significantly stronger in the long run (6 basis points). In particular, in contrast to the euro area, food commodity price shocks have only a temporary impact on consumer prices in the US. The latter finding is consistent with De Winne and Peersman (2016). In addition to the fact that the US is a net food commodity exporter and the euro area a net importer, the more aggressive monetary policy response in the US and the stronger long-run rise of consumer prices in the euro area can potentially explain the deprecation of the euro against the dollar. On the other hand, Figure A10 suggest that the decline of economic activity is larger in the US.

Appendix g: Some Individual Country Results

Figure A11-A14 show some detailed results for the individual member states. Specifically, Figure A11 shows the impulse responses of consumer prices to a one-percent increase in international food commodity prices. The peak and long-run effects of these responses are reported in Table 2 of the paper. Figure A12 shows the effects on import prices (import deflator), the GDP deflator and unit labor costs. The peak-effects are also reported in Table 2. Figure A13 shows the differences of these responses relative to the area-wide effects, together with confidence intervals. Finally, Figure A14 shows the scatter plots of the peak effects, which corresponds to the correlations reported in Table 2 of the paper.

References

Baker, S., N. Bloom, and Davis S. (2016) "Measuring Economic Policy Uncertainty," *Quarterly Journal of Economics*, Vol. 131, pp. 1593–1636.

Baumeister, Christiane and Gert Peersman (2013) "The Role of Time-Varying Price Elasticities in Accounting for Volatility Changes in the Crude Oil Market," *Journal of Applied Econometrics*, Vol. 28, pp. 1087–1109.

De Winne, J. and G. Peersman (2016) "The Macroeconomic Effects of Disruptions in Global Food Commodity Markets: Evidence for the United States," *Brookings Papers on Economic Activity*, pp. 183–286.

Elliott, Graham (1998) "On the robustness of cointegration methods when regressors almost have unit roots," *Econometrica*, Vol. 66, pp. 149–158.

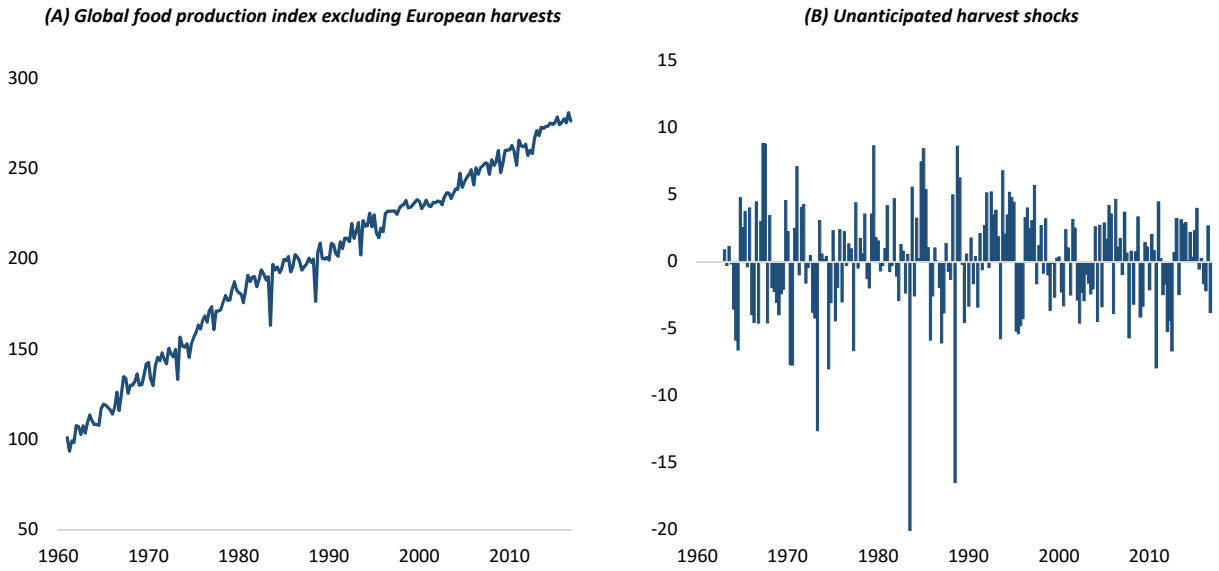
Kanzig, D. (2018) "The macroeconomic effects of oil supply news: Evidence from OPEC announcements," *London Business School Working Paper*.

Plagborg-Moller, M. and C. Wolf (2019) "Local Projections and VARs Estimate the Same Impulse Responses," *Princeton University Working Paper*.

Sims, Christopher A. (2000) "Using a likelihood perspective to sharpen econometric discourse: Three examples," *Journal of Econometrics*, Vol. 95, pp. 443–462.

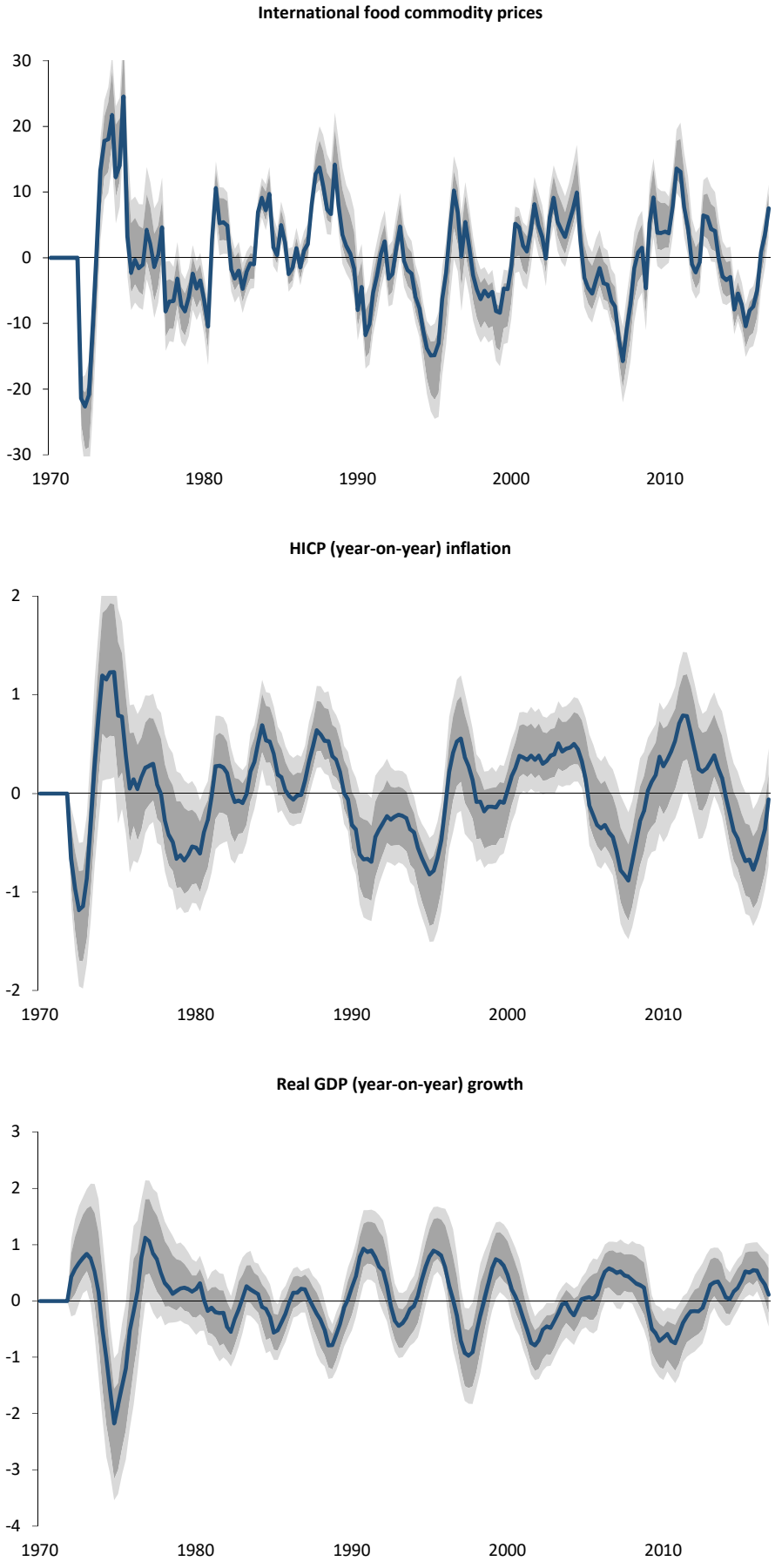
Sims, Christopher A., James H. Stock, and Mark W. Watson (1990) "Inference in Linear Time Series Models with some Unit Roots," *Econometrica*, Vol. 58, pp. 113–144.

Figure A1 - Global food production index excluding European harvests and unanticipated harvest shocks



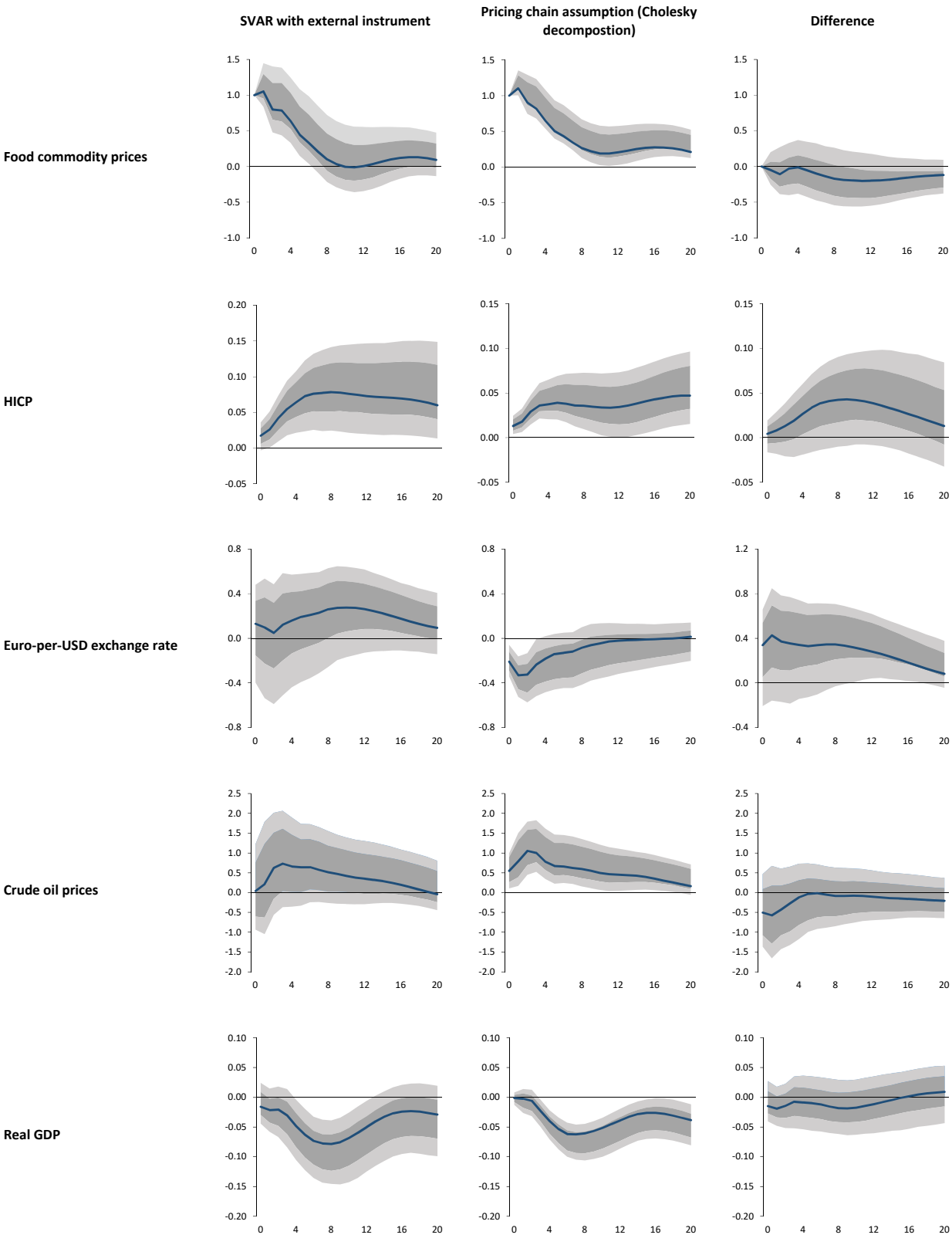
Note: Panel (A) shows 100 times the natural log of the food production index excluding European harvests; the production index aggregates the harvests of corn, wheat, rice and soybeans, and is seasonally adjusted.
Panel (B) shows the estimated unanticipated harvest shocks (percentage points changes in the food production index).

Figure A2 - Contribution of international food commodity price shocks: full sample



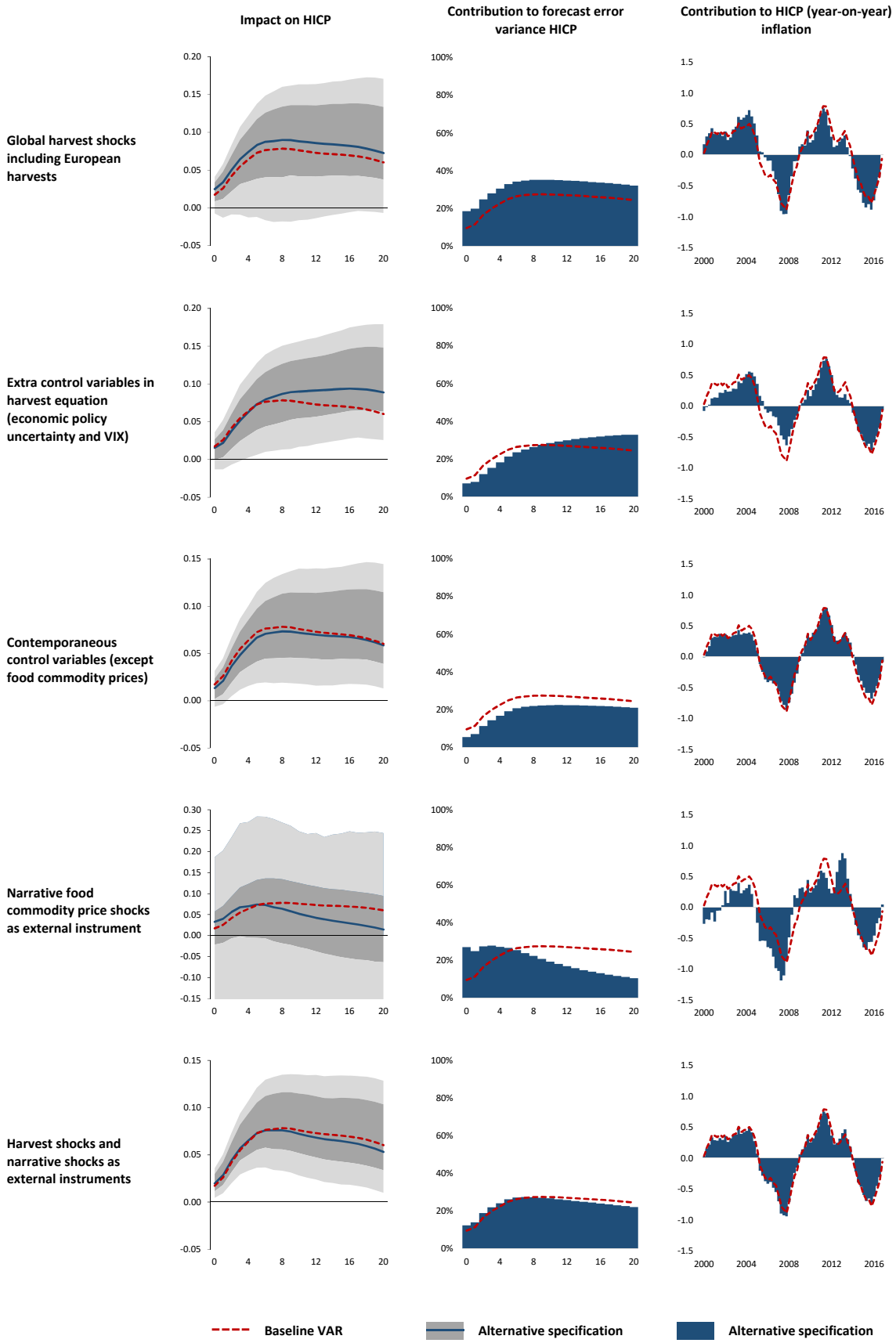
Note: 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly

Figure A3 - Difference between SVAR identified with an external instrument and a Cholesky decomposition



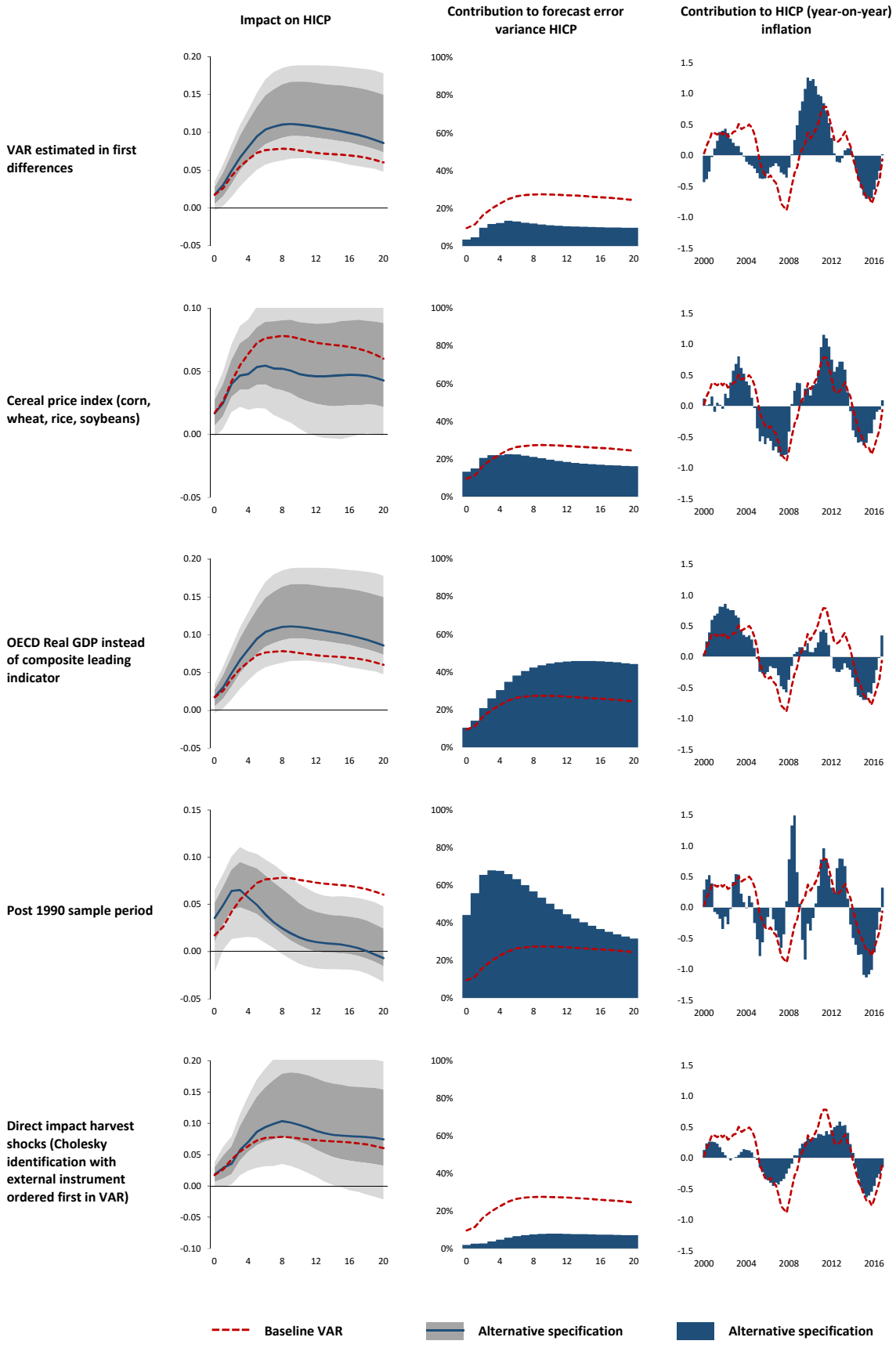
Note: Impulse responses are only shown for some key variables; 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly.

Figure A4 - Sensitivity of benchmark results: construction of the external instrument



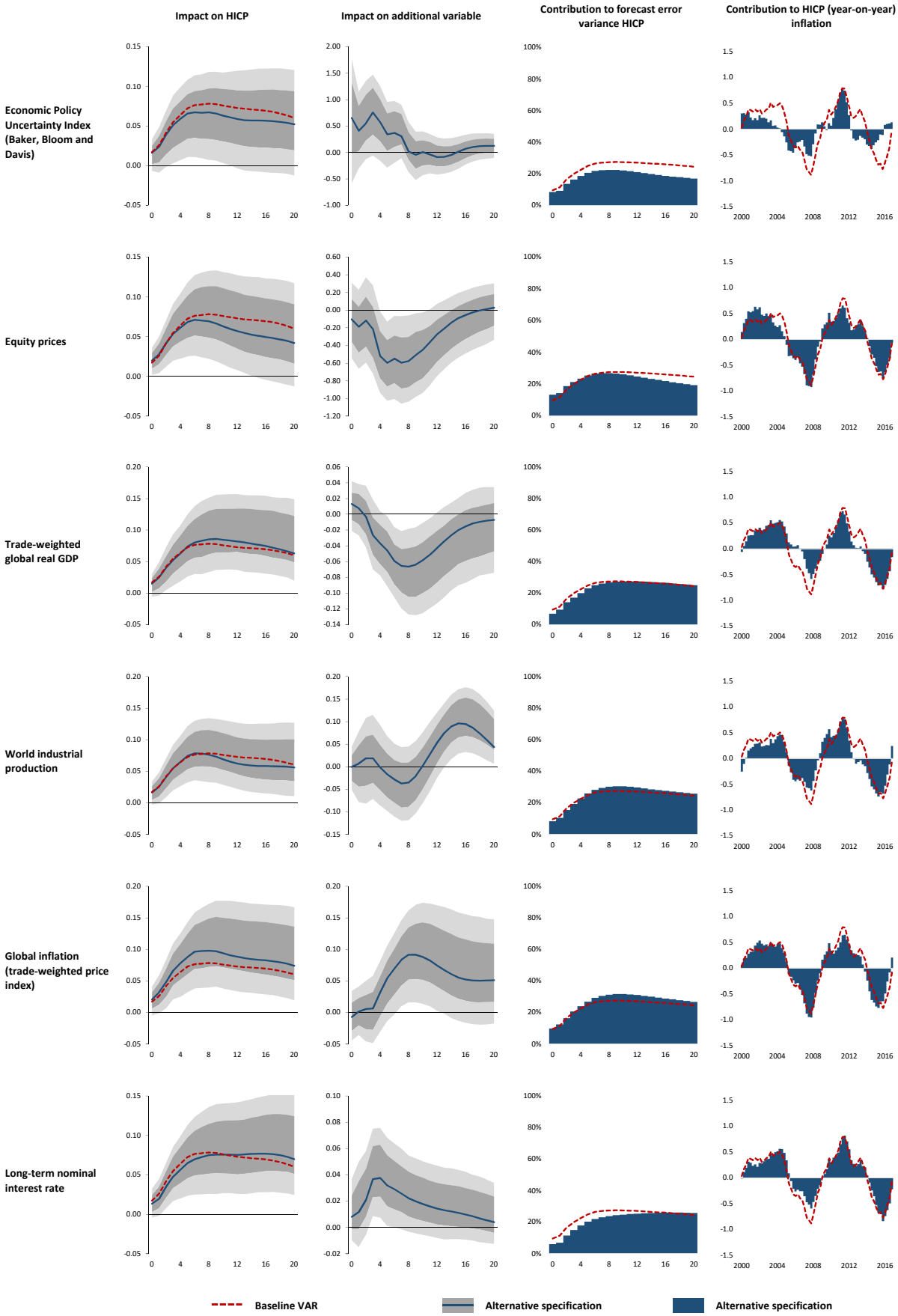
Note: Impulse responses, variance decompositions and historical contributions are only shown for the HICP and inflation; 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly.

Figure A5 - Sensitivity of benchmark results: alternative VAR specifications



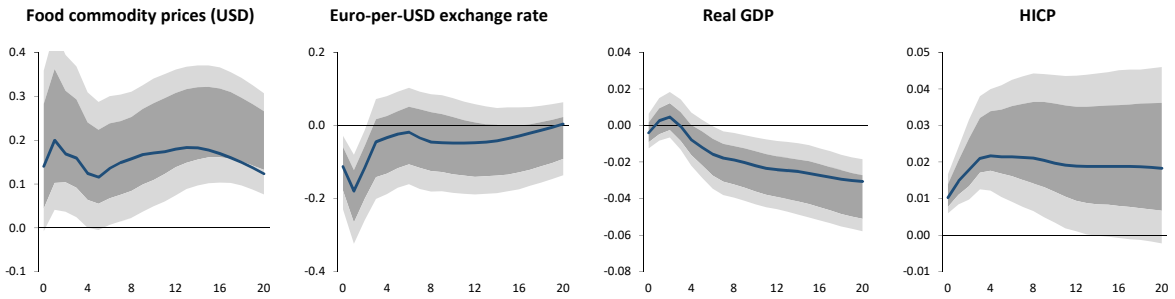
Note: Impulse responses, variance decompositions and historical contributions are only shown for the HICP and inflation; 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly.

Figure A6 - Sensitivity of benchmark results: VAR with additional variables



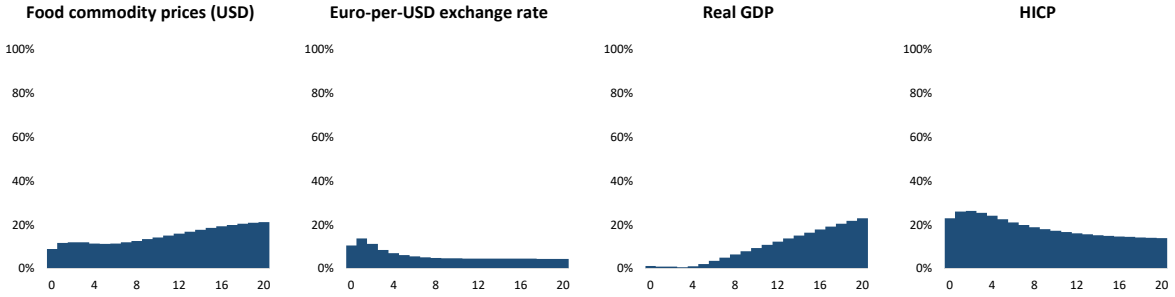
Note: Impulse responses, variance decompositions and historical contributions are only shown for the HICP and inflation; 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly.

Figure A7 - Effects of a 1% increase in international crude oil prices



Note: 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly.

Figure A8 - Contribution of crude oil price shocks to forecast error variance decompositions



Note: horizon is quarterly.

Figure A9 - Counterfactual evolution of HICP inflation without oil and food commodity price shocks

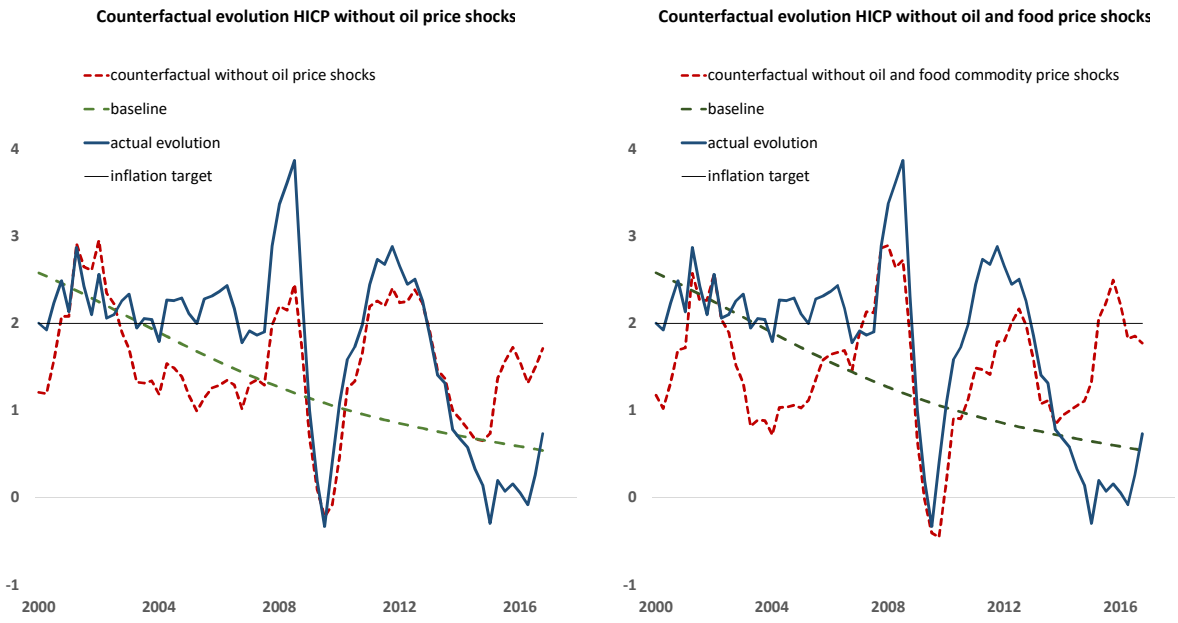
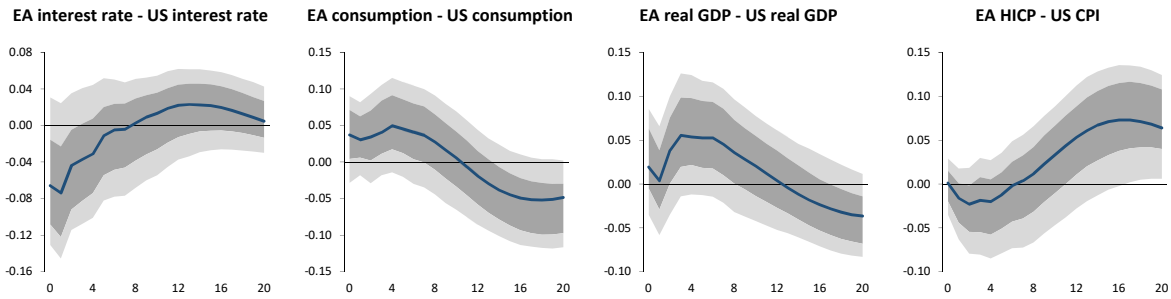
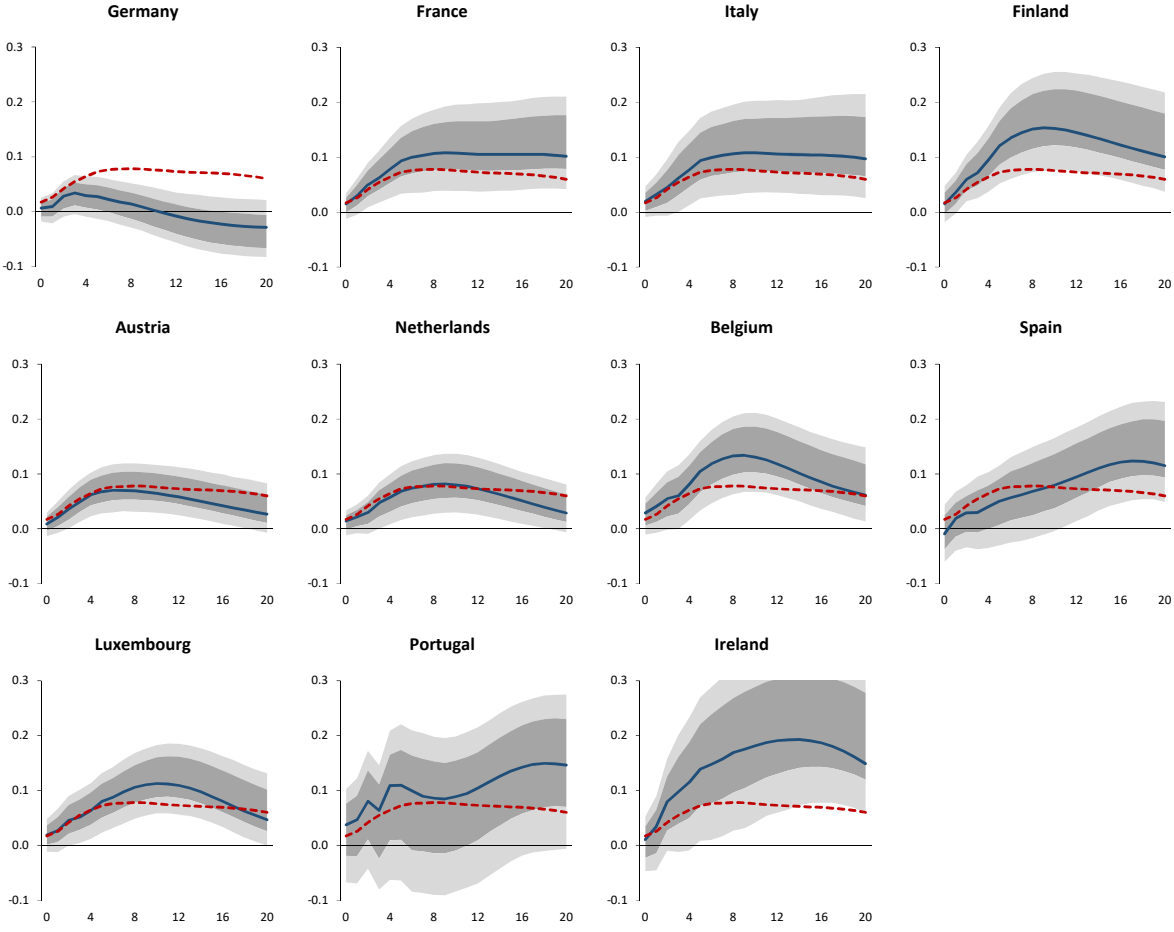


Figure A10 - Relative effects of 1% rise in international food commodity prices in the euro area versus the US



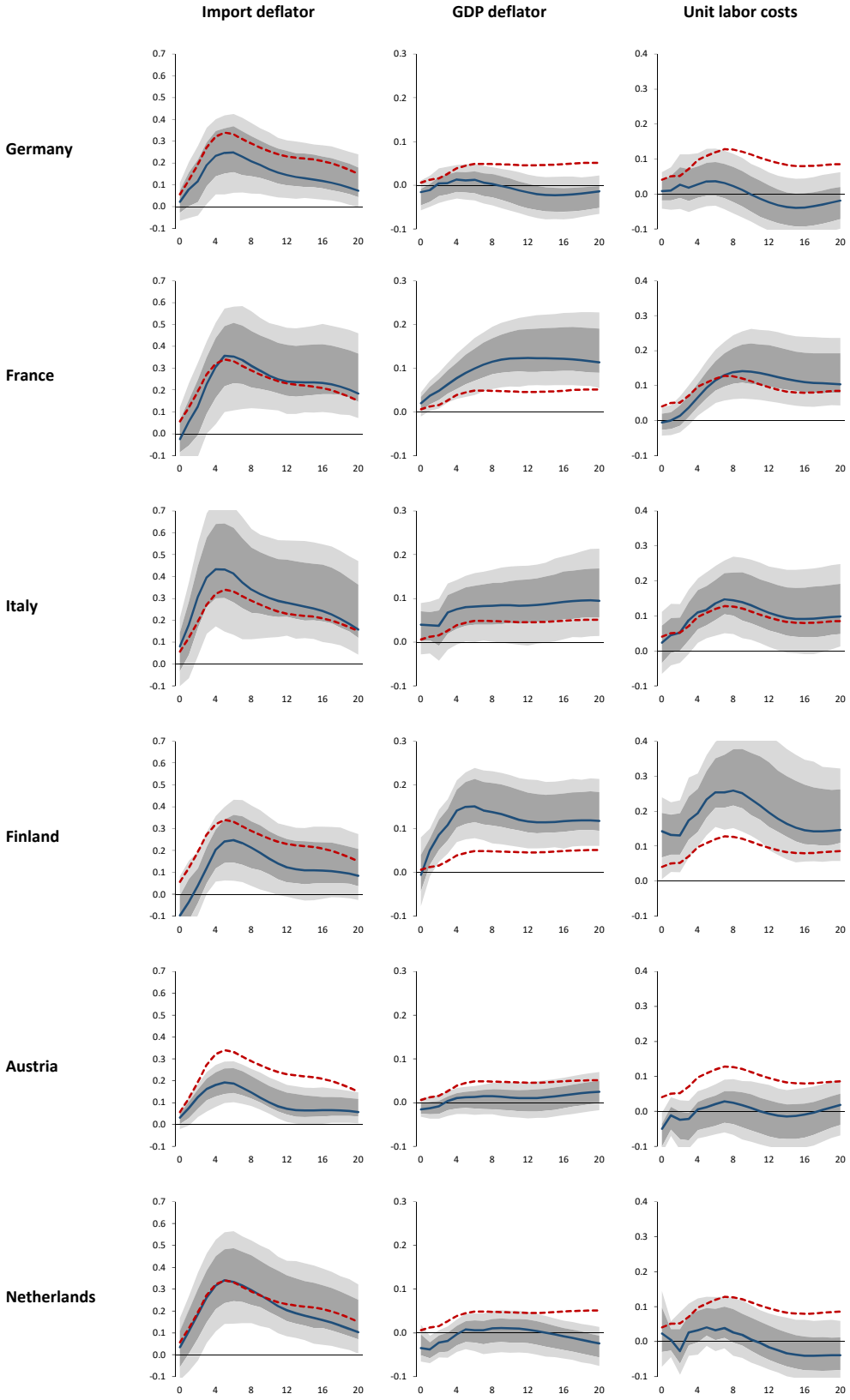
Note: 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly.
Re-estimation of benchmark VAR with relative (EA-US) variables.

Figure A11 - Effects of a 1% increase in international food commodity prices on consumer prices in member states



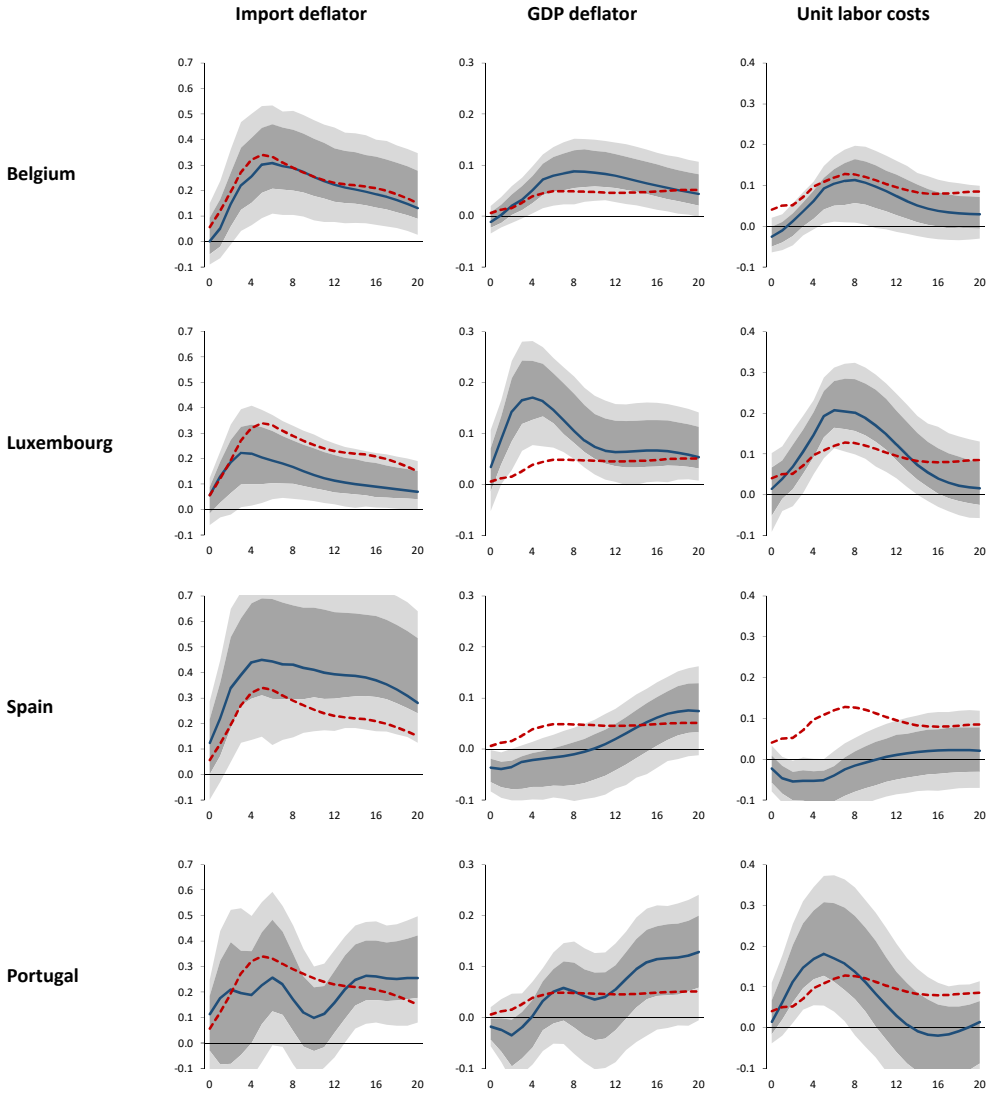
Note: 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly. Dashed red line is response of euro area HICP.
Differences with response of euro area HICP, together with confidence bands, are shown in the appendix.

Figure A12 - Effects of a 1% increase in international food commodity prices in member states



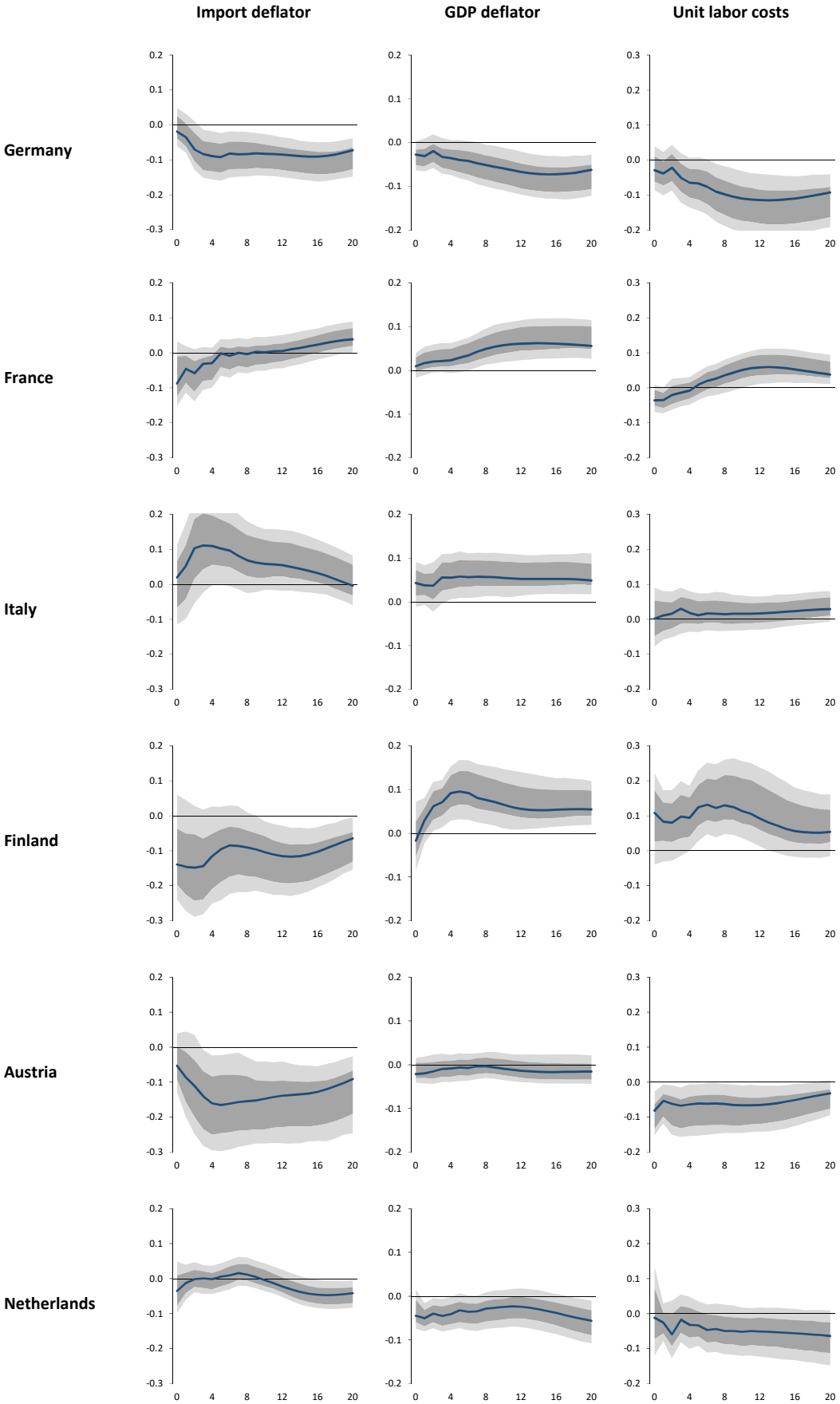
Note: 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly. Dashed red line is response of euro area.

Figure A12 (continued) - Effects of a 1% increase in international food commodity prices in member states



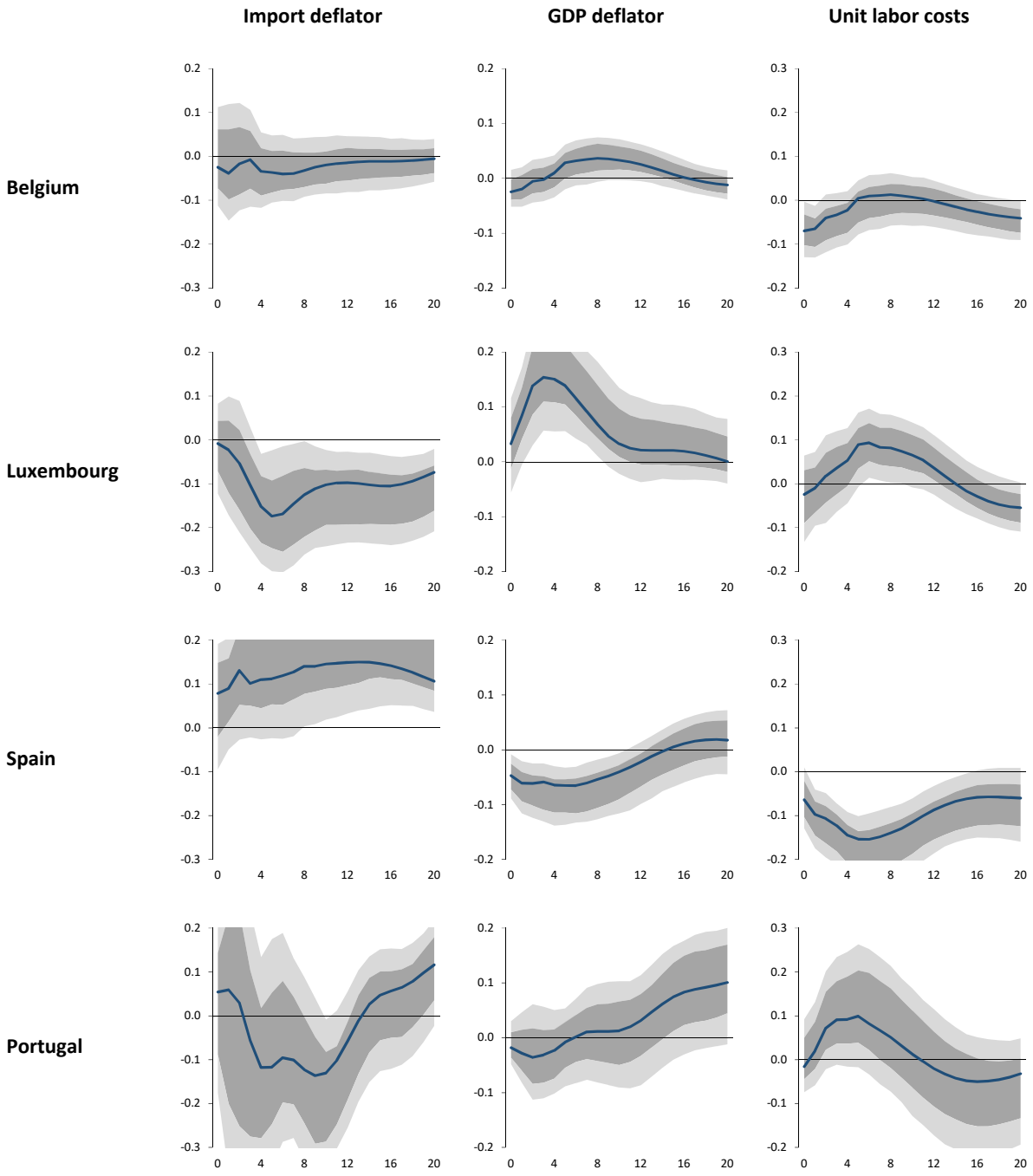
Note: 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly. Dashed red line is response of euro area.

Figure A13 - Difference between individual member state and area-wide effects



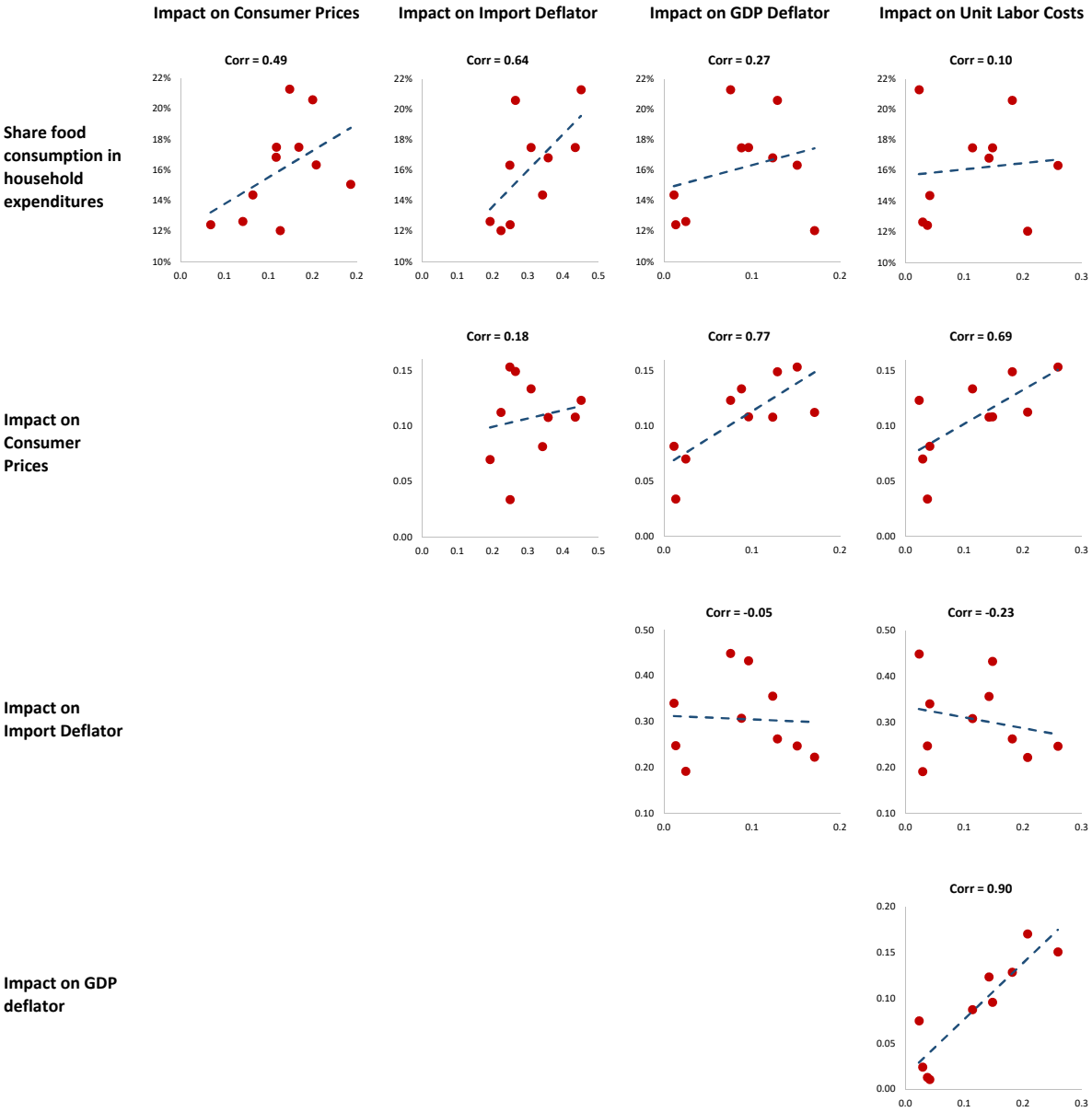
Note: 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly.

Figure A13 (continued) - Difference between individual member state and area-wide effects



Note: 68% and 90% confidence intervals constructed using a moving block bootstrap; horizon is quarterly.

Figure A14 - Impact of Food Commodity Price Shocks across Member States: Correlations of the Peak Effects



Note: Red dots are peak effects of food commodity price shocks in euro area member states.