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INTERNATIONAL FOOD COMMODITY PRICES AND MISSING (DIS)INFLATION IN THE EURO AREA

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

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Abstract

This paper examines the causal effects of shifts in international food commodity prices on euro area inflation dynamics using a structural VAR model that is identified with an external instrument (i.e. a series of global harvest shocks). The results reveal that exogenous food commodity price shocks have a strong impact on consumer prices, explaining on average 25%-30% of inflation volatility. In addition, large autonomous swings in international food prices contributed significantly to the twin puzzle of missing disinflation and missing inflation in the era after the Great Recession. Specifically, without disruptions in global food markets, inflation in the euro area would have been 0.2%-0.8% lower in the period 2009-2012 and 0.5%-1.0% higher in 2014-2015. An analysis of the transmission mechanism shows that international food price shocks have an impact on food retail prices through the food production chain, but also trigger indirect effects via rising inflation expectations and a depreciation of the euro.

JEL classification: E31, E52, Q17

Keywords: Food commodity prices, inflation, twin puzzle, euro area, SVAR-IV

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1 Introduction

Global food commodity markets are characterized by substantial price swings. For example, the standard deviation of quarterly changes in global food commodity prices since the start of the millennium has been 7.3%. Notwithstanding this considerable volatility, little is known about the causal effects of fluctuations in international food prices on inflation dynamics in the euro area and other advanced economies. This is surprising since food commodities are a critical input factor in the production function of the food-processing sector, while, as documented in Table 1, food-related items account for more than 27% of the euro area Harmonised Index of Consumer Prices (HICP).[1] Moreover, several studies have found that households weigh food prices much higher than its share in expenditures when forming inflation expectations, which, in turn, is a key driver of inflation dynamics in any forward-looking macroeconomic model with sticky prices (e.g. Smets and Wouters 2007).[2]

Swings in international food prices could also have contributed to the so-called "twin puzzle" of euro area inflation developments in the era after the Great Recession; that is, inflation was expected to be much lower in the period 2009-2012 as a consequence of the downturn, while inflation was expected to be higher in the recovery from 2013 onwards (Constàncio 2015). Popular explanations for the apparent disconnect between inflation and real activity during these periods are a decline in the slope of the Phillips Curve (e.g. Ball and Mazumder 2011; Blanchard et al. 2015) and a de-anchoring of inflation expectations (e.g. Coibion and Gorodnichenko 2015). However, as can be observed in panel (A) of Figure 1, international real food commodity prices rose by 46% between 2010 and 2012. A major reason for the surge in food prices was a substantial decline in global cereal production due to serious droughts around the world in the summers of 2010 and 2012 (De Winne and Peersman 2016). In the subsequent years, which was a period of excellent harvest conditions, food commodity prices collapsed by almost 70%. The concurrent evolution of international food prices and euro area headline inflation in this era is remarkable. Given the importance of food-related items in the HICP, developments in global food markets could thus have contributed to the twin puzzle.

[1] I am not aware of data for European countries, but according to the US Department of Agriculture's Economic Research Service data, the share of agricultural commodities (including meat and seafood) in final food products and beverages expenditures is approximately 14% for US households, which corresponds to 928 USD per capita per year (De Winne and Peersman 2016).

[2] According to a survey of the Norges Bank, 61% of households consider the "prices of food and non-alcoholic drinks" as the factor that influences their inflation expectations most, compared to e.g. 12% "overall prices", 4% "house prices" and 3% "gasoline prices" (Larsson 2015). Trehan (2011) and Murphy and Rohde (2018) document that households in the US are more sensitive to food prices in forming inflation expectations than the expenditure share of food in the CPI.

Another observation is that policymakers and researchers consider fluctuations in food commodity prices often only in tandem with other commodities or crude oil prices. Specifically, food and other commodities are typically aggregated into a broad commodity price index to analyze the impact on inflation developments. The reasoning is that the prices of commodities are jointly determined by the global business cycle. This interpretation is, however, not unequivocal. In contrast to industrial commodities, which are primarily affected by input demands, along with crude oil, food commodities are also subject to major independent supply disruptions (Blomberg and Harris 1995). For example, panel (B) of Figure 1 shows that food commodity prices have broadly varied in conjunction with oil prices over the past two decades, but the timing diverges and movements have often been in the opposite direction. More generally, Table 2 shows that the correlation of fluctuations in international food commodity prices with changes in crude oil and industrial commodity prices is positive but modest. These observations suggest that it is important to examine shifts in food commodity prices as an independent driver of inflation dynamics.

There exist several empirical studies from policy institutions that have explored the link between food commodity prices and inflation (e.g. Furlong and Ingenito 1996; Vavra and Goodwin 2005; Pedersen 2011; Ferrucci et al. 2012; Furceri et al. 2015). However, a caveat of these studies is that they are all based on reduced-form time series models that only explore unconditional co-movement in the data and cannot establish causal links. Inference in these studies is based on a so-called pricing chain approach, which assumes that food commodity price innovations can contemporaneously affect retail prices, but the opposite takes time. More precisely, all (reduced-form) food commodity price innovations are considered as shocks that are transmitted along the supply chain from producer to wholesale and to retail levels. The point in question is that this approach is not well defined because changes in international food commodity prices could be triggered by both supply and demand shocks. Most studies acknowledge this issue but argue that food commodity prices can be expected to lead the adjustment along the price chain, regardless of the source of the initial shock. For example, Blomberg and Harris (1995) and Ferrucci et al. (2012) argue that the first signs of an aggregate demand shock might be visible in flexible commodity markets and affect final consumer prices only with a delay due to price stickiness in final good markets. Whereas this reasoning is in itself correct, such estimates can at best be informative about the signaling role of food prices for future inflation, but they cannot be given a causal interpretation. If one is interested in a causal interpretation, it is crucial to isolate changes in food commodity prices that are strictly exogenous and not endogenous responses to other macroeconomic shocks.

In this paper, I estimate the causal effects of fluctuations in international food prices on euro area inflation dynamics using a structural vector autoregressive model in which exogenous international food commodity price shocks are identified with an external instrument; that is, an SVAR-IV or proxy SVAR in the spirit of Stock and Watson (2012) and Mertens and Ravn (2013). Specifically, by elaborating on De Winne and Peersman (2016), I first construct a quarterly series of unanticipated harvest shocks of the world's four most important staple food commodities (corn, wheat, rice and soybeans) that occurred outside Europe and were unrelated to global economic developments and oil price changes. In a second step, the harvest shocks are used as an instrument to identify exogenous international food commodity price shocks within the VAR model.

The estimates reveal that international food commodity price shocks have sizable effects on euro area consumer prices, explaining on average between 25% and 30% of the forecast error variance of the HICP. A one-percent exogenous increase in international food commodity prices (which reaches a peak of 1.36% after one quarter) augments the HICP by 0.08% after six quarters. The impact turns out to be much larger than an average (reduced-form) one-percent rise in food commodity prices. The use of an external instrument hence matters for inference. Moreover, the results show that disturbances in international food markets contributed significantly to both the missing disinflation and missing inflation periods after the Great Recession. In particular, according to counterfactual simulations based on the SVAR-IV model, euro area inflation would have been 0.2%-0.8% lower in the period 2009-2012 and 0.5%-1.0% higher in 2014-2015 without the autonomous food commodity market shocks that occurred during this era.

A closer inspection of the pass-through further shows that shifts in international food prices quickly spill-over to EU farm-gate and internal food commodity market prices, and ultimately food retail prices, although this is always less than proportional. On the other hand, unfavorable shocks in international markets also trigger a depreciation of the euro against the dollar, which augments import prices of non-food items in the HICP. In addition, the shocks raise inflation expectations and nominal wages, which also magnifies the impact on consumer prices.

This paper is related to various other studies. First, there are several studies that have stressed the importance of global factors for domestic inflation developments (e.g. Borio and Filardo 2007; Monacelli and Sala 2009; Ciccarelli and Mojon 2010; Mumtaz and Surico 2012; Eickmeier and Pijnenburg 2013). My results are consistent with this conclusion and suggest that global food commodity price shocks may be a key driver of such a relationship. Furthermore, several studies have analyzed the reasons of the missing disinflation in the post-crisis episode (e.g. Ball and Mazumder 2011; Gordon 2013; Coibion and Gorodnichenko 2015), the missing inflation in the euro area since 2013 (e.g. Ferroni and Mojon 2015; Ciccarelli and Osbat 2017; Conti et al. 2017) or both puzzles simultaneously (e.g. Friedrich 2016; Bobeica and Jarocinski 2017). Although some of these studies find an impact of external shocks or global drivers of inflation (e.g. Bobeica and Jarocinski 2017), none of the existing studies explicitly examines the influence of food commodity market shocks, which turns out to be an important source of the puzzles.

Finally, this paper is related to De Winne and Peersman (2016), which was the first study that examined the causal effects of disruption in global food commodity markets. However, whereas De Winne and Peersman (2016) explore the impact of food market shocks on economic activity in the United States (US), the present study focuses on the inflationary consequences and the twin puzzle of missing (dis)inflation in the euro area. Moreover, there is an important difference in the methodology. De Winne and Peersman (2016) construct an indicator of global harvests, which is then embedded in a standard recursive VAR model to estimate the effects of food production shocks on the US economy. However, as explained in section 2, it is more appropriate to use an SVAR-IV approach since the harvest shocks are only a noisy proxy and a limited subset of global food market shocks, which does not allow to study the overall relevance for inflation dynamics. We can conclude that fluctuations in international food commodity prices are indeed very important for euro area inflation developments.

Section 2 describes the benchmark SVAR-IV model for the euro area and the construction of a series of unanticipated harvest shocks that is used to identify exogenous international food commodity price shocks. The baseline estimation results are reported in section 3, as well as the contribution of the shocks to the missing (dis)inflation puzzle in the aftermath of the crisis. Section 4 analyzes the sensitivity of the results, while section 5 examines the transmission mechanism in more detail. Finally, section 6 concludes.

2 Methodology

Since Sims (1980), there is a large literature that has used VAR models to estimate the effects of structural shocks on the macroeconomy. A VAR model represents the relationships between a set of macroeconomic variables within a linear system and allows to measure the dynamic effects of exogenous shocks on all the variables that are included in the system. The key challenge is the identification of shocks that have a structural interpretation, which requires restrictions that have to be imposed on the system. In this regard, following Stock and Watson (2012) and Mertens and Ravn (2013), an increasing number of studies use external instruments that represent an exogenous component of the target shocks to achieve identification. This SVAR-IV approach is also the methodology that I use in this paper. Section 2.1 discusses the baseline SVAR-IV model, while section 2.2 describes the external instrument that will be used to identify exogenous shocks to international food commodity prices.

2.1 SVAR-IV Model for the Euro Area Economy

I assume that the euro area economy can be described by the following reduced-form linear VAR-system:[3]

$$Y_t = \alpha + A(L)Y_t + u_t \tag{1}$$

where Y_t is a vector of endogenous variables, α is a vector of constants, $A(L)$ is a polynomial in the lag operator L, while u_t represents a vector of reduced form residuals that are related to a set of structural shocks as follows:

$$u_t = B\varepsilon_t \tag{2}$$

B is a nonsingular (invertible) matrix. The vector of endogenous variables Y_t contains eight international and euro area variables. For the benchmark estimations, I include international real (USD) food commodity prices, international real (USD) crude oil prices, the euro/USD bilateral exchange rate, real GDP, real export, real personal consumption, the short-term interest rate and the HICP. The data are expressed in (100 times) natural logarithms and seasonally adjusted, except the interest rate, which is expressed in percentage.

Euro area data and the bilateral USD exchange rate are collected from the ECB's Area-Wide Model dataset. For global food commodity prices, I use a weighted index of the four major staple food commodities; that is, corn, wheat, rice and soybeans. These four food commodities account for approximately 75% of the caloric content of food production worldwide, are storable and traded in integrated global markets and, closely resemble with the external instrument that will be used to achieve identification.[4] The prices, which are measured in US dollars, are collected from IMF Statistics Data. For more details, I refer to the data appendix of the paper. To retrieve real prices, the food commodity price index and crude oil prices are deflated by US consumer prices excluding food and energy. Besides real GDP, the benchmark

[3]Ferrucci et al. (2012) argue that the pass-through of food commodity price shocks to consumer prices may be nonlinear and depend on the sign and size of the shock. Although this may indeed be the case, the analysis of nonlinearities is, however, out of the scope of this paper.

[4]The prices of other food commodities are also typically strongly related to these four staple food items (Roberts and Schlenker 2013).

VAR includes real export and personal consumption. Real export should capture fluctuations in economic activity in the euro area's trade partners that have an impact on the euro area economy, while personal consumption is most closely related to the HICP. In section 4, I will discuss the sensitivity of the results with respect to the variables included in the VAR system.

A structural analysis requires the identification of the coefficients of B. Because I am only interested in the effects of exogenous food commodity price shocks, and real food commodity prices are included as the first variable in Y_t, only the coefficients of the first column of B have to be identified. In the existing studies that investigate the effects of food price shocks (e.g. Blomberg and Harris 1995; Zolli 2009; Pedersen 2011; Ferrucci et al. 2012), this is typically done by assuming that B is a lower triangular matrix (i.e. a Cholesky decomposition of the variance-covariance matrix of the reduced form residuals). The implicit assumption is that shifts in international food commodity prices can have an immediate impact on all other variables in the system, but not the other way around for other shocks. For a structural analysis, this assumption is not reasonable since food commodities are traded in highly competitive and flexible markets. The shocks that are identified this way are in essence a combination of exogenous food price shocks and endogenous responses to other structural shocks. At best, such results can be informative about the signaling role of changes in food prices for future inflation, but are not instructive about causal effects.

To identify shifts in international food commodity prices that are strictly exogenous, in this paper I follow an approach that has been proposed by Stock and Watson (2012) and Mertens and Ravn (2013). Both studies show how structural shocks can be identified with an external instrument. Specifically, an external instrumental variable Z_t can be used to estimate the coefficients of the first column of B if the following conditions are satisfied:

$$E\left[Z_t \varepsilon_t^{1'}\right] \neq 0 \tag{3}$$

$$E\left[Z_t \varepsilon_t^{2'}\right] = 0 \tag{4}$$

where ε_t^1 is an exogenous food commodity price shock and ε_t^2 a vector of all other structural shocks affecting the economy. Equations (3) and (4) postulate respectively that the external instrumental variable should be correlated with exogenous food commodity price shocks and uncorrelated with all other structural shocks. These requirements correspond to the so-called instrument relevance and exogeneity condition, respectively. Notice that the instrumental variable is not the full shock series, but rather captures an exogenous component of the shock, which is typically measured with error. In this regard, Mertens and Ravn (2013) call such an instrument a noisy measure of the true shocks. For more details and implementation, I refer to Stock and Watson (2012) and Mertens and Ravn (2013). Below, I propose an instrument that can be used for the identification of exogenous food price shocks.

2.2 Unanticipated Harvest Shocks

I elaborate on De Winne and Peersman (2016) to construct an instrumental variable that should have a meaningful effect on food commodity prices and is plausibly uncorrelated with other macroeconomic shocks. Although food prices can immediately respond to macroeconomic shocks, the construction of the instrument explores the fact that this is not the case for the production of cereal commodities because there is a time lag of at least 1 quarter (i.e. 3-10 months) between the decision to produce (planting) and actual production (harvest) of cereal commodities. At the same time, harvest volumes are subject to shocks that are unrelated to the macro-economy, such as changing weather conditions or crop diseases.

More specifically, De Winne and Peersman (2016) construct a quarterly global food production index that aggregates the harvests of corn, wheat, rice and soybeans. To do this, annual harvest volumes of 192 countries are combined with these country's planting and harvesting calendars for each of the four crops in order to assign the harvest volumes to a specific quarter. The harvests are then aggregated across crops and countries using calorie weights to obtain a proxy for global food production. In a next step, De Winne and Peersman (2016) embed the composite food production index in a VAR-model that also includes global food commodity market and US macroeconomic variables, and identify shocks to the production index using a Cholesky decomposition with the production index ordered first. Due to the time lag of at least one quarter between the planting season and the harvest of the crops, the shocks to the production index are exogenous with respect to the macroeconomy. It turns out that a fall in the production index raises food commodity prices and depresses economic activity in the US.

In this paper, I use the same procedure to construct a composite global food production index. However, in contrast to De Winne and Peersman (2016), I do not include the harvests of European countries in the index. The reason is that disruptions in European harvests could, for example, be caused by weather shocks that simultaneously affect European harvest volumes, agricultural production and economic activity. The presence of possible direct effects of weather shocks on the euro area economy; that is, beyond changes in food commodity prices, could distort the estimations. For the same reason, in the estimations below, I orthogonalize the food production index to global weather phenomena that may simultaneously affect European and non-European harvests.

Furthermore, in contrast to De Winne and Peersman (2016), I do not include the production index directly into the VAR-model, but only use it as an external instrument for the identification of exogenous international food commodity price shocks. The reason is threefold. First, innovations to the food production index are conceptually a noisy measure of food production shocks rather than the full shock series. For example, De Winne and Peersman (2016) managed to assign only two-thirds of annual global food production to a specific quarter, while the allocation procedure encompasses measurement errors.[5] It is thus more appropriate to consider the innovations as an instrumental variable. Second, the innovations to the index only capture food production shocks during the harvesting quarter. In particular, anticipated food production shocks (e.g. due to weather conditions before the start of the harvesting season) may already be reflected in food commodity prices before the start of the quarter. Put differently, the production shocks represent only a confined subset of all exogenous food price disturbances, which would imply a serious underestimation of the relevance for inflation developments and the contribution to the missing (dis)inflation in the euro area. Finally, the SVAR-IV approach allows for more flexibility. For example, the sample period, variables and number of lags for the construction of the instrumental variable can be different from the VAR model.

To obtain the instrumental variable series, I estimate the following harvest equation:

$$q_t = \beta_0 + \beta_1 t + \beta_2 \Theta_t + B_1(L) X_t + B_2(L) q_t + \xi_t \tag{5}$$

where q_t is the natural logarithm of the quarterly global food production index excluding European harvests. The index is seasonally adjusted using the Census X-13 ARIMA-SEATS Seasonal Adjustment Program (method X-11). t is a linear time trend. Θ_t is a vector of the Multivariate ENSO Index (MEI), the Oceanic Niño Index (ONI) and a dummy variable based on the US National Oceanic and Atmospheric Administration (NOAA) definition of El Niños, which should control for global weather phenomena that may simultaneously affect European and non-European harvests. X_t is a vector of control variables that could have a lagged (after one quarter) influence on global food production: the corresponding real food commodity price index (weighted average of corn, wheat, rice and soybeans), the real price of other food

[5] For several crops of individual countries, it is not possible to assign the annual harvest volumes to a specific quarter because there is more than one harvesting period within a calendar year, or there is an overlap of the planting and harvesting seasons at the quarterly frequency. Overall, the index covers 84% of global corn production, 16% of rice production, 96% of soybean production and 82% of wheat production. Notice also that, whenever a single harvesting season is spread over two subsequent quarters, the production volume is allocated to the first quarter, which might imply measurement errors. See De Winne and Peersman (2016) for a detailed discussion of the harvest data.

commodities (broad food commodity price index that also includes meat, seafood, fruit and vegetables), the real price of oil and an index of global economic activity (worldwide industrial production). $B_1(L)$ and $B_2(L)$ are polynomials in the lag operator, with $L = 8$. Equation (5) is estimated over the period 1961Q1-2016Q4, which is the longest sample available for all series. It is important to mention that the results are not sensitive to the choice of the control variables, number of lags or sample period that is used to estimate equation (5). If we assume that the information set of local farmers is not greater than equation (5), the residuals ξ_t can be considered as a series of unanticipated harvest shocks that can be used as an external instrument to identify exogenous international food commodity price shocks, as described in section 2.1. Figure 2 shows the global food production index and harvest shocks. The variability of harvest volumes and magnitude of the shocks have been substantial in the sample. For example, the standard error of changes in the production index and the shocks has been 6.5 and 4.3 percentage points, respectively.

3 Benchmark Estimation Results

Since the most recent Area-Wide Model dataset covers the period 1970-2016, I estimate the benchmark SVAR-IV model over the sample period 1970Q1-2016Q4 with four lags. To allow for possible cointegration relationships between the variables, the VAR is estimated in levels (Sims et al. 1990). I use the unanticipated harvest shocks as an external instrument to identify the first column of B. As argued in section 2.2, these shocks are plausibly uncorrelated with other macroeconomic shocks, which fulfills the exogeneity condition postulated in equation (4). In addition, the first-stage F-statistic and robust F-statistic of the instrument turn out to be respectively 13.9 and 17.4, which is safely above the Stock and Yogo (2005) threshold for having possible weak instrument problems. The harvest shocks thus also fulfill the instrument relevance condition of equation (3). In section 3.1, I discuss the impulse response analysis of international food commodity price shocks, while section 3.2 evaluates the relevance for euro area inflation dynamics and the contribution to the missing (dis)inflation in the period after the Great Recession.

3.1 Impulse Response Analysis

Figure 3 shows the impulse responses to a one-percent exogenous rise in real international food commodity prices on all the variables included in the VAR model, together with 68% and

90% confidence intervals.[6] The rise in food commodity prices reaches a peak of 1.36% after one quarter, followed by a gradual decline back to the baseline after about eight quarters. In line with the evidence reported in De Winne and Peersman (2016) for the US, the shock leads to a temporary decline in economic activity that is statistically significant. More specifically, euro area real GDP decreases by 0.06% at its peak, which is attained after roughly eight quarters. The fall in real personal consumption expenditures is slightly more subdued; that is, a peak decline by 0.04%. In contrast, the decline in real export by 0.15% is much stronger than real GDP.

The key variable in the context of the present study is the response of the euro area HICP. A one-percent exogenous rise in international food commodity prices augments consumer prices by 0.08% after six quarters. The impact on consumer prices is also very persistent. In particular, the HICP is still 0.06% higher and statistically significant after five years. Another interesting observation is the significant depreciation of the euro exchange rate vis-à-vis the US dollar triggered by the international food price shock. The weakening of the euro implies that also (non-food) import prices increase after the shock, which may partly explain the overall inflationary effects. A possible reason for the depreciation is the fact that the euro area is a net-importer of primary food and beverages, while the US is a net-exporter of food commodities. Furthermore, there appears to be no significant shift of crude oil prices on impact. The shocks that are identified are thus unrelated to oil price changes. There is, however, a moderate increase of oil prices at longer horizons. Finally, there is a temporary monetary policy tightening in order to stabilize the inflationary consequences. This policy tightening likely contributes to the negative output effects of the food shocks.

3.2 International Food Price Shocks and Euro Area Inflation Dynamics

Montiel Olea et al. (2016) show how the covariances between an external instrument and the reduced-form VAR innovations can also be used to estimate the contribution of the target shock to the forecast-error variance of the variables that are included in the VAR-system, to identify the target structural shock series and to calculate historical decompositions. The former is very useful to assess the average relevance of exogenous international food commodity price shocks for euro area inflation fluctuations, while historical decompositions can be used to measure the influence on the missing (dis)inflation puzzles.[7]

[6] The confidence intervals are constructed using a recursive design wild bootstrap procedure as in Mertens and Ravn (2013) based on 5,000 replications. Notice that an instrumental variable estimation with generated regressors yields a consistent estimator of the true standard errors (Pagan 1984).

[7] Notice that it is not possible to construct confidence intervals for the historical decompositions and coun-

Figure 4 shows the forecast error variance decompositions of the benchmark variables. On impact, 63% of the forecast-error variance of international food commodity prices is caused by exogenous food market disturbances. The contribution, however, declines substantially at longer horizons. Food commodity market shocks explain only 25% of food commodity price volatility in the long run. In other words, food commodity price fluctuations are predominantly endogenous responses to other shocks in the economy. Nevertheless, international food commodity price shocks explain on average a relative large fraction of the forecast error variance of consumer prices in the euro area. In particular, roughly 30% of HICP volatility is caused by such shocks at the two-year horizon, in order to moderately decline to 25% in the long run. Developments in global food commodity markets are thus quite important for euro area inflation fluctuations. Since international food price shocks explain only 11% of the forecast error variance of real GDP (16% at its peak), this is less the case for output fluctuations. The contribution to the variance of the other variables is even more subdued.

Have disruptions in global food commodity markets been relevant for euro area inflation in the aftermath of the Great Recession? Figure 5 depicts the time series of the the identified exogenous international food commodity price shocks and the contribution to the evolution of respectively international food commodity prices, HICP (year-on-year) inflation and real GDP (year-on-year) growth, while Figure 6 shows the counterfactual evolution of these variables since 2000 in the absence of food commodity price shocks. Some interesting observations are worth mentioning. First, the surge of international food commodity prices since the start of the millennium, a period that has often been described as the "global food crisis", as well as the subsequent fall in food prices, was mainly an endogenous response to macroeconomic shocks that occurred outside food commodity markets. This can clearly be observed in Figure 6, which includes the baseline projection of international food commodity prices; that is, the evolution of food commodity prices in the absence of all shocks implied by the VAR model. Specifically, the bulk of the deviation from baseline appears not to be caused by exogenous food price shocks. This finding is consistent with several studies that have analyzed the reasons of the food crisis. For example, Abbott et al. (2011) argue that soaring oil prices, in combination with policies to encourage biofuels production, triggered a significant rise in the demand for food commodities between 2004 and 2010. Furthermore, Enders and Holt (2014) document that economic growth in emerging economies (e.g. China, India, Russia and Brazil), low interest rates and the depreciation of the U.S. dollar also contributed to the changes in food commodity prices during this period.

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terfactuals because such an analysis conditions on a particular realization of the data. I therefore only show the point estimates in this section.

The figures, however, reveal that exogenous food commodity market disturbances also contributed to the large swings in global food commodity prices in the era surrounding the Great Recession. In particular, while the contribution was persistently negative in the period 2005-2007, which was a period of several upward revisions of world cereal output forecasts, exogenous unfavorable food market shocks augmented international food commodity prices by almost 25% in 2008-2009, more than 15% in 2011 and again more than 10% in the summer of 2012. These hikes are consistent with severe droughts in Russia and Eastern Europe in the summer of 2010, and in Russia, Eastern Europe, Asia and the US in the summer of 2012, respectively. In contrast, international food commodity prices were between 20% and 25% lower in 2014 as a consequence of autonomous developments in food commodity markets. The latter episode has indeed been characterized by excellent harvest conditions.

As can be observed from the historical contribution and counterfactual evolution of HICP inflation in both figures, these events in food commodity markets had an important impact on inflation in the euro area. Specifically, inflation would have been between 0.2% and 0.8% lower in the period 2009-2012 (0.5% on average), and not above the target of the Eurosystem in 2011-2012. On the other hand, euro area inflation would have been 0.5%-1.0% higher in 2014-2015 (0.7% on average). These magnitudes are economically meaningful. Thus, we can conclude that exogenous food commodity market shocks were partly responsible for both the missing disinflation in the aftermath of the Great Recession and the missing inflation in the subsequent recovery. Interestingly, unfavorable food commodity price shocks also aggravated the economic downturn in the euro area. According to the contribution to real GDP growth, the food market shocks reduced economic growth by roughly 1.0% in the Great Recession and by more than 0.5% when the euro area economy was suffering from the Sovereign Debt Crisis in 2012. On the other hand, favorable food commodity market shocks supported the European recovery in 2015 and early 2016.

4 Sensitivity and Robustness of the Results

In this section, I examine the sensitivity of the baseline results. I first assess the relevance of using an external instrument to identify the shocks in section 4.1. In section 4.2, I discuss the robustness of the results for several perturbations to the VAR model.

4.1 The Use of an External Instrument

A pertinent question is whether the use of an external instrument to identify food commodity price shocks matters. To investigate this question, I compare 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. As argued above, such estimates are not informative about causality because the reduced-form innovations likely represent a mixture of exogenous food market disturbances and endogenous responses to other shocks in the economy, such as changes in global economic activity, oil prices, interest rates and exchange rates. 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. However, the source of the structural shock that triggered the shift in food commodity prices may have very different ultimate effects on inflation, which could even distort the signaling role of food price changes for future inflation.

Figure 7 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. The difference between both approaches is also statistically significant.

The reason for the different effects on the HICP is likely the results of the fact that an exogenous food commodity price shock (SVAR-IV approach) triggers a depreciation of the euro. In contrast, an average rise of food commodity prices (recursive identification) appears to be associated with an appreciation of the euro against the US dollar. The latter suggests that average food commodity price innovations partly reflect endogenous responses to shifts in the US dollar. Specifically, since international food commodity prices are expressed in US dollars, a depreciation of the dollar (i.e. appreciation of the euro) implies that food commodities become less expensive in local currency for countries that do not use the dollar for local transactions, which boosts their demand for food commodities. The rise in demand, in turn, augments food commodity prices expressed in US dollar.[8]

The endogenous nature of average food commodity price shocks that are identified based on the pricing-chain assumption is further illustrated by the impulse responses of crude oil prices and real GDP. In particular, these shocks are characterized by an instantaneous rise in crude oil prices and real GDP, a co-movement that is consistent with a demand-driven rise of food commodity prices. Finally, as shown in the top-row of the figure, the shift in food commodity prices after an exogenous shock is somewhat less persistent than an average food price innovation. Overall, the use of an external instrument to disentangle exogenous food price shocks from endogenous responses to other shocks appears to be important for the measurement of the ultimate inflationary consequences.

4.2 Alternative SVAR-IV Specifications

In this section, I discuss the robustness of the results for several perturbations to the benchmark VAR model. In particular, I assess the sensitivity of the impact of food commodity price shocks on the HICP, the contribution of the shocks to the forecast error variance of HICP and the historical contribution to inflation in the era after the Great Recession. The results of some relevant checks are summarized in Figure 8.

SVAR in first differences As discussed in section 3, the benchmark VAR model is estimated in (log) levels. Sims et al. (1990) demonstrate that a log levels specification gives consistent estimates when the variables have stochastic trends and are cointegrated.[9] 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 6 of section 3.2, there is very little variation in the baseline

[8]When I extend the baseline VAR with the US dollar nominal effective exchange rate, average food commodity price shifts (recursive identification) are associated with a depreciation of the effective dollar exchange rate that is of the same magnitude as the bilateral euro exchange rate. Thus, there is a depreciation of the dollar against the rest of the world, which could explain the rise in food prices expressed in US dollar. On the other hand, after an exogenous food commodity price shock (SVAR-IV approach), there is a modest appreciation of the dollar effective exchange rate that is statistically insignificant and much smaller than the bilateral exchange rate shift (results available on request). De Schryder and Peersman (2015) find a similar mechanism for crude oil prices. In particular, De Schryder and Peersman (2015) find that a depreciation of the US dollar leads to a rise in oil demand of oil-importing countries.

[9]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. Notice also that the results are robust when I include a linear or quadratic trend in the VAR model.

(deterministic) projection of the variables implied by the VAR. To further address this issue, the first row of Figure 8 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 in Figure 8 reveal that the impact on the HICP is much stronger when the VAR is estimated in first differences. The long-run effects of a one-percent increase in international food commodity prices turns out to be 0.15%, which is almost twice as large as the benchmark results. Notwithstanding the difference in the impulse responses, the contribution to the forecast error variance of the HICP is quite comparable. Furthermore, although there are difference for the period before 2008, the contribution to inflation developments in the aftermath of the recession is also consistent with the benchmark results.

Choice of variables The results are not sensitive when I extend the benchmark VAR model with several additional variables. For example, the results are very similar when I include the index of global industrial production that was used to estimate the harvest shocks, aggregate real GDP of OECD countries or a weighted sum of GDP of the main trading partners of the euro area in the VAR (in addition to real export, which is already included in the benchmark VAR). Furthermore, the results are robust when I extend the VAR with equity prices, implied US stock market volatility (VXO), the US dollar or the euro effective exchange rates. On the other hand, the effects on the HICP turn out to be larger when I re-estimate the benchmark VAR with the IMF broad food commodity price index instead of the weighted average of the four major staple food items. The results for the broad index, which also includes meat, seafood, fruit and some other food commodities, are shown in the second row of Figure 8. The peak impact of a one-percent rise in the broad food commodity price index on HICP is 0.11%, compared to 0.08% for the benchmark index. The contribution to the forecast error variance of HICP is also slightly larger: roughly 37% at the two-year horizon and 28% in the long run, compared to 30% and 25% for the benchmark. The contribution to the missing (dis)inflation puzzle is, in contrast, quite similar.

Alternative external instrumental variable As mentioned in section 2.2, the results are robust for several perturbations to the specification that I have used to estimate the unanticipated harvest shocks (equation 5). The third row of Figure 8 shows the results when I use the narrative food commodity price shocks of De Winne and Peersman (2016) as an alternative external instrumental variable. Specifically, De Winne and Peersman (2016) rely on FAO reports, newspaper articles and several other sources to identify 13 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 also be used as an external instrument. A caveat of this robustness check is that the first-stage F-statistic and robust F-statistic of the instrument are only 5.7 and 4.4, respectively, which could imply that the results are distorted due to weak instrument issues. As shown in Figure 8, the effects on the HICP are lower (peak rise of 0.05%) and less persistent than those obtained based on the harvest shocks. The same applies to the forecast error variance decomposition, with a maximum contribution to inflation variation of 18%. Conversely, the historical decompositions still show that international food commodity price shocks had an important impact on the missing (dis)inflation after the Great Recession.

Sample period As a final robustness check, I assess the sensitivity of the results for possible time variation. More specifically, I re-estimate the benchmark VAR model over the sample period 1990Q1-2016Q4. Given the relative large number of variables in the VAR, I use only three lags for this exercise.[10] The results are reported in the bottom row of Figure 8. A first notable observation is that the impact on the HICP is much lower than the estimates based on the full sample period. The peak rise in the HICP is only 0.05%, compared to 0.08% for the full sample. The effects on the HICP are also less persistent and become statistically insignificant in the long run. Thus, it seems that the pass-through has changed over time. In section 5, I will analyze this in more detail. On the other hand, the contribution of international food commodity market shocks to the HICP forecast error variance is much higher for the more recent sample period. In particular, food price shocks now explain 48% of the forecast variance at the one-year horizon and 27% in the long run, compared to 30% and 25% for the estimations based on the whole sample period. The larger contribution to the variance, despite the smaller impact of food price shocks on the HICP in the recent sample, 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 has been comparable over time (and has even increased). This is also the case for the contribution to the evolution of HICP inflation in the post-crisis period, which turns out to be similar as the contribution based on the benchmark VAR. Overall, the sizable influence of food commodity market shocks on the "twin puzzle" of euro area inflation developments appears to be quite robust.

[10] In fact, standard lag length criterions suggest that two lags should be sufficient for this sample period.

5 Transmission Mechanism of Food Commodity Price Shocks

An advantage of the isolation of food commodity price shocks that are plausibly exogenous is that it also allows to examine the transmission mechanism in more detail. The aim of this section is to better understand the pass-through to the HICP. To do this, I estimate an extended version of the baseline VAR model for a number of relevant additional variables. In particular, for each additional variable, I estimate the following near-VAR model:

$$\begin{bmatrix} Y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \alpha \\ c \end{bmatrix} + \begin{bmatrix} A(L) & 0 \\ C(L) & D(L) \end{bmatrix} \begin{bmatrix} Y_t \\ x_t \end{bmatrix} + \begin{bmatrix} B & 0 \\ b & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^Y \\ \varepsilon_t^x \end{bmatrix} \tag{6}$$

where Y_t are the variables of the benchmark VAR model and x_t is the additional variable of interest. For these estimations, I assume that the additional variable does not affect the dynamics of the benchmark variables. The main reason is the short sample available for most of the additional variables. For example, the data series of domestic (EU) food commodity prices, the HICP components and survey of professional forecasts (inflation expectations) are only available from respectively 1991, 1996 and 1999 onwards. By estimating a block exogenous system, it is possible to estimate the parameters of the benchmark variables over the full sample period (which corresponds to the baseline results) and those of the additional variables over a shorter sample period. Accordingly, the underlying food commodity price shocks and interaction among the benchmark variables are invariant to the inclusion of the additional variable, which allows for a proper comparison of the dynamic effects across the variables. To save degrees of freedom, I set $L = 2$ in $C(L)$ and $D(L)$ for the variables that are only available for a short sample period. The sources of the data and construction of some of the series are described in the appendix. The results of the estimations are shown in Figures 9 to 13. To discuss the pass-through, I distinguish between indirect effects triggered by other mechanisms (section 5.1) and direct effects on the HICP through the production chain (section 5.2).

5.1 Indirect Effects on the HICP

Figure 9 shows the effects of a one-percent increase in real international food commodity prices on the main components of the HICP. A first observation is that there is a rise in energy prices by 0.17% at its peak after two quarters. This is surprising given the insignificant impact on crude oil prices in the benchmark VAR, but can be explained by the depreciation of the euro against the US dollar by 0.25% discussed in section 3.1 (see Figure 3). Specifically, crude oil prices are usually traded in US dollar, while all euro area countries are oil-importing countries. Notice further that, in more recent periods, food commodities are used for the production of biofuels, which could also increase energy prices. The rise in energy prices is, however, only temporary and gradually returns to its baseline at longer horizons, a pattern that is again consistent with the response of the exchange rate. Hence, it does not contribute to the rise in the HICP in the long run.

Figure 9 reveals that there is also a rise in the HICP excluding energy and food prices by 0.04%, which is statistically significant. Again, this may be an indirect consequence of the depreciation of the exchange rate triggered by the food commodity price shock, which raises import prices. As can be observed in Figure 10, there is indeed a depreciation of the nominal effective exchange rate by roughly 0.20%, although somewhat less than the depreciation against the dollar. Overall, the depreciation of the euro seems to matter for the ultimate effects on consumer prices. The analysis of the exact reason why the exchange rate depreciates is out of the scope of this paper. As discussed in section 3.1, a possible explanation is the fact that the euro area is a food-importing region (and the US a net food exporter), which implies that a rise in international food commodity prices deteriorates the current account. For example, a recent study by Giovannini et al. (2018) finds that commodity price changes are the main driver of fluctuations in the euro area current account. In addition, De Winne and Peersman (2018) find that a rise in international food commodity prices depresses output much more in countries with a low share of agriculture in GDP, food-importing countries and non-food exporters compared to other countries. Since all these characteristics apply to the euro area, a stronger decline in economic activity could also be an explanation for the depreciation of the euro.

Another indirect mechanism is the existence of so-called second-round effects via rising wages and inflation expectations. More specifically, as shown in Figure 10, nominal wages and unit labor costs increase significantly after a food price shock. This is likely the consequence of employees asking for higher nominal wages in the wage bargaining process to compensate for their loss in purchasing power. If firms producing non-energy and non-food products and services pass these costs through to their selling prices, this reinforces the inflationary consequences of the food price shocks. Similar second-round effects have been documented by Peersman and Van Robays (2009) for oil supply shocks.

The presence of second-round effects on inflation is also consistent with the response of inflation expectations collected from the ECB's survey of professional forecasters, and the qualitative measure of price expectations derived from the monthly households survey of the European Commission. As can be seen in Figure 10, both measures of inflation expectations increase significantly, which is plausibly passed through to actual pricing behavior of firms. An important impact of food prices on inflation expectations has also been documented by Trehan (2011) and Murphy and Rohde (2018) for the US, and by Larsson (2015) for Norway.

5.2 Effects on the HICP Through the Food Production Chain

Impact on EU farm-gate and internal market prices There is clearly an influence of international food commodity prices on retail prices of food in the euro area through the food supply chain. As can observed in Figure 9, there is a rise in unprocessed as well as processed food prices by 0.10% and 0.15%, respectively, which is much larger than the impact on core inflation. There are two channels that could explain this. First, a lot of food commodities that are ultimately consumed by euro area households are imported from non-euro countries. These food commodities become more expensive for domestic residents when international food commodity prices rise. Together with the depreciation of the euro, this increases import prices of food commodities. The presence of this channel is reflected in the stronger rise of import prices (import deflator) relative to the depreciation of the euro nominal effective exchange rate depicted in Figure 10.

Second, since food commodities are traded in integrated and competitive global markets, also domestic food commodity prices could increase when there is a rise in international prices. To assess whether this is the case, I construct four measures of European food commodity prices; that is, an index for cereal, meat, dairy and fruit commodity prices, respectively. Similar to Ferrucci et al. (2012), I use the farm-gate and wholesale market prices in the European Union (EU) that are made available by DG AGRI of the European Commission over the period 1991-2017. The indices of the four product groups are, in turn, unweighted averages of the price series of specific food commodities. I refer to the data appendix for more details.

The results are shown in Figure 11. There is indeed a pass-through of international to European food commodity prices, although this is less than proportional. In particular, the index of domestic cereal commodity prices increases by 0.60% on impact and 1.20% after two quarters.[11] The pattern of EU cereal prices is also very similar to the dynamics of international

[11] Since the aim of this section is an analysis of the pass-through to the level of the HICP, the impulse responses of these variables are shown in nominal values, whereas international food commodity prices are expressed in real values (deflated by US consumer prices excluding food and energy). Notice also that international food commodity prices are expressed in US dollar, while EU prices are measured in euros. When I measure EU commodity prices in real US dollars and re-estimate the impulse responses, domestic real cereal prices increase by 0.42% on impact and 1.26% after two quarters.

food commodity prices after the shocks. In addition, there is a rise in domestic meat, dairy and fruit commodity prices by 0.42%, 0.39% and 0.65%, respectively. The prices of these food commodities might rise because they are possible substitutes for the consumption of calories. Another explanation for the rise of fruit prices is a positive correlation between global (non-European) fruit and cereal harvest shocks, since the harvests of both commodities depend on weather conditions. Furthermore, the prices of meat commodities and their byproducts (dairy products) could rise because a large fraction of cereal commodities are used to sustain the animals, which augments the production costs of meat and puts upward pressure on meat and dairy prices. One calorie of meat, for example, requires more than one calorie of feed stock. Overall, these findings suggest that the Common Agricultural Policy (CAP) in Europe, which tries to cushion the transmission of international food price shocks to EU internal prices, is only partly successful to do this and cannot fully isolate domestic agricultural producers from developments in global food commodity markets.[12]

Effects on food-related items in the HICP Higher food commodity prices are not necessarily passed on to consumer prices. The shock could, for example, be partly absorbed in profit margins at various stages of the production chain and margins of retailers. Furthermore, the cost share of food commodities in the production of final food products and food consumption expenditures is often limited and different across products.[13] To evaluate this, Figure 12 shows the pass-through to the food-related products that are included in the HICP. The panels also show the response of HICP excluding food and energy as a reference point (dotted red lines) to assess whether the prices have increased in real terms.

Some interesting observations are worth mentioning. First, the prices of food items increase more than the overall HICP. Whereas the HICP excluding energy and food increases by 0.05%, the prices of unprocessed and processed food products rise by 0.10% and 0.15%, respectively (see Figure 9). Additionally, the transmission of EU food commodity prices to retail prices is incomplete. The strongest pass-through is found for milk, cheese and eggs. In particular, whereas dairy commodity prices increase by 0.39%, the corresponding retail prices increase by 0.20%. The pass-through to meat and fruit retail prices is somewhat more subdued. These components of the HICP increase by 0.13% and 0.16%, respectively, while the corresponding commodity prices rise by 0.42% and 0.65%. The pass-through to bread and

[12] The CAP consists of several measures in order to influence prices and quantities of agricultural commodities within the EU. Examples are crop subsidies for EU farmers, price support mechanisms and tariffs on agricultural products imported from non-EU countries. An overview is provided in European Commission (2010).

[13] As explained in footnote 1, the share of food commodities in final food and beverages expenditures in the US is approximately 14%. For the euro area, this is probably similar.

cereal consumer prices is even more modest; that is, the rise of EU cereal commodity prices by 1.20% appears to result in a rise of the prices of bread and cereals by 0.16%.

Figure 12 further reveals that there seems to be a lot of variation in the transmission to the prices of different types of unprocessed and processed food items. The impact is strongest on prices that consumers have to pay for milk, cheese and eggs; that is, an increase by 0.20%. On the other hand, fish prices increase by only 0.07%. The impact on the prices of other unprocessed and processed food products of the HICP fall in between these values. Of all these components, only the impact on vegetables prices is not statistically larger than the impact on the HICP excluding food and energy. Finally, the pass-through to prices that consumers have to pay in restaurants or catering prices is modest and very similar to the rise in HICP excluding food and energy. Canteen prices increase even less than core inflation. Overall, it appears that catering services are not differently affected than non-food products and services. In fact, this is not very surprising given the very small share of food commodities to produce these services.

5.3 Pass-through in the Post-1990 Sample Period

As discussed in section 4.2, and shown in Figure 8, the impact of a one-percent rise in food commodity prices on the HICP is smaller and less persistent for a sample that only starts in 1990Q1. To evaluate whether also the transmission mechanism has changed over time, Figure 13 depicts the impulse responses of several relevant variables for the post-1990 sample period. The dashed red lines in the panels are the benchmark responses for the full sample period. A first observation is that the transmission through the food production chain has remained more or less stable over time. The magnitudes and patterns of international food commodity prices and EU internal market prices are very similar for both sample periods, while there is still a significant pass-through to retail prices of unprocessed and processed food in the recent sample.

The indirect effects, in contrast, turn out to be quite different for both sample periods. First, the magnitude of the depreciation of the euro and rise of import prices is lower in the post-1990 sample period. Second, despite the relative strong rise in inflation expectations, nominal wages and unit labor costs increase much less in the recent sample period. As a consequence, there is also no impact of the shocks on the HICP excluding energy and food. The insignificant impact on core inflation is, in turn, the reason for the smaller magnitude and lower persistence of the overall effects on the HICP since the 1990s.

Another interesting difference between both samples is the impact on energy prices. As can be observed in Figure 13, food commodity price shocks trigger a significant contemporaneous rise in crude oil prices in the post-1990 sample period, whereas the contemporaneous impact on oil prices is essentially zero over the whole sample period. Accordingly, there is also a stronger pass-through to the HICP energy. This finding is consistent with the results of Peersman et al. (2018), who estimate an SVAR with time-varying parameters for global crude oil and food markets, and document that there have been positive spillovers between both commodity prices since the early 2000s, in contrast to earlier periods. Specifically, oil supply shocks trigger a rise in food commodity prices, and vice versa for food supply shocks. There are two potential explanations for the spillovers. First, since the 2000s, there has been a substantial rise in the use of food commodities to produce energy goods. As a result, crude oil and food commodities have become substitutes over time for the production of energy, which synchronizes the evolution of their prices. Second, there is a growing literature that finds that, as a consequence of informational frictions in commodity markets, the enhanced financialization of commodity trading over the past two decades has resulted in more price synchronization across commodities (e.g. Singleton 2013; Sockin and Xiong 2015). Although the exact reason is not clear, the existence of a positive spillover effect is confirmed by the subsample analysis.

6 Conclusions

Food items represent a considerable share of euro area household expenditures, while food prices have accounted for a large part of HICP volatility since the start of the euro. Since food commodities are a key input factor in the food production function, understanding the dynamics of food commodity prices is very important for monetary policymakers. In this paper, I have examined the causal effects of fluctuations in international food commodity prices on inflation dynamics and the transmission mechanism to consumer prices in the euro area. To address endogeneity issues, I explore the time lag between planting and harvesting of at least three months to construct a series of unanticipated global (non-European) harvest shocks, which is then used as an instrument to achieve identification in an SVAR-IV model for the euro area economy.

The effects of an exogenous shift in international food commodity prices on euro area inflation turns out to be quite strong and economically meaningful. On average, exogenous swings in international food commodity prices have historically accounted for 25%-30% of HICP volatility. Developments in global food commodity markets should thus be closely monitored by policymakers. I document a direct pass-through along the food production chain via spillovers on EU farm-gate and internal wholesale market prices to retailer prices of food items. However, there also appear to be indirect effects since an exogenous rise in international food commodity prices triggers a depreciation of the euro exchange rate, resulting in higher import prices, and second-round effects due to a rise in inflation expectations and nominal wages.

A remarkable observation is that large and persistent autonomous swings in international food commodity prices had an important impact on euro area inflation developments in the era after the Great Recession. Specifically, a counterfactual simulation reveals that inflation would have been between 0.2% and 0.8% lower in the period 2009-2012, and between 0.5% and 1.0% higher in 2014-2015. These two periods have often been described as the missing disinflation and missing inflation episodes, respectively, and have led economists to question and reassess the relation between real activity and inflation. The counterfactual simulation, however, suggests that both episodes might be less puzzling than previously thought and can at least partly be explained by developments in global food commodity markets.

Overall, the analysis in this paper stresses the importance of the global nature of inflation, a conclusion that is in line with earlier studies (e.g. Borio and Filardo 2007; Monacelli and Sala 2009; Ciccarelli and Mojon 2010; Mumtaz and Surico 2012; Eickmeier and Pijnenburg 2013). On the other hand, there are still a number of issues that require additional investigation. A pertinent question is the reason for the depreciation of the euro following a rise in international food prices. Another relevant question is whether the pass-through of food commodity price shocks to consumer prices is nonlinear, or whether there has been time-variation in the transmission mechanisms. These are all questions that are left for future research.

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Appendix: Data

Benchmark SVAR model data series The euro/USD bilateral exchange rate, real GDP, real export, real personal consumption, the short-term nominal interest rate and the HICP are collected from the ECB's Area-Wide Model dataset. Following De Winne and Peersman (2016, 2018), the international food 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. 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 nominal price index has been deflated by US consumer prices excluding food and energy. Finally, the real crude oil price index is the refiner acquisition cost of imported crude oil, deflated by US consumer prices excluding food and energy.

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 over the period 1961-2013. 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 broader food commodity price index is collected from IMF Statistics Data. The index is a trade-weighted average of different benchmark food prices in USD 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 index has been seasonally adjusted using Census X-13 (X-11 option), and deflated by US consumer prices excluding food and energy. 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).

Alternative SVAR-IV specifications The weighted sum of GDP of the main euro area trading partners is collected from the Area-Wide Model database, and aggregate real GDP of OECD countries from the OECD database. The USD effective exchange rate, implied stock market volatility (VXO) and equity prices (S&P500) are collected from the Federal Reserve Bank of St-Louis (Fred) database. The narrative food commodity price shocks are from De Winne and Peersman (2016).

Additional variables The HICP-components are from Eurostat and downloaded from the ECB Statistical Data Warehouse. 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, while the import deflator, nominal effective exchange rate, unit labor costs and nominal wage per head are from the Area-wide Model dataset.

The indexes of domestic (EU) food commodity prices are all based on data from DG AGRI of the European Commission. The dataset puts together series of farm-gate and wholesale market prices from 1991 onwards. The cereal commodity price index is 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, meat commodity prices are an unweighted average of beef (cows), pork (piglets) and chicken prices, while dairy commodity prices are an unweighted average of the prices of (raw) milk, butter, cheese (cheddar) and eggs. Finally, fruit commodity prices are the average of lemon, strawberries, pears and apples (golden).

Table 1 - Composition of euro area Harmonised Index of Consumer Prices

HICP - Food-related items		27.40
Processed food incl. alcohol and tobacco	*12.10*	
Unprocessed food	*7.48*	
Catering services	*7.83*	
HICP - Industrial goods excl. energy		26.33
HICP - Energy		9.70
HICP - Services excl. Catering		36.57
HICP - Overall index		100.00

Note: HICP weights per 100 EUR household final monetary consumption expenditures. Source: Eurostat.

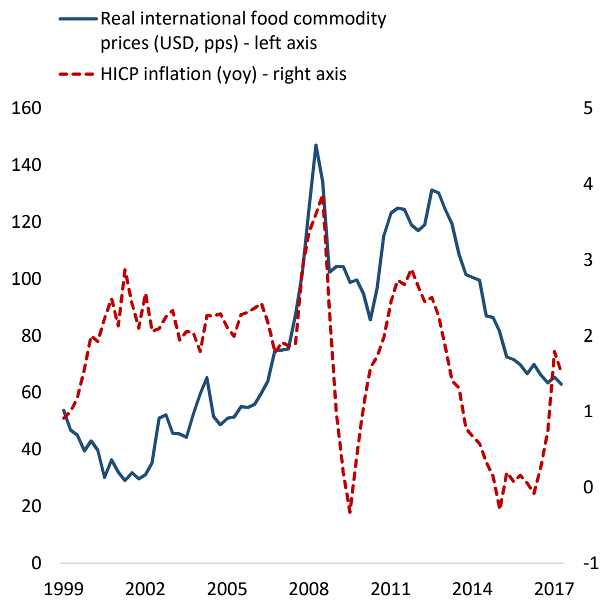
Table 2 - Correlation of monthly and quarterly changes in commodity prices

Correlation 1970-2017	***Monthly data***		***Quarterly data***	
	Crude oil	Industrial commodities	Crude oil	Industrial commodities
Broad food commodity price index	0.15	0.34	0.27	0.48
Narrow food commodity price index	0.09	0.17	0.21	0.24
Correlation 1999-2017	***Monthly data***		***Quarterly data***	
	Crude oil	Industrial commodities	Crude oil	Industrial commodities
Broad food commodity price index	0.29	0.39	0.49	0.49
Narrow food commodity price index	0.18	0.23	0.34	0.29

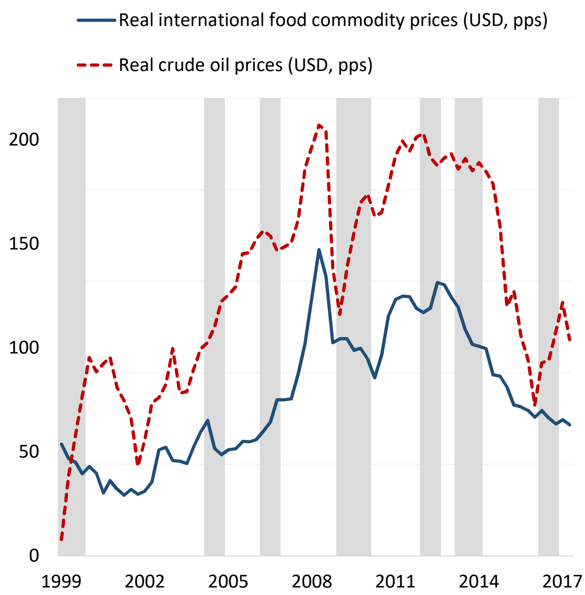
Note: Broad food commodity price index is trade-weighted average of benchmark food prices in US dollars for cereal, vegatable oils, meat, seafood, suger, bananas and organges. Narrow index is weighted average of the prices of corn, wheat, rice and soybeans. Source: IMF and own calculations.

Figure 1 - Fluctuations in international food commodity prices, euro area inflation and crude oil prices

(A) Real international food commodity prices and HICP inflation



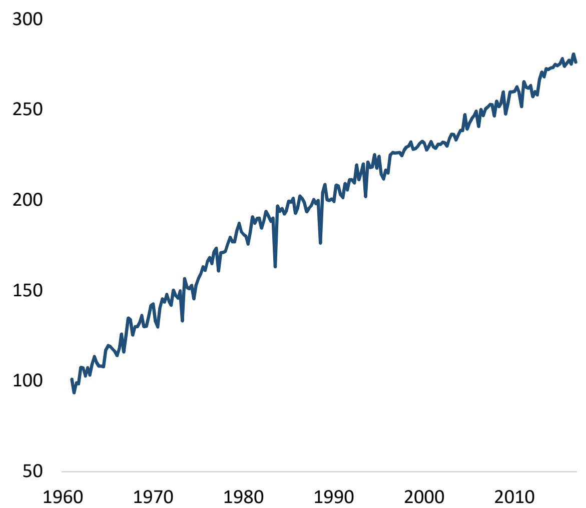
(B) Real international food commodity prices and crude oil prices



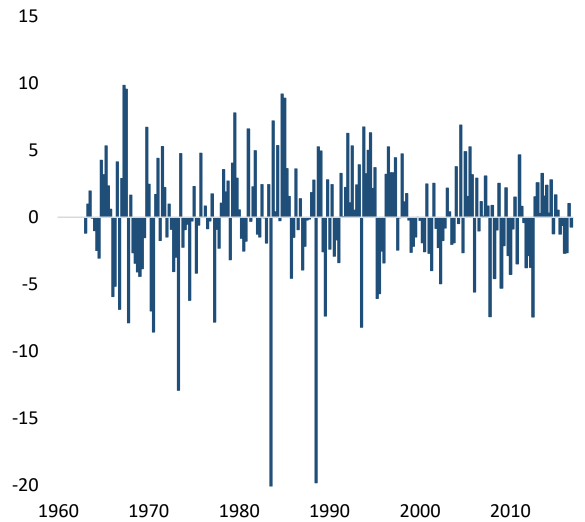
Note: international food commodity price index is a weigted average of the prices of corn, wheat, rice and soybeans (source: IMF). Crude oil prices is an index of refiner acquisition cost of imported crude oil. The figures show 100 times the natural log of the index deflated by US consumer prices excluding energy and food. Grey areas represent shifts of food commodity prices and crude oil prices in opposite direction for at least two consecutive quarters.

Figure 2 - Global food production index excluding European harvests and unanticipated harvest shocks

(A) Global food production index excluding European harvests

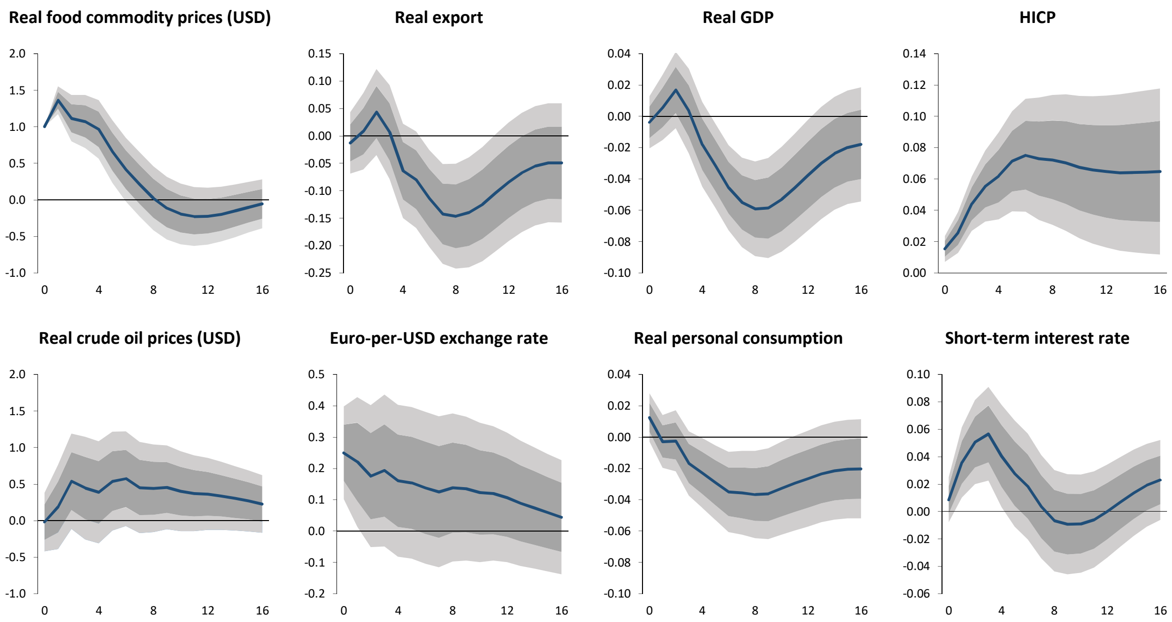


(B) Unanticipated harvest shocks



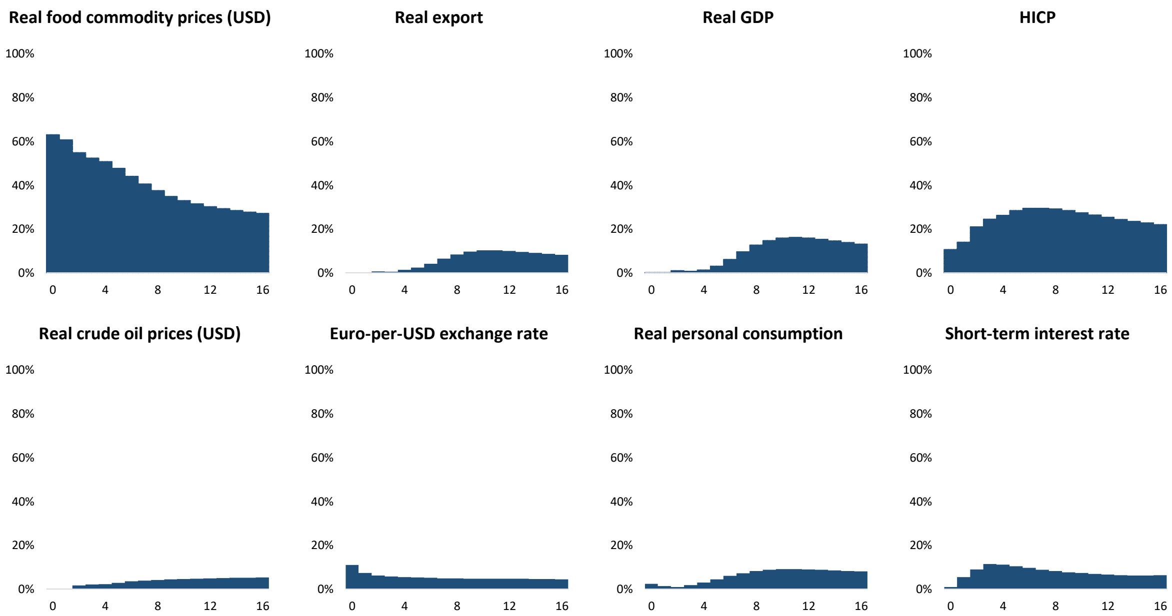
Note: Panel (A) shows 100 times the natural log of the food production index excluding European harvests; the production index aggregates the harvests of corn, wheat, rice and soybeans, and is seasonally adjusted.
Panel (B) shows the estimated unanticipated harvest shocks (percentage points changes in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

Figure 3 - Effects of a 1% increase in international food commodity prices



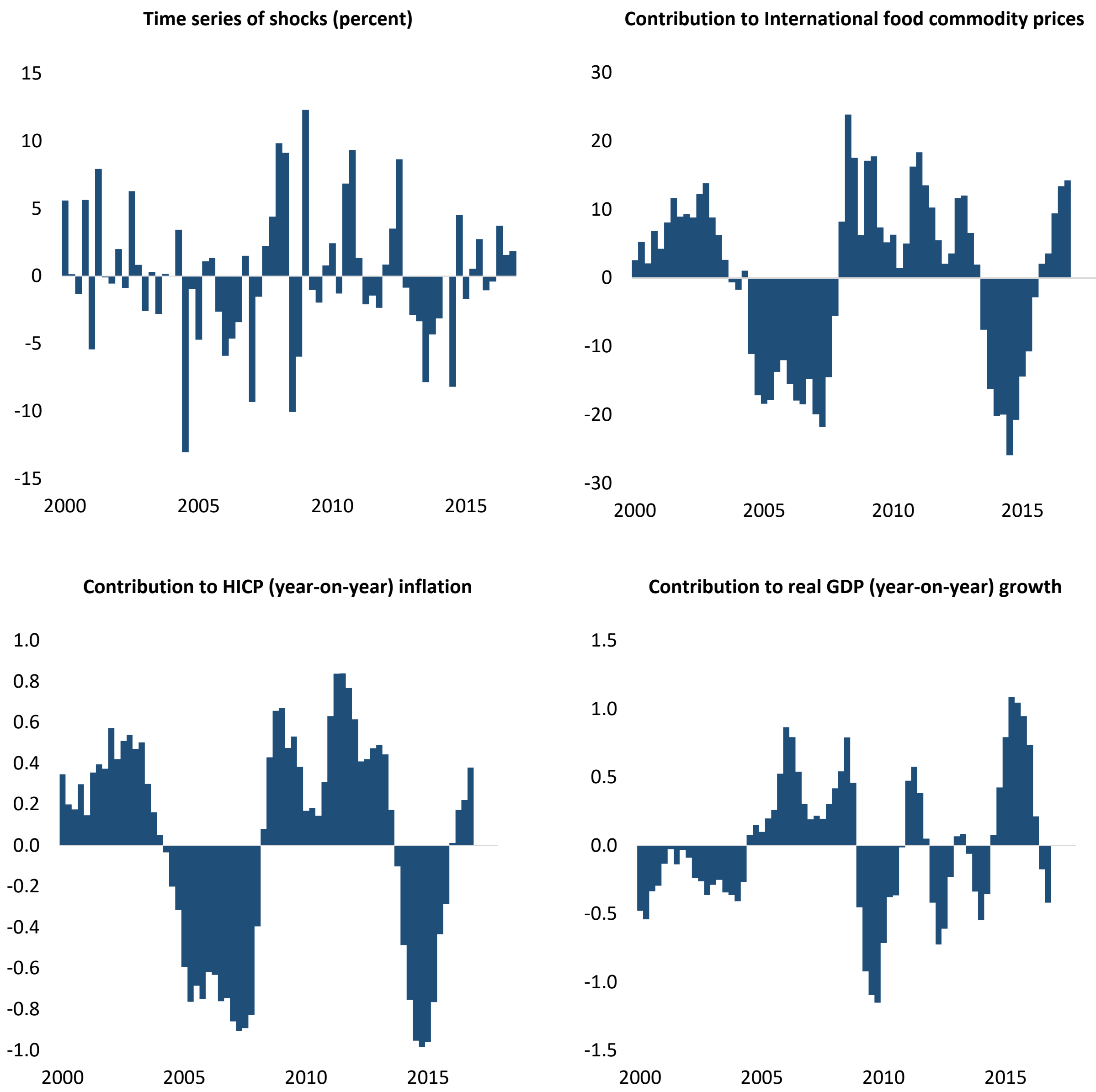
Note: 68% and 90% confidence intervals constructed using a recursive-design wild bootstrap; horizon is quarterly.

Figure 4 - Contribution of international food commodity price shocks to forecast error variance decompositions



Note: horizon is quarterly.

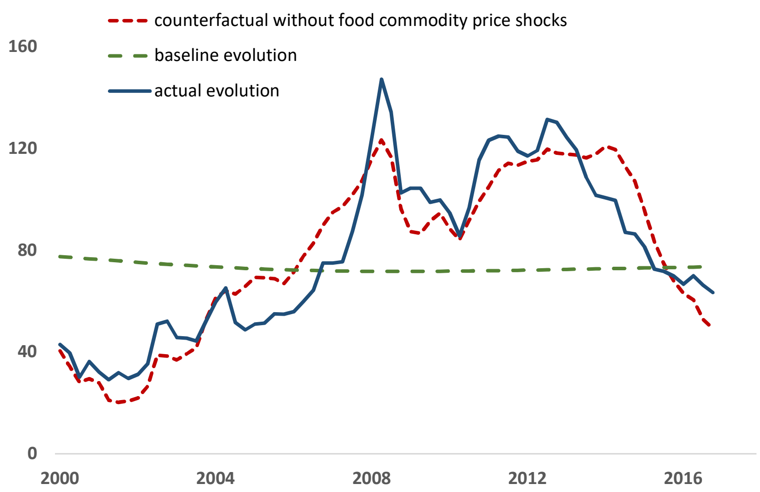
Figure 5 - Contribution of international food commodity price shocks since the start of the millennium



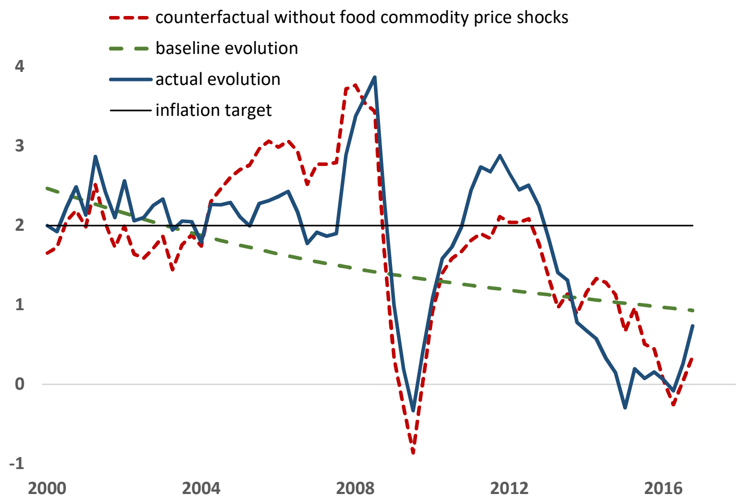
Note: time series of food commodity price shocks and contribution to some key variables implied by the VAR model; year-on-year growth rates are re-calculated based on the contribution to the level of the variables.

Figure 6 - Counterfactual evolutions in absence of international food commodity price shocks

International food commodity prices



HICP (year-on-year) inflation



Real GDP (year-on-year) growth

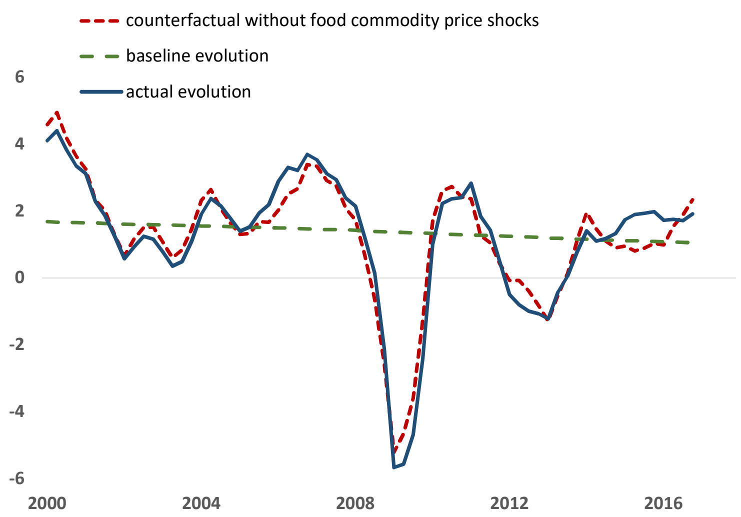
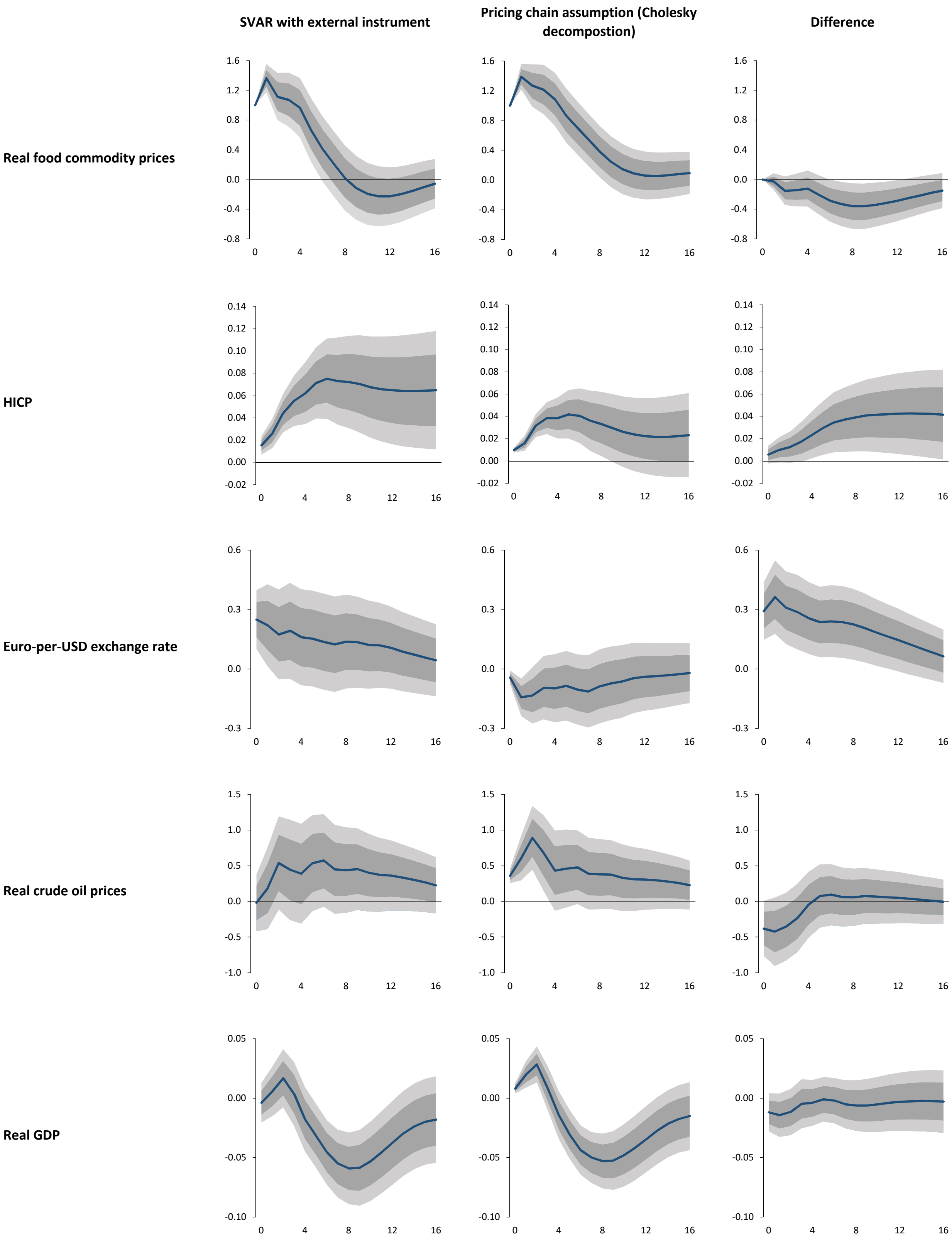
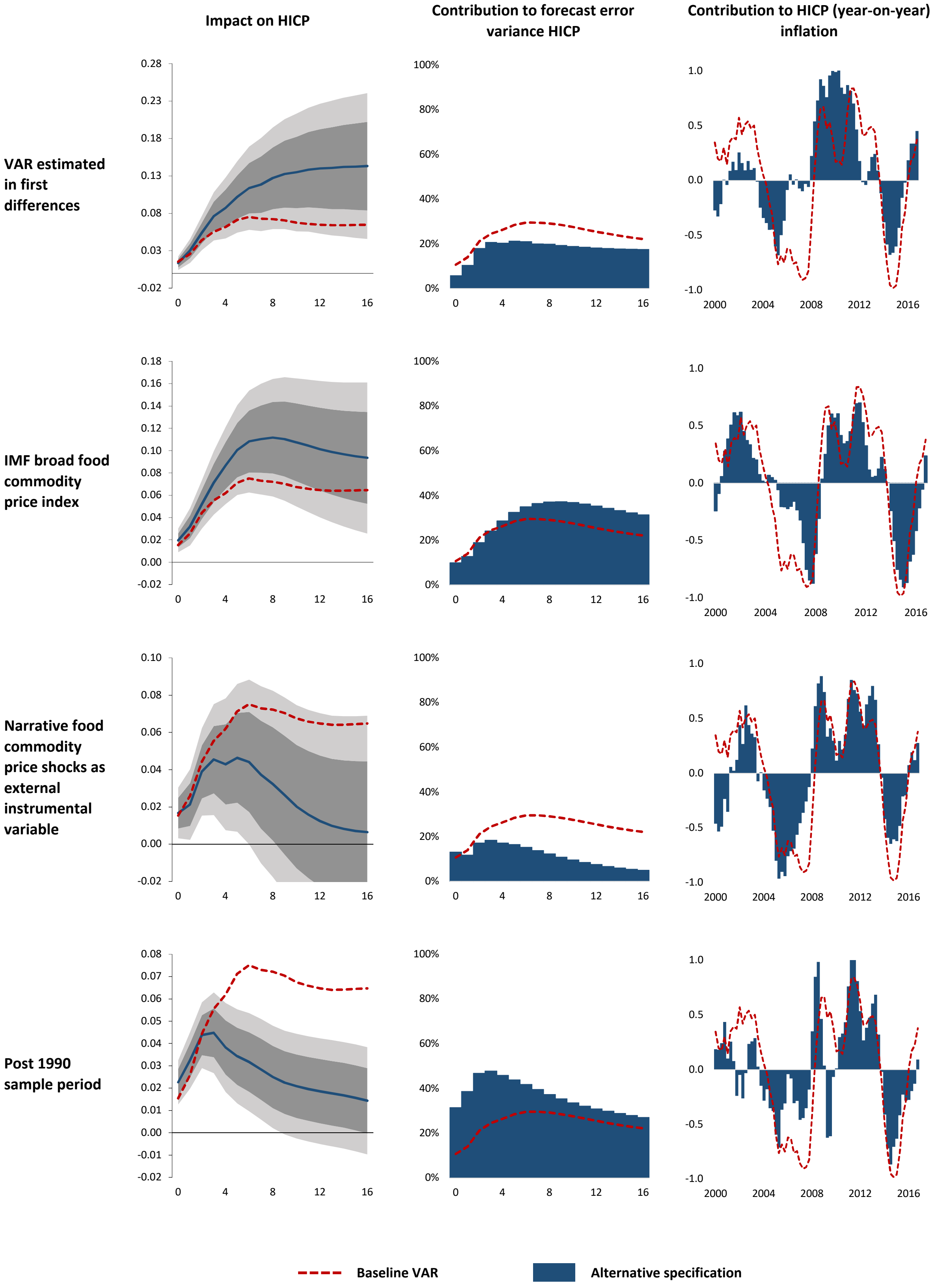


Figure 7 - Difference between SVAR identified with an external instrument and a Cholesky decomposition



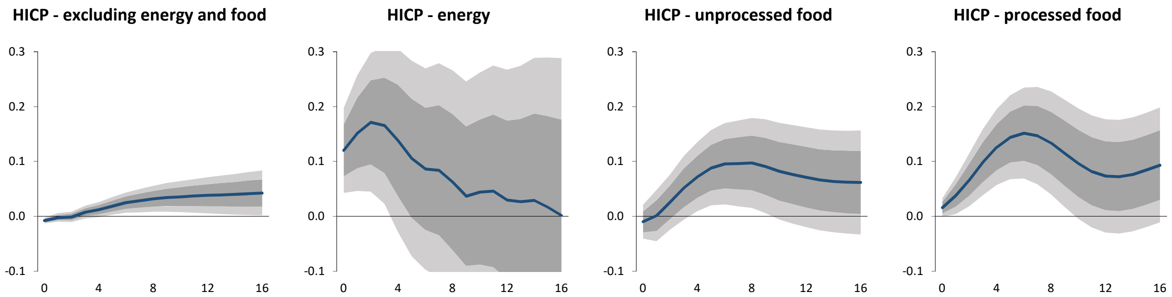
Note: Impulse responses are only shown for some key variables; 68% and 90% confidence intervals constructed using a recursive-design wild bootstrap; horizon is quarterly.

Figure 8 - Alternative SVAR-IV specifications



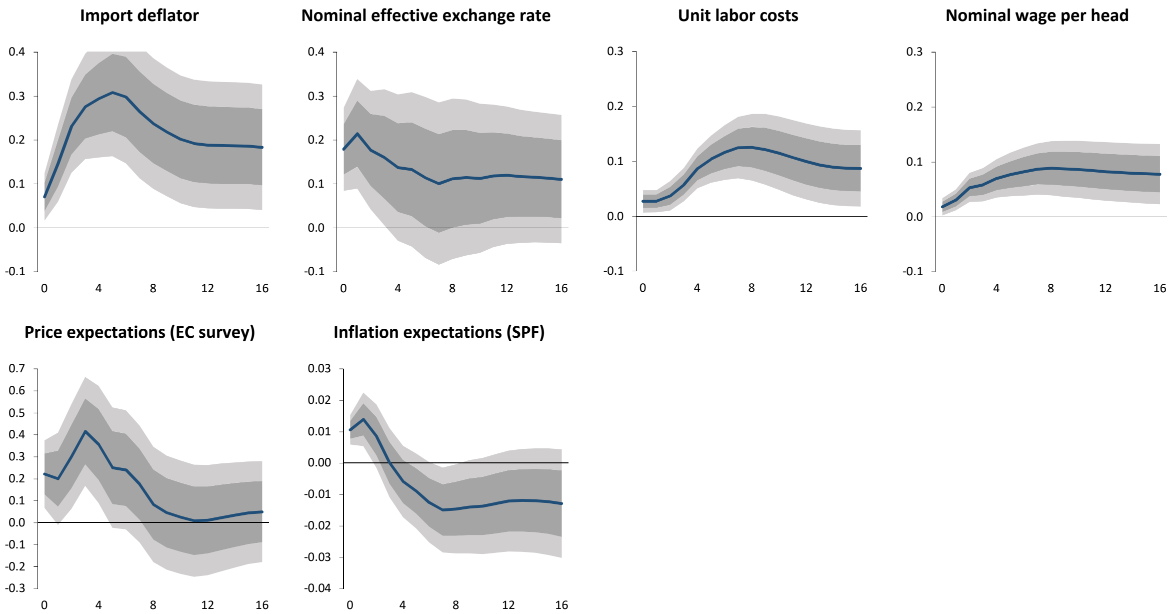
Note: Impulse responses, variance decompositions and historical contributions are only shown for the HICP and inflation; 68% and 90% confidence intervals constructed using a recursive-design wild bootstrap; horizon is quarterly.

Figure 9 - Effects of a 1% increase in international food commodity prices on HICP components



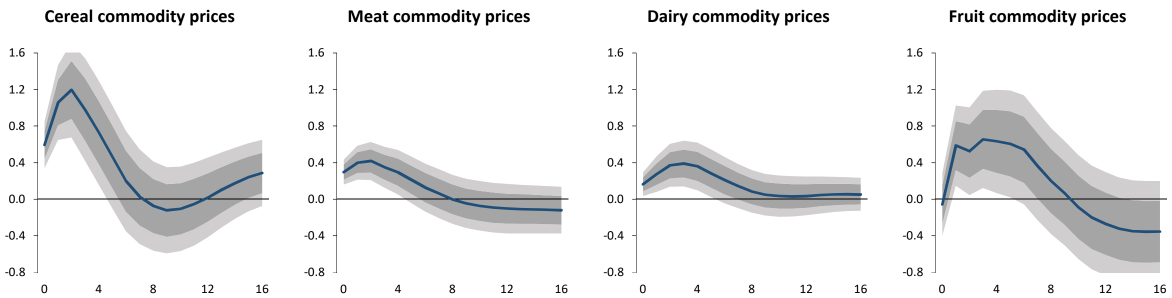
Note: 68% and 90% confidence intervals constructed using a recursive-design wild bootstrap; horizon is quarterly.

Figure 10 - Effects of a 1% increase in international food commodity prices on other variables



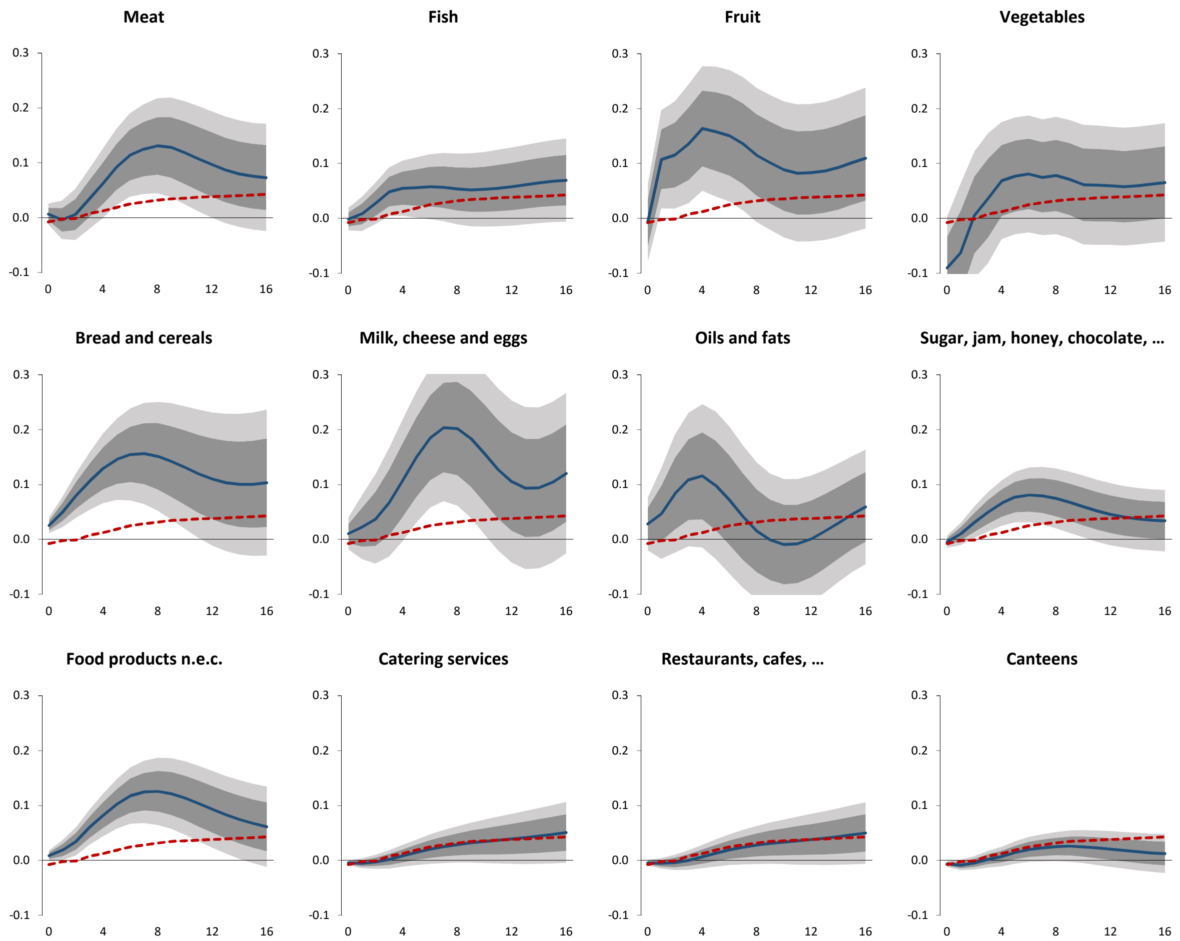
Note: 68% and 90% confidence intervals constructed using a recursive-design wild bootstrap; horizon is quarterly.

Figure 11 - Effects of a 1% increase in international food commodity prices on domestic (EU) food commodity prices



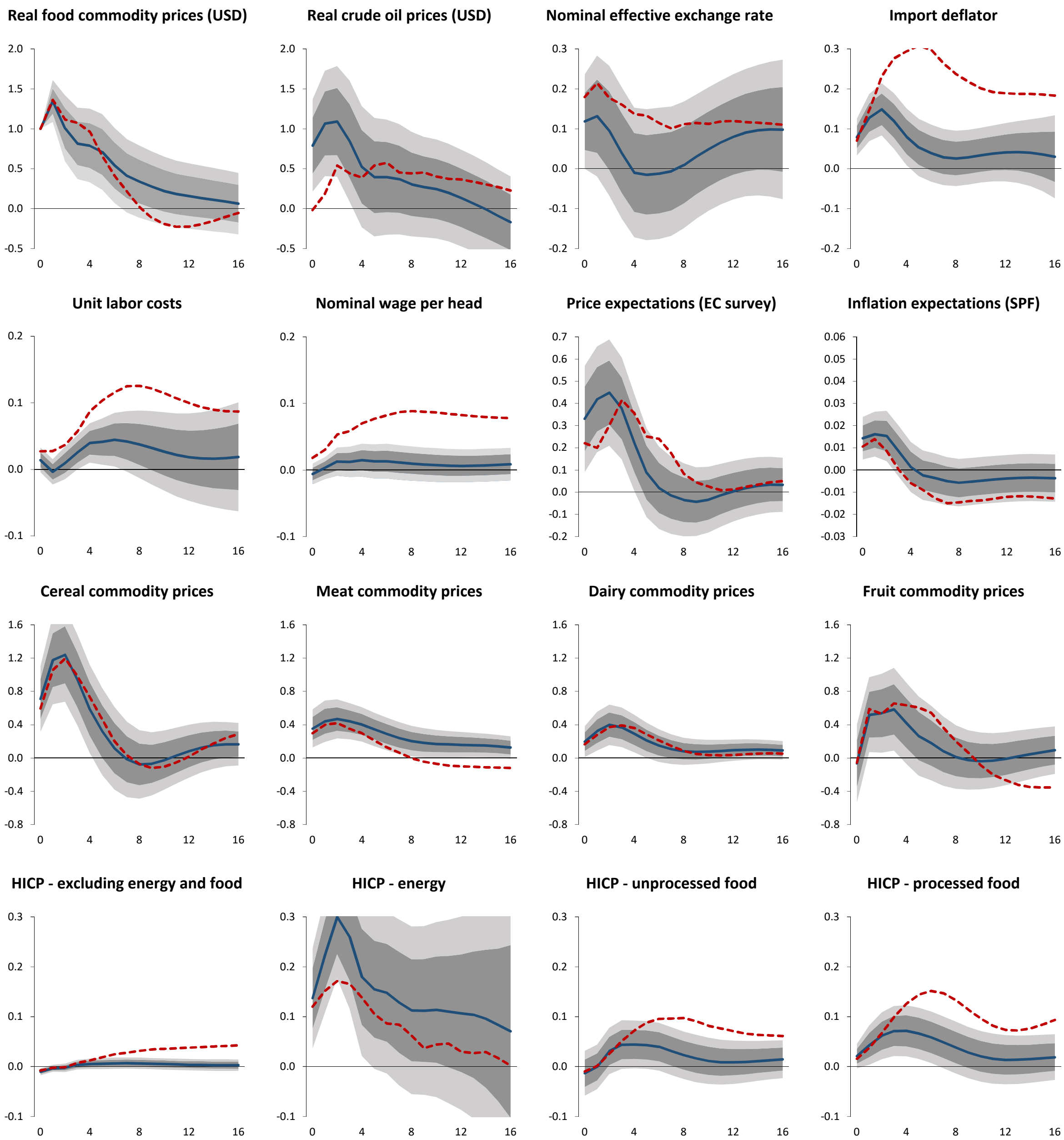
Note: 68% and 90% confidence intervals constructed using a recursive-design wild bootstrap; horizon is quarterly.

Figure 12 - Effects of a 1% increase in international food commodity prices on HICP food related products



Note: 68% and 90% confidence intervals constructed using a recursive-design wild bootstrap; horizon is quarterly.
Dashed red line is response of HICP excluding food and energy.

Figure 13 - Effects of a 1% increase in international food commodity prices in the post-1990 sample period



Note: Impulse responses are only shown for some relevant variables; 68% and 90% confidence intervals constructed using a recursive-design wild bootstrap; horizon is quarterly. Dashed red lines are the benchmark responses for the full sample period.