FACULTEIT ECONOMIE
EN BEDRIJFSKUNDE

TWEEKERKENSTRAAT 2
B-9000 GENT
Tel. : 32 - (0)9 – 264.34.61
Fax. : 32 - (0)9 – 264.35.92

WORKING PAPER

Macroeconomic Effects of Disruptions in Global Food Commodity Markets: Evidence for the United States

Jasmien De Winne Gert Peersman

October 2016
2016/924

D/2016/7012/08

Macroeconomic Effects of Disruptions in Global Food Commodity Markets: Evidence for the United States*

Jasmien De Winne
Ghent University

Gert Peersman
Ghent University

October 2016

Abstract

We use two approaches to examine the macroeconomic consequences of disruptions in global food commodity markets. First, we embed a novel quarterly composite global production index for the four basic staples (corn, wheat, rice and soybeans) in a standard vector autoregression (VAR) model, and we estimate the dynamic effects of global food commodity supply shocks on the US economy. As an alternative, we also estimate the consequences of thirteen narratively identified global food commodity price shocks. Both approaches deliver similar conclusions. Specifically, an unfavorable food commodity market shock raises food commodity prices, and leads to a rise in food, energy and core inflation, and to a persistent fall in real GDP and consumer expenditures. A closer inspection of the pass-through reveals that households do not only reduce food consumption. In fact, there is a much greater decline in durable consumption and investment. Overall, the macroeconomic effects turn out to be a multiple of the maximum impact implied by the share of food commodities in the consumer price index and household consumption.

*Email: jasmien.dewinne@ugent.be; gert.peersman@ugent.be. This paper has been written for the September 2016 Conference of the Brookings Papers on Economic Activity. We thank the editor, Jim Stock, for his valuable comments and guidance in revising the paper. We are also grateful to our discussants, Wolfram Schlenker and Mark Watson, and participants at the Brookings Conference for helpful comments. We thank Bruno Albuqerque, Selien De Schryder, Gert Elaut, Kevin Lampaert, Viooltje Lebuf, Karel Mertens, Chris Sims and Joris Wauters, as well as seminar and conference participants at the Sao Paulo School of Economics, the Erasmus University Rotterdam, the Banca d'Italia, the Norges Bank, the Ghent-Lille Economics Workshop (2015), the T2M Annual Meeting in Paris (2016), the Birkbeck Centre for Applied Macroeconomics Workshop (2016) and the IAAE Annual Meeting in Milan (2016) for useful suggestions and feedback on earlier versions of the paper. We acknowledge financial support from the Research Foundation Flanders (FWO) and the UGent Special Research Fund (BOF). All remaining errors are ours.

1 Introduction

> *"It is almost a truism to say that the characters of the seasons exert a very great influence on the amount and quality of our home-produce of wheat from year to year; and that upon the amount of food which the crop supplies depends very materially, though less than formerly, the general prosperity of the nation."*
>
> Lawes and Gilbert (1868)

Until the beginning of the 20th century, agricultural fluctuations were considered very important for the business cycles of advanced economies (e.g., Giffen, 1879), but that attention vanished as agricultural sectors in developed countries contracted. However, the huge swings in food commodity prices since the start of the millennium, depicted in Figure 1, have reignited interest in the linkages between food commodity markets and the macroeconomy. In particular, the surge of real global food commodity (cereal) prices by 67 (112) percent between 2002 and 2011, a period that has been described as a "global food crisis", and their subsequent fall by 40 (77) percent, have attracted a vast interest in understanding the economic causes and consequences of developments in food commodity markets.[1]

Yet little is known about the repercussions of disruptions in global food commodity markets on the business cycles of the US and other advanced countries, which is surprising. The lack of quantitative evidence on the macro effects might be justified by the relatively low and declining share of agriculture in real GDP, and the fact that the US is a (modest) net exporter of cereals, two features that are documented in Figure 2, but this appears to be misleading. The share of agriculture in real GDP has on average indeed been slightly below 2 percent since the 1960s, but this ignores the fact that food commodities are a critical input factor in the production function of the food processing sector, while food and beverages have accounted for approximately 17 percent of US household spending between the 1960s and today.[2] Accordingly, there could also be important indirect effects of food commodity market

[1] Two examples of newspaper articles addressing this topic are "The World Food Crisis" (New York Times, April 10, 2008) and "Global food crisis forecast as prices reach record highs" (The Guardian, October 25, 2010). In 2012, the NBER directed a panel of academic experts to study the economics of food price volatility (Chavas et al., 2014). See also a number of reports from policy institutions on the sources and potential consequences of the surge in food prices (e.g., Headey and Fan, 2010; Abbott et al., 2011; Trostle et al., 2011) or recent microeconomic studies that examine the welfare implications of food prices shocks for households in developing economies (e.g., Ivanic and Martin, 2008; Baquedano and Liefert, 2014; Dawe and Maltsoglou, 2014).

[2] According to the Bureau of Economic Analysis, the average share of food and beverages in total household expenditures has been 17.3 percent between 1960 and 2015. The share of food commodities in final food products and beverages expenditures, in turn, has been 14.1 percent (USDA Economic Research Service data; only available for the period 1993-2014). This corresponds to 928 USD food commodities expenditures per

fluctuations on the US economy; i.e., food commodity market shocks may affect the economy through their impact on consumer spending. Examples include costs of reallocating labor and capital across alternative production activities, precautionary savings, or a monetary policy response amplifying the output effects. Such effects have been put forward in the literature on oil and energy price shocks (e.g., Bernanke et al. 1997, Hamilton 2008), but could also apply to food commodity price shocks. Moreover, there has been a substantial rise in the use of food commodities to produce energy goods in recent periods. For example, the share of biofuels in petroleum consumption is currently more than 5 percent (see Figure 2). Fluctuations in food commodity markets may therefore also affect the economy via energy prices.

Quantitative evidence on the macro consequences is not only important for a better understanding of business cycle fluctuations. It is also vital in examining the optimal monetary policy response to changes in food prices or in assessing the usefulness of public food security programs, such as the Federal Agricultural Improvement and Reform (FAIR) Act and the US Supplemental Nutrition Assistance Program (SNAP, previously known as the Food Stamp Program). Furthermore, it is necessary to analyze the repercussions of several policy measures that may influence the price of food, such as trade policies (e.g., export bans or restrictions on food imports) or policies to reduce CO_2 emissions (e.g., ethanol subsidies or carbon offset programs). Finally, empirical evidence on the macro effects of food market disruptions should help to assess the consequences of climate change, which could increase the likelihood of significant weather shocks in agriculture.

In this paper, we estimate the effects of disturbances in global food commodity markets on the US economy over the period 1963Q1-2013Q4. An empirical analysis of the macroeconomic effects of fluctuations in food commodity markets is challenging because food prices likely respond substantially to both supply and demand conditions, implying that reverse causality effects from macroeconomic aggregates to food prices are also present. The unconditional correlation between changes in real global food commodity prices and US real GDP is, for instance, positive. If one is interested in a unique causal interpretation, it is thus crucial to isolate movements in food prices that are strictly exogenous. We explore two strategies for identifying such movements.

The first strategy is a joint structural VAR model for the global food commodity market

capita per year (measured in constant 2015 dollar values). Overall, only housing and utilities absorb a greater share (17.8 percent) of household expenditures. The share of oil products (heating oil and motor fuel), for example, has on average been only 3.8 percent over the same period, while numerous studies have analyzed the macroeconomic effects of shocks in the global crude oil market (e.g., Hamilton, 1983; Kilian, 2009; Peersman and Van Robays, 2009). Notice that about half of gasoline prices are determined by the cost of crude oil. Combined with an average share of oil products in household expenditures of 3.8 percent, this implies that crude oil expenditures are roughly 764 USD per capita per year.

and the US economy. To identify food market disturbances that are unrelated to macroeconomic conditions, we construct a novel quarterly composite global production index for the four most important staples: corn, wheat, rice and soybeans. Together, these commodities comprise approximately 75 percent of the caloric content of food production worldwide. Annual production data for these four crops are available from the Food and Agriculture Organization (FAO) for 192 countries since the early 1960s. Roberts and Schlenker (2013) aggregate the four crops on a caloric-weighted basis to construct an annual indicator of world food production. We use the same principium to construct a quarterly indicator, which is an appropriate frequency for a business cycle analysis. Specifically, we combine the annual production data of each individual country with that country's planting and harvesting calendars for the four crops. Because most countries have only one relatively short harvest season for each crop, and there is a delay between planting and harvesting, we can assign two-thirds of world food production (harvests) to a quarterly production index that fulfills the condition that the decision to produce (planting) did occur in an earlier quarter. Accordingly, in a quarterly VAR, innovations to the food production index (essentially unanticipated harvest shocks) are by construction exogenous to the macroeconomy, and the subsequent changes in real GDP, consumer prices and other macro variables can be given a causal interpretation.

The estimation results assert a considerable influence of global food market disruptions on the US economy. A one standard deviation unfavorable innovation to the global food production index raises real food commodity prices by approximately 1.7 percent, which in turn leads to a 0.16 percent rise in consumer prices and a persistent fall in real GDP and personal consumption of almost 0.3 percent. According to a simple back-of-the-envelope calculation, the effects on consumer prices and personal consumption are approximately four to six times larger than the maximum impact implied by the share of food commodities in the consumer price index and total consumption expenditures (i.e., maximum discretionary loss in purchasing power). This denotes that indirect effects prevail and magnify the macroeconomic consequences. As a reference point, the effects on real GDP are roughly twice as large as the impact of a similar rise in global crude oil prices induced by an oil supply shock identified within the same VAR model. Additionally, Edelstein and Kilian (2009) find that the response of personal consumption to an energy price shock is approximately four times the magnitude of the maximum discretionary purchasing power loss.

The stylized facts obtained from the VAR turn out to be robust for a battery of sensitivity tests and perturbations to the benchmark model. We also verify whether the innovations to the global production index are picking up other shocks, such as oil price or aggregate demand shocks, whether the underlying disturbances have effects on the economy other than via fluctuations in food commodity markets (e.g., through direct effects of weather conditions on economic activity), and whether the results are distorted by possible time variation or nonlinearities. Overall, we do not find support for these conjectures nor that such effects have a meaningful influence on the results.

As an alternative strategy to address the identification problem, we use a narrative approach in the spirit of Hamilton (1983), Romer and Romer (1989, 2010), Ramey and Shapiro (1998) and Ramey (2011). The advantage of narrative methods compared to the VAR analysis is that it requires less assumptions, and that we can use a very large information set to identify exogenous food market shocks. More precisely, based on FAO reports, newspaper articles and several other sources, we identify thirteen historical episodes in which major changes in food commodity prices were mainly driven by exogenous disturbances that had little to do with macroeconomic conditions. Examples of unambiguously unfavorable food commodity market shocks were the Russian Wheat Deal (combined with a failed monsoon in South-Asia) in the summer of 1972, or the more recent Russian and Ukrainian droughts in 2010 and 2012. In contrast, a number of unanticipated significant upward revisions in the expected harvest volume can be classified as episodes of favorable food market shocks (e.g., in 1975, 1996 and 2004). In a next step, we construct a dummy variable based on these episodes, which is then used as an instrument to estimate the consequences of global food commodity price shocks on the US economy.

The dynamic effects of the narratively identified shocks are estimated using Jordà's (2005) local projection method. The results confirm the conclusions of the VAR analysis. Whereas the narratively identified shocks have a more persistent impact on global food commodity prices and macroeconomic variables, the magnitudes of the effects on economic activity are very similar to the VAR results. The effects on consumer prices are even greater. Overall, the macroeconomic consequences of food market disturbances turn out to be substantial.

In a next step, we use the VAR model to examine the pass-through to consumer prices and economic activity in more detail. To do this, we extend the VAR and estimate the effects of food commodity supply shocks on inflation components, household expenditures categories and other relevant variables, while we also compare the dynamics with oil supply shocks. The results reveal that not only do food prices increase after an unfavorable food commodity supply shock, but so does core inflation, as well as inflation expectations and in recent periods even energy prices. Oil supply shocks, in contrast, only raise energy prices. The significant effects on core inflation and inflation expectations are presumably the reason why we also observe a monetary policy tightening of the Federal Reserve in response to food market disruptions, in contrast to a policy easing following unfavorable oil supply shocks. A closer inspection of the impact on the components of output further unveil that households do not only reduce food consumption expenditures. A key mechanism whereby food market shocks affect the economy is through a decline in spending on other goods and services, in particular durable consumption and investment.

The monetary policy response can be considered as a first amplification mechanism for the strong impact of food commodity supply shocks on economic activity. We argue that this can explain at most one-third of the overall output consequences, and that the magnitudes and propagation of the remaining (non-monetary policy) output effects are comparable to those of oil supply shocks. More specifically, while food supply shocks have a significant impact on food consumption, and oil supply shocks on energy consumption (and not the other way around), the pass-through of both shocks to all other components of household expenditures and investment appear to be quantitatively and qualitatively very much alike. This is even the case for the consumption of motor vehicles and parts, a component of expenditures that is typically considered to be complementary in use with oil, and thus perceived as much more sensitive to oil shocks. Our results suggest that other effects are more important for the propagation of both shocks. We discuss a number of alternative channels that could potentially explain the amplification and composition of the output effects, but the relevance of these mechanisms is hard to identify definitively with the methods used in this paper and is left for future research.

In sum, the macro effects of food market disturbances are compelling, and should be taken into account for business cycle analysis, countercyclical policies, public risk management schemes for the stabilization of food markets, and the assessment of climate change and policy measures that may influence food prices.

In section 2, we describe the baseline VAR model, the construction of the global food production index and the other variables that are used for the estimations. In section 3, we discuss the VAR results and several sensitivity checks. The narrative approach is reported in section 4. The comparison with oil supply shocks and the pass-through to inflation and economic activity is analyzed in section 5. Finally, section 6 concludes.

2 VAR model for the global food market and US economy

2.1 Methodology

To estimate the macro consequences of disruptions in global food commodity markets, it is crucial to identify unanticipated shocks in these markets that are exogenous with respect to the macroeconomy. Our first strategy is a structural VAR approach in the spirit of Sims (1980), which has been a popular tool in the literature for the estimation of the effects of monetary policy (e.g., Bernanke and Mihov, 1998), fiscal policy (e.g., Blanchard and Perotti, 2002), oil market (e.g., Kilian, 2009), technology (e.g., Galí, 1999) and news (e.g., Beaudry and Portier, 2006) shocks. This method allows us to capture the dynamic relationships between macroeconomic variables within a linear model, isolate structural innovations in the variables that are independent of each other, and measure the dynamic effects of these innovations on all the variables in the VAR system.

The VAR model that we use has the following reduced form representation:

$$Z_t = \alpha + A(L) Z_{t-1} + u_t \tag{1}$$

where Z_t is a vector of endogenous variables representing the global food commodity market and the US economy, α is a vector of constants and seasonal dummies, $A(L)$ is a polynomial in the lag operator L, and u_t is a vector of reduced form residuals. The frequency t of the data is quarterly because, as we discuss below, this is essential for the identification of exogenous food commodity market shocks.

Because food commodity prices are determined in global markets, Z_t contains six key variables characterizing these markets: global food commodity production, real food commodity prices, global economic activity, the real price of crude oil, global crude oil production and the volume of seeds set aside for planting. It is evident that global food production and prices portray fluctuations in food markets. Global economic activity measures changes in global income and the business cycle that could affect the demand for food commodities.[3] Global oil production and the real price of crude oil capture a possible link between oil prices and food commodity prices because biofuels can be considered a substitute for crude oil to produce refined energy products.[4] For example, corn is used for producing ethanol, and soybeans for producing biodiesel. Alternatively, food commodity prices may be affected by oil prices because oil is used in the production, processing and distribution of food commodities. The VAR also includes the volume of harvested seeds that are set aside for planting, which should be an important determinant of future food production. Finally, the VAR contains a set of conventional variables representing the US macroeconomy: real GDP, real personal consumption, an index of consumer prices (CPI) and the Federal Funds rate.

[3] This is also typically done in VAR models analyzing the crude oil market (e.g., Peersman and Van Robays, 2009; Kilian, 2009; Baumeister and Peersman, 2013a).

[4] We include both oil market variables because this allows us to also identify oil supply shocks in section 5.

2.2 Identifying exogenous food market disturbances

US and global macroeconomic variables typically have an influence on food commodity markets, implying that there is reverse causality from macro aggregates to food market variables.[5] For example, a surge in global or US economic activity very likely leads to higher food commodity prices relatively quickly. This problem is ignored in existing studies from policy institutions (e.g., the Fed, ECB and the IMF) analyzing the pass-through of changes in food commodity prices to consumer prices.[6] These studies typically impose a pricing chain assumption, i.e., innovations in food commodity prices are not contemporaneously affected by shifts in consumer prices. The motivation is that commodity prices are determined in flexible markets, whereas consumer prices respond to shocks with a delay due to the presence of frictions in final goods markets. It is, however, possible (and likely) that innovations to real GDP also have an immediate impact on food commodity prices, and a delayed effect on consumer prices. Similarly, oil shocks could simultaneously affect food commodity prices (on impact) and consumer prices (with a delay). At best, such estimates or correlations can be informative about the signaling role of food commodity prices for future inflation, but they cannot be given a causal interpretation. The same endogeneity problem applies for the analysis of the output effects of fluctuations in food prices.

To investigate the causal macroeconomic effects of disruptions in global food markets, it is hence crucial to isolate a series of exogenous shocks that are specific to global food commodity markets. In this section, we identify unanticipated supply shocks to global food production. To achieve identification, we explore the time lag between the decision to produce (planting) and the actual production (harvest), and the fact that actual production is subject to random shocks due to, for example, changes in weather conditions. More specifically, while farmers can respond contemporaneously (within the quarter) to macroeconomic developments by increasing/decreasing the volume of planting, this is not the case for actual production because of the time lag between both activities. In section 2.3, we derive a quarterly global food commodity production index that explicitly fulfills this criterion. Hence, innovations to this index are exogenous food market disruptions (essentially unanticipated harvest shocks) that are uncorrelated with other structural shocks. This is identical to a Cholesky decomposition of the variance-covariance matrix $u_t u_t'$ of the VAR in which the food production index is

[5] In essence, the reduced form residuals in equation (1) can be thought of as linear combinations of, on the one hand, the contemporaneous (within the quarter) endogenous response of a variable to innovations in the other variables and on the other hand, exogenous structural shocks.

[6] For example Furlong and Ingenito (1996), Ferrucci et al. (2010), Pedersen (2011) and Furceri et al. (2015). See also Rigobon (2010) for a similar approach.

ordered before the other variables.[7]

2.3 Quarterly composite global food production index

Measuring world food commodity production is not straightforward. Many distinct commodities matter for food consumption and can be considered as close substitutes for each other. To simplify the analysis, we follow Roberts and Schlenker (2013) by transforming the quantities of the four most important staples (corn, wheat, rice and soybeans) into caloric equivalents, which are then aggregated into a single composite index. Together, these four commodities account for approximately 75 percent of the caloric content of global food production, whereas the prices and quantities of other staple food items are also typically linked to these four commodities (Roberts and Schlenker, 2013).[8]

Annual production data for each of the four commodities are published by the FAO of the United Nations for 192 countries over the period 1961-2013 (FAO Statistics Divison, 2015). Roberts and Schlenker (2013) convert the production data, which are measured in ton, into edible calories using the conversion factors of Williamson and Williamson (1942). The calories are then aggregated across countries and crops. However, annual production data are not suitable for our analysis. In particular, the time lag between planting and the actual production of a crop typically varies between 3 and 10 months, which implies that production could endogenously respond to macroeconomic developments when annual data are used. We therefore extend the Roberts and Schlenker (2013) approach to a quarterly frequency by combining the annual production data with the crop calendars of each individual country. This is feasible because the bulk of the countries have only one harvest season for each crop, which lasts for only a few months.

The harvesting and planting dates of the crop calendars are obtained from various sources: the AMIS Crop Calendar for the largest producers and exporters (Agricultural Market Information System, 2012), GIEWS Country Briefs (Global Information and Early Warning System, 2014) and the FAO Crop Calendar (FAO, 2015). These calendars have a monthly frequency. For some very small producers, for which no crop calendar was found, the harvest and planting dates of the nearest relevant country are used. The final crop calendar, including

[7] Notice that the ordering of the other variables does not matter for the identification and the estimation of the dynamic effects of food commodity market shocks.

[8] Corn and soybeans have respectively the greatest and smallest shares of the four major staples. Wheat and rice are between the other two and have approximately equal shares. Roberts and Schlenker (2013) use the composite index of the four staples to estimate annual global supply and demand elasticities of agricultural commodities.

country and crop specific sources and assumptions, can be found in an online appendix of this paper. If a single harvest season is spread over two subsequent quarters, we allocate the production volume to the first quarter. We only consider harvests for which there is no overlap with the planting season at a quarterly frequency. Figure 3 shows some examples to illustrate how we have assigned the annual food production data to a specific quarter based on the crop calendars (planting and harvesting seasons) of the countries.

- For several crops and countries, the allocation to a specific quarter is very obvious. Examples in Figure 3 are Kazakhstan (wheat), the Russian Federation (rice), South Africa (corn) and Argentina (soybeans). The harvest seasons clearly fall within a single quarter, whereas the planting seasons are one or more quarters beforehand.

- Whenever a single harvest season is spread over two subsequent quarters, we allocate the production volume to the first quarter. Examples are Mexico (wheat), China (corn), the United States (rice) and Brazil (soybeans).

- Some countries have two planting seasons for some of the crops, such as winter and summer wheat in the Russian Federation, and spring and winter wheat in Canada. However, given that their harvest seasons still fall within a single quarter and the planting seasons are in an earlier quarter, it is possible to allocate the production to a specific quarter.

- Whenever part of the planting and harvesting seasons overlap at the quarterly frequency, e.g., Brazil (wheat), we do not allocate the production. This production is not included in the index.

- For some countries it is not possible to assign the annual production data to a specific quarter because there is more than one harvest period, or because the crops are harvested almost uniformly throughout the year. Examples in Figure 3 are Thailand (soybeans) and India (rice). This production is not included in the index.

Accordingly, we have managed to assign approximately two-thirds of world annual food production to a specific quarter.[9] Because of the time lag between planting and harvesting of at least one quarter, innovations to food production are thus by construction predetermined or exogenous relative to the other variables included in the VAR. After aggregating the quarterly production data across crops and countries, the quarterly global food production index

[9] For the individual crops, the index covers 84 percent of global corn production, 16 percent of rice production, 96 percent of soybeans production and 82 percent of wheat production. The coverage of rice production is quite low due to the existence of more than one harvest season in several important producing countries.

is seasonally adjusted using the Census X-13 ARIMA-SEATS Seasonal Adjustment Program (method X-11).

A couple of points about the index in the context of the VAR analysis are worth mentioning. First, although this index does not capture all disturbances to global food production, the production volume covered by the index should be sufficiently meaningful to influence global food commodity markets, including food commodity prices, which is a prerequisite to examine the impact of exogenous food supply shocks on the US macroeconomy. Second, the identified shocks only capture unanticipated innovations to food production in the harvesting quarter. More specifically, anticipated changes in food production before the start of the harvest season (e.g., bad weather conditions between planting and harvesting) should already be reflected in the other variables and innovations in the VAR, particularly food commodity prices.[10] Third, our approach assumes that the information sets of local farmers are no greater than the global VAR model. Since we do not consider food production forecasts by country, the innovations are hence not necessarily identified using the full information sets available to the farmers when planting. Finally, our identification strategy also assumes that food producers cannot influence the production volume (anymore) in the harvesting quarter. For example, a rise in economic activity or food commodity prices could endogenously induce farmers to increase food production by raising fertilization activity. Several studies, however, have shown that in-season fertilization is not efficient to increase grain yields and not recommended for the food commodities that we consider (e.g., Mallarino 2010, Schmitt et al. 2001, Fanning 2012, Scharf et al. 2002). Specifically, the best timing for fertilizer applications on these crops is before or shortly after planting, while fertilization should be completed before the jointing stage. In fact, fertilizer strategies in the last months before the harvest may even be counterproductive and lead to irreversible yield loss.[11] Whereas some endogenous response might be present, this should be meager relative to variation induced by other factors, e.g., weather conditions.[12]

[10] An arbitrage condition ensures that changes in futures prices also shift spot prices of storable commodities (Pindyck, 1993). If there is a rise in expected food commodity prices, i.e., futures prices increase, traders will buy inventories in the spot market. Hence, spot commodity prices also increase.

[11] The bottom line is that fertilization strategies (e.g., nitrogen and phosphate applications) enhance plant cell multiplication and stimulate vegetative growth of the plant in order to grow as much as possible before the onset of the ripening phase. However, applying such strategies after the vegetative stage implies that the plant can spend less energy on ripening, which could result in lower grain yields. In principle, farmers could always reduce food production, e.g., by destroying crops or an insufficient treatment of diseases during the harvest season, but that is not likely to happen at a large scale.

[12] Notice also that the production volume of the four staples that is not covered by our index cannot endogenously respond to macroeconomic conditions within the quarter due to a standard time lag between planting and harvesting of at least 3 months.

Figure 4 shows the time series of the (100*log) global food commodity production index. There has been an upward trend in food production since the 1960s. However, there has also been considerable variation around that trend, with spikes of up to 10 percent, suggesting that there have been serious food production disruptions. The figure also shows an index of global food production excluding US production, and an index of global production yields. Both indicators will be used in a sensitivity analysis of the benchmark results (section 3.4). Production yields are the ratio of food production divided by the area harvested, which is also obtained from the FAO database. The upward trend in this variable is flatter than the production volume, implying that part of the food production expansion is driven by a rise of the land that is used in crop production.

2.4 Other variables

For the baseline estimations, we use the broad food commodity price index 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 of the global market and determined by the largest exporter of each commodity. The nominal price index has been deflated by US CPI. The time series has been shown in Figure 1 of the introduction. Real food commodity prices reached a peak in the 1970s, after which there was a steady decline until the early 2000s. The trend is again positive until the summer of 2012, and negative afterwards. However, there have also been many fluctuations around the long-run evolution of commodity prices, with noticeable upward spikes in the second half of the 1970s, 1983, 1987-1988, 1995-1996, 2002-2004, 2007-2008, 2010 and 2012. Overall, the standard deviation of the quarter-on-quarter change in real food commodity prices is 5.7 percent.[13]

Because our production index is limited to the four major staples, we have also constructed an alternative composite cereal price index containing only the price of corn, wheat, rice and soybeans. This index, which has also been shown in Figure 1, is based on the (trend) production weights of the four commodities and will be used in another sensitivity check of the benchmark results. As observed in the figure, the correlation with the broad index from the IMF is very high, which is in line with the premise that prices for all food commodities tend to vary synchronously. The variation of the cereal price index has, however, been higher than the broader food prices index, with a quarterly standard deviation of 7.8 percent.

[13] As a benchmark, the standard deviation of the change in real crude oil prices is 11.3 percent over the same period.

The volume of seeds from harvest that are set aside for planting is also made available by the FAO on an annual basis. We have used the same procedure to allocate the annual data to a quarterly series as described in section 2.3 for the production index. Other data are standard. As in Baumeister and Peersman (2013b), global oil production is obtained from the Oil & Gaz Journal for the period before 1973, and from the U.S. Energy Information Administration afterwards. Similar to Kilian (2009) amongst others, the real oil price series is the refiner acquisition cost of imported crude oil, deflated by US CPI. To proxy global economic activity, we follow Baumeister and Peersman (2013a) by using the world industrial production index from the Dutch Bureau for Economic Policy Analysis, which is backcasted for the period before 1991 using the growth rate of industrial production from the United Nations. Finally, US macro data are obtained from the St. Louis Federal Reserve's FRED database.

3 VAR results

3.1 Inference

The benchmark VAR model for the global food commodity market and US economy has been estimated over the sample period 1963Q1-2013Q4. All variables are seasonally adjusted natural logarithms (multiplied by 100) except the Federal Funds rate, which is measured in percent. Estimation in (log) levels gives consistent estimates and allows for implicit cointegrating relationships in the data.[14] Based on the Akaike information criterion (AIC), we include five lags of the endogenous variables. The qualitative results are, however, not sensitive to the lag order choice. In section 3.4.3, we examine the robustness of the results across subsamples. In the figures, we show the median estimates of the impulse responses, together with the 16th-84th and/or 5th-95th percentiles error bands based on 10,000 draws. These are constructed as proposed by Sims and Zha (1999).

3.2 Identified shocks and contribution to real food commodity prices

Figure 5 shows the historical contribution of the identified global food commodity supply shocks to the evolution of real food commodity prices (full blue line), as well as the con-

[14] See Sims et al. (1990) for inference in VAR models when some or all the variables have unit roots. In particular, they show that even when variables have stochastic trends and are cointegrated, the log levels specification gives consistent estimates. Conversely, pretesting and imposing the unit root and cointegration relationships could lead to serious distortions when regressors almost have unit roots (Elliott, 1998). Notice that the results are robust when we estimate the VAR with a linear (and/or quadratic) time trend.

tribution of all shocks implied by the VAR model (red dotted line). Overall, the shocks explain approximately 10 percent of food commodity price volatility. The contribution of the shocks to real food commodity prices corroborate very well with several episodes that have been described as (un)favorable developments in food markets. For example, the VAR model identifies major favorable food supply shocks in the periods 1967-1972, the mid-1980s, 1992, 1994, 1996-2000 and 2004-2005. In contrast, innovations to the global food production index have been unfavorable in the periods 1972-1977, 1985-1988, 1996, 2000-2003, 2005-2007 and 2009-2012. Almost all these episodes were characterized by significant falling or rising food commodity prices and correlate with many spikes discussed in section 2.4.

The cumulative contribution of the identified food commodity supply shocks to the surges in food commodity prices between 2005-2007 and 2009-2012 has been more than 10 percentage points each time. Accordingly, unfavorable harvests contributed significantly to the so-called global food crisis between 2002 and 2011. Nevertheless, as observed in the figure, the bulk of the crisis has been caused by other shocks. This is not surprising and in line with common perception and several studies that have analyzed the sources of the food crisis. A popular source that has been postulated by pundits is the considerable rise of food commodity demand induced by biofuels. Specifically, policy measures to encourage biofuels production, e.g., the Renewable Fuels Standard (RFS) mandates, and the simultaneous surge in oil prices appear to have triggered a persistent demand for corn and upward pressure on corn and food commodity prices (Abbott et al., 2011). For instance, the share of US corn production used to produce ethanol increased from 12 percent in 2004 to almost 40 percent in 2010, and ethanol production absorbed 70 percent of the increase in global corn production over that period (Headey and Fan, 2010).[15] Examples of other shocks mentioned in the literature are the strong income growth in the BRIC countries during that period, which allowed citizens in these countries to incorporate larger quantities of cereals, meat and other proteins into their diets (Zhang and Law, 2010), low interest rates, the depreciation of the US dollar and financial market speculation (Enders and Holt, 2014). A final interesting feature revealed by the historical contribution of the identified global food commodity market disturbances is that favorable harvests seemed to have lowered food commodity prices by more than 10 percent in 2013.

[15] Notice that biofuels demand did not only strongly account for corn price increases during that period but also price rises in other staples. For example, the rapid expansion of US corn area by 23 percent in 2007 resulted in a 16 percent decline in soybeans area, which reduced soybeans production, contributing to the strong rise in soybean prices (Mitchell, 2008). Furthermore, European biofuels production has mainly been concentrated on biodiesel, which resulted in a crowding-out of wheat area by oilseeds and hence higher wheat prices.

3.3 Impact of food market disruptions on the US economy

The impulse responses to a one standard deviation shock in the global food production index are shown in Figure 6. These should be interpreted as the dynamic effects of an unanticipated decline in the food production index on all the variables in the VAR, controlling for other changes in the economy that may also have an impact on the variables. The shock corresponds to a fall in the food production index by 4 percent. The drop in food production leads to a significant temporary rise in real (nominal) food commodity prices, which reaches a peak of approximately 1.7 percent (1.8 percent) after one quarter, and a persistent fall in global economic activity. Global oil production starts to decrease after approximately two quarters, which is in line with the pattern of the fall in global economic activity, while the impact on the real price of oil is insignificant at all horizons.

Global food commodity production returns to baseline after one quarter. This pattern, together with the persistent response of food commodity prices, is consistent with Muth's rational expectations model for commodity markets with speculation, and at odds with the so-called cobweb theorem. Specifically, Muth (1961) shows that the introduction of rational expectations in a linear model with a production lag of storable commodities and random shocks to production, should generate first-order serial correlation in prices, while actual production is just a perturbation around its steady state. Cobweb models, in contrast, predict negative serial correlation in prices and oscillatory commodity cycles (Ezekiel, 1938). Our findings clearly support the former, which is in line with most empirical studies testing the rational expectations competitive storage model of agricultural commodities (Gouel, 2012). The contemporaneous decline in the volume of seeds that are set aside for planting, followed by a similar rise one year after the shock, also suggests that farmers use inventories to smooth sales and production over time.

The influence of global food market disruptions on the US economy is considerable. In particular, real GDP starts to decrease after two quarters, reaching a maximum decline of 0.28 percent after five to six quarters, and gradually returns to the baseline afterwards. Although the rise in real food commodity prices lasts for only four quarters, the fall in real GDP is still significant after two years. The macroeconomic consequences are thus very persistent. A similar pattern appears for the response of real personal consumption expenditures of households. The shock in global food commodity markets also leads to a temporary surge in consumer prices with a peak of 0.16 percent, while there is a rise in the Federal Funds rate of 8 basis points on impact.

The magnitudes of the effects are striking. According to a simple back-of-the-envelope calculation, the responses of consumer prices and total consumption are about four to six times larger than the maximum direct influence that food commodities may have on the consumer price index and personal consumption. More precisely, the rise of nominal commodity prices is 1.8 percent at its peak. Given an average share of food commodities in final food products and beverages of 14.1 percent and a share of food and beverages in total household expenditures of 17.3 percent, the maximum direct effect of the rise in food commodity prices on consumer prices and total consumption is approximately 0.04-0.05 percent.[16] This suggests that indirect effects are important in magnifying the macroeconomic repercussions, i.e., not only food prices but also other components of the consumer price index should increase after a surge in food commodity prices, while the fall in consumption cannot solely be the consequence of a discretionary income effect. In section 5, we analyze this in more detail.

Whereas disturbances in food commodity markets have obviously not been the main driver of the US business cycle, the identified global food market shocks did contribute to several post-WWII recessions. This can be observed in Figure 7, which shows the cumulative contribution of the identified shocks to real GDP over time (full blue line), the contribution of all shocks to real GDP implied by the benchmark VAR model (red dotted line), and the NBER recession periods (gray bars). Although our index only captures a subset of food market disruptions, unfavorable shocks to global food production seem to have contributed to the recessions in 1974 (0.3 percent decline in real GDP), 1982 (0.6 percent), the early 1990s (0.2 percent), 2001 (0.7 percent) and the Great Recession in 2008-2009 (0.5 percent). In non-recessionary periods, food commodity market shocks also had a meaningful influence on economic activity. For example, favorable food supply shocks increased real GDP by roughly 2 percent in the period 1967-1972, 1.7 percent in the mid-1980s, 1.8 percent in 1997-2000 and 1.7 percent between 2003 and 2005. In sum, the macroeconomic repercussions of food market disturbances have been important for the US economy.

3.4 Sensitivity and robustness of benchmark results

In section 4, we examine the robustness of the results by using a narrative approach that does not rely on the global food commodity production index and VAR methodology. Before doing this, we consider a set of alternative VAR specifications to assess the sensitivity of the

[16]The implicit assumption for the upper bound of the direct effect on total consumption is that the rise in food commodity prices is fully induced by higher prices for imported food commodities, which leads to a reduction in discretionary income of households to buy consumption goods. In addition, households are assumed not to borrow or dissave in response to the shock. For the average share of food and beverages in total household expenditures over the sample period, and the share of food commodities in final food products and beverages, we refer to Figure 2 and footnote 2.

results that are based on the production index. We also investigate whether the estimations are picking up some other effects and the stability of the results across subsamples.

3.4.1 Did we identify exogenous food commodity market shocks?

Due to the time lag between the planting and the harvesting seasons, innovations to the global food commodity production index should in principle be exogenous with respect to the macroeconomy. In section 2.3, we have also argued that farmers cannot influence grain yields anymore in the harvesting quarter, for example by raising fertilization activity. Fertilizer applications have to be implemented before or early in the growing season and may even lead to yield loss if they are implemented shortly before harvesting. Nevertheless, it is worth verifying whether the innovations are picking up other shocks, such as oil price or aggregate demand shocks. Furthermore, it is important to check whether the identified disturbances have effects on the economy other than via fluctuations in food commodity markets. In particular, given that food production shocks are primarily the consequence of weather variation, changes in US weather conditions may simultaneously affect food production and economic activity. For example, several panel studies find significant negative effects of hotter temperatures on agricultural output, as well as on labor productivity and labor supply at the spatial level (Dell et al., 2014).[17] Boldin and Wright (2015) find that unusual temperatures have a statistically significant effect on US real GDP growth in the first and second quarters.[18] Additionally, storms may distort the estimations and exaggerate the role of food commodity markets for macroeconomic developments.

Overall, we do not find compelling support for the hypothesis that the innovations are picking up other shocks or have meaningful direct effects on economic activity other than through food commodity markets for several reasons. First, a closer inspection of the impulse responses shown in Figure 6 conveys that both issues probably do not have an important influence on the results. Specifically, global economic activity and US real GDP only start to decline with a delay of at least two quarters after the identified food market disruptions. Put differently, the shocks are not reflected in economic activity on impact, which implies

[17] Notice that this evidence is usually found for poor countries, i.e., there are several papers that found that temperature shocks have little effects on per capita income or industrial value-added output at the spatial level in rich countries (Dell et al., 2014).

[18] Boldin and Wright (2015) do not find a significant impact of unusual snowfall on real GDP growth. Based on their estimations, they construct a counterfactual weather adjusted series for GDP growth. Unfortunately, we cannot use their series as a robustness check because the series only starts in 1990Q1. Notice also that the series has the property that weather shocks cannot have a permanent effect on the level of real GDP. Any influence of weather conditions on the level of real GDP is therefore "neutralized" in subsequent quarters. This is clearly different from the pattern of the impulse responses in Figure 6.

that the innovations are not aggregate demand shocks and that the direct effects of the underlying global weather conditions on the US economy cannot be large.[19] Similarly, global oil production only decreases after approximately three quarters, whereas the response of crude oil prices is never significant and even slightly negative at longer horizons.

Also the return to baseline of global food production after one quarter in the benchmark VAR confirms that the innovations do not capture endogenous responses to macroeconomic conditions. If food producers endogenously adjust their production yields to changes in economic activity, we should instead observe a persistent response function. Specifically, if farmers are able to augment (reduce) grain yields within one quarter, this should also (and even more) be the case in the subsequent quarter. The absence of autocorrelation in the production response, however, is at odds with such endogenous behavior. Notice that it is also unlikely that the identified shocks capture an endogenous response of farmers to changes in expected (future) economic activity. This is illustrated in panel (A) of Figure 8. The panel shows the dynamic effects of food commodity supply shocks on equity prices (S&P 500) and implied stock market volatility (VIX). These impulse responses have been estimated by adding both variables one by one to the benchmark VAR model. If the innovations pick up shocks in expected economic activity or economic uncertainty, there should be a significant contemporaneous shift in equity prices and/or stock market volatility. This is clearly not the case. Equity prices only start to decline with a delay, whereas the impact on stock market volatility is insignificant at all horizons.

In contrast to the macroeconomic and financial market variables, the contemporaneous responses of all global food commodity market variables in the benchmark VAR are statistically significant. The patterns of the impulse response functions, i.e., food production and prices shifting in opposite directions, are also consistent with food supply shocks and hard to reconcile with other types of disturbances. Moreover, as can be observed in panel (B) of Figure 8, the estimated innovations coincide quite well with USDA forecast revisions. Since the early 1980s, the USDA regularly publishes projections for world annual grains production (United States Department of Agriculture, 2016). The projections are always for the period (marketing year) May-April, and are an aggregate (millions metrics tons) of wheat, coarse grains (corn, sorghum, barley, oats, rye, millet and mixed grains) and milled rice. In order to match with the (calendar year) frequency of the supply shocks obtained from the VAR, we take the sum of the USDA forecast revisions between May-December, and between December-

[19]We also find no correlation between the series of the (annualized) food commodity supply shocks and respectively the annual occurrence (-0.09), the total number of deaths (0.11) and the total dollar damage estimate (0.07) of US natural disasters reported in the EMDAT database.

April, respectively. Despite the different compositions and weighting schemes, and the fact that the (annual) USDA forecast revisions also capture anticipated production innovations before the planting and harvesting quarter, the correlation between both series (0.53) turns out to be relatively high. In sum, both the impulse responses and shock series corroborate that we have identified global food commodity market disruptions, and it is unlikely that the innovations capture important other effects or endogenous responses to the macroeconomy.

This reasoning is also confirmed by the first sensitivity check reported in Figure 9, which shows the results of several alternative VAR models. The first sensitivity check orders the global food production index after global oil production, the real price of oil and global economic activity in the Cholesky decomposition. This implies that the identified food commodity production shocks are by construction orthogonal to all possible innovations in global economic activity and the crude oil market. All variables are the same as in the benchmark VAR. To save space, however, we only show the impulse responses of six key variables. As observed in panel (A) of the figure, the impulse responses are nearly identical to the benchmark results.

As a second sensitivity test, we exclude US food commodity production from the global production index and re-estimate the VAR model with this alternative index. Accordingly, we only identify external food commodity supply shocks, which could in principle not have a direct effect on US real GDP.[20] The results are shown in panel (B) of Figure 9 and turn out to be very similar to the benchmark results. Notice that this is also the case when we additionally exclude food production of the neighboring countries from the global production index. These impulse responses are not shown in the figure, but available upon request. In sum, it is unlikely that the identified innovations are picking up other shocks, nor that there are significant direct effects of weather variation on the US economy.

[20] That is, unless there is a systematic correlation of non-US food production shocks and US food production. If so, this is probably small given the global level of our analysis. For example, the correlation between the estimated global food supply innovations and 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 varies between -0.10 and -0.11. The correlation between food production shocks excluding US production and the El Niño variables varies between -0.14 and -0.16. None of the correlations are statistically significant. Notice that this exercise does not rule out that weather variation has an effect on economic activity beyond food commodity markets in other countries, which could in turn affect the US economy via trade. In section 5, however, we document that trade effects are relatively small and that export is not an important driver of the output consequences.

3.4.2 Alternative VAR specifications

The results are also robust for several other perturbations to the benchmark VAR. More precisely, panel (C) of Figure 9 exhibits the impulse responses of the benchmark VAR model estimated with the real cereal price index instead of the broad food commodity price index. This index, which only contains the price of corn, wheat, rice and soybeans, is less representative of the global food commodity market but corresponds more directly to the production index. As observed in the figure, cereal prices increase much more than the broad commodity price index after a decline in the production index. The maximum impact of a one standard deviation shock on real cereal prices is 3.0 percent, while the rise in the broad index is 1.7 percent. However, the responses of all other variables are analogous to the benchmark effects. The results are thus not sensitive to the choice of the food price measure. Panel (D) of Figure 9 shows the results with global food production yields as a measure of food production, which also takes into account the area harvested (and planted). The results are again in line with the benchmark findings. The magnitude of the shock is somewhat lower, but the effects on real food commodity prices, real GDP, consumer prices and all other variables are quite similar to the benchmark estimations.

Finally, we check the robustness of the results for the modeling choices we have made. Specifically, panel (E) of Figure 9 shows the results of the benchmark VAR model estimated in first differences, while panel (F) depicts the impulse responses of the key variables estimated with a FAVAR model. Differencing the data does not account for cointegrating relationships in the data, but it is less likely that the results are distorted because initial conditions explain an unreasonably large share of the low-frequency variation in the variables.[21] The advantage of a FAVAR model is that it uses information from a large number of time series, which reduces the possibility of an omitted variable bias. We borrow the 207-variable FAVAR model that Stock and Watson (2016) have used to estimate the effects of oil market shocks. The FAVAR is estimated with five lags of two observed (i.e., the global food production index and real food commodity prices) and six unobserved factors.[22]

[21] VARs estimated with OLS or flat priors tend to attribute an implausibly large share of the variation in the data to a deterministic component. The reason is that the criterion of fit does not penalize parameter values that make the initial conditions unreasonable as draws from the model's implied unconditional distribution. As a result, the model attributes the low-frequency behavior of the data to a process of return from the initial conditions to the unconditional mean. This issue has been raised in the context of Mark Watson his discussion of our paper. See also Sims (2000) for a discussion on the role of initial conditions for the low frequency variation in observed time series.

[22] This model has also been used by Mark Watson for the discussion of our paper. We are grateful to him for sharing the codes and datasets. The 207 times series consist of real activity, prices, productivity, earnings, interest rates, spreads, money, credit, asset, wealth and oil market variables, as well as variables representing

The impulse responses of the alternative models in panels (E) and (F) of Figure 9 have been accumulated and are shown in levels. There are some interesting observations worth mentioning, which mostly apply to both models. First, the contemporaneous decline in global food production is somewhat greater than in the benchmark VAR. Second, there is a permanent fall in global food production, and a very persistent rise in real food commodity prices. The finding that a bad harvest in one region leads to a long-run decline of food production in another region (despite higher food prices) is rather surprising. A possible explanation is that both models do not account for cointegrating relationships amongst the variables. Third, whereas the magnitudes are in the same neighborhood of the benchmark VAR results, the shapes of the output effects turn out to be different. In particular, the estimated peak effects of food market shocks on economic activity are approximately one year later in the FAVAR and the VAR estimated in first differences, compared to the VARs estimated in (log) levels. Fourth, the impact of food commodity market disturbances on consumer prices seems to be much larger than the benchmark effects, particularly in the FAVAR model. Notice, however, that the uncertainty of the estimates is quite high, while the error bands overlap. Finally, there is also a stronger rise of the Federal Funds rate in the FAVAR. Overall, although the shapes of several impulse responses are somewhat different, we can conclude that the magnitudes of the macroeconomic consequences of food commodity market shocks are not sensitive to the modeling choices we have made.[23]

3.4.3 Subsample analysis

We now assess the robustness of the results across subsamples. A constraint in doing this is the relatively large number of variables and lags in the benchmark VAR model, which causes overparameterization problems for short sample periods. We therefore report the results of two exercises. First, we re-estimate the benchmark VAR model for the sample periods 1963Q1-1999Q4 and 1985Q1-2013Q4, respectively. The former sample period does not take into account the global food crisis of the 2000s and the subsequent collapse of food

international activity. All variables are transformed to a stationary form. See Stock and Watson (2016) for details.

[23] By estimating food production equations (with all lagged VAR variables as RHS variables), and implementing the residuals in a simple local projection framework, we have also explored whether the existence of nonlinearities could have influenced the estimation results. Specifically, we have examined whether the macro consequences are different (i) when we allow food production to react differently to increases and decreases of the lagged RHS variables, (ii) depending on the quarter of the shock, and (iii) for unfavorable versus favorable shocks. Overall, we do not find evidence that nonlinearities have distorted the *average* effects reported in this paper. We do find support for the hypothesis that unfavorable shocks have stronger macroeconomic effects than favorable shocks (respectively greater and smaller than the average effects). The standard errors are, however, relatively large. It is worth investigating this more carefully in future research.

commodity prices, as well as the recent rising relevance of biofuels in energy consumption depicted in Figure 2. The latter sample period, in contrast, excludes the major swings of food commodity prices in the 1970s and the so-called Great Inflation monetary policy regime.

The results for the subsamples are shown in Figure 10. Interestingly, despite the reduced relevance of food consumption in total household expenditures over time, the effects of global food commodity supply shocks on real GDP, personal consumption and consumer prices are quite similar for both subsamples and comparable to the benchmark VAR results. A possible explanation is the increased share of biofuels in energy consumption in recent times, which could have offset the falling share of food consumption in household expenditures. In particular, the increased ethanol production in the second half of the 2000s could have led to a tighter link between agricultural and energy prices, magnifying the consequences of food commodity market disruptions on the US economy at the end of the sample.

An enhanced link between food commodity markets and energy prices is confirmed by the second exercise to assess time-variation. For this exercise, we borrow results from Peersman et al. (2016). More specifically, elaborating on the present study, Peersman et al. (2016) estimate a more parsimonious version of the benchmark VAR across subsamples, as well as time-varying parameter VARs with stochastic volatility in the spirit of Primiceri (2005) to examine whether crude oil and food commodities have become more closely linked in recent periods. The VAR in Peersman et al. (2016) contains the global food production index, real cereal prices, global crude oil production, the real price of crude oil and global economic activity. Within the VAR model, global food commodity supply and crude oil supply shocks are identified. The results reveal that unfavorable food commodity supply shocks have no impact on global crude oil prices until 2003, after which the impact starts to gradually rise over time. A similar story emerges for oil supply shocks, i.e., there are no significant effects of oil supply shocks on real cereal prices until 2003, after which the effects become significant. Hence, crude oil and food commodities seem to have become closer substitutes over time, in line with the rising share of biofuels in petroleum consumption.

In panel (A) of figure 11, we reproduce the Peersman et al. (2016) results for the sample periods 1985Q1-2002Q4 and 2003Q1-2014Q4 for global food commodity supply shocks.[24] As can be observed in the figure, a food market disturbance that raises real cereal prices also

[24]Notice that the VARs in Peersman et al. (2016) are estimated with real cereal prices because cereal prices are more directly linked to biofuels. It is also easier to compare the magnitudes with real crude oil prices and examine their interplay. The impulse responses in both periods have been normalized to the maximum rise of real cereal prices obtained in section 3.4. Furthermore, because the VAR model does not contain the volume of seeds that are set aside for planting, there is one extra year of data available at the end of the sample period relative to the benchmark VAR in the present paper.

triggers an immediate shift of crude oil prices in the post-2003 period. In panel (B), we show the macroeconomic consequences of the shocks in both periods by adding a set of US variables one by one to the 5-variables VAR model. Some caution when interpreting the magnitudes of the responses is required because the rise in real cereal prices is more persistent in the first subsample period. If we take this into account, we can again conclude that the consequences on real GDP, personal consumption and consumer prices have not dramatically changed over time. This is, however, not the case for CPI energy. In particular, food commodity supply shocks turn out to have a significant impact on CPI energy in the recent period, in contrast to an insignificant effect in the period before 2003. Put differently, due to the rising share of biofuels in energy consumption, food market disturbances currently also have inflationary effects via energy prices.

4 Narrative approach to identify food market disturbances

As an alternative approach to examine the consequences of food commodity market disruptions on the US economy, we rely in this section on historical documents to identify exogenous food market shocks. Narrative methods to address the identification problem have a long-standing tradition in macroeconomics. They have, for example, been used by Romer and Romer (1989) to estimate the effects of monetary policy changes. By examining the minutes of the Federal Open Market Committee (FOMC) policy deliberations, they identify six episodes of large independent restrictive monetary policy shocks, which are then included as a dummy variable in an autoregressive model to estimate the macroeconomic consequences. Similarly, by reading through Business Week, Ramey and Shapiro (1998) create a dummy variable capturing major military buildups. The dummy is then embedded in a standard VAR to examine the impact of government spending shocks. Ramey (2011) extends this approach by creating a quantitative narrative series of exogenous news shocks on government spending. Romer and Romer (2010) use the narrative record, including presidential speeches and Congressional reports, to identify major tax policy shocks. Perhaps most closely related to our application, Hamilton (1983, 2003) considers a number of historical episodes in which changes in oil prices were almost solely driven by exogenous disturbances to supply that had little to do with macroeconomic conditions, e.g., due to political and military conflicts in oil-producing countries, to estimate the dynamic effects of oil market shocks.

Whereas VARs are constrained by relatively small information sets, the advantage of a narrative approach is the possibility of incorporating a large amount of information, including expectations. It also requires less assumptions, and there is no need for the identification of a structural form. However, it implies judgment on the part of the researcher, whereas shocks may still contain endogenous components. It can thus be considered a useful complementary analysis for the VAR results based on the global food production index. In section 4.1, we describe the narrative approach to identify exogenous food commodity market shocks. Section 4.2 discusses the estimation method, while section 4.3 presents the results.

4.1 Historical episodes of major exogenous food commodity market shocks

To quantify the macroeconomic consequences of changes in food commodity prices, it is crucial to identify changes in food commodity prices that are unrelated to the state of the economy, i.e., movements in which the proximate causes are disturbances in global food commodity markets. We rely on FAO reports, newspaper articles (e.g., the *Financial Times* archive), disaster databases (e.g., Centre for Research on the Epidemiology of Disasters, 2015) and several other online sources (e.g., *Google news*) to identify historical episodes of such movements. The task is daunting given the global level of the analysis. There are continuously, many times even conflicting, events affecting food commodity markets somewhere in the world. We therefore only select episodes that fulfill the following criteria:

1. There has to be an event that is important enough to affect food commodity markets at the global level, such as weather shocks in a major food producing region, or unanticipated news on the volume of global food production (e.g., a sizable revision of expected agricultural production by the USDA).

2. The event should have an unambiguous significant effect on global food commodity prices. A shift in commodity prices is considered to be significant if either the quarterly change in food commodity prices or the accumulated change over two subsequent quarters differs at least one standard deviation from the sample mean.[25]

3. There should be no developments in the macroeconomy, alternative events or macroeconomic news that may also have a discernible impact on food commodity prices. For example, we do not consider admissible food market events if there is simultaneously a significant shift in crude oil prices (one standard deviation different from its sample mean) or in economic activity (e.g., a global or US recession). Put differently, we eliminate or minimize possible endogenous movements in food commodity prices to current

[25] The standard deviations of the quarterly change in food commodity prices and accumulated change over two subsequent quarters are 5.7 and 9.1 percent, respectively, while the means are -0.31 and -0.62 percent, respectively.

or future fluctuations in the business cycle, i.e., the event in food commodity markets has to be the proximate cause of the price shift.[26] All ambiguous cases are not selected as episodes.

A narrative approach to identify exogenous shocks involves judgment calls, which is a concern we acknowledge. We believe, however, that we have identified thirteen episodes that could reasonably be interpreted as major exogenous food commodity market disturbances that are unrelated to the state of the economy. The estimation results are not driven by a single episode because they are relatively similar if we exclude individual events from the estimations. Six episodes are unfavorable food market disruptions, whereas we have detected seven favorable shocks to food commodity markets. Examples of unambiguously unfavorable shocks include the Russian Wheat Deal (combined with a failed monsoon in South Asia) in the summer of 1972 and the more recent Russian and Ukrainian droughts in 2010 and 2012. Conversely, a number of unanticipated significant upward revisions in the expected harvest volume (e.g., in 1975, 1996 and 2004) can clearly be classified as episodes of favorable food market shocks. The dates (quarters) as well as a brief description of all global food commodity market events are reported in Table 1. A detailed motivation for the selected quarters can be found in an online appendix of the paper (De Winne and Peersman, 2016). In every case, we attempt to give explanations and quotations such that other researchers can see our reasoning for classifying the episodes as food commodity market disruptions. To give an idea of our approach, appendix A reproduces the motivation for the most recent shock that we identified in 2012Q3.

4.2 Estimation method

There is no one-to-one mapping between the true structural shocks and the observed changes in food commodity prices in these thirteen episodes. We therefore first construct a dummy variable, which is equal to 1 for the unfavorable food market disturbances that we have identified and -1 for favorable food market events. The idea is that this dummy variable series is a noisy measure of the true food market shocks and can be used as an external instrument to identify exogenous changes in global food commodity prices. In this context, Mertens and Ravn (2013) show that a series based on narrative evidence is robust to many types of measurement problems and a valid instrument as long as the series is contemporaneously correlated with the structural shock and contemporaneously uncorrelated with all other structural shocks in the economy.

[26]Crude oil is not only used in the food production process or a close substitute for food commodities to produce energy products. A shift in crude oil prices could also signal changes in (expected) demand for commodities more generally.

In the next step, we examine the dynamic effects of shocks to global food commodity prices on the US economy using Jordà's (2005) local projection method for estimating impulse responses.[27] The advantage of the local projections method is that it is more robust to misspecification than VARs because it does not impose implicit dynamic restrictions on the shape of the impulse responses, and not all variables are required to be included in all equations. In addition, joint or point-wise analytic inference is simple, and it is easy to incorporate instrumental variables.[28]

For each variable and each horizon, we estimate the following single regression model:

$$z_{t+h} = \alpha_h + \lambda_h (L) z_{t-1} + \psi_h(L)X_{t-1} + \theta_h RFCP_t + \varepsilon_{t+h} \tag{2}$$

where z is the variable of interest at horizon h. We consider real food commodity prices and a set of variables representing the US economy: real GDP, real personal consumption, CPI and the Federal Funds rate. α_h is a vector of deterministic terms, i.e., a constant, linear and quadratic time trend, $\lambda_h (L)$ and $\psi_h (L)$ are polynomials in the lag operator ($L = 5$), and X is a set of control variables. Although the control variables do not have to be the same for each regression, we include all other z variables. Finally, θ_h is the estimated response of z at horizon h to a shock in real food commodity prices ($RFCP_t$) at period t. Because real food commodity prices may be partly endogenous to the US economy, we estimate equation (2) with the narrative dummy and first lag of the dummy as external instruments for $RFCP_t$. The reason that we also use the first lag of the narrative dummy as an instrument is that some of the episodes encompass more than one quarter (see online appendix). The F-statistic of the instruments (dummy and lagged dummy) is 12.6. The t-statistic of the dummy and lagged dummy are 4.9 and 1.9, respectively.

4.3 Narrative results

The estimated impulse responses to a 1 percent increase in real food commodity prices are shown in Figure 12. Because the error terms follow some form of moving-average structure,

[27] A similar approach has been used by Ramey and Zubairy (2014) to estimate the effects of narratively identified government spending shocks.

[28] Because this method imposes fewer restrictions, the estimates are often less precise and more erratic at longer horizons because of a loss of efficiency (Ramey, 2016). If the data generating process is adequately captured, impulse responses of VARs are in contrast optimal at all horizons. We have therefore also estimated two VAR models based on the narrative food commodity market shocks. On the one hand, we have embedded the episodes as dummy variables in a standard VAR to estimate the macro effects, an approach similar to Ramey and Shapiro (1998). On the other hand, we have used the dummy variable as an instrument to identify food commodity prices shocks within a VAR model, as proposed by Mertens and Ravn (2013). The results of both exercises, which are available upon request, confirm the conclusions of the local projections.

with an order that is a function of the horizon h, they are serially correlated. Accordingly, we calculate and report Newey-West standard error bands in all figures. The rise in real food commodity prices reaches a peak of 1.9 percent after three to four quarters. This corresponds to a rise in nominal food commodity prices by approximately 2.1 percent, a magnitude that is somewhat higher than the maximum effect in the benchmark VAR. The narratively identified shocks also have a much more persistent impact on food commodity prices because real food commodity prices only return to baseline after approximately 12 quarters, compared to 4 quarters in the benchmark VAR.

The persistent rise in real food commodity prices is also reflected in more persistent effects on the US economy relative to the benchmark VAR results. Real GDP and real personal consumption decrease by approximately 0.3 percent, reaching its peak after 10 quarters. Taking into account the more persistent and slightly greater rise in global food commodity prices, the magnitudes of the consequences on the real economy are comparable to the VAR results reported in section 3. In contrast, the impact on consumer prices and monetary policy response seems to be stronger for the narrative shocks. Specifically, consumer prices and the Federal Funds rate increase by 0.4 and 0.2 percent, respectively, which is roughly twice the impact obtained with the VAR model and global food production index.

Overall, despite being a very different approach, the results of the narratively identified food commodity market disturbances confirm the main messages of the VAR analysis. Hence, we can safely conclude that the repercussions of disruptions in global food commodity markets on the US economy are compelling. In the next section, we examine the pass-through in more detail.

5 Pass-through to consumer prices and economic activity

In section 3.3, we have argued that several indirect effects should be at play, amplifying the macroeconomic consequences of food market disruptions. In particular, not only food prices but also other components of the consumer price index should increase after a surge in food commodity prices, while the fall in consumption cannot solely be driven by the direct loss in purchasing power. In other words, there is more than just a discretionary income effect of the rise in food commodity prices on household expenditures. In this section, we pursue a tentative attempt at better understanding the mechanisms and interpreting the magnitudes of these effects.[29]

[29] To interpret the magnitudes, we conduct a number of back-of-the-envelope calculations, in particular to assess the role of monetary policy. Given the simplicity of the exercise and uncertainty about the exact values

To do this, we extend the VAR analysis of section 2 along two dimensions. First, we compare the dynamic effects of food supply shocks with the effects of crude oil supply shocks identified within the same VAR model. The macroeconomic effects of oil supply shocks can serve as a benchmark because several studies have documented that oil and energy shocks also have an influence on the US economy that is disproportionately large compared to its share in GDP and consumer expenditures. For example, Edelstein and Kilian (2009) find that the response of total consumption to an energy price shock is approximately four times larger than the maximum reduction in discretionary income associated with the shift in energy prices. We identify oil supply shocks by imposing theoretically plausible sign restrictions on the impulse responses, as proposed in Peersman and Van Robays (2009) and Baumeister and Peersman (2013a). Specifically, (unfavorable) oil supply shocks are identified as innovations that are orthogonal to the identified food commodity supply shocks and characterized by a fall in global oil production and a rise in the real price of oil, while world economic activity does not expand.[30] Second, we re-estimate the VAR by adding an additional variable of interest each time. We consider a set of price variables to investigate the pass-through to consumer prices, and we examine the effects on several components of real GDP and household expenditures to learn more about the output effects.

5.1 Comparison with oil shocks

Figure 13 compares the impulse responses of the benchmark variables to a one standard deviation crude oil and food commodity supply shock. Some interesting facts are worth mentioning. First, a one standard deviation oil supply shock corresponds to a rise in real crude oil prices of 4.9 percent on impact, which reaches a peak of 5.6 percent after one quarter, and gradually returns to baseline after four quarters. The pattern of oil prices after an oil supply shock is very similar to the pattern of food commodity prices after a food

of several parameters, these calculations should be taken with a grain of salt and interpreted with more than the usual degree of caution.

[30] Since the sign restrictions are based on competitive market forces and the oil price was regulated prior to 1974, the results for oil supply shocks are based on VARs that have been estimated over the sample period 1974Q1-2013Q4. As an alternative approach, Kilian (2009) uses (zero) exclusion restrictions to identify oil supply shocks in a monthly VAR that includes global oil production, a measure of economic activity, and the real price of crude oil. In particular, he assumes that the short-run oil supply curve is vertical, implying that global oil production does not respond to all other (oil demand) shocks in the VAR instantaneously. This assumption might be plausible at the monthly frequency but is not appropriate when quarterly data are used. Notice also that we rely on a uniform Haar prior distribution to implement the sign restrictions. Baumeister and Hamilton (2015) show that this could imply non uniform distributions for key objects of interest and that Bayesian inference with informative priors can be an improvement. Although this is a promising avenue, this approach is beyond the scope of this paper given that the identification of oil supply shocks is not the focus of this study.

supply shock, although the magnitude is approximately three times larger. Second, with a peak effect of -0.39, the consequences of a one standard deviation oil supply shock on real GDP are approximately 1.5 times stronger. Put differently, the impact of a rise in real food commodity prices on economic activity is roughly twice as large as the impact of a rise in crude oil prices of equal size. Third, the dynamic effects of both shocks on real personal consumption are more or less the same, whereas an average food commodity supply shock has a slightly stronger and more persistent impact on consumer prices than an average oil supply shock. Finally, oil supply shocks reduce global economic activity for a period of two years, have no significant effects on global food production and food commodity prices, and have a negative impact on the Federal Funds rate.

A noteworthy difference between both shocks is the monetary policy response, i.e., the Federal Funds rate increases by 8 basis points after a food commodity market shock, whereas the policy rate decreases by 11 basis points on impact, and 20 basis points after one quarter in response to an oil supply shock. In other words, monetary policy seems to amplify the consequences of food market disruptions on economic activity, while partly stabilizing the real effects of oil supply shocks. This is relevant to interpret the magnitudes of the indirect effects of both shocks. Specifically, a reasonable rule of thumb for monetary policy effects is that a rise in the Federal Funds rate by 10 basis points leads to a fall in real GDP between 0.05 and 0.1 percent.[31] If we take these values seriously, this implies that the contemporaneous monetary policy response to food market disturbances can potentially explain almost one-third of the output effects, while the remaining effects on personal consumption are still at least four times the discretionary loss in purchasing power. In contrast, a similar immediate response to oil supply shocks would have resulted in much stronger output effects of such shocks. If the results of Edelstein and Kilian (2009) are representative for oil supply shocks, i.e., they find that the impact of an energy price shock on total consumption is approximately four times larger than the maximum reduction in discretionary income, this also implies that the magnitudes of the (non-monetary policy) indirect effects of food commodity and oil supply shocks on consumption are probably in the same neighborhood.[32]

[31] Christiano et al. (1999) find that an interest rate innovation of 60 basis points reduces real GDP by 0.5 percent. Bernanke and Mihov (1998) find that a monetary policy shock that raises the Federal Funds rate by 0.4 percent leads to a decline of real GDP by 0.3 percent. When we also identify a monetary policy shock within the benchmark VAR model (by ordering the Federal Funds rate last in the Cholesky decomposition), as discussed in section 5.3, we find that a 60 basis points rise in the Federal Funds rate leads to a fall in real GDP and personal consumption by approximately 0.4 percent.

[32] In contrast to food commodities, which are only an input factor in the food processing sector (except biofuels in recent periods), it is very difficult to calculate the exact share of crude oil in household expenditures because oil is an input factor that is used for several product categories (as well as investment goods and government purchases). If we only consider the (direct) share of heating oil and motor fuel in household

5.2 Consumer prices

A consumer price index is calculated as a weighted average of prices of different types of goods and services, which can be divided into food (17%), energy (6%) and core (77%) CPI. A rise in food commodity prices can affect these components via several channels. First, there is a direct effect on the food component of CPI. The exact pass-through of food commodity prices to final prices of food products should depend on competition and demand conditions in the food sector. Second, a rise in food commodity prices may augment energy prices because food commodities are also used for the production of biofuels, i.e., from home heating to vehicle fuel, which are a source of energy. Third, if energy prices rise, production costs for firms could increase. If firms pass these costs on to their selling prices, consumer prices of non-energy goods may increase as well. Finally, higher inflation (expectations) could trigger so-called second round effects that can greatly amplify and protract the effects of the shock on (core) inflation. For example, employees could demand higher nominal wages in subsequent wage bargaining rounds to maintain their purchasing power, leading to mutually reinforcing feedback effects between wages and prices. Similar channels have been documented for oil shocks.

The impulse responses of food, energy and core CPI are depicted in the top row of Figure 14. Not surprisingly, there is a strong and significant effect of a rise in food commodity prices on CPI food, with a peak of 0.27 percent after four quarters. Given a share of food commodities in final food products and beverages of approximately 14 percent and a rise of nominal food commodity prices of 1.8 percent, this implies that changes in food commodity prices are more or less fully passed on to food consumer prices. Furthermore, the effects of food commodity market disturbances on CPI energy are positive, but not statistically significant at the 10 percent level. Notice, however, that the insignificant impact is misleading because it ignores time variation. The use of biofuels as a source of energy is only a recent phenomenon. As has been shown in section 3.4.3 (Figure 11), the impact of food commodity market shocks on CPI energy was insignificant before 2003. Conversely, food market shocks seem to have had a significant and strong impact on CPI energy since 2003, in line with the rising share of biofuels in petroleum consumption. Because the latter period is more representative of the current situation, we conclude that fluctuations in food commodity prices likely also affect consumer prices via energy prices.[33] Finally, there is a significant rise of core CPI after

expenditures, and take into account that about half of gasoline prices are determined by the cost of crude oil, the effects of oil supply shocks on real GDP obtained with the VAR model are also roughly four times the discretionary loss in purchasing power.

[33]Notice also that the error bands of the effects on CPI energy in Figure 14 are relatively large, while the

an unfavorable food market disturbance, which reaches a peak of 0.14 percent after seven quarters. Given the share of core CPI in the consumer price index, this is about two-thirds of total inflationary consequences. The rise in core inflation is hence the reason why the ultimate impact on consumer prices is considerably larger than the effects implied by the share of food commodities in the CPI.[34]

The pass-through of oil supply shocks to consumer prices turns out to be very different. As observed in Figure 14, unfavorable oil supply shocks augment CPI energy but do not raise food consumer prices. There is even a decline of CPI food at longer horizons, and core inflation also does not increase. An interesting difference between both types of shocks is that oil supply shocks seem to trigger inflationary effects via a rise in import prices and a depreciation of the US dollar exchange rate, while food commodity supply shocks increase the (domestic) GDP deflator significantly. In addition, despite the decline in economic activity, nominal wages remain more or less constant after a food market disturbance. In contrast, nominal wages decrease significantly after an oil supply shock. Additionally, real (consumer) wages decline immediately after oil supply shocks, whereas the response of real wages is much stickier after food market shocks.

Overall, these different patterns indicate that second-round effects are a key explanation for the stronger pass-through of food commodity supply shocks to consumer prices compared to oil supply shocks. This hypothesis is confirmed by the impulse responses of inflation expectations in Figure 14. We observe a persistent and significant rise of inflation expectations after a food supply shock, while the impact of oil supply shocks is very short-lived and statistically insignificant. Higher inflation expectations are typically passed through to actual pricing behavior, in particular the prices of non-food and non-energy goods and services. Furthermore, higher inflation expectations augment the demand for nominal wages in the wage bargaining process, which further increases costs of firms and the prices of non-food and non-energy goods and services. The presence of second-round effects and greater impact of food market disruptions on inflation expectations and core inflation probably also explain the monetary policy tightening of the Federal Reserve after such shocks, in contrast to a policy easing following oil supply shocks.[35]

---

magnitudes of the effects are quite strong, i.e. CPI energy increases by 0.31 percent on impact and 0.37 percent at its peak. In contrast, when we re-estimate the VAR over a sample period that ends in 2002Q4, the effects on CPI energy are essentially zero. The difference between the point estimates also suggest that the pass-through to energy prices has become an important channel in recent periods.

[34]Notice that core CPI also increases when we estimate VAR models over more recent sample periods, e.g., excluding the Great Inflation. Second-round effects of food market shocks are thus still important and have not vanished over time.

[35]The finding that inflation expectations (and core inflation) respond more to food prices than energy prices

5.3 Household expenditures and economic activity

Because food is a basic necessity, food demand is considered to be quite inelastic. Unless households increase borrowing, higher food prices consequently erode the disposable income to purchase other goods and services, leading to a fall in expenditures. In section 3.3, we have argued that the upper bound of such a discretionary income effect is 0.04-0.05 percent, while personal consumption declines by almost 0.3 percent after a one standard deviation food commodity supply shock. Hence, other propagation mechanisms should also be at play. A first plausible channel is the monetary policy response to control inflation, which curtails aggregate demand. However, as discussed in section 5.1, the monetary policy response can explain at most one-third of the overall effects.

Besides the monetary policy effects, how are food commodity market disruptions transmitted to the real economy? There are several reasons to believe that the underlying mechanisms are similar to the pass-through of oil supply shocks to economic activity. First, as argued in section 5.1, the magnitudes of the (non-monetary policy) indirect effects of both shocks are within the same neighborhood. Most importantly, also the dynamic effects of both shocks on the components of household expenditures are very much alike. This can be observed in Figure 15, which shows the effects of food commodity and crude oil supply shocks on several components of household expenditures and investment. Not surprisingly, unfavorable food supply shocks have a significant negative impact on nondurable food consumption, i.e., food and beverages for off-premises consumption, while oil supply shocks reduce the consumption of energy goods and services, not the other way around.[36] However, all other impulse responses behave qualitatively and quantitatively similarly. Strikingly, this is even the case for the consumption of motor vehicles and parts, a subcomponent of durable consumption that is typically considered to be complementary in use with oil, and thus perceived as being much more sensitive to oil shocks relative to other shocks. Overall, these findings suggest that the dominant mechanisms that lead to a decline in a household's purchases of non-food and non-energy nondurables and services, as well as purchases of durable consumption goods, are quite similar.

has also been documented by Clark and Davig (2008) amongst others. Several studies also find that economic agents weigh food prices considerably higher than its share in expenditures when forming inflation expectations, in contrast to energy prices (e.g. Murphy and Rohde, 2015). A possible explanation why food prices have larger effects on inflation expectations and core inflation is that energy prices are substantially more volatile than food prices.

[36]The demand for food and energy products is hence not completely inelastic to shifts in their own prices. In contrast, the impact of food commodity shocks on the consumption of food services and accommodations turns out to be insignificant at the 10 percent level.

The impulse responses further reveal that a crucial channel whereby food commodity market shocks (and oil supply shocks) affect the economy is a shift in the consumption of durables and investment. Specifically, durable consumption decreases by 0.93 percent after a food market disruption, which is three times larger than the overall fall in personal consumption. Likewise, there is a reduction in investment of 0.93 percent. The relevance of both output components in explaining the consequences of food market disruptions is illustrated in Table 2. The first column of the table shows the maximum effects of both shocks on all the components of Figure 15, while the second column lists the relative responses of the components to the response of total personal consumption. The third column shows the weighted effects of the components, where the weights are calculated as the ratio to GDP of each component. As observed, durables and investment are considerably more sensitive to food supply shocks than other components of household expenditures, followed by nondurable food consumption. In addition, despite their limited weights, both components account for the bulk of the output effects.[37]

One argument that could be made against our reasoning is that the stronger effects of food market shocks on the consumption of durables and investment is driven by the monetary policy response rather than other mechanisms because both aggregates are typically much more sensitive to interest rate changes. While being true, we believe that this does not change our conclusion. To illustrate this, we identify a monetary policy shock within the VAR model.[38] The maximum effects of a shift in the Federal Funds rate by 8 basis points, i.e., the estimated contemporaneous monetary policy response to a food commodity supply shock, on all components are reported in the fourth column of Table 2. Durable consumption and investment indeed react much more to a monetary policy shock than the other components. However, the magnitudes are too small to account for the stronger responses to food commodity supply shocks depicted in the first column of the table. Even in the absence of monetary policy tightening, the effects on durables and investment are still a multiple of the effects on the other expenditures components. Hence, the greater impact on durable consumption and investment compared to other goods and services categories can only partly be explained by the monetary policy tightening and thus other effects on both aggregates are crucial in explaining the consequences of food market shocks.

[37]There is also a decline in the volume of export of 0.37 percent after a food commodity supply shock. The contribution to the overall output effects, however, is relatively low. The export effects are also statistically insignificant at the 10 percent level. For oil supply shocks, in contrast, there is a strong and significant decline in export that matters for the overall output effects.

[38]For simplicity, we use the Christiano et al. (1999) identification strategy by ordering the Federal Funds rate last in the Cholesky decomposition. Other approaches typically find similar output effects. One caveat is that we obtain a so-called price puzzle.

5.4 Potential explanations for magnitude and composition of output effects

The remaining question is which (non-monetary policy) mechanisms could magnify the consequences of both shocks on personal consumption. In spite of the voluminous literature on the effects of oil price shocks, there is little consensus on the dominant mechanism. Popular channels that have been put forward in the oil and energy literature are the postponement of irreversible purchases of investment and durable consumption goods because of increased uncertainty about future energy prices and a shift in consumption of durables that are complementary in use with energy (e.g., Edelstein and Kilian 2009, Hamilton 2008). It is, however, not likely that the postponement of irreversible purchases applies to food prices. Furthermore, given that the purchases of motor vehicles react in a similar way to food and oil shocks, complementary effects can also not be dominant.[39]

There are, however, various other channels that have been documented for oil and energy price shocks, which could also apply to food commodity price shocks. For example, Rotemberg and Woodford (1996) demonstrate that imperfect competition considerably amplifies the effects of shocks to factor prices. In a calibrated one-sector stochastic growth model with energy input, they show that allowing for a modest degree of imperfect competition increases the predicted effects of a rise in energy prices on economic activity by a factor of five, and that such market imperfections can account for their estimates of the consequences on US output. Finn (2000) shows that variable capital utilization also greatly intensifies the repercussions of shifts in factor prices on the real economy, even in perfect competitive markets, and can explain the magnitudes found in the empirical literature. Given the critical role of food commodities as an input factor in the food processing sector, these theories could also apply to food commodity price shocks.

Another class of models in the oil literature focus on frictions in reallocating capital and labor across (sub)sectors that may be differently influenced by oil price shifts (e.g., Davis and Haltiwanger 2001, Hamilton 1988). Such frictions lead to higher unemployment and lower capacity utilization at affected sectors that can magnify the effects on economic activity.[40] A popular example in the oil literature is a reallocation of capital and labor away from the automobile sector when consumers purchase less cars, or a reallocation of resources within the automobile sector when consumers switch towards more energy-efficient cars in response to oil price hikes. However, also food market shocks could lead to a changed composition of

[39]The only possible exception for both arguments is the role of food commodities to produce energy goods in recent periods, but this cannot be the case for the average effects since the 1960s.

[40]These additional effects can be very large. For example, Acemoglu et al. (2016) show that small shocks can cause sizable aggregate fluctuations due to their propagation through the production network.

aggregate demand, which results in a reallocation of capital and labor across (sub)sectors that is costly and reduces economic activity. For example, there could be substitution between the use of food services and accommodations to purchases of food and beverages for off-premises consumption. Most importantly, the results in Figure 15 show that food price shocks lead to a considerably greater decline in the expenditures on durable goods compared to nondurables and services, which could trigger sectoral shifts throughout the economy that further amplify the macroeconomic consequences.[41]

In fact, a stronger response of durable consumption to shocks in purchasing power of households, and possible reallocation effects that protract the macroeconomic consequences, may be a plausible mechanism to explain our empirical results, i.e., both the amplification and composition of the output effects, as well as the similarity with the dynamics of oil shocks. Specifically, consumer theory shows that expenditures on luxuries and durables should be more sensitive to transitory income shocks than expenditures on necessities and nondurables. For example, Browning and Crossley (2009) demonstrate that households can significantly reduce total expenditures without a significant fall in welfare if they concentrate their budget reductions on durables. The reason is that a substantial reduction in durables *expenditures* can be realized with only a modest fall in durables *consumption* because existing durables stocks could continue to provide a flow of services.[42] Such a mechanism can explain why purchases of motor vehicles respond considerably stronger than several other goods and services to both food price and oil price shocks, without the requirement of being complementary in use. In essence, when food and energy bills increase, households can continue to drive with their existing car for a while, rather than buying a new car. Although the welfare losses of this behavior at the individual household level might be small, the macroeconomic accelerator effects may be substantial.

Notice that this accelerator mechanism may be particularly important for food and energy price shocks because the share of food and energy consumption in household expenditures is substantially higher for low-income households. For example, according to the Bureau of Labor Statistics Consumer Expenditure Survey, the share of food and beverages consumption

[41]Notice that the presence of significant reallocation effects implies that the consequences of food price increases on household expenditures should be stronger than food price decreases because such effects amplify the former, while dampening the latter. As mentioned in footnote 23, we find support for this prediction in the data.

[42]Also Hamermesh (1982), Parker (1999) and Browning and Crossley (2000) discuss mechanisms how transitory changes in income could have a disproportionately greater effect on expenditures of luxuries and durables. Bils and Klenow (1998) confirm this prediction in US data for 57 types of consumer goods. Dynarski et al. (1997) find that the elasticity of durables to changes in income in the US is eight times larger than for nondurables.

in total expenditures of the lowest income quintile was 16.2 percent in 2014, compared to only 12.1 percent for the highest quintile. For energy expenditures (natural gas, electricity, fuel oil, other fuels, gasoline and motor fuels), the shares are 10.7 and 6.4 percent, respectively, for the lowest and highest quintiles. Measured as a percentage of total income after taxes, the differences are even more dramatically, i.e., respectively 35.8 and 9.1 percent for food consumption, and 23.6 and 4.8 percent for energy consumption. While food and energy are basic necessities, low-income households typically also have borrowing constraints and no liquid assets to smooth consumption over time, and have thus little other options than reducing durables expenditures.

Finally, when food prices increase, households may decide to consume less and increase their precautionary savings because of a rise in uncertainty or a greater perceived likelihood of future unemployment and income loss. According to Cochrane (2016), precautionary savings and risk aversion are prominent ingredients for business cycle fluctuations. In particular, he argues that higher risk premiums and increases in risk aversion triggered by relatively small shocks affecting consumers, rather than risk-free rates and intertemporal substitution, are the central features of recessions. Edelstein and Kilian (2009) provide empirical evidence that shifts in precautionary savings and deteriorating consumer confidence are likely an important determinant of the excess response of household consumption to energy price shocks.

To assess the possibility of precautionary savings effects, the final panel of Figure 15 shows the impulse responses of the University of Michigan Index of Consumer Sentiment to food commodity and crude oil supply shocks. As can be observed, there is a significant decline in consumer sentiment after both shocks, which is consistent with increased uncertainty by households. Precautionary savings effects may thus also be an important propagation mechanism of food market disruptions to the real economy. Whether this is indeed the case, and the relevance of the different mechanisms to explain the overall effects, are questions that cannot be answered with the methods used in this paper. This requires other methods, such as general equilibrium models that incorporate food markets, and is left for future research.

6 Conclusions

Food commodity markets have historically been subject to considerable volatility. In particular, since the start of the millennium, there have been large swings in global food commodity prices. Although it is important for designing policies that can ameliorate the consequences of those swings, the linkages between food commodity market fluctuations and the macroeconomy are poorly understood. With global temperatures expected to rise substantially over the next decades, understanding these relationships will become even more important in the future. In this paper, we have estimated the consequences of disruptions in global food commodity markets on the US economy over the past fifty years. Because food markets also respond to developments in the macroeconomy, the main challenge in doing this is the identification of exogenous shifts in food commodity prices. We have used two different approaches for identifying such movements. The first strategy is a joint structural VAR model for global food commodity markets and the US economy in which food market disruptions are identified as unanticipated changes in a quarterly global food production index that we have constructed based on the planting and harvesting calendars of the four major staples (corn, wheat, rice and soybeans). As an alternative identification strategy, we relied on FAO reports, newspaper articles, disaster databases and several other sources to identify 13 historical episodes in which significant changes in food commodity prices were mainly caused by exogenous food market events.

The structural VAR analysis and the narrative approach deliver similar conclusions. We find a considerable impact of fluctuations in food commodity markets on the US economy. On the one hand, a rise in food commodity prices augments food and core consumer prices as well as energy prices more recently. On the other hand, there is a persistent fall in real GDP and household expenditures. The effects are approximately four to six times larger than the maximum impact implied by the share of food commodities in the consumer price index and household consumption. An intriguing finding is that households reduce durable consumption much more than food consumption. Additionally, investment declines considerably. Both effects can only partly be explained by a moderate monetary policy tightening to stabilize the inflationary consequences of the shocks. A better understanding of the exact mechanisms of these indirect effects remains complex and is an interesting topic for future research. The construction of dynamic general equilibrium models with food markets may be useful to answer this question. Other avenues for future research are the analysis of cross-country differences and the question whether policies, such as public food security programs or monetary policy, could dampen the macroeconomic consequences of food market disruptions.

References

Abbott, Philip C., Christopher Hurt, and WE Tyner (2011) "What's driving food prices in 2011?,"Technical report, Farm Foundation.

Acemoglu, Daron, Ufuk Akcigit, and William Kerr (2016) "Networks and the Macroeconomy: An Empirical Exploration," in Martin Eichenbaum and Jonathan Parker eds. *NBER Macroeconomics Annual 2015*: University of Chicago Press, pp. 276–335.

Agricultural Market Information System (2012) "Crop calendars," URL: `http://www.amis-outlook.org/amis-about/calendars/en/`.

Baquedano, Felix G. and William M. Liefert (2014) "Market integration and price transmission in consumer markets of developing countries," *Food Policy*, Vol. 44, pp. 103–114.

Baumeister, Christiane and James D. Hamilton (2015) "Sign Restrictions, Structural Vector Autoregressions, and Useful Prior Information," *Econometrica*, Vol. 83, pp. 1963–1999.

Baumeister, Christiane and Gert Peersman (2013a) "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.

——— (2013b) "Time-Varying Effects of Oil Supply Shocks on the US Economy," *American Economic Journal: Macroeconomics*, Vol. 5, pp. 1–28.

Beaudry, Paul and Franck Portier (2006) "Stock Prices, News, and Economic Fluctuations," *American Economic Review*, Vol. 96, pp. 1293–1307.

Bernanke, Ben S., Mark Gertler, and Mark W. Watson (1997) "Systematic Monetary Policy and the Effects of Oil Price Shocks," *Brookings Papers on Economic Activity*, Vol. 28, pp. 91–157.

Bernanke, Ben S. and Ilian Mihov (1998) "Measuring monetary policy," *Quarterly Journal of Economics*, Vol. 113, pp. 869–902.

Bils, Mark and Peter J. Klenow (1998) "Using Consumer Theory to Test Competing Business Cycle Models," *Journal of Political Economy*, Vol. 106.

Blanchard, Olivier and Roberto Perotti (2002) "An empirical characterization of the dynamic effects of changes in government spending and taxes on output," *Quarterly Journal of Economics*, Vol. 117, pp. 1329–1368.

Boldin, Michael and Jonathan H. Wright (2015) “Weather-Adjusting Economic Data,” *Brookings Papers on Economic Activity*.

Browning, Martin and Thomas F. Crossley (2000) “Luxuries Are Easier to Postpone: A Proof,” *Journal of Political Economy*, Vol. 108, pp. 1022–1026.

——— (2009) “Shocks, Stocks, and Socks: Smoothing Consumption Over a Temporary Income Loss,” *Journal of the European Economic Association*, Vol. 7, pp. 1169–1192.

Centre for Research on the Epidemiology of Disasters (2015) “EMDAT Disaster List,” URL: `http://www.emdat.be/database`.

Chavas, Jean-Paul, David Hummels, and Brian D. Wright eds. (2014) *The Economics of Food Price Volatility*: National Bureau of Economic Research.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans (1999) “Monetary policy shocks: What have we learned and to what end?,” in J.B. Taylor and M. Woodford eds. *Handbook of Macroeconomics*, Vol. 1: Elsevier Science B.V. Chap. 2, pp. 65–148.

Clark, Todd E. and Troy Davig (2008) “An Empirical Assessment of the Relationships Among Inflation and Short- and Long-Term Expectations,” *Federal Reserve Bank of Kansas City Research Working Paper*, Vol. 5.

Cochrane, John H. (2016) “Macro-Finance,” *NBER Working Paper Series*.

Davis, Steven J. and John Haltiwanger (2001) “Sectoral job creation and destruction responses to oil price changes,” *Journal of Monetary Economics*, Vol. 48, pp. 465–512.

Dawe, David and Irini Maltsoglou (2014) “Marketing margins and the welfare analysis of food price shocks,” *Food Policy*, Vol. 46, pp. 50–55.

De Winne, Jasmien and Gert Peersman (2016) “Narrative Global Food Commodity Market Shocks,” *Ghent University Working Paper*.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken (2014) “What Do We Learn from the Weather? The New Climate-Economy Literature,” *Journal of Economic Literature*, Vol. 52, pp. 740–798.

Dynarski, Susan, Jonathan Gruber, Robert A. Moffitt, and Gary Burtless (1997) “Can Families Smooth Variable Earnings ?,” *Brookings Papers on Economic Activity*, Vol. 1997, pp. 229–303.

Edelstein, Paul and Lutz Kilian (2009) “How sensitive are consumer expenditures to retail energy prices?,” *Journal of Monetary Economics*, Vol. 56, pp. 766–779.

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

Enders, Walter and Matthew T. Holt (2014) “The Evolving Relationships between Agricultural and Energy Commodity Prices: A Shifting-Mean Vector Autoregressive Analysis,” in Jean-Paul Chavas, David Hummels, and Brian D. Wright eds. *The Economics of Food Price Volatility*: University of Chicago Press, Chap. 4, pp. 135–187.

Ezekiel, Mordecai (1938) “The Cobweb Theorem,” *The Quarterly Journal of Economics,*, Vol. 52, pp. 255–280, DOI: http://dx.doi.org/10.2307/1881734.

Fanning, Bob (2012) “Fertilizer Timing for Wheat,” URL: http://igrow.org/agronomy/wheat/fertilizer-timing-for-wheat/.

FAO (2015) “Crop calendar,” URL: http://www.fao.org/agriculture/seed/cropcalendar/welcome.do.

FAO Statistics Divison (2015) “Production - Crops,” URL: http://faostat3.fao.org/.

Ferrucci, Gianluigi, Rebeca Jiménez-Rodríguez, and Luca Onorante (2010) “Food price pass-through in the euro area: The role of asymmetries and non-linearities,” *ECB Working Paper*, Vol. No. 1168.

Finn, Mary G. (2000) “Perfect Competition and the Effects of Energy Price Increases on Economic Activity,” *Journal of Money, Credit and Banking*, Vol. 32, pp. 400–416.

Furceri, Davide, Prakash Loungani, John Simon, and Susan Wachter (2015) “Global Food Prices and Domestic Inflation: Some Cross- Country Evidence,” *IMF Working Paper*.

Furlong, Fred and Robert Ingenito (1996) “Commodity prices and inflation,” *Economic Review-Federal Reserve Bank of San Francisco*, Vol. No. 2.

Galí, Jordi (1999) “Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations?,” *American Economic Review*, Vol. 89, pp. 249–271.

Giffen, Robert (1879) “On the Fall of Prices of Commodities in Recent Years,” *Journal of the Statistical Society of London*, Vol. 42, pp. 36–78.

Global Information and Early Warning System (2014) "GIEWS Country Briefs," URL: `http://www.fao.org/giews/countrybrief/index.jsp`.

Gouel, Christophe (2012) "Agricultural price instability: A survey of competing explanations and remedies," *Journal of Economic Surveys*, Vol. 26, pp. 129–156.

Hamermesh, Daniel S. (1982) "Social Insurance and Consumption: An Empirical Inquiry," *American Economic Review*, Vol. 72, pp. 101–113.

Hamilton, James D. (1983) "Oil and the Macroeconomy since World War II," *Journal of Political Economy*, Vol. 91, pp. 228–248.

——— (1988) "A Neoclassical Model of Unemployment and the Business Cycle," *Journal of Political Economy*, Vol. 96.

——— (2003) "What is an oil shock?," *Journal of Econometrics*, Vol. 113, pp. 363–398.

——— (2008) "Oil and the Macroeconomy," in Steven N. Durlauf and Lawrence E. Blume eds. *The New Palgrave Dictionary of Economics*: Palgrave Macmillan, 2nd edition.

Headey, Derek and Shenggen Fan (2010) "Reflections on the global food crisis: How did it happen? How has it hurt? And how can we prevent the next one?,"Technical report, International Food Policy Research Institute, Washington.

Ivanic, Maros and Will Martin (2008) "Implications of higher global food prices for poverty in low-income countries," *Agricultural Economics*, Vol. 39, pp. 405–416.

Jordà, Òscar (2005) "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, Vol. 95, pp. 161–182.

Kilian, Lutz (2009) "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *American Economic Review*, Vol. 99, pp. 1053–1069.

Lawes, John Bennet and Joseph Henry Gilbert (1868) *On the home produce, imports and consumption of wheat*, London: Longmans, Green.

Mallarino, Antonio P. (2010) "Is In-Season Fertilization for Soybean Effective," URL: `http://crops.extension.iastate.edu/cropnews/2010/06/season-fertilization-soybean-effective`.

Mertens, Karel and Morten O. Ravn (2013) "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States," *American Economic Review*, Vol. 103, pp. 1212–1247.

Mitchell, Donald (2008) "A Note on Rising Food Prices," *World Bank Policy Research Working paper*.

Murphy, Robert G. and Adam Rohde (2015) "Rational Bias in Inflation Expectations," *Eastern Economic Journal*.

Muth, John F. (1961) "Rational Expectations and the Theory of Price Movements," *Econometrica*, Vol. 29, pp. 315–335.

Parker, Jonathan A. (1999) "The Reaction of Household Consumption to Predictable Changes in Social Security Taxes," *American Economic Review*, Vol. 89, pp. 959–973.

Pedersen, Michael (2011) "Propagation of Shocks to Food and Energy Prices: An International Comparison," *Central Bank of Chile Working Papers*, Vol. No. 648.

Peersman, Gert, Sebastian Rüth, and Wouter Van der Veken (2016) "The interplay between oil and food commodity prices: has it changed over time?," *Mimeo*.

Peersman, Gert and Ine Van Robays (2009) "Oil and the Euro area economy," *Economic Policy*, Vol. 24, pp. 603–651.

Pindyck, Robert S. (1993) "The Present Value Model of Rational Commodity Pricing," *Economic Journal*, Vol. 103, pp. 511–530.

Primiceri, Giorgio E. (2005) "Time Varying Structural Vector Autoregressions," *Review of Economic Studies*, Vol. 72, pp. 821–852.

Ramey, Valerie A. (2011) "Identifying government spending shocks: It's all in the timing," *Quarterly Journal of Economics*, Vol. 126, pp. 1–50.

——— (2016) "Macroeconomic Shocks and Their Propagation," *NBER Working Paper Series*.

Ramey, Valerie A. and Matthew D. Shapiro (1998) "Costly capital reallocation and the effects of government spending," *Carnegie-Rochester Conference Series on Public Policy*, Vol. 48, pp. 145–194.

Ramey, Valerie A. and Sarah Zubairy (2014) "Government Spending Multipliers in Good Times and in Bad: Evidence from U.S. Historical Data," *NBER Working Paper Series*, Vol. 20719.

Rigobon, Roberto (2010) "Commodity prices pass-through," *Central Bank of Chile Working Papers*, Vol. No. 572.

Roberts, Michael J. and Wolfram Schlenker (2013) "Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate," *American Economic Review*, Vol. 103, pp. 2265–2295.

Romer, Christina D. and David H. Romer (1989) "Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz," in *NBER Macroeconomics Annual 1989*, Vol. 4, pp. 121–184.

——— (2010) "The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks.," *American Economic Review*, Vol. 100, pp. 763–801.

Rotemberg, Julio J. and Michael Woodford (1996) "Imperfect Competition and the Effects of Energy Price Increases on Economic Activity," *Journal of Money, Credit and Banking*, Vol. 28, pp. 549–577.

Scharf, Peter C., William J. Wiebold, and John A. Lory (2002) "Corn yield response to nitrogen fertilizer timing and deficiency level," *Agronomy Journal*, Vol. 94, pp. 435–441.

Schmitt, Michael A., John A. Lamb, Gyles W. Randall, James H. Orf, and George W. Rehm (2001) "In-Season Fertilizer Nitrogen Applications for Soybean in Minnesota," *Agronomy Journal*, Vol. 93, pp. 983–988.

Sims, Christopher A. (1980) "Macroeconomics and Reality," *Econometrica*, Vol. 48, pp. pp. 1–48.

——— (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.

Sims, Christopher A. and Tao Zha (1999) "Error bands for impulse responses," *Econometrica*, Vol. 67, pp. 1113–1155.

Stock, James H. and Mark W. Watson (2016) "Factor Models and Structural Vector Autoregressions in Macroeconomics," *Unpublished Manuscript*, pp. 1–111.

Trostle, Ronald, Daniel Marti, Stacey Rosen, and Paul Westcott (2011) "Why Have Food Commodity Prices Risen Again?,"Technical report, USDA.

United States Department of Agriculture (2016) "World Agricultural Supply and Demand Estimates," URL: `http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1194`.

Williamson, Lucille and Paul Williamson (1942) "What We Eat," *Journal of Farm Economics*, Vol. 24, pp. 698–703.

Zhang, Wenlang and Daniel Law (2010) "What Drives China's Food-Price Inflation and How does It Affect the Aggregate Inflation?," *Hong Kong Monetary Authority Working Paper*.

Appendix A - Example of narratively identified global food commodity market shock: droughts around the globe in 2012Q3

Type Unfavorable food commodity market shock

Food commodity market event Due to droughts in Russia, Eastern Europe, Asia and the US, there was a significant decline in global cereal production. In retrospect, annual global cereal production contracted by 2.4%. In July, the USDA decreased its previous (June) estimate for US corn by 12% because of the worst Midwest drought in a quarter century. Heatwaves in southern Europe added serious concern about global food supplies later that month, as well as below-average rainfall in Australia. In August, there was news about a late monsoon affecting the rice harvest in Asia negatively. According to the International Food Policy Institute, production of food grains in the South Asia region was expected to decline by 12% compared to a year earlier. Also in August, the Russian grain harvest forecasts were reduced because of drought. In October 2012, wheat output in the Russian Federation was estimated some 30% down from 2011, in Ukraine, a decrease of about 33% was expected, while in Kazakhstan, output was reported to be just half of last year's good level. Wheat harvest indeed declined in 2012, respectively by 33%, 29%, 57% in Russia, Ukraine and Kazakhstan. The EMDAT Database of international disasters lists droughts in Ukraine (15/04/2012-31/07/2012), Russia (06/2012-09/2012) and the US (06/2012-12/2012).

We allocate the shock to 2012Q3 because this is the period when the severe scaling back of the expected harvests started, resulting in considerable price increases. Real food commodity prices increased by 7.9% in that quarter, whereas oil prices decreased by 1.6%. The same comment about the Greek debt crisis reported for the 2010Q3 shock applies for 2012Q3 (the Second Economic Adjustment Programme for Greece was approved in March 2012). There were no other events that could explain the rise in food commodity prices.

Relevant articles

Midwest drought slashes corn estimate, jolts market

Reuters. Charles Abbott, (12 July 2012).

"**The worst Midwest drought in a quarter century is doing more damage to U.S. crops than previously expected with the government on Wednesday slashing its estimate for what was supposed to be a record harvest.** The U.S. Department of Agriculture said the **corn crop will average just 146 bushels an acre, down 20 bushels from its June estimate and a much more dramatic drop than analysts had projected**. **The report initially reignited a near-record rally in grain prices** that could eventually hit consumer grocery bills in North America, although the impact could be more immediate for the world's poor if the drought persists. T**he severe scaling back of the harvest has sent corn and soybean prices up by more than a third over the past month**, as extreme heat and dry conditions stunt growth in the world's largest grower and exporter."

Available at:

http://www.reuters.com/article/2012/07/12/us-usa-crops-idUSBRE86A0LL20120712

Europe Heat Wave Wilting Corn Adds to U.S. Drought

BloombergBusiness. Rudy Ruitenberg, (24 July 2012).

"**Heat waves in southern Europe are withering the corn crop and reducing yields in a region that accounts for 16 percent of global exports at a time when U.S. drought already drove prices to a record**.

Temperatures in a band running from eastern Italy across the Black Sea region into Ukraine reached 35 degrees Celsius (95 degrees Fahrenheit) or more this month, about 5 degrees above normal, U.S. government data show. Corn, now in the pollination phase that creates kernels, risks damage above 32 degrees, said Cedric Weber, the head of market analysis at Bourges, France-based Offre et Demande Agricole, which advises farmers on sales.

The heat wave in Europe is adding to concern about global food supplies as U.S. farmers face the worst drought since 1956, India delays sowing because of a late monsoon and Australian crops endure below-average rainfall. Soybeans and corn rose to all-time highs yesterday and wheat surged 42

percent since June 1. The United Nations says food prices will probably rebound after falling the most in three years in the second quarter."
Available at: http://www.bloomberg.com/news/articles/2012-07-23/europe-heat-wave-wilting-corn-adds-to-u-s-drought-commodities

Rice Harvest in India Set to Drop as Drought Curbs Sowing

BloombergBusiness. Prabhudatta Mishra, (16 August, 2012).

"Rice production in India, the world's second-biggest grower, is poised to slump from a record as the worst monsoon since 2009 reduces planting, potentially lowering exports and boosting global prices.

The monsoon-sown harvest may be between 5 million metric tons and 7 million tons below a record 91.5 million tons a year earlier, said P.K. Joshi, director for the South Asia region at the Washington-based International Food Policy Research Institute. **Production of food grains, including corn and lentils, may slide as much as 12 percent from 129.9 million tons a year earlier**, he said.

Rice has rallied 6.3 percent in Chicago since the end of May on prospects for a lower Indian crop and export curbs, adding to global food costs that the United Nations estimates jumped 6.2 percent in July. **Corn and soybeans have soared to records as the worst U.S. drought in half a century killed crops**. **Global rice production this year will be smaller than previously forecast**, according to the UN's Food & Agriculture Organization."
Available at: http://www.bloomberg.com/news/articles/2012-08-15/rice-harvest-in-india-set-to-decline-as-drought-curbs-planting

Russia harvest forecasts cut as drought hits crop in east

Reuters. Polina Devitt, (20 August 2012).

"**Two leading Russian agricultural analysts cut their forecasts for Russia's grain harvest on Monday** after harvest data from two drought-stricken eastern growing regions reduced the outlook for the overall crop.

SovEcon narrowed their grain forecast to 71-72.5 million metric tons (78.3- 79.9 million tons) from a previous 70-74 million tonnes after the start of harvesting campaign in Urals and Siberia regions showed weak crop prospects. It has also cut wheat harvest forecast to 39-41 million tonnes from earlier 40.5-42.5 million tonnes.

The Institute for Agricultural Market Studies (IKAR) has cut its 2012 grain crop forecast to 73 million tonnes from a previously expected 75.4 million tonnes, its chief executive, Dmitry Rylko, said. It has not yet estimated wheat harvest. 'I see the possibility of further downgrading,' Rylko said."

Available at: http://www.reuters.com/article/2012/08/20/us-grain-russia-harvest-idUSBRE87J0BE20120820

Crop Prospects and Food Situation No.3 October 2012

Food and Agriculture Organisation, (2012). Rome: FAO.

"**FAO's latest forecast for world cereal production in 2012 has been revised downward slightly (0.4 percent) since the previous update in September**, to 2 286 million tonnes. The latest adjustment mostly reflects a smaller maize crop in central and southeastern parts of Europe, where yields are turning out lower than earlier expectations following prolonged dry conditions. At the current forecast level, world cereal production in 2012 would be 2.6 percent down from the previous year's record crop but close to the second largest in 2008. The overall decrease comprises a 5.2 percent reduction in wheat production, and a 2.3 percent reduction for coarse grains, while the global rice crop is seen to remain virtually unchanged. **Severe droughts this year in the United States and across a large part of Europe and into central Asia have been the main cause of the reduced wheat and coarse grains crops**.

[...]

FAO's latest forecast for global wheat production in 2012 stands at 663 million tonnes, 5.2 percent below last year's level, but close to the average of the past five years. This level is considerably below expectations earlier in the year, largely reflecting the impact of the severe drought that set-in across eastern Europe and central Asia, but also on account of downward revisions for the key southern hemisphere producing countries where weather and policy factors in some cases have reduced prospects for the 2012 crop yet to be harvested.

Most of the decline in global wheat production, compared to last year, reflects the negative effects of drought in the major producing CIS

countries in Europe and Asia. Wheat output in the Russian Federation is estimated some 30 percent down from 2011, in Ukraine, latest information points to a decrease of about 33 percent, while in Kazakhstan, output is reported to be just half of last year's good level. In other parts of Europe, wheat output also declined, particularly in some central and southeastern countries on the edge of the drought-affected zone. The aggregate output of the EU countries is estimated to be down by 2.6 percent. In the other Asian subregions, record crops have been gathered in the key producers in the Far East, namely, China and India, while in the Near East, results have been mixed: good crops were gathered in Afghanistan and the Islamic Republic of Iran but outputs were down elsewhere, reflecting dry conditions and/or the negative impact of civil disturbances. The 2012 harvest results were also mixed in North Africa, where production recovered in Algeria but was sharply reduced in Morocco due to dry conditions. In the United States, this year's wheat production is estimated to have increased by 13.4 percent to an above-average level of 61.7 million tonnes. In Canada, output is expected to be above average and almost 7 percent higher than in 2011.

In South America, the subregion's aggregate wheat production is forecast at about 21 million tonnes, 12 percent down from the previous year and below average. The expected reduction reflects a general decline in the area planted in response to changes in marketing policy and **due to dry weather at sowing time in June and July**. In Oceania, prospects for the wheat crop in Australia are mixed, reflecting varied winter rainfall and moisture conditions: overall output is forecast down by about 24 percent from last year's record crop due to lower yields expected in some major producing areas affected by dry conditions."
Available at: http://www.fao.org/docrep/016/al992e/al992e00.pdf#page=30

Table 1 - Overview of narrative food commodity market shocks

Date	Type	(Cumulative) change in food commodity prices: Impact	After 1Q	Food commodity market event
1972Q3	Unfavorable	1.4%	18.3%	**Russian Wheat Deal and failed monsoon in Southeast Asia** Wheat production in the USSR declined by 13% due to disastrous weather conditions. This resulted in purchases on an unprecedented scale by the Soviet Union on the world market, leading to large price increases from July and August 1972 onwards. The negative consequences of the bad weather conditions in the USSR were only known very late, and were percieved as a considerable shock worldwide since only a few months earlier there were reports of heavy surplus stocks building. The sales involved a series of subsidized transactions following an agreement whereby the US made available credit to the USSR for the purchases (Russian Wheat Deal). The rise in wheat prices was further accelerated by a decision of the US to suspend the subsidies normally paid on exports. At the same time, the global agricultural sector was severely affected by monsoon failure in most of southeast Asia during summer, followed by extremely dry weather throughout autumn and early winter. Rice production decreased in Cambodia, India, Malaysia and Thailand by respectively 29%, 9%, 13% and 10%. In 1972Q3 and 1972Q4, real cereal prices rose by respectively 9.7% and 16.5%. Overall, annual global cereal production declined by 1.6% in 1972, compared to a rise of respectively 9.2% and 7.4% in 1971 and 1973.
1975Q2	Favorable	-10.9%	-9.9%	**Significant improved estimate of world grain production** In April 1975, the USDA predicted a significant increase in world grain production (the previous forecast was in December 1974), indicating an easing of the tight supply-demand balance of the previous two years. Furthermore, in May 1975, the USDA increased its US wheat production estimate for 1975 because of favorable May field conditions. A record wheat harvest was expected. In retrospect, annual global cereal production increased by 6.9% relative to the previous year.
1975Q4	Favorable	-4.7%	-10.7%	**Optimistic rice forecast because of very favorable monsoon season** In September 1975, there were expectations of a record rice crop because of a favorable monsoon season. As a consequence, rice prices started to decrease from October 1975 onwards, which is the start of the harvesting season. Real cereal prices fell by 19% over two subsequent quarters. Ex post, 1975 proved indeed to be a very favorable rice year for India, Japan and Thailand, with an acceleration of production yields relatively to 1974 by respectively 23%, 7% and 14%.

1977Q3	Favorable	-20.9%	-12.9%	**Predictions of record US and Soviet harvests** Several favorable and/or increased food production forecasts were published throughout July and August: predictions of record US corn crops (July 1977), increased forecasts of world wheat and feed grains production (July 1977), news on record Soviet wheat harvest (August 1977), and predictions of record US soybeans crops (August 1977).
1977Q4	Unfavorable	8.0%	15.6%	**Record grain harvests did not materialize** Despite expectations of record harvests in the previous quarter, global grain production turned out to be below trend in 1977 as a result of unfavorable weather conditions in the major producing areas. In November 1977, the Financial Times announced that the Soviet crop would be roughly 10% below the latest estimate predicted by the USDA. In addition, the International Wheat Council lowered its estimate of world wheat output by 2%-3%. In retrospect, Soviet wheat production decreased by 5% compared to the previous year. Chinese wheat production declined by 18% and in the US wheat production shrunk by 5%. It is clear that this came as an unexpected shock in 1977Q4, given the extreme optimistic forecasts in 1977Q3.
1984Q3	Favorable	-10.4%	-14.1%	**Favorable weather in North America and exceptionally good cereal harvest in Western Europe** In July 1984, the USDA improved its June estimate for US wheat production, and predicted record grain production worldwide. Much of this increase was a consequence of the North American recovery from the sharp decline of 1983 as a consequence of increased planting, as well as favorable weather. Western Europe also had exceptionally good harvests of cereals. In retrospect, US maize production rose considerably, i.e. 84%. Furthermore, wheat production increased in China, India and France by respectively 8%, 33% and 6%. Overall, global cereal production increased by 11.4% in 1984, which was the largest annual rise since the 1960s.
1988Q4	Favorable	-4.5%	-9.4%	**Expectations of global surge in wheat production** In December 1988, it was announced by the International Wheat Council that worldwide wheat production was expected to rise considerably in 1989, amongst others because of a reduction in the requirement for US set-aside of arable land, from 27.5% to only 10% of the wheat acreage in the next year, which was a farm policy response to the 1988 drought in the US (The Disaster Relief Act of 1988). In response to drought-shortened crop inventories, the 1989 version of the farm bill was expected to encourage larger crop planting. Wheat production in 1989 increased indeed in all large wheat producing countries (China 6%; France 10%; India 17%; US 12%; USSR 11%). Ex post, annual global cereal production increased by more than 10% in 1989.

1995Q3	Unfavorable	6.6%	7.8%	**Significant downward revised world cereal estimates** In 1995Q3, there were large downward revisions of 1995 world cereal production. This was especially the case for wheat and coarse grains production in the US (poor weather conditions, predominantly hot and dry weather during early September) and the Commonwealth of Independent States, and for wheat production in Argentina and China. In Central America, a below-normal coarse grain crop was in prospect in Mexico due to a combination of reduced plantings and dry weather in parts. In retrospect, wheat production declined in the US and Russia by 6%, and in Argentina by 16%. Mexican maize production stagnated in 1995, but US maize production decreased by 26%. Annual global production of the four major staples ultimately declined by 2.6% in 1995.
1996Q3	Favorable	-4.5%	-12.5%	**Expectations of excellent global cereal harvest** The FAO issued a first provisional favorable forecast for world 1996 cereal output (6.5% up from the previous year) in June 1996. The largest increase was expected in coarse grains output, mostly in the developed countries. Additionally, wheat output was forecast to increase significantly, and rice production to rise marginally. In September 1996, the International Grains Council increased its forecast (compared to a month earlier) for 1996-97 global wheat production in response to a confirmation of favorable harvests in the Northern Hemisphere and excellent prospects in the Southern Hemisphere.
2002Q3	Unfavorable	9.4%	10.7%	**Significant downward revised global cereal estimates** The FAO's July forecast pointed to a global cereal output which is considerably less than the previous forecast in May. It would be the smallest wheat crop since 1995. The downward revision was mostly a result of a deterioration of production prospects for several of the major wheat crops around the globe because of adverse weather in the northern hemisphere or for planting in the southern hemisphere. The forecast for global coarse grain output was also revised downwards since the last report mainly because of dry weather conditions in the Russian Federation. In September, the Australian Bureau of Agricultural and Resource Economics announced that drought will slash the country's winter grain production. Australia is one of the big five wheat exporters. In retrospect, US wheat production decreased by 18% in 2002 and Australian wheat production by 60%.
2004Q3	Favorable	-6.9%	-10.9%	**Significant improved forecast of world cereal output** Favorable weather conditions triggered expectations of significant higher cereal production in Europe, China, Brazil and the US. In July 2004, the International Grains Council announced an expected rise in the global volume of coarse grain. In september 2004, the FAO's raised its forecast for world cereal output since the previous report in June. Annual global cereal production increased by more than 9% in 2004.

2010Q3	Unfavorable	8.6%	22.1%	**Droughts in Russia and Eastern Europe** The 2010 cereal output in the Republic of Moldova, Russian Federation, Kazakhstan and Ukraine was seriously affected by adverse weather conditions. Russian Federation, Kazakhstan and Ukraine (all three amongst the world's top-10 wheat exporters) suffered the worst heatwave and drought in more than a century, while the Republic of Moldova was struck by floods and hail storms. In the Russian Federation, the most severely affected by adverse conditions, the 2010 cereal crop was 33% lower than the previous year. In Ukraine the wheat harvest decreased 19%. Accordingly, in July 2010, wheat prices have seen the biggest one-month jump in more than three decades, i.e. a rise of nearly 50% since late June. In September, wheat prices were even 60% to 80% higher due to a decision by the Russian Federation to ban exports.
2012Q3	Unfavorable	7.9%	6.9%	**Droughts around the globe** Due to droughts in Russia, Eastern Europe, Asia and the US, there was a signifcant decline in global cereal production. In retrospect, annual global cereal production contracted by 2.4%. In July, the USDA decreased its previous (June) estimate for US corn by 12% because of the worst Midwest drought in a quarter century. Heatwaves in southern Europe added serious concern about global food supplies later that month, as well as below-average rainfall in Australia. In August, there was news about a late monsoon affecting the rice harvest in Asia negatively. According to the International Food Policy Institute, production of food grains in the South Asia region was expected to decline by 12% compared to a year earlier. Also in August, the Russian grain harvest forecasts were reduced because of drought. In October 2012, wheat output in the Russian Federation was estimated some 30% down from 2011, in Ukraine, a decrease of about 33% was expected, while in Kazakhstan, output was reported to be just half of last year’s good level. Wheat harvest indeed declined in 2012, respectively by 33%, 29%, 57% in Russia, Ukraine and Kazakhstan.

Note: a detailed motivation and description of the episodes can be found in the online appendix of the paper.

Table 2 - Maximum effects on household expenditures and economic activity

	One stdv shock[1]		Ratio to total consumption[2]		Weighted impact[3]		8 basis points monetary policy shock[4]
	Food	oil	Food	Oil	Food	Oil	
Real GDP	**-0.27**	**-0.39**	0.93	1.39	**-0.27**	**-0.39**	**-0.06**
Personal consumption	**-0.29**	**-0.28**	1.00	1.00	**-0.18**	**-0.18**	**-0.05**
Energy goods and services	-0.13	**-0.44**	0.45	1.57	-0.01	**-0.02**	**-0.05**
Nondurables: food	**-0.28**	-0.03	0.97	0.11	**-0.02**	0.00	-0.01
Services: food	-0.13	-0.21	0.45	0.75	0.00	-0.01	**-0.04**
Nondurables and services: other	**-0.20**	**-0.26**	0.69	0.93	**-0.09**	**-0.11**	**-0.03**
Durables	**-0.93**	**-1.11**	3.21	3.96	**-0.08**	**-0.09**	**-0.13**
Motor vehicles and parts	**-1.06**	**-1.25**	3.66	4.46	**-0.04**	**-0.04**	**-0.16**
Investment	**-0.93**	**-1.14**	3.21	4.07	**-0.16**	**-0.20**	**-0.18**
Export	-0.37	**-1.04**	1.28	3.71	-0.03	**-0.09**	**-0.13**
Federal Funds rate (horizon = 0)	0.08	-0.11					**0.08**

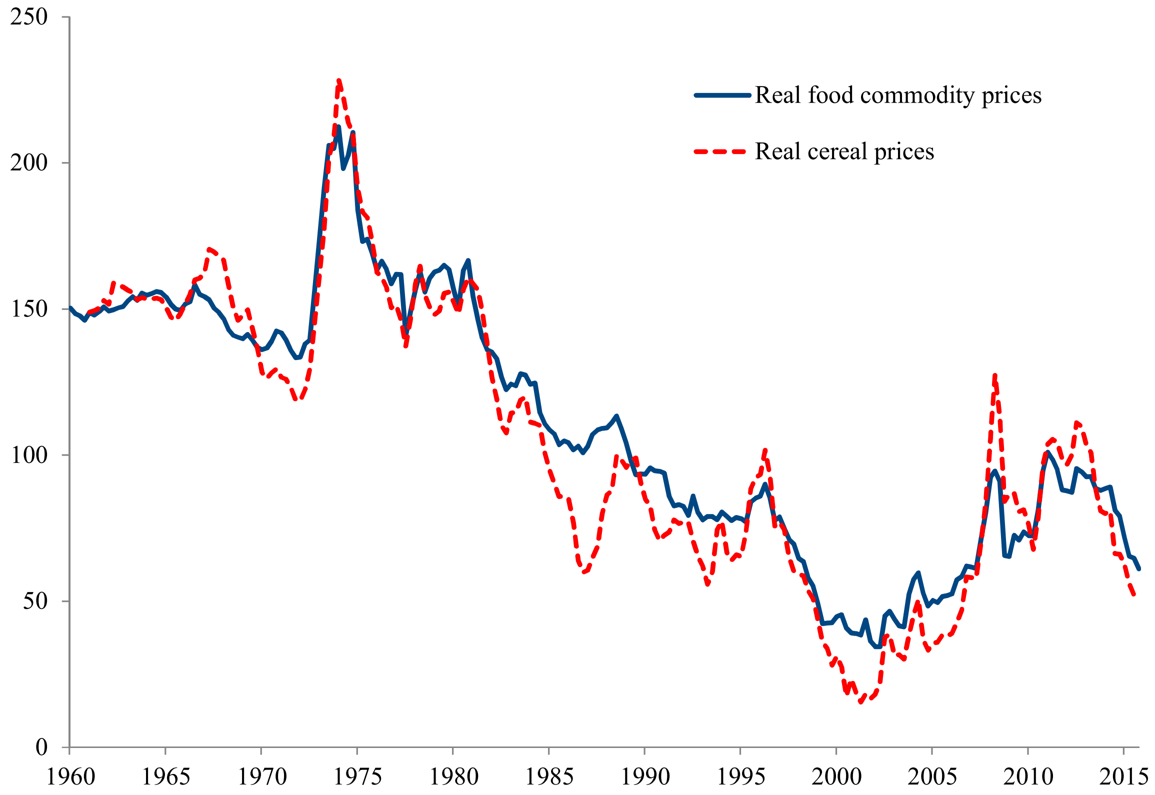
[1] Maximum impact of one standard deviation food commodity supply and oil supply shock; bold figures are significant at 10%

[2] Ratio (maximum impact on variable X / maximum impact on total consumption)

[3] Maximum impact * ratio of component to real GDP

[4] Maximum impact of monetary policy shock of 8 basis points; bold figures are significant at 10%

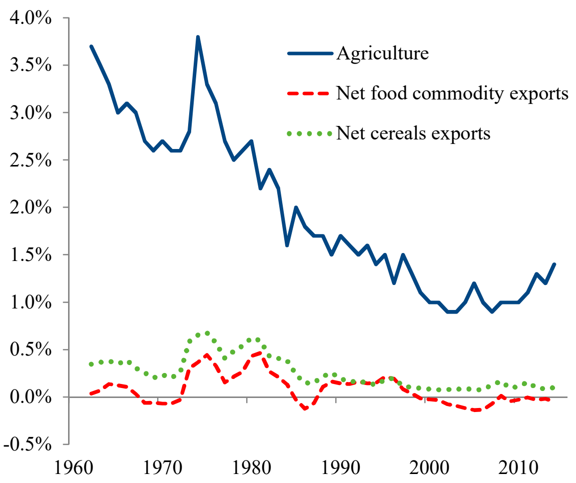
Figure 1 - Evolution of food commodity prices over time



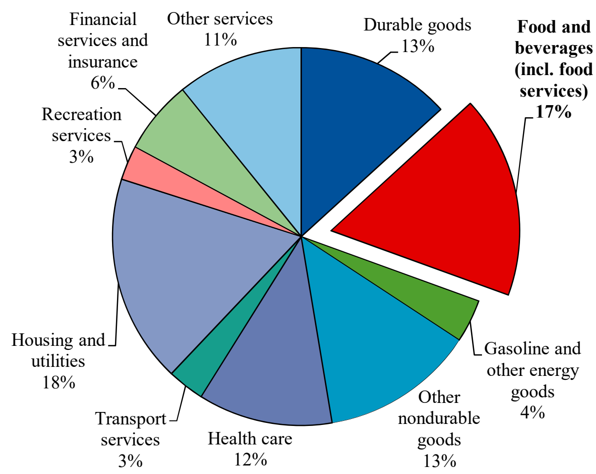
Note: variables are measured as 100*log of index deflated by US CPI. Real food commodity prices is a trade-weighted average of benchmark food prices in US dollars for cereals, vegetable oils, meat, seafood, sugar, bananas and oranges. Cereal prices aggregates the prices of corn, wheat, rice and soybeans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

Figure 2 - Food and the US economy

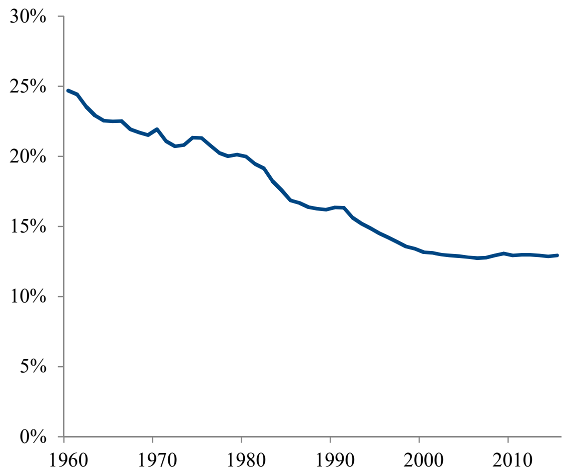
Share of agriculture and net food commodity exports in GDP



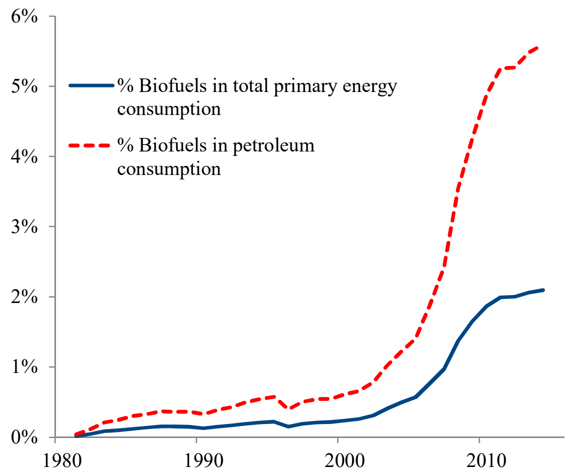
Personal consumption expenditures components (1960-2015)



Share of food and beverages in personal consumption



Share of biofuels in energy



Note: Sources: Gross Domestic Product (GDP) and Personal Consumption Expenditures (PCE) components: US. Bureau of Economic Analysis
Crude Oil, Biofuel Shares: US Energy Information Administration; Trade Data: UN Comtrade Database (SITC 1 Classification).

Figure 3 - Examples of crop calendars

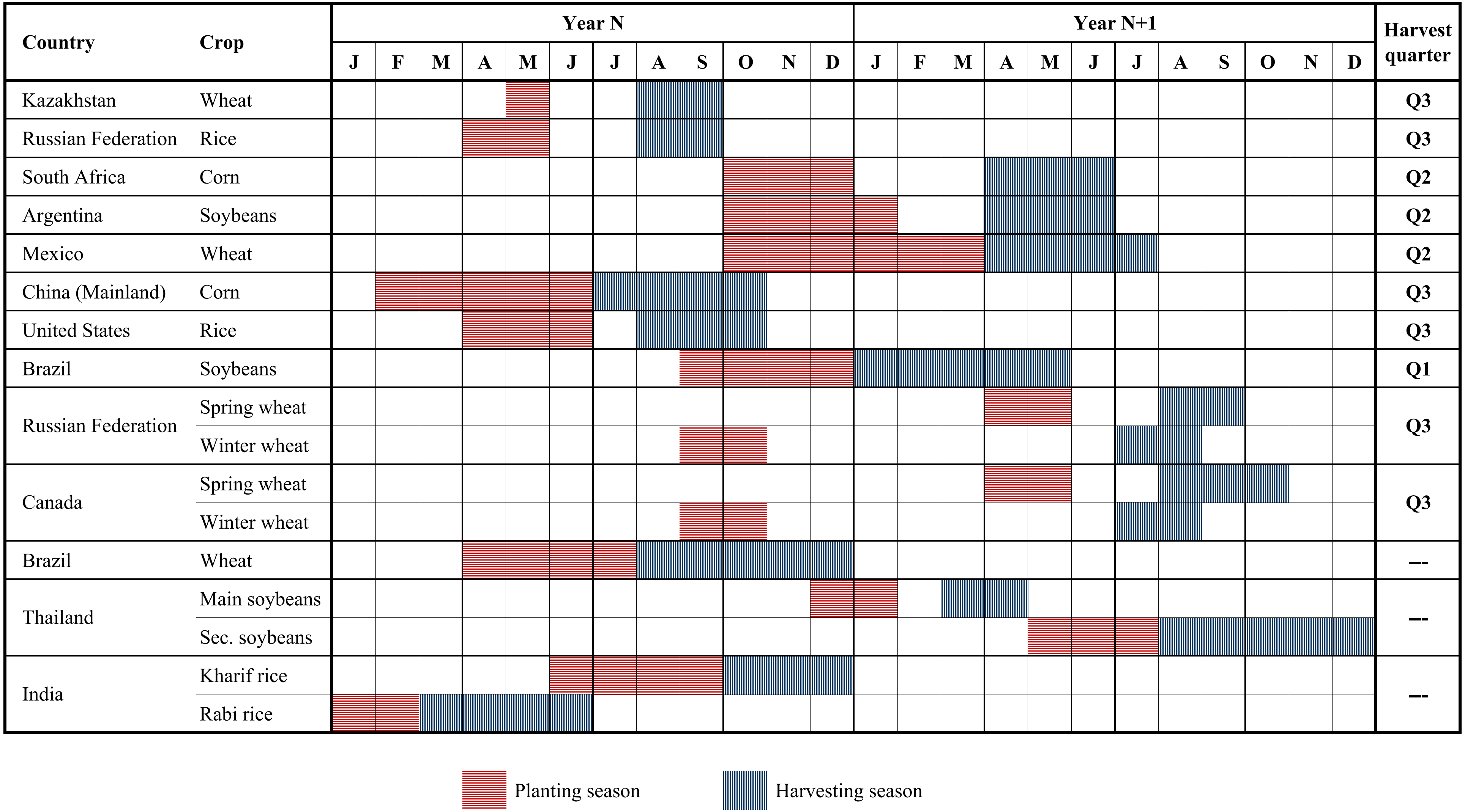
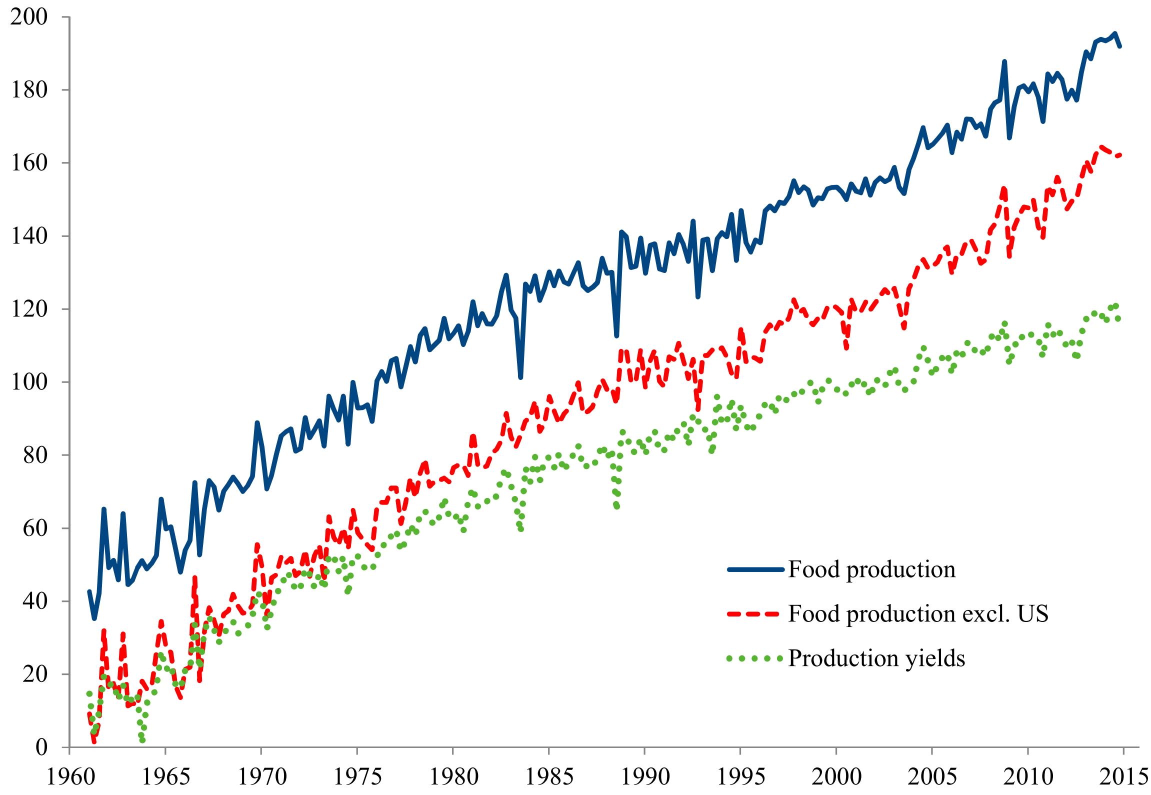
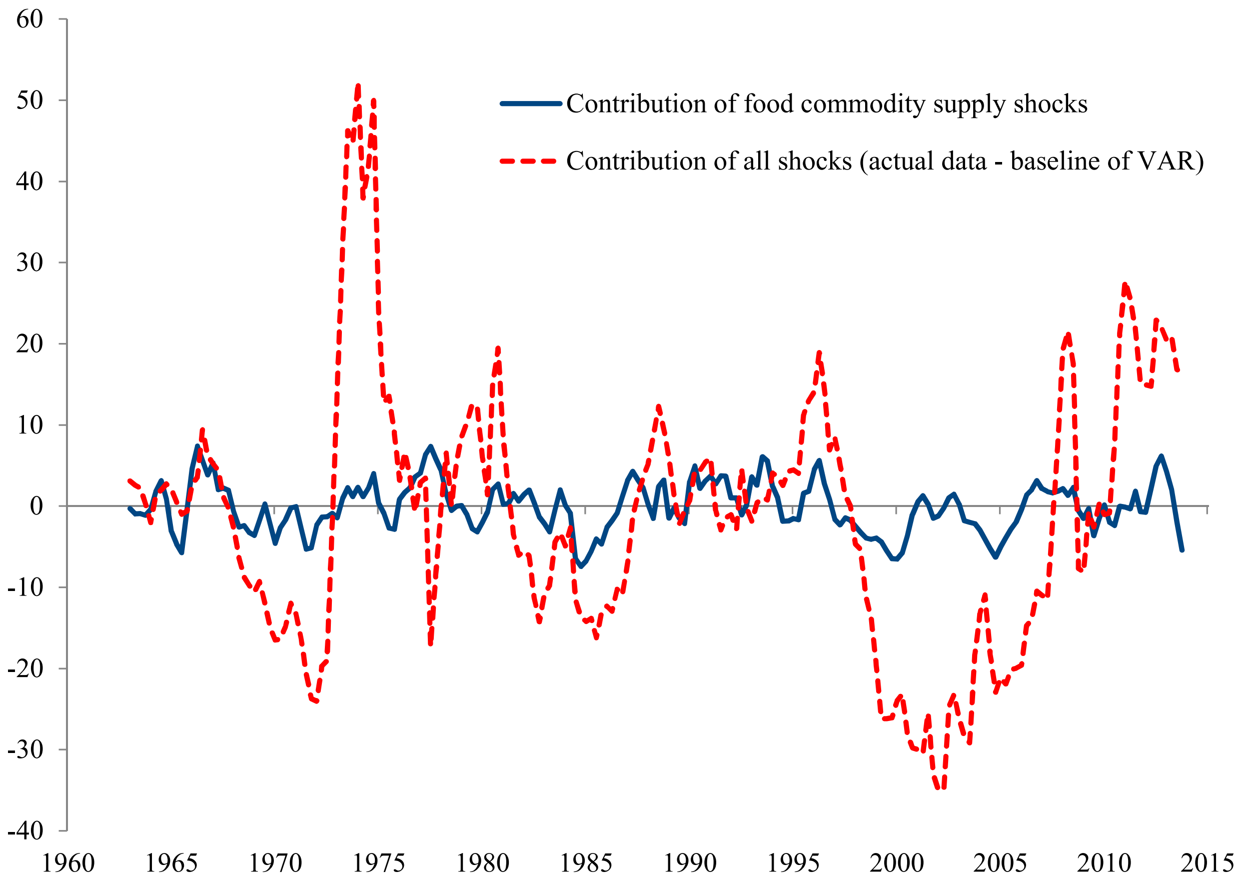


Figure 4 - Global food commodity production index



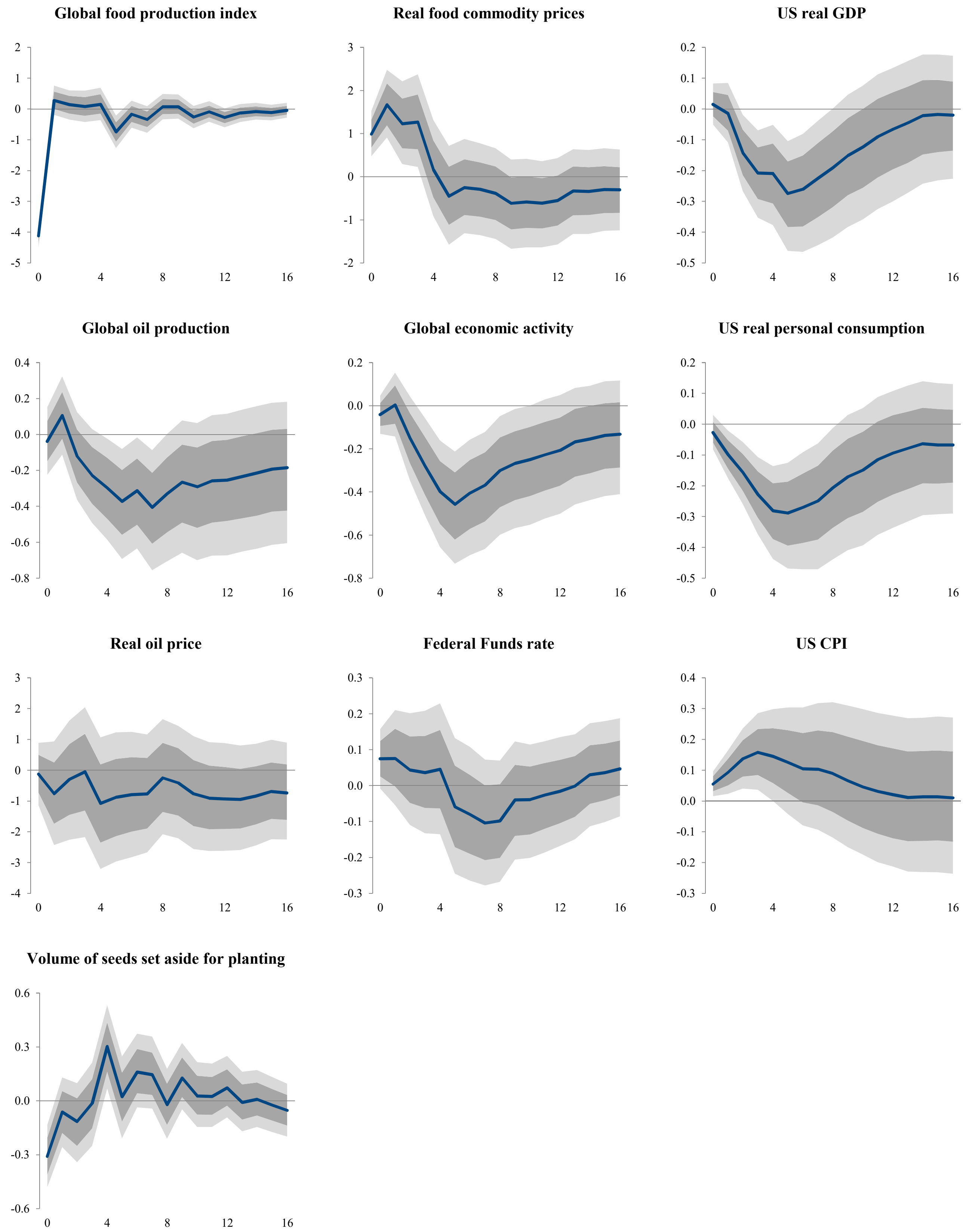
Note: variables are measured as 100*log of index. Production yields are a ratio of food production divided by area harvested
The production index aggregates the production of corn, wheat, rice and soybeans on a caloric-weighted basis

Figure 5 - Historical contribution of identified shocks to real food commodity prices



Note: Historical contribution (in percent) to real food commodity prices implied by the benchmark VAR model

Figure 6 - Impulse responses to global food commodity supply shocks: benchmark VAR results

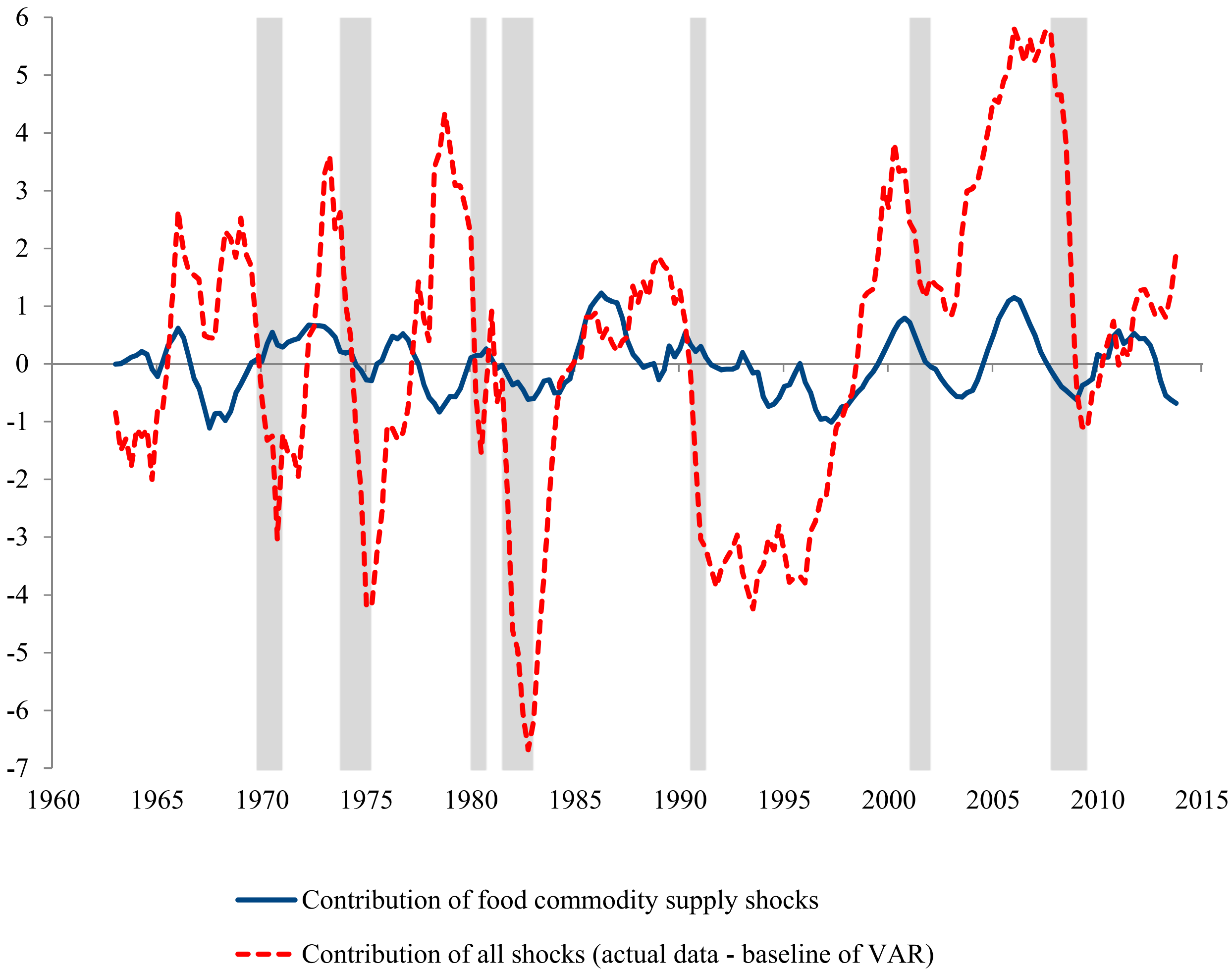


Note: sample period is 1963Q1-2013Q4, horizon is quarterly.

16th and 84th percentiles

5th and 95th percentiles

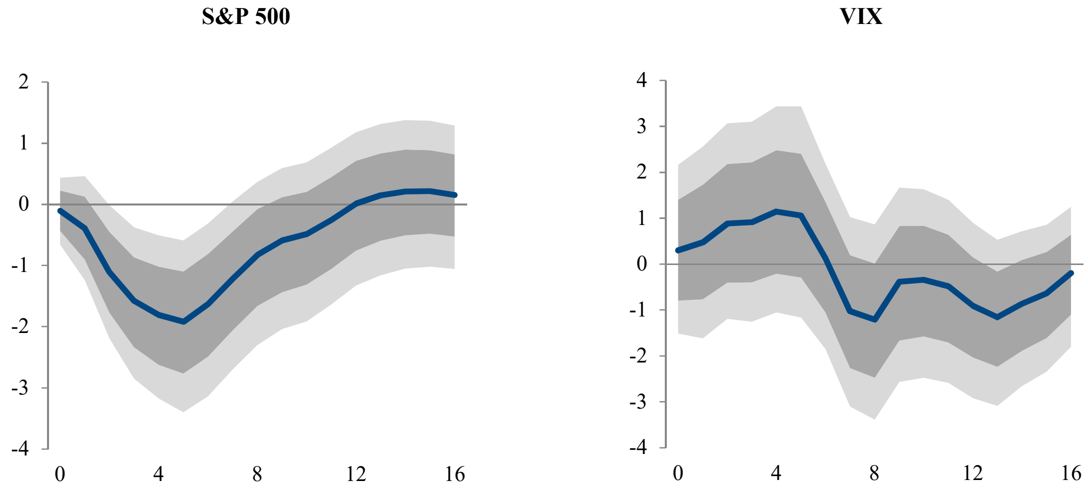
Figure 7 - Historical contribution to US real GDP



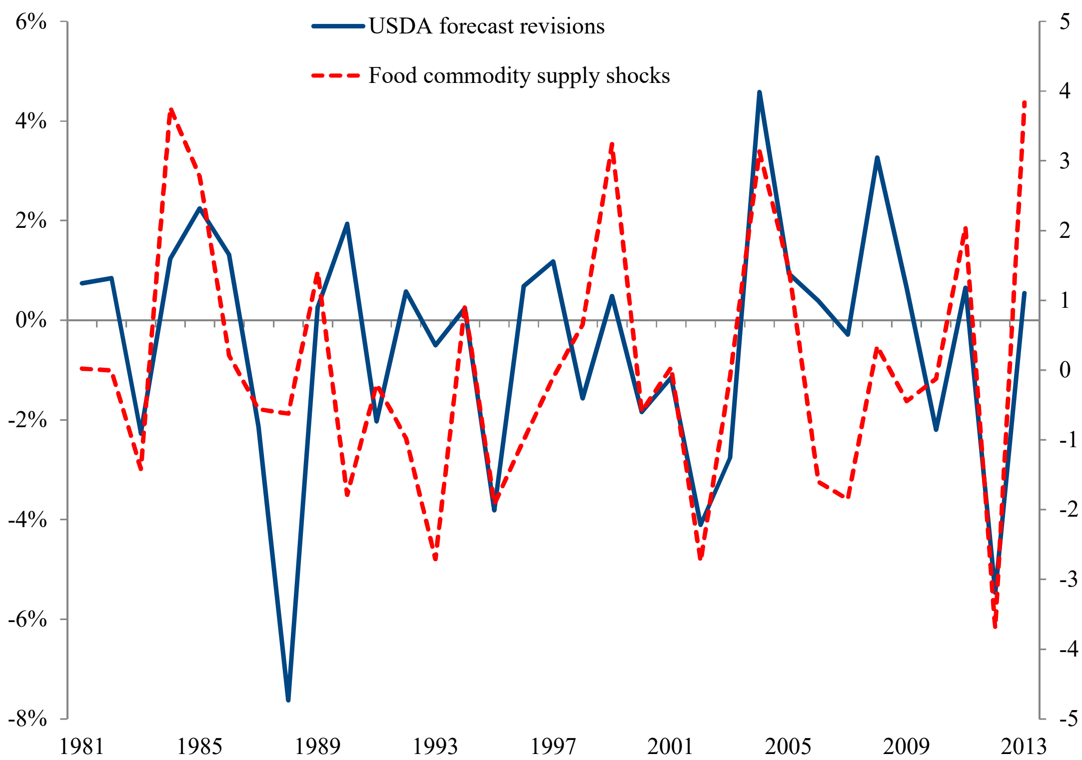
Note: Historical contribution (in percent) to real GDP implied by the benchmark VAR model. Grey areas are NBER recessions.

Figure 8 - Did we identify exogenous food commodity market shocks?

Panel (A) - Impact of food commodity supply shocks on financial markets



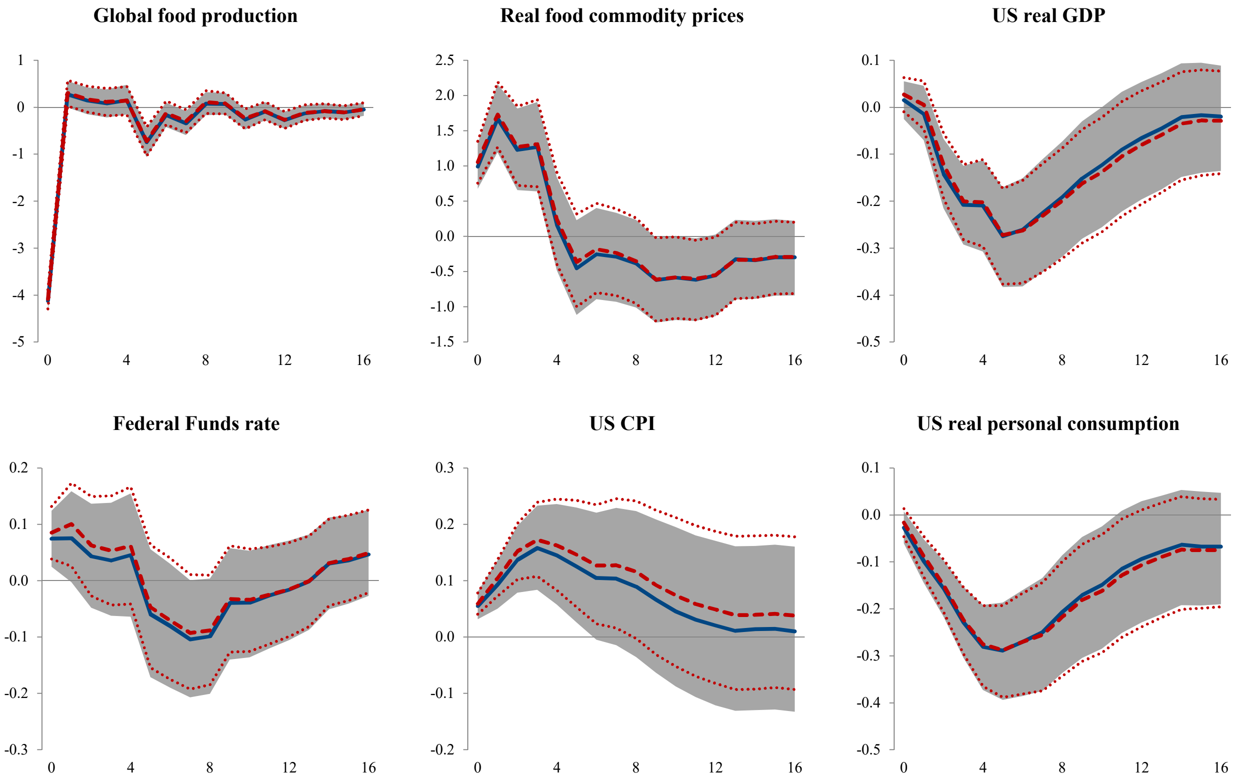
Panel (B) - Correlation of food commodity supply shocks and USDA forecast revisions



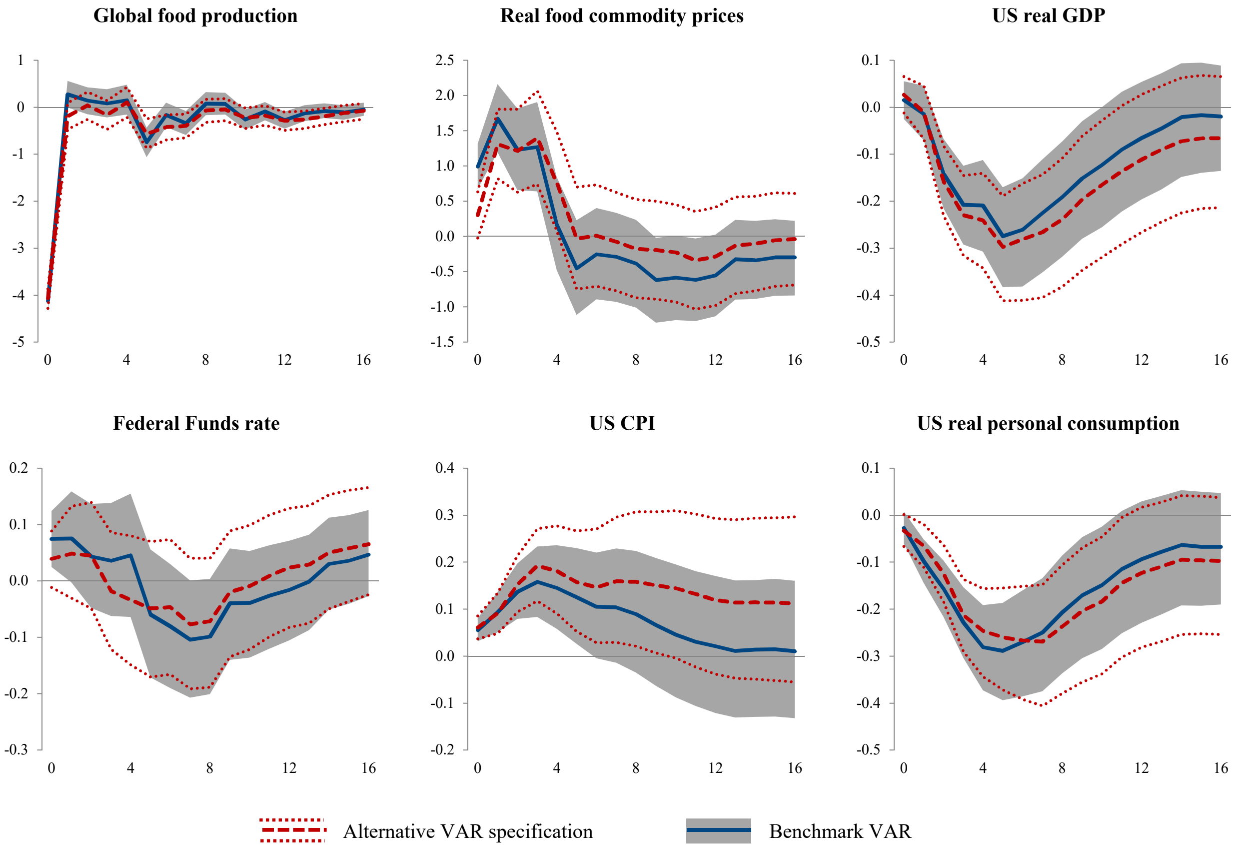
Note: Panel (A) shows the impulse response functions of the S&P 500 and the VIX stock market volatility index by adding these variables to the benchmark VAR. Panel (B) shows the annual USDA forecast revisions for world grains output (percent) and annual food commodity supply shocks (standard deviations). Forecast revisions are sum (December forecast - May forecast) and (April forecast - December forecast); shocks are sum of 4 quarters. USDA forecasts are (millions metric tons) of wheat, coarse grains (corn, sorghum, barley, oats, rye, millet and mixed grains) and milled rice. Food commodity supply shocks are caloric weighted aggregate of corn, wheat, rice and soybeans.

Figure 9 - Effects of global food commodity supply shocks on key variables: sensitivity analysis

Panel (A) - Alternative ordering of food production in VAR



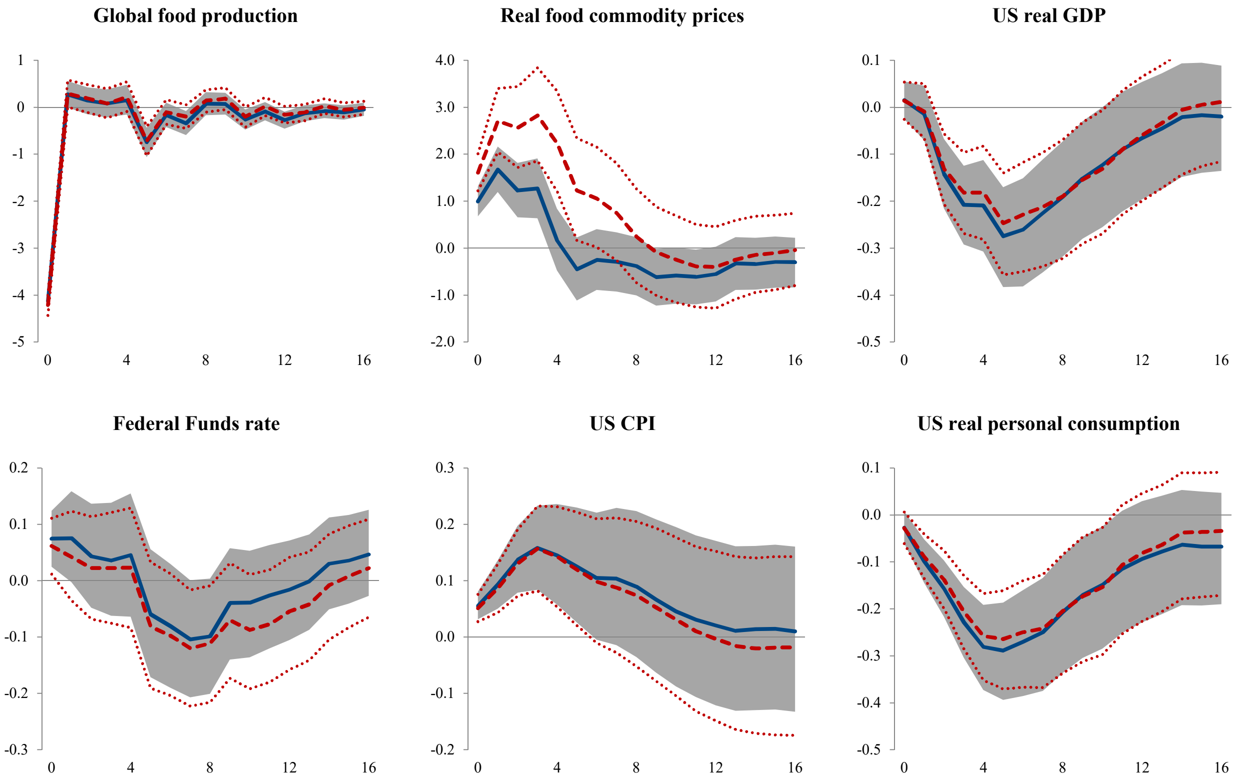
Panel (B) - Global food production index excluding US food production as measure of food production



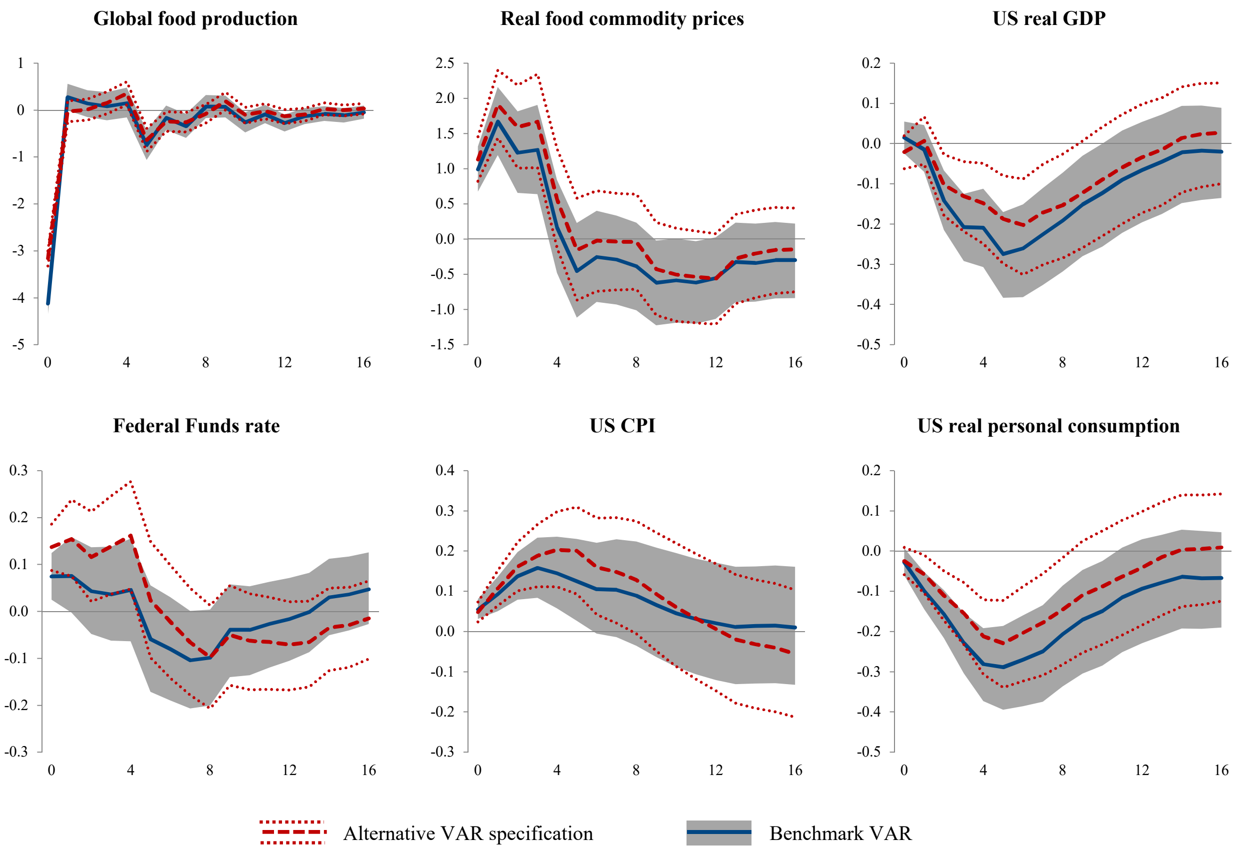
Note: horizon is quarterly; 16th and 84th percentiles. The panels only show the impulse responses of some key variables.

Figure 9 (continued) - Effects of global food commodity supply shocks on key variables: sensitivity analysis

Panel (C) - Real cereal prices as measure of food commodity prices



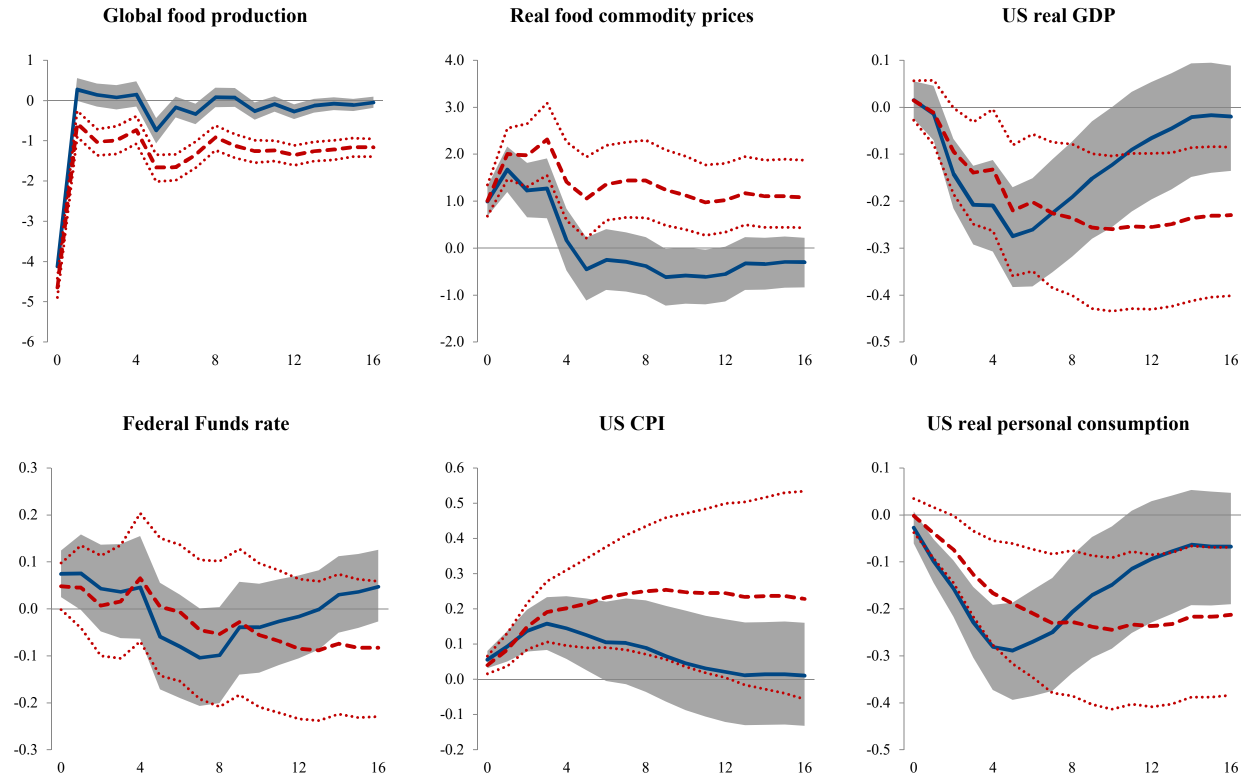
Panel (D) - Global food production yields as measure of food production



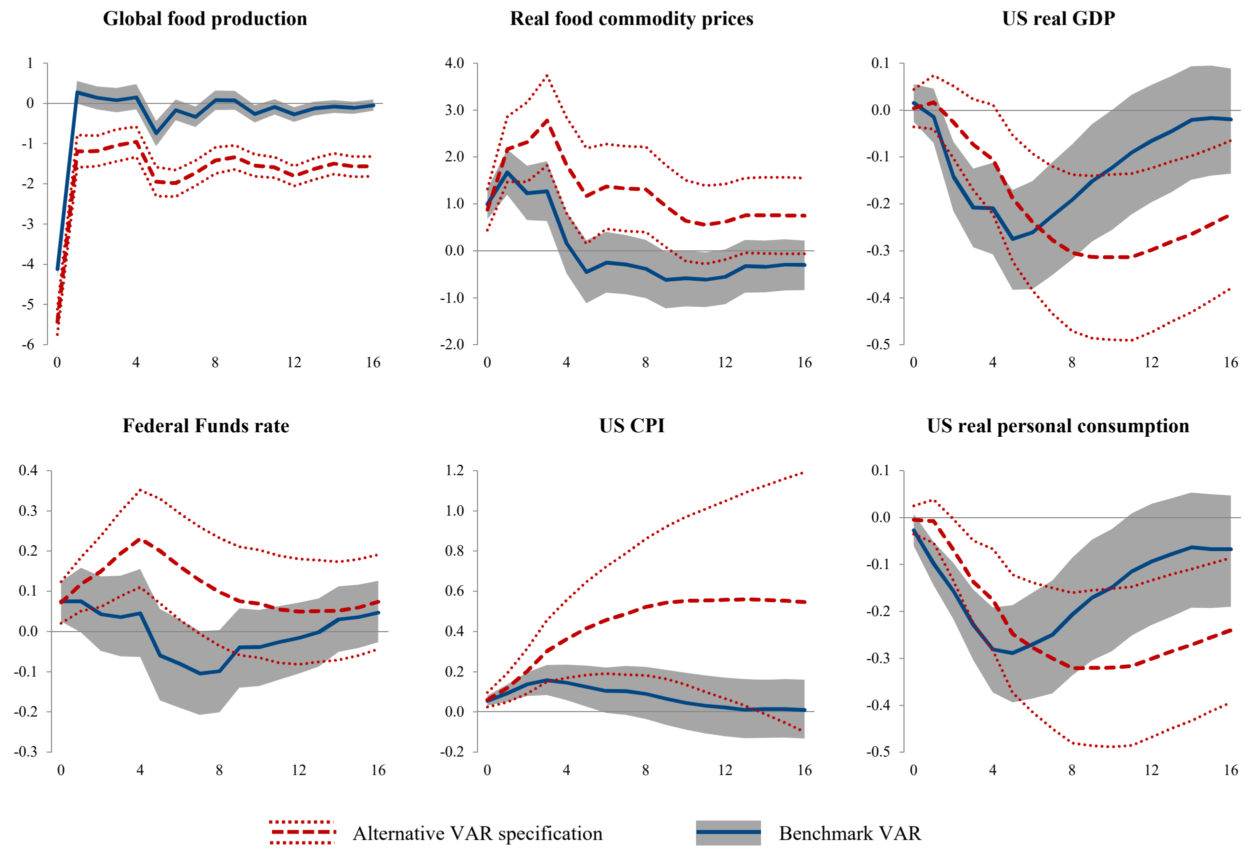
Note: horizon is quarterly; 16th and 84th percentiles. The panels only show the impulse responses of some key variables.

Figure 9 (continued) - Effects of global food commodity supply shocks on key variables: sensitivity analysis

Panel (E) - VAR estimated in (log) differences

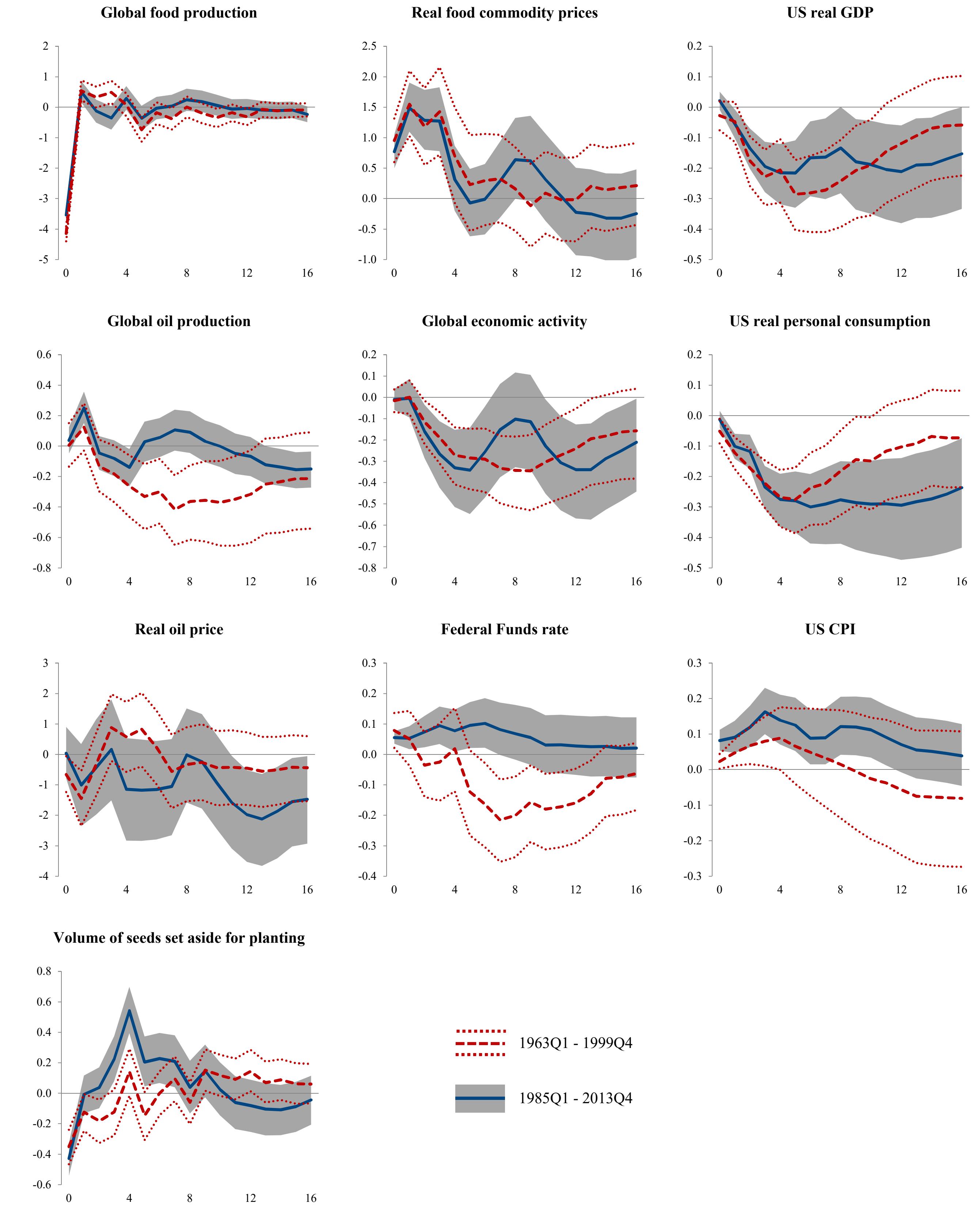


Panel (F) - FAVAR with 6 unobserved macro factors, global food production and real food commodity prices



Note: horizon is quarterly; 16th and 84th percentiles. The panels only show the impulse responses of some key variables.

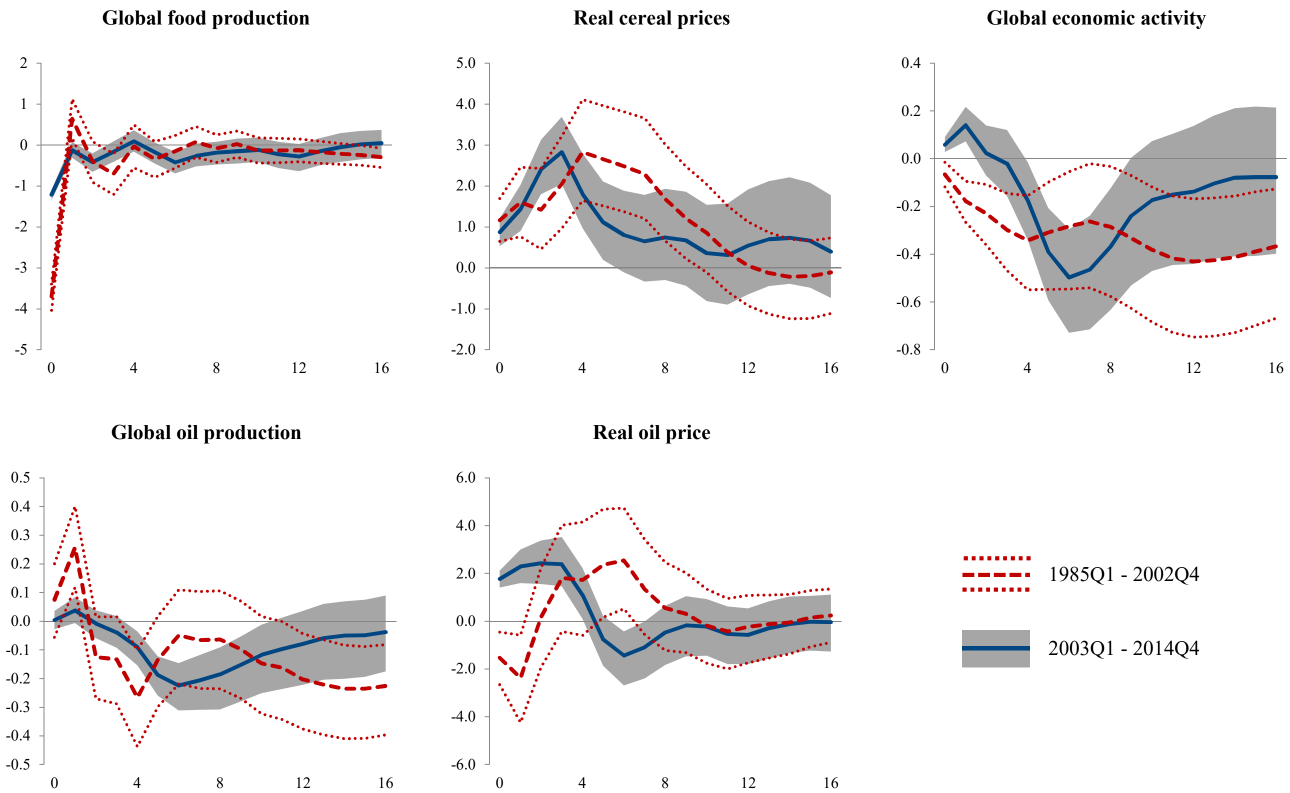
Figure 10 - Subsample analysis: 1963-1999 versus 1985-2013 episodes (benchmark VAR)



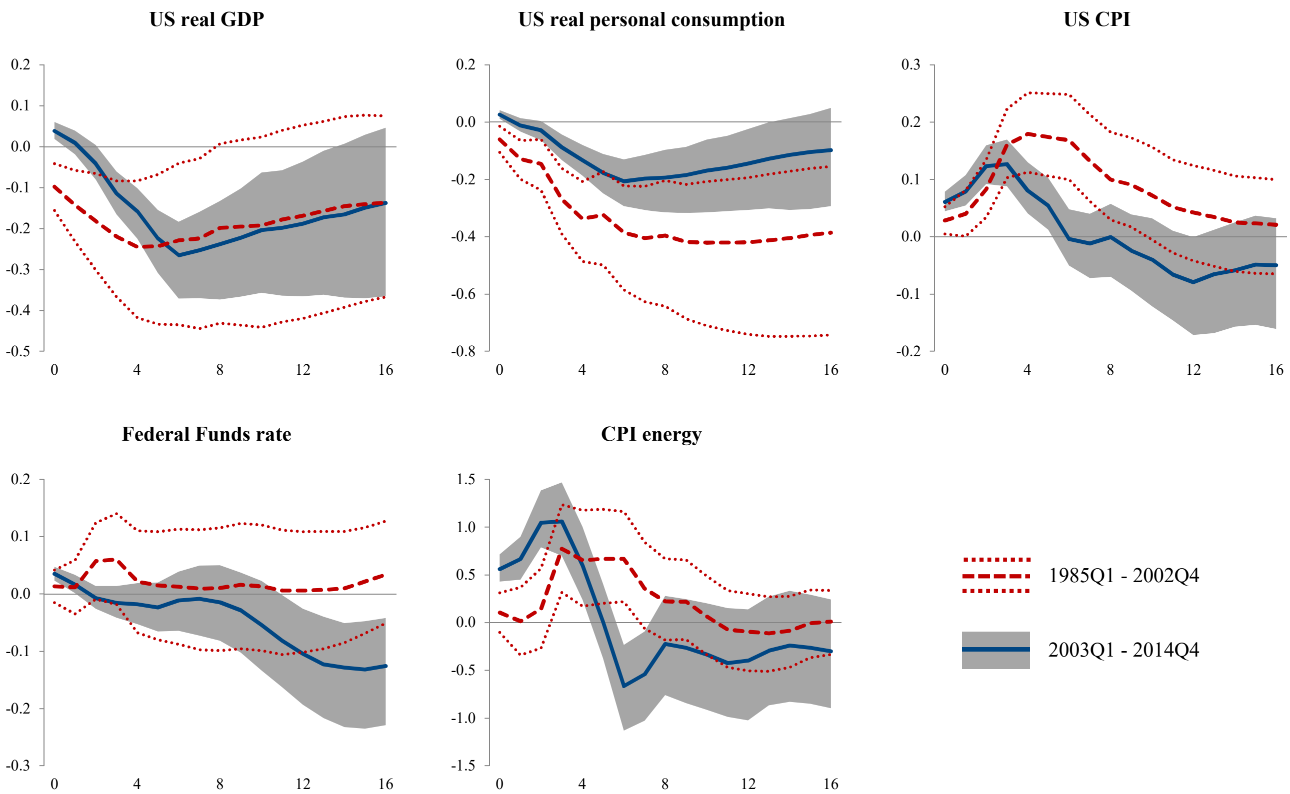
Note: horizon is quarterly; 16th and 84th percentiles error bands.

Figure 11 - Subsample analysis based on smaller VARs: 1985-2002 versus 2003-2014 episodes

Panel (A) - Results 5-variables VAR model of Peersman et al. (2016)

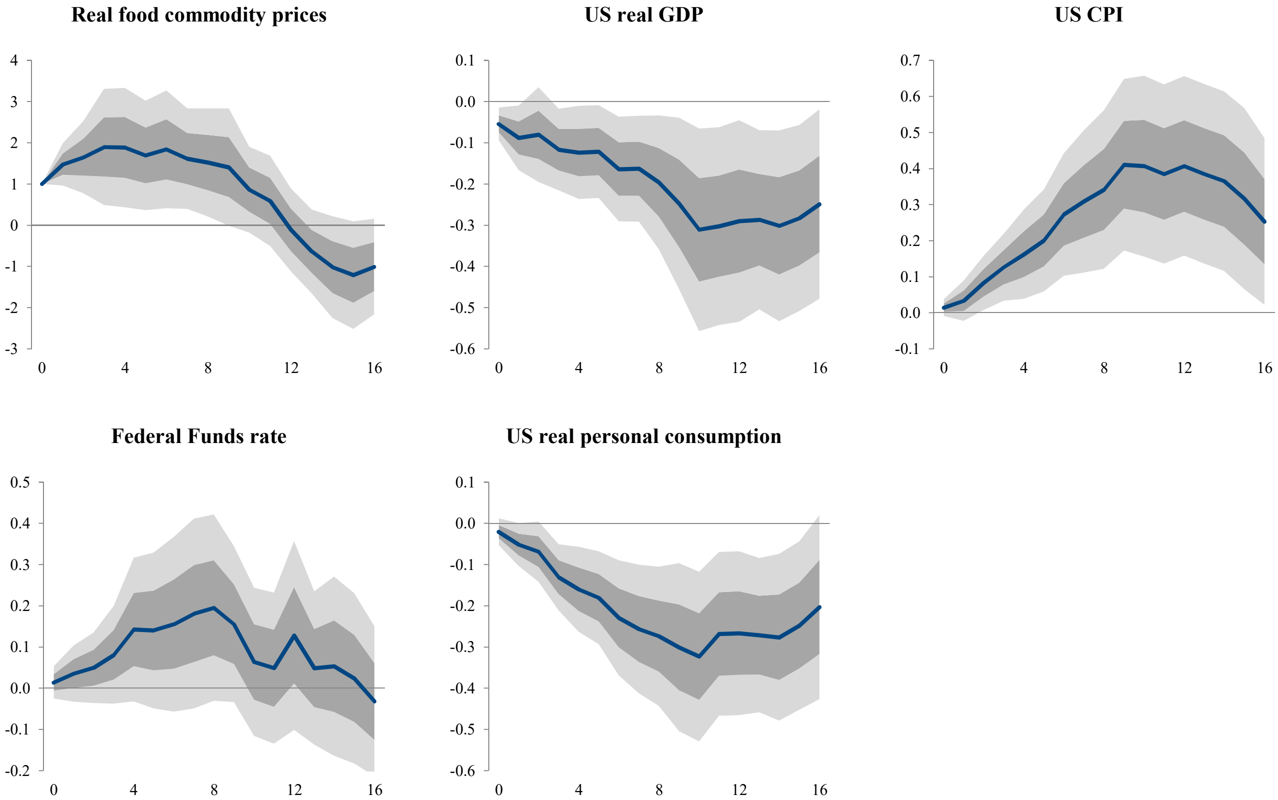


Panel (B) - Impact on US variables



Note: horizon is quarterly; 16th and 84th percentiles. Panel (A) shows results for 5-variables global VAR model for crude oil and food commodity markets. Panel (B) shows results for US variables added one by one to the global VAR model. Source: Peersman et al. (2016).

Figure 12 - Impulse responses to narrative food commodity supply shocks: local projections

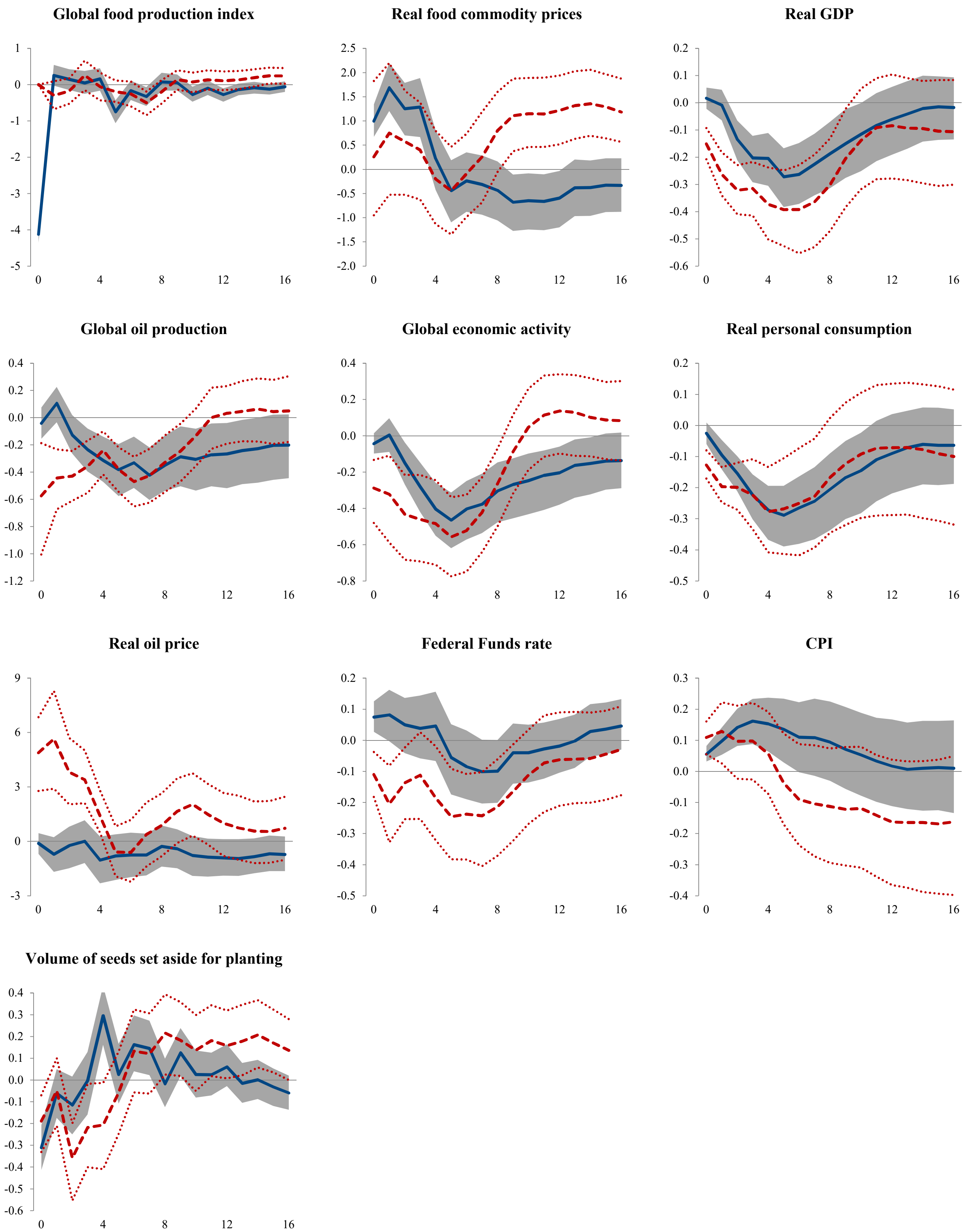


Note: Newey-West standard errors; quarterly horizon.

one-standard error bands

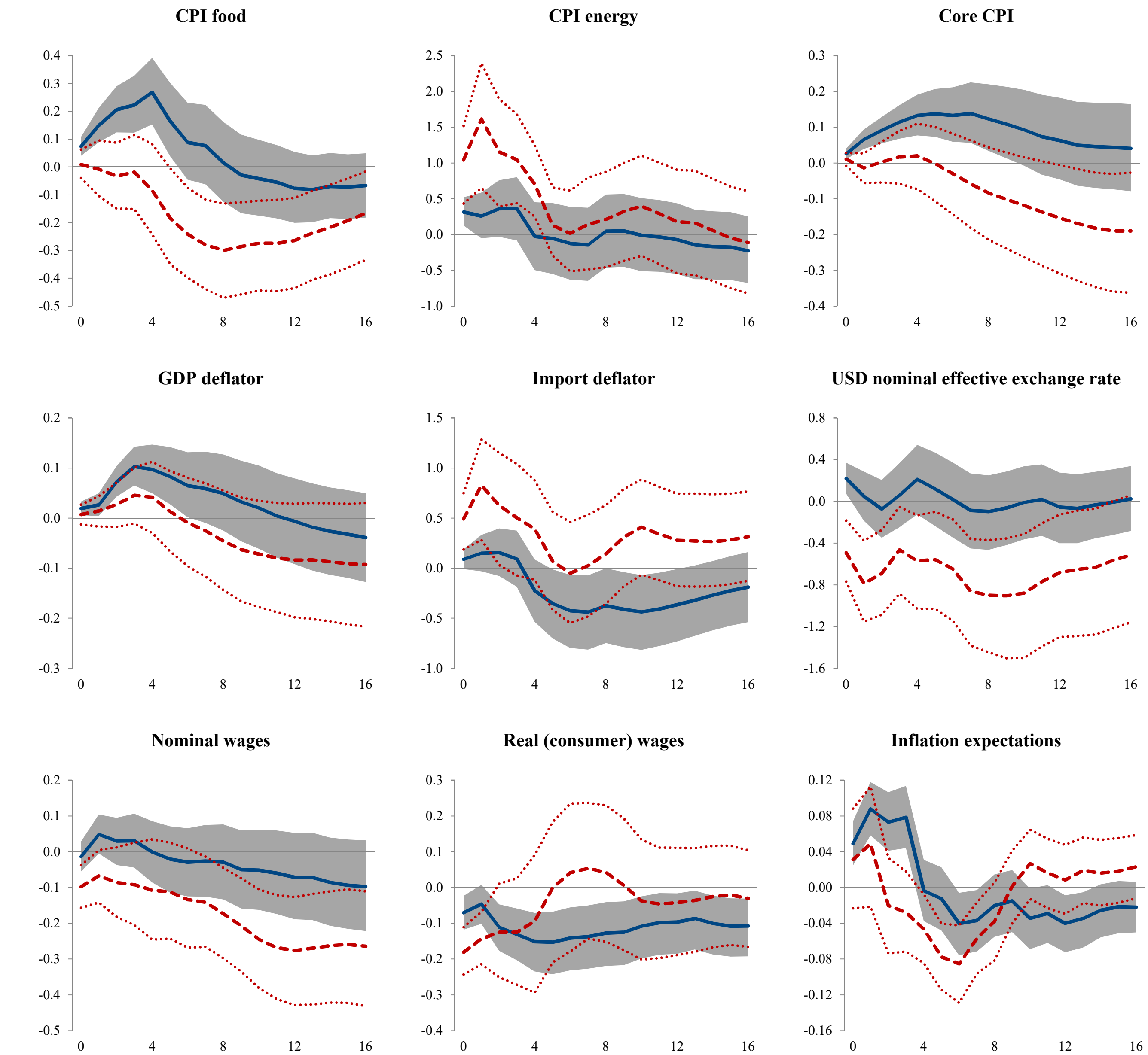
two-standard error bands

Figure 13 - Comparison with oil supply shocks



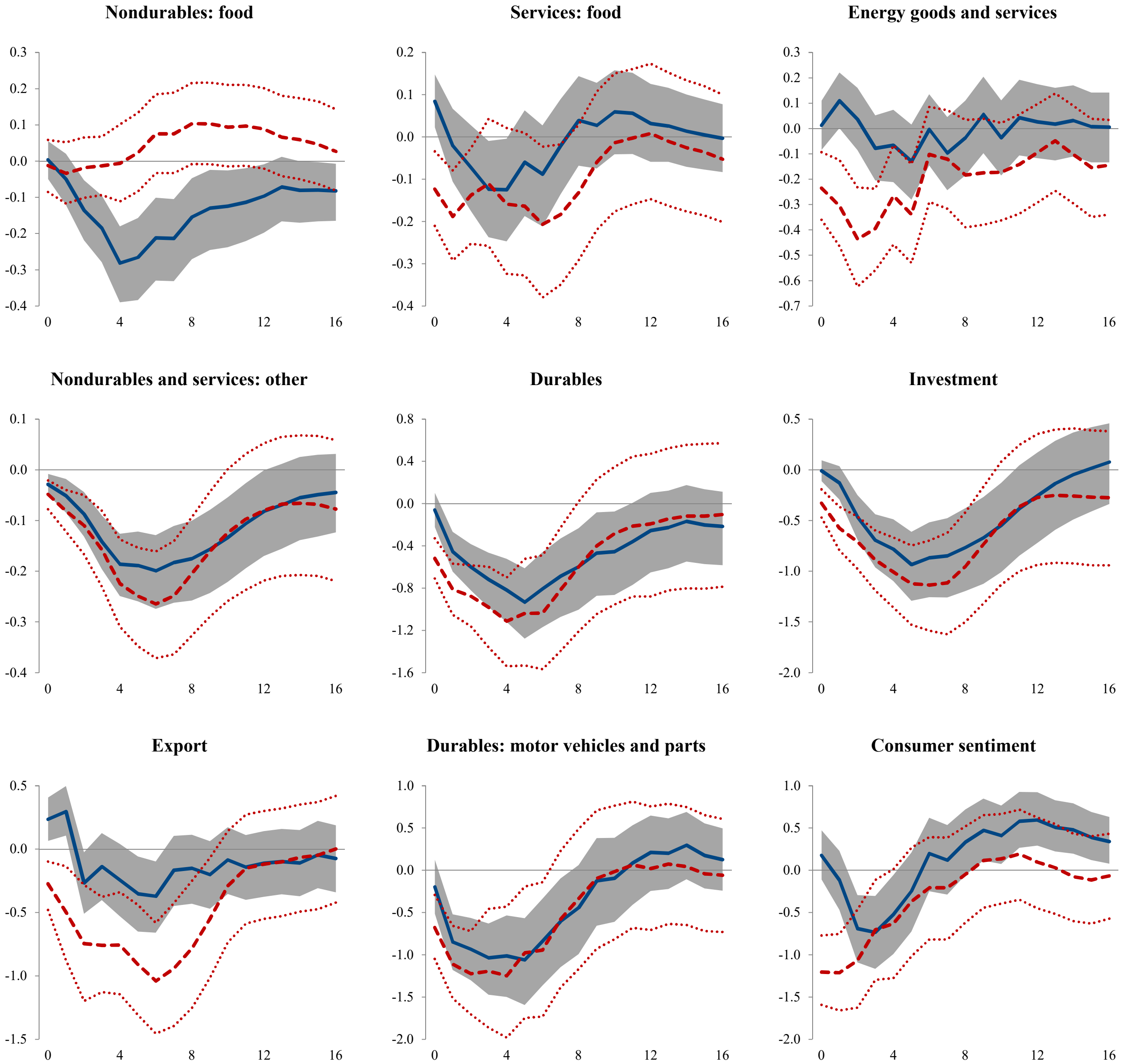
Note: horizon is quarterly; 16th and 84th percentiles. Oil supply shocks Food commodity supply shocks

Figure 14 - Pass-through to consumer prices



Note: horizon is quarterly; 16th and 84th percentiles. Oil supply shocks Food commodity supply shocks

Figure 15 - Pass-through to household expenditures



Note: horizon is quarterly; 16th and 84th percentiles. Oil supply shocks — Food commodity supply shocks