FACULTY OF ECONOMICS AND BUSINESS ADMINISTRATION

THE CONSEQUENCES OF FOOD PRICE CHANGES: A MACROECONOMIC PERSPECTIVE

Jasmien De Winne

Supervisor: Prof. Dr. Gert Peersman

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Jasmien De Winne,

Ghent, 14 February 2018

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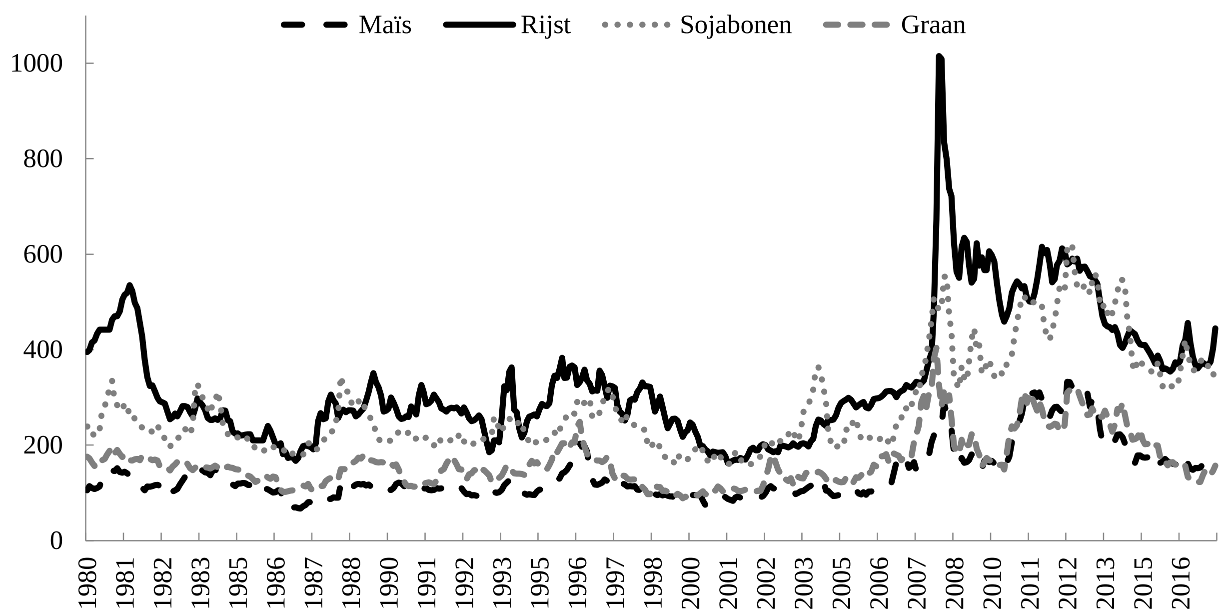
NEDERLANDSTALIGE SAMENVATTING

Twee vaststellingen lagen aan de basis om een doctoraatsproefschrift te schrijven over de gevolgen van wijzigingen van voedselgrondstoffenprijzen. Ten eerste werden de voedselprijzen in het afgelopen decennium gekenmerkt door grote verschuivingen. Figuur 1 toont de prijsevolutie tussen 1980 en 2017 van de vier belangrijkste internationale voedselgrondstoffen. Na een lange en relatief stabiele periode begonnen de internationale prijzen van voedselgrondstoffen te stijgen vanaf 2000. In 2008 bereikten de voedselprijzen ongekende hoogtes. Na een sterke daling, werden nieuwe – doch lagere – pieken bereikt in 2011 en opnieuw in 2012. Sindsdien zijn de voedselprijzen gestaag gedaald. Tussen het dieptepunt in 2000-2001 en de piek in 2008 namen de nominale prijzen van maïs, graan en sojabonen ongeveer toe met een factor vier en die van rijst met een factor zes.



Figuur 1 – Internationale Voedselgrondstoffenprijzen 1980-2017 (Dollar per ton) Bron: IMF

De tweede vaststelling is dat, hoewel voedsel dagelijks in ieders gedachten is, het tot nog toe geen belangrijke rol speelde in macro-economisch onderzoek. Dit in tegenstelling tot de olieprijzen. Er wordt verondersteld dat voedsel een belangrijkere rol speelt in ontwikkelingslanden, waardoor de meeste studies die focussen op voedsel voornamelijk behoren tot het domein van de ontwikkelingseconomie, landbouweconomie, politieke economie of een combinatie van deze onderzoeksdomeinen. Het is correct dat in lage inkomenslanden, een groter aandeel van het huishoudbudget wordt besteed aan voedsel. Desalniettemin is het zo dat zelfs in de Verenigde Staten, het studie-onderwerp van de meeste macro-economische studies, 17 procent van het huishoudbudget wordt besteed aan eten en drinken (gemiddeld tussen 1960 en 2015). Enkel huisvesting en nutsvoorzieningen namen een groter deel van de uitgaven in (17.8 procent over dezelfde periode). Daarenboven worden voedselgrondstoffen meer en meer gebruikt als een inputfactor voor energieproductie. In 2010 werd bijvoorbeeld 40 procent van alle maïs in de Verenigde Staten gebruikt voor de productie van ethanol. In 2004 was dit nog slechts 12 procent. Gezien deze twee elementen stelden we ons de vraag *of* en *hoe* wijzigingen in voedselprijzen een effect hebben op de economie.

Als men echter de gevolgen van veranderingen in voedselgrondstoffenprijzen op, bijvoorbeeld, de Amerikaanse economie wil bestuderen is er één groot obstakel. Enerzijds hebben hogere voedselprijzen ten gevolge van een mislukte oogst waarschijnlijk een negatief effect op de economie. Anderzijds zal een bloeiende economie de vraag doen toenemen en bijgevolg ook de prijs van, onder meer, voedsel. Voedselprijzen kunnen dus tegelijkertijd een oorzaak en een gevolg zijn van economische sterkte. Indien men geen onderscheid maakt tussen deze twee tegengestelde kanalen, is het erg moeilijk om iets zinvol te zeggen over de gevolgen van voedselprijswijzigingen: als deze twee tegengestelde effecten elkaar opheffen, zou men – foutief – kunnen besluiten dat wijzigingen in voedselprijzen geen enkel effect hebben op de economie.

In dit doctoraatsproefschrift overwinnen we deze hindernis door te focussen op voedselprijswijzigingen die enkel het gevolg zijn van schokken in het aanbod van voedsel. Deze aanbodschokken kunnen bijvoorbeeld het gevolg zijn van ongunstige weersomstandigheden of van een plaag die oogsten vernietigt. Door enkel te focussen op voedselaanbodschokken kunnen we het ware causale effect op de economie bestuderen. We hebben twee verschillende methodes ontwikkeld om deze aanbodschokken te identificeren. Voor de eerste methode gebruiken we data over voedselproductie en oogstkalenders. We isoleren wijzigingen in geoogste hoeveelheden voedsel die plaatsvinden ná het planten. Deze wijzigingen kunnen niet meer het gevolg zijn van vraagschokken, maar enkel van aanbodschokken. Voor de tweede methode, een narratieve methode, hebben we aan de hand van onder meer krantenarchieven periodes geïsoleerd wanneer grote aanbodschokken plaatsvonden.

Doorheen dit doctoraatsproefschrift zullen we deze methodologie toepassen op verschillende onderzoeksvragen. In de eerste twee hoofdstukken analyseren we de macro-economische effecten van wijzigingen in de voedselgrondstoffenprijzen. We beginnen met de Amerikaanse economie, om vervolgens in het tweede hoofdstuk het onderzoek uit te breiden naar een grote groep van landen. In het derde hoofdstuk verleggen we de focus naar het onderzoeksdomein van de politieke economie en bestuderen we het effect van voedselprijswijzigingen op conflict in Afrika.

In het eerste hoofdstuk, waarin we ook de voornaamste methodologische innovaties ontwikkelen, focussen we op de causale effecten van voedselprijswijzingen op de Amerikaanse economie in de periode van 1963 tot 2013. We vinden dat verstoringen in globale voedselmarkten een aanzienlijke invloed hebben op de Amerikaanse economie: hogere voedselgrondstoffenprijzen leiden tot een stijging van de algemene consumentenprijzen en tot een persistente daling in het reële bruto binnenlands product (BBP) en in de private consumptie. De effecten op het reële BBP zijn ongeveer twee keer zo groot als de impact van een gelijkaardige stijging in ruwe olieprijzen door een olie-aanbodschok. Verder vinden we ook dat het effect op de consumentenprijzen en op private consumptie veel groter is dan de impact die men zou verwachten op basis van het aandeel van voedselgrondstoffen in de index van consumentenprijzen. Dit betekent dat er indirecte effecten zijn die de macro-economische gevolgen vergroten. Als we deze indirecte effecten van naderbij bekijken, vinden we dat niet enkel voedselprijzen stijgen na een ongunstige aanbodschok, maar ook de kerninflatie en de inflatieverwachtingen. In recente periodes stijgen zelfs de energieprijzen. Monetair beleid verstrakt bovendien na verstoringen in de voedselmarkt: de centrale bank verhoogt haar rentevoet als reactie op de hogere prijzen, maar dit remt de economie verder af. Wanneer voedselprijzen stijgen, zien we ten slotte dat huishoudens niet enkel de consumptie van voedsel verminderen, maar ze gaan vooral ook minder spenderen aan andere goederen en diensten, in het bijzonder aan duurzame consumptiegoederen en investeringen.

Van alle landen in de wereld zijn de Verenigde Staten het land waar huishoudens het minst spenderen aan voedsel relatief ten opzichte van hun totale uitgaven. In alle andere landen wordt een (aanzienlijk) groter aandeel van het huishoudbudget gespendeerd aan voedsel. In het tweede hoofdstuk breiden we daarom onze analyse uit naar de macro-economische gevolgen van veranderingen in voedselprijzen voor economieën van 75 landen. Ten eerste tonen we aan dat stijgingen in de internationale landbouwprijzen ten gevolge van aanbodschokken een negatief effect hebben op de wereldeconomie. Ten tweede vinden we dat de effecten veel sterker zijn in hoge-inkomenslanden. Dit is verrassend omdat deze landen meer ontwikkelde financiële markten en een lager aandeel van voedsel in het huishoudbudget hebben in vergelijking met lage-inkomenslanden. We argumenteren dat dit het resultaat kan zijn van het feit dat lage-inkomenslanden een groter aandeel van landbouw in het BBP hebben, omdat ze typisch netto exporteurs zijn van landbouwproducten, en omdat ze minder beïnvloed worden door een wereldwijde groeivertraging als het gevolg van een beperktere integratie in de wereldeconomie. Wanneer we controleren voor deze landenspecifieke karakteristieken, vinden we inderdaad dat de effecten op economische activiteit kleiner worden als het inkomen per capita hoger is.

In het derde hoofdstuk gebruiken we opnieuw dezelfde methodologie om exogene prijswijzigingen te identificeren, maar we passen de methodologie nu toe op een onderzoeksvraag in het domein van de politieke economie. We bestuderen hoe veranderingen in voedselprijzen een effect hebben op conflict in Afrika. We tonen dat een exogene stijging in de internationale voedselprijzen de frequentie en de intensiteit van conflict aanzienlijk doen toenemen. Het grootste deel van dit effect vindt plaats na één jaar en dit effect is groter en persistenter voor conflicttypes zoals rellen en protesten. Dit contrasteert met de resultaten van een "naïeve" regressie van conflict op voedselprijs waarbij de relatie invers is. Daarenboven vinden we dat hogere voedselprijzen tot nog meer conflict leiden in gebieden met meer landbouw. We tonen dat de traditionele aanpak in de literatuur om dit effect te berekenen geen rekening houdt met positieve basiseffecten voor gebieden met en zonder landbouw.

Samengevat, in dit doctoraatproefschrift tonen we aan dat stijgingen in voedselgrondstoffenprijzen ten gevolge van aanbodschokken een negatief effect hebben op de Amerikaanse economie: de prijsstijging van voedselgrondstoffen sijpelt door naar consumentenprijzen, consumenten gaan hun consumptie aanpassen en inkrimpen, en het beleid van de centrale bank versterkt bovendien het initiële negatieve effect op de economie. We vinden dit negatieve effect vervolgens terug bij een heleboel andere landen, en - verrassend genoeg - meer bij hoge-inkomenslanden dan bij lage-inkomenslanden. Ten slotte tonen we ook aan dat voedselprijsstijgingen ook hebben geleid tot meer conflict in Afrika.

Onze bevindingen hebben verstrekkende gevolgen voor mede-economen, centrale bankiers, fiscale beleidsmakers, handelsbeleidsmakers, en klimaatonderzoekers. Ten eerste, macro-economen zijn al decennia bezig met het bestuderen van de conjunctuurcyclus: daarbij houden ze vaak rekening met de olieprijzen, maar niet met de voedselprijzen. Onze resultaten impliceren dat het de moeite waard zou kunnen zijn om landbouwmarkten te integreren in deze modellen. Ook het monetaire beleid zou kunnen baten bij een nadere studie van voedselgrondstoffenprijzen, want we tonen aan dat in de Verenigde Staten de centrale bank het initieel negatieve effect van een voedselschok nog verergerd heeft in de voorbije decennia.

Ten tweede kunnen onze resultaten handelsbeleidsmakers helpen om de gevolgen van het beleid dat een effect kan hebben op landbouwprijzen beter te evalueren. Het gaat dan om handelsmaatregelen zoals een exportverbod of invoerheffingen op landbouwgoederen. Sinds de stijgingen van de internationale voedselprijzen in 2007-2008 en opnieuw in 2010 zijn er al initiatieven genomen om beter om te gaan met de gevolgen van deze prijsveranderingen of om ze zelfs te vermijden. In 2011 bijvoorbeeld hebben de Ministers van Landbouw van de G20 het Agricultural Market Information System (AMIS) gelanceerd: dit is een platformorganisatie die de transparantie op de voedselmarkt en de beleid rond voedselzekerheid moet verbeteren. Hoewel onze resultaten impliceren dat een diepere handelsintegratie landen méér kwetsbaar kan maken voor internationale landbouwschokken, is het bekend dat anticyclische handelsmaatregelen voordelig kunnen lijken voor individuele landen, maar een ineffectieve manier vormen om nationale prijzen te stabiliseren. Ze zetten andere landen er namelijk toe aan om gelijkaardige maatregelen te nemen, waardoor de internationale prijsinstabiliteit net toeneemt. Wetende dat individuele landen altijd in de verleiding zullen kopen om dergelijke *beggar-thy-neighbor*–maatregelen te nemen, maakt het initiatieven die doelen op informatiedeling en internationale coördinatie zoals AMIS des te meer de moeite om na te streven.

Ten derde, beleidsmakers hebben in het verleden vaak gefocust op het stabiliseren van landbouwinkomens. In de EU bijvoorbeeld werd in 2015 39 procent van het totale Europese budget gespendeerd aan het gemeenschappelijk landbouwbeleid. Onze bevindingen suggereren dat consumenten niet verwaarloosd mogen worden. In de Verenigde Staten hebben kleine wijzigingen in de voedselprijzen grote effecten op de gehele economie door veranderingen in het gedrag van consumenten. Vooral in lage-inkomenshuishoudens, die typisch niet kunnen lenen, zijn er weinig andere opties dan de uitgaven voor andere producten te verminderen als de prijs van een basisproduct zoals voedsel stijgt. Voor Afrika vinden we dat hogere voedselprijzen leiden tot meer conflict in gebieden met meer landbouw omdat de inkomenskloof tussen consumenten en producenten toeneemt. Bijgevolg ondersteunen onze resultaten het type beleidsaanbevelingen dat focust op het verzekeren van armen tegen negatieve inkomensschokken. Maatregelen die enkel op de armste consumenten mikken zijn bovendien eenvoudiger vol te houden dan brede consumentensubsidies (in Egypte namen de subsidies voor landbouw en brandstof bijvoorbeeld toe van 1,4 procent van het BNP in 2002 tot 8 procent in 2011). Bovendien veroorzaken ze minder internationale beroering dan een exportverbod of -restrictie (een strategie die bijvoorbeeld gevolgd werd door China en India in 2008).

Ten slotte, klimaatonderzoekers die de link onderzoeken tussen klimaatverandering en economische activiteit zouden er rekening moeten mee houden dat veranderingen in de temperatuur of neerslag in één deel van de wereld een weerslag kunnen hebben op de economische groei in een ander deel van de wereld via een effect op voedselgrondstoffenprijzen. Onze resultaten suggereren dat door dit kanaal te verwaarlozen de bestaande studies het economisch effect van klimaatverandering op hoge-inkomenslanden onderschatten.

INTRODUCTION

There are two main reasons that lead to the decision to write a dissertation on the consequences of changes in food commodity prices. First of all, food prices have shifted tremendously in the past decade. After a long, relatively stable period, food commodity prices started to rise after 2000. In 2008 the prices of different food commodity types reached unprecedented heights. After a large plunge, new – although lower – peaks were reached in 2011 and again in 2012. Food prices have been declining steadily ever since. Figure 1 shows the price evolution (nominal U.S. dollar per metric ton) of the four most important food commodities: maize, rice, soybeans and wheat.[1] Together, these four commodities account for approximately 75 percent of the caloric content of global food production. Between the trough in 2000-2001 and the peak in 2008, prices multiplied by a factor 4 (for maize, soybeans and wheat) and by a factor 6 for rice.

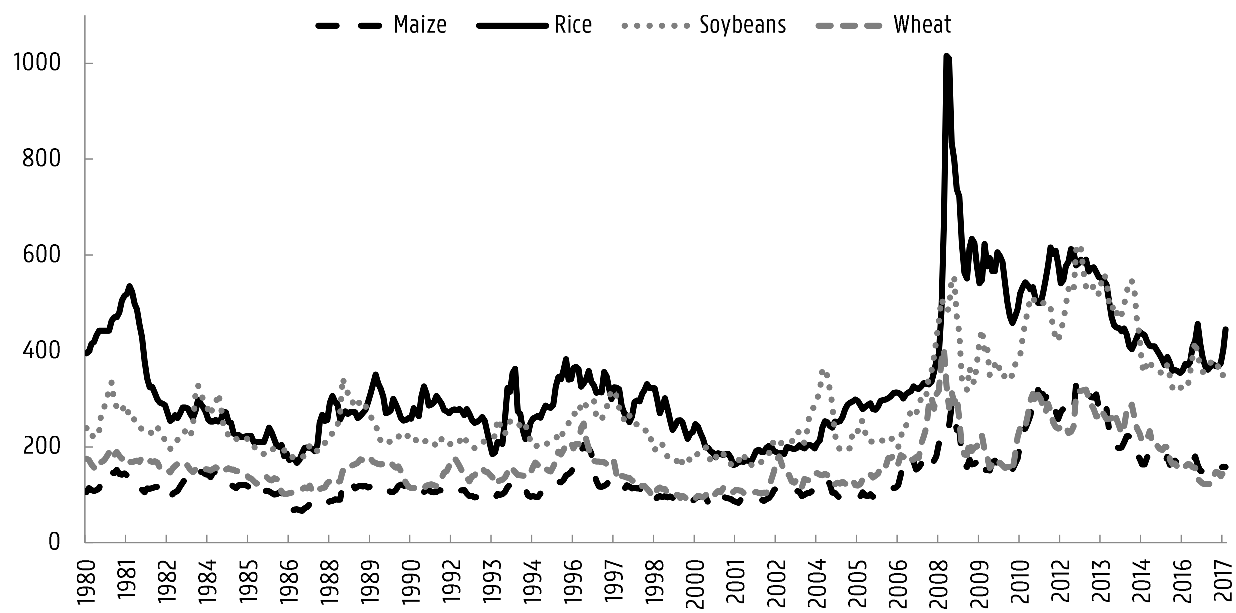


Figure 1 - International Food Commodity Prices 1980-2017 (U.S. Dollar per metric ton) Source: IMF.

Second, although food is on everyone's mind on a daily basis, it does not feature high on the agenda of macroeconomists. Food is deemed to play a larger role in developing economies, and therefore studies focusing on food are almost exclusively situated in the field of developing economics, agricultural economics, political economy or a combination of these fields. It is true that in lower-income countries, a larger part of the household budget is spent on food. However, even in the U.S., object of the majority of macroeconomic studies, 17 percent of consumer expenditures was spent on food and beverages (on average between 1960 and 2015). Only housing and

[1] For an evolution of real food commodity prices over a longer time span see Chapter 1 – Figure 1.

utilities absorbed a greater share of household expenditures (17.8 percent over the same period). Additionally, food commodities are more and more being used as an input factor for energy production. This lead us to ask the question how changes in food prices affect the economy, either through changes in consumption, production or both.

However, if one wants to study the consequences of changes in food prices on, for example, the U.S. economy, there is one major obstacle. Higher food prices due to a failed harvest will likely have a negative effect on the economy. A booming economy, on the other hand, will push up demand, and hence also the price of, amongst others, food. Hence, food prices are at the same time a driver and an outcome of economic performance. Without disentangling these two opposing channels, it is very hard to say anything meaningful on the consequences of food price changes.

In this dissertation we overcome this obstacle by focusing on food price changes that are only the result of food supply shocks, such as a harvest failure due to bad weather or a pest. Focusing on these food supply shocks allows us to study the true causal effect on the economy. We have developed two different methods to identify these food supply shocks. For the first method we use data on food production and harvest calendars. We isolate changes in harvested quantities that occur *after* the planting season. Hence, these changes cannot be the consequence of demand shocks, but only of supply shocks. For the second method, a narrative method, we have used amongst others newspapers archives to isolate periods when large food supply shocks took place.

Throughout this dissertation we apply this basic concept to different research questions. In the first two chapters we analyze the macroeconomic effects of changes in food prices. First on the U.S. economy and in the second chapter on a large set of countries. In the third chapter we shift to the field of political economy and we study the effect of changes in food prices on conflict in Africa.

In the first chapter, in which we also develop the main methodological innovations, we focus on the causal effects of changes in food prices on the U.S. economy during the period 1963:Q1 – 2013:Q4. We find that global food market disruptions have a considerable influence on the U.S. economy: higher food commodity prices raise overall consumer prices, and lead to a persistent decline in real GDP and personal consumption. 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. We also find that the effects on consumer prices and personal consumption are much larger than the impact implied by the share of food commodities in the consumer price index and total consumption. This means that indirect effects prevail and magnify the macroeconomic consequences. When taking a closer look at these indirect effects, we find that not only food prices increase after an unfavorable food commodity supply shock, but also core inflation, as well as inflation expectations—and, in recent periods, even energy prices. Additionally, monetary policy tightens in response to food market disruptions, thereby amplifying the initial negative effect on the economy. Finally we see that, when food prices increase, households do not only reduce food consumption expenditures, but they also reduce spending on other goods and services, in particular durable consumption and investment.

Of all countries in the world the U.S. is the country where households spend the least on food in comparison with total expenditures. In all other countries a (considerably) larger share of the household budget is dedicated to food. In the second chapter we therefore extend our analysis to the macroeconomic consequences of changes in food prices on the economies of a set of 75 countries. First of all, we show that exogenous increases in global agricultural prices depress worldwide economic activity. Second, we find that the effects are much stronger in high-income countries. This is surprising because these countries have more developed financial markets and lower shares of food in household expenditures compared to low-income countries. We argue that this may be the result of the fact that low-income countries have higher shares of agriculture in GDP, are typically net exporters of agricultural products and less affected by the global slowdown due to limited non-agricultural trade integration with the rest of the world. When we control for these country characteristics, we find indeed that the effects on economic activity become smaller when income per capita is higher.

In the third chapter we use the same methodology to identify exogenous changes in food prices, but we apply it to a research question in the field of political economy. We study how changes in food prices affect conflict in Africa. We show that an exogenous increase in international food prices raises conflict incidence and intensity considerably. The bulk of the effect takes place beyond one year, and the effect is larger and more persistent for conflict types such as riots and protests. This contrasts with the results from a "naive" regression of conflict on food prices showing an inverse relationship. Additionally, we find that higher food prices lead to even more conflict in areas with more agriculture. We show that the traditional approach in the literature to evaluate this effect wipes out the positive baseline effects for areas with and without agriculture.

Our findings have far-reaching consequences for fellow economists, central bankers, fiscal policy makers, trade policy makers, and climate researchers. First, macro-economists have been studying business cycle fluctuations for decades. Our results imply that it could be worth including agricultural markets in those models. Also monetary policy would benefit from a closer look at food commodity prices, because in the U.S. the central bank has amplified the adverse effect of unfavorable food shocks in the past decades.

Second, our results can help trade policy makers to better assess the consequences of policies that may affect agricultural prices, such as agricultural export bans, or import tariffs. Since the global food price hikes in 2007/08 and 2010 some initiatives have already been taken to deal with the consequences of these price changes or even to avoid them. In 2011 for example the G20 Ministers of Agriculture launched the Agricultural Market Information System (AMIS): an inter-agency platform to enhance food market transparency and policy response for food security. Although our findings imply that deeper trade integration can make countries more vulnerable to global agricultural shocks, it is well-known that counter-cyclical trade policies might appear beneficial for individual countries, but they are an ineffective way to stabilize domestic prices, because they push other countries to take similar measures, thereby increasing international price volatility. Knowing that individual countries will always be tempted to invoke such beggar-thy-neighbor policies, makes initiatives aiming at information sharing and international coordination such as AMIS even more worthwhile pursuing.

Third, policy makers have often focused on stabilizing farm incomes. In the EU for example, 39 percent of the total EU budget for 2015 was spent on its 'common agricultural policy'.[2] Our findings suggest that consumers should not be overlooked. In the U.S. small changes in food prices have large effects on the overall economy through changes in consumer behavior. Especially low-income households, which typically have borrowing constraints, have few other options than to reduce expenditures on other goods when the price of food, a basic necessity, increases. For Africa we find that higher food prices lead to more conflict in areas with more agriculture, because the income gap between net consumers and net producers increases. Consequently, our results support the type of policy recommendations oriented at insuring the poor against negative income shocks. Measures targeting only the poorest consumers are easier to maintain than broader consumer subsidies (Egyptian government food and fuel subsidies increased from 1.4 percent in 2002 to 8 percent of GDP in 2011) and cause less international turmoil than export bans or restrictions (a strategy followed by China and India in 2008).[3]

Finally, climate researchers assessing the link between climate change and economic activity should take into account that changes in temperature or precipitation in one part of the globe can affect economic performance

[2] Note that the Common Agricultural Policy was originally designed to provide a fair standard of living for farmers *and* affordable food for EU citizens.

[3] Source: Hendrix, Cullen S. and Stephan Haggard (2015) "Global food prices, regime type, and urban unrest in the developing world," *Journal of Peace Research*, Vol. 52, pp. 143–157.

of countries in another part of the world via the effect on food commodity prices. Our results suggest that by neglecting this channel the existing studies have underestimated the economic effect of climate change in high-income countries.

CHAPTER 1: MACROECONOMIC EFFECTS OF DISRUPTIONS IN GLOBAL FOOD COMMODITY MARKETS: EVIDENCE FOR THE UNITED STATES

JASMIEN DE WINNE
Ghent University

GERT PEERSMAN
Ghent University

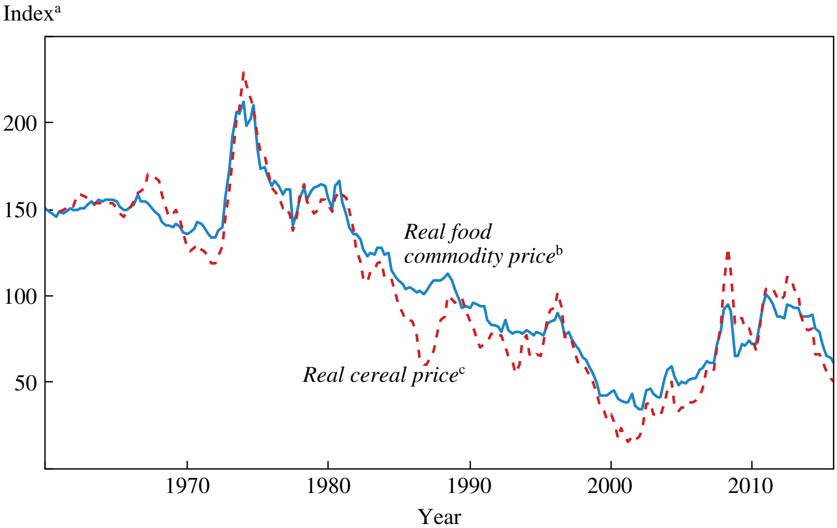
Macroeconomic Effects of Disruptions in Global Food Commodity Markets: Evidence for the United States

ABSTRACT We use two approaches to examine the macroeconomic consequences for the United States 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 model, and we estimate the dynamic effects of global food commodity supply shocks on the U.S. economy. As an alternative, we also estimate the consequences of 13 narratively identified global food commodity price shocks. Both approaches lead to 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 also to a persistent decline 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.

> 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.
>
> —John Bennet Lawes and Joseph Henry Gilbert (1868, p. 359)

Until the beginning of the 20th century, agricultural fluctuations were considered very important for the business cycles of advanced economies (Giffen 1879), but the attention given to these fluctuations vanished

Figure 1. Evolution of Food Commodity Prices over Time, 1960–2015



Source: International Monetary Fund.

a. Variables are measured as 100 times the natural log of the index deflated by the U.S. consumer price index.

b. Real food commodity price is a trade-weighted average of benchmark food prices in U.S. dollars for cereals, vegetable oils, meat, seafood, sugar, bananas, and oranges.

c. Real cereal price is an aggregate of the price of corn, wheat, rice, and soybeans on a trend production-weighted basis.

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 prices by 67 percent between 2002 and 2011, a period that has been described as a "global food crisis," and their subsequent decline by 40 percent, have attracted a vast interest in understanding the economic causes and consequences of developments in food commodity markets.[1]

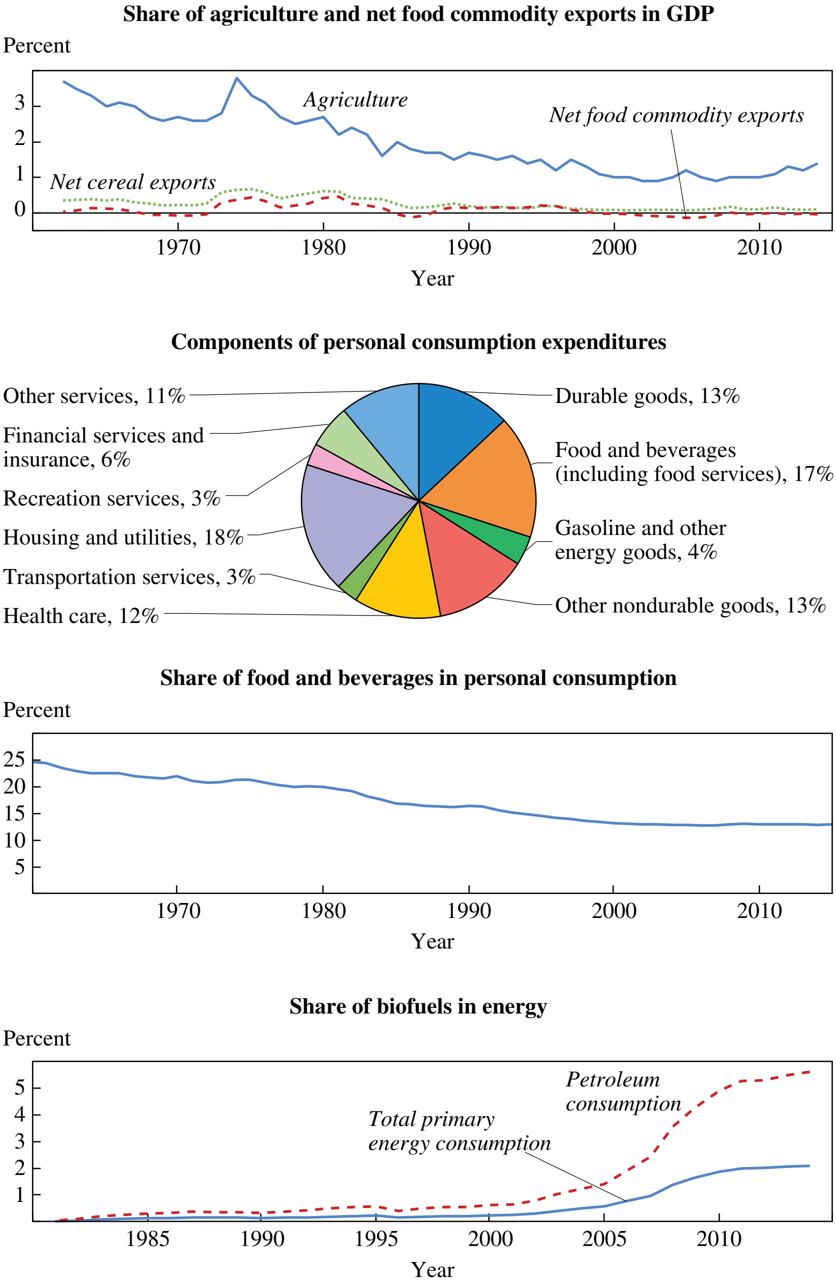
1. Two examples of newspaper articles addressing this topic are "The World Food Crisis" (*New York Times,* April 10, 2008) and "Global Food Crisis Forecast as Prices Reach Record Highs" (*The Guardian,* October 25, 2010). In 2012, the National Bureau of Economic Research directed a panel of academic experts to study the economics of food price volatility (Chavas, Hummels, and Wright 2014). See also a number of reports from policy institutions on the sources and potential consequences of the surge in food prices (Headey and Fan 2010; Abbott, Hurt, and Tyner 2011; Trostle and others 2011) or recent microeconomic studies that examine the welfare implications of food price shocks for households in developing economies (Ivanic and Martin 2008; Baquedano and Liefert 2014; Dawe and Maltsoglou 2014).

However, surprisingly little is known about the repercussions of disruptions in global food commodity markets for the business cycles of the United States and other advanced countries. This lack of quantitative evidence for the macroeconomic effects might be justified by the relatively low and declining share of agriculture in real GDP, and the fact that the United States is a modest net exporter of cereals, two features that are documented in figure 2; but these explanations appear 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 U.S. household spending between the 1960s and today.[2] Accordingly, food commodity market fluctuations could also have important indirect effects on the U.S. economy; that is, food commodity market shocks could affect the economy through their impact on consumer spending. Examples include the costs of reallocating labor and capital across alternative production activities, precautionary savings, or a monetary policy response amplifying output effects. Such effects have been put forward in the literature on oil and energy price shocks (Bernanke, Gertler, and Watson 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 for the macroeconomic consequences is not only important for gaining a better understanding of business cycle fluctuations. It is also vital for examining the optimal monetary policy response

2. According to the U.S. Bureau of Economic Analysis, the average share of food and beverages in total household expenditures was 17.3 percent between 1960 and 2015. The share of food commodities in final food products and beverages expenditures, in turn, was 14.1 percent, according to the U.S. Department of Agriculture's Economic Research Service data, which are only available for the period 1993–2014. This corresponds to $928 in food commodity expenditures per 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, was on average only 3.8 percent over the same period, while numerous studies have analyzed the macroeconomic effects of shocks in the global crude oil market (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 per capita per year.

Figure 2. Food and the U.S. Economy, 1960–2015



Sources: U.S. Bureau of Economic Analysis; U.S. Energy Information Administration; UN Comtrade Database (1-digit SITC).

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 Supplemental Nutrition Assistance Program (SNAP, formerly 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 (for example, export bans or restrictions on food imports) or policies to reduce carbon dioxide emissions (for example, ethanol subsidies or carbon offset programs). Finally, empirical evidence for the macroeconomic 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 U.S. economy during the period 1963:Q1–2013:Q4. 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 there are also reverse causality effects from macroeconomic aggregates on food prices. For instance, the unconditional correlation between changes in real global food commodity prices and U.S. real GDP is 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 vector autoregression (VAR) model for the global food commodity market and the U.S. 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 make up 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 of the United Nations (FAO) for 192 countries starting in the early 1960s. Michael Roberts and Wolfram Schlenker (2013) aggregate the four crops on a calorie-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 for 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 (or harvests) to a quarterly production index that fulfills the condition that the decision to produce (that is, to plant) 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 macroeconomic variables can be given a causal interpretation.

The estimation results assert that global food market disruptions have a considerable influence on the U.S. economy. An unfavorable shock to the global food production index of 1 standard deviation 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 decline 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 (CPI) and total consumption expenditures (that is, 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, Paul Edelstein and Lutz 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 (for example, 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 or 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 James Hamilton (1983), Christina and David Romer (1989, 2010), Valerie Ramey and Matthew Shapiro (1998), and Ramey (2011). The advantage of narrative methods compared with the VAR analysis is that it requires fewer assumptions, and 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 13 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 are the Russian Wheat Deal (combined with a failed monsoon in southeast Asia) in the summer of 1972, and the more recent Russian and Ukrainian droughts of 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 (for example, in 1975, 1996, and 2004). As the 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 for the U.S. economy.

The dynamic effects of the narratively identified shocks are estimated using Òscar 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 those of 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 our 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 expenditure 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 too 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 by 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 reveal 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 (nonmonetary policy) output effects are comparable to those of oil supply shocks. More specifically, though food supply shocks have a significant impact on food consumption, and oil supply shocks have a significant impact 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 is 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 macroeconomic 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 I, 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 II, we discuss the VAR results and several sensitivity checks. The narrative approach is discussed in section III. The comparison with oil supply shocks and the pass-through to inflation and economic activity are analyzed in section IV. Section V concludes.

I. A VAR Model for the Global Food Market and the U.S. Economy

In this section, we discuss our benchmark VAR model. We propose a strategy to identify exogenous food market disturbances within the VAR model, and explain the construction of the quarterly global composite food production index. We discuss other variables used in the model in subsection I.D.

I.A. Methodology

To estimate the macroeconomic 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 Christopher Sims (1980), which has been a popular tool in the literature for estimating the effects of shocks related to monetary policy (Bernanke and Mihov 1998), fiscal policy (Blanchard and Perotti 2002), the oil market (Kilian 2009), technology (Galí 1999), and news (Beaudry and Portier 2006). 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 U.S. 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

3. This is also typically done in VAR models analyzing the crude oil market (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 IV.

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 U.S. macroeconomy: real GDP, real personal consumption, the CPI, and the federal funds rate.

I.B. Identifying Exogenous Food Market Disturbances

U.S. and global macroeconomic variables typically have an influence on food commodity markets, implying that there is reverse causality from macroeconomic aggregates to food market variables.[5] For example, a surge in global or U.S. economic activity very likely leads to higher food commodity prices relatively quickly. This problem is ignored in existing studies from policy institutions (for example, the Federal Reserve, the European Central Bank, and the International Monetary Fund) analyzing the pass-through of changes in food commodity prices to consumer prices.[6] These studies typically impose a pricing chain assumption; that is, 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. However, it is possible (and likely) that innovations to real GDP will 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 to 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 subsection, we identify unanticipated supply shocks to global food production. To achieve identification, we explore the time lag between the decision to produce

5. In essence, the reduced form residuals in equation 1 can be thought of as linear combinations of, on 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. See, for example, Furlong and Ingenito (1996); Ferrucci, Jiménez-Rodríguez, and Onorante (2012); Pedersen (2011); and Furceri and others (2015). For a similar approach, see Rigobon (2010).

(planting) and the actual production (harvest), and the fact that actual production is subject to random shocks, which are caused, for example, by changes in weather conditions. More specifically, though farmers can respond contemporaneously (within the quarter) to macroeconomic developments by increasing or decreasing the volume of planting, this is not the case for actual production because of the time lag between both activities. In subsection I.C, 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 ordered before the other variables.[7]

I.C. 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 calorie 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 Statistics Division for 192 countries over the period 1961–2013.[9] Roberts and Schlenker (2013) convert the production data, which are measured in tons, into edible calories using the conversion factors developed by Lucille and Paul 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

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.

9. This database is available at http://faostat3.fao.org/.

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 harvesting 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 Agricultural Market Information System (AMIS) crop calendars for the largest producers and exporters; the Global Information and Early Warning System (GIEWS) country briefs; and FAO crop calendars.[10] These calendars have a monthly frequency. For some very small producers, for which no crop calendar was found, the harvesting and planting dates of the nearest relevant country are used. The final crop calendar, including country- and crop-specific sources and assumptions, can be found in the online appendix to this paper.[11] If a single harvesting 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. The examples given in figure 3 are for Kazakhstan (wheat), Russia (rice), South Africa (corn), and Argentina (soybeans). The harvesting seasons clearly occur within a single quarter, whereas the planting seasons are one or more quarters beforehand.

—Whenever a single harvesting season is spread over two subsequent quarters, we allocate the production volume to the first quarter. The examples given in figure 3 are Mexico (wheat), China (corn), the United States (rice), and Brazil (soybeans).

—Some countries have two planting seasons for some crops, such as winter and spring wheat in Russia and Canada. However, because their harvesting seasons still occur within a single quarter and the planting seasons

10. The AMIS crop calendars are available at http://www.amis-outlook.org/amis-about/calendars/en/; the GIEWS country briefs are available at http://www.fao.org/giews/countrybrief/index.jsp; and the FAO crop calendars are available at http://www.fao.org/agriculture/seed/cropcalendar/welcome.do.

11. The online appendixes for this and all other papers in this volume may be found at the *Brookings Papers* web page, www.brookings.edu/bpea, under “Past BPEA Editions.”

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—for example, for wheat in Brazil—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 harvesting period, or because the crops are harvested almost uniformly throughout the year. Examples given 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 annual world food production to a specific quarter.[12] 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 is seasonally adjusted using the U.S. Census Bureau's X-13ARIMA-SEATS seasonal adjustment program.[13]

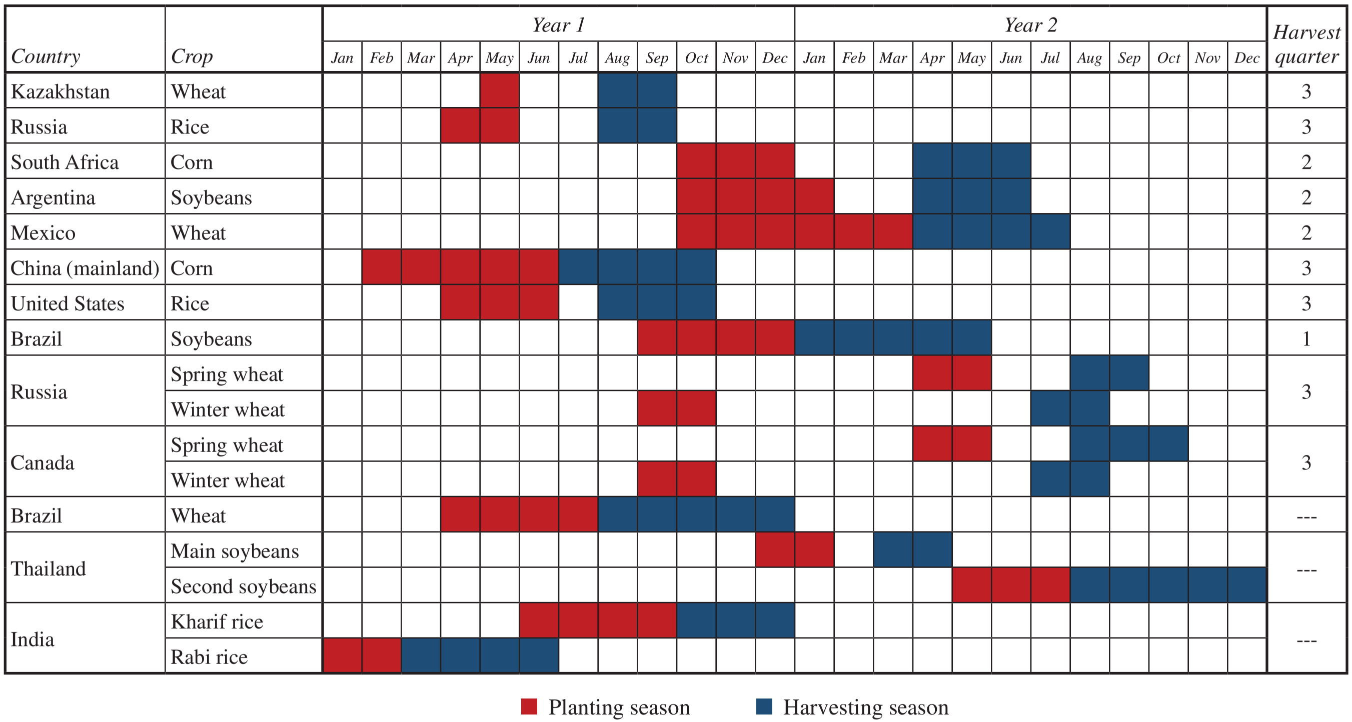
A couple of points about the index in the context of the VAR analysis are worth mentioning. First, although this index does not capture all disturbances to global food production, the production volume covered by the index should be sufficiently meaningful to influence global food commodity markets, including food commodity prices, which is a prerequisite for examining the impact of exogenous food supply shocks on the U.S. macroeconomy. Second, the identified shocks only capture unanticipated changes in food production in the harvesting quarter. More specifically, anticipated changes in food production before the start of the harvesting season (for example, bad weather between planting and harvesting) should already be reflected in the other variables and innovations in the VAR, particularly food commodity prices.[14] Third, our approach assumes that the information

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

13. Information about the program can be found at https://www.census.gov/srd/www/x13as/.

14. 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—that is, futures prices increase—traders will buy inventories in the spot market. Hence, spot commodity prices also increase.

Figure 3. Examples of Crop Calendars



Sources: U.S. Bureau of Economic Analysis; U.S. Energy Information Administration; UN Comtrade Database (1-digit SITC).

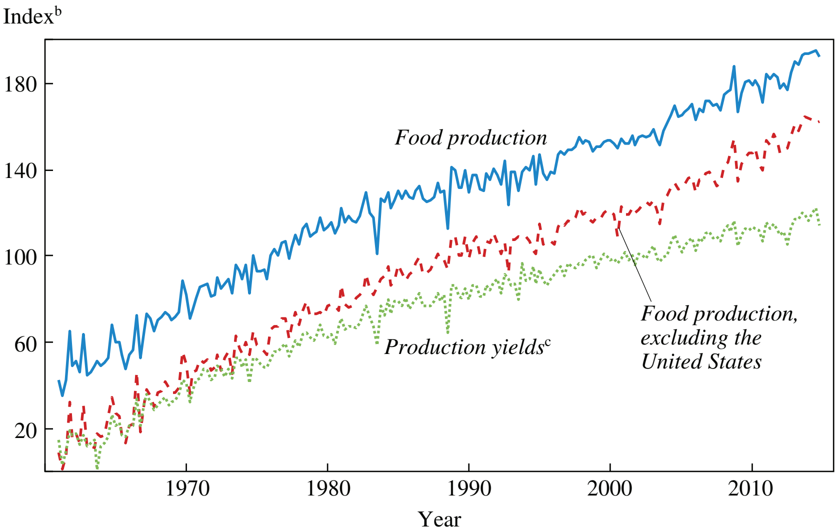
sets of local farmers are no greater than the global VAR model. Since we do not consider food production forecasts by country, the shocks are hence not necessarily identified using the full information sets available to the farmers when planting. Finally, our identification strategy also assumes that food producers cannot influence the production volume within the harvesting quarter. For example, a rise in economic activity or food commodity prices could endogenously induce farmers to increase food production by increasing fertilization activity. Several studies, however, have shown that in-season fertilization is not an efficient way to increase grain yields and is not recommended for the food commodities that we consider (Mallarino 2010; Schmitt and others 2001; Fanning 2012; Scharf, Wiebold, and Lory 2002). Specifically, the best times to apply fertilizer to these crops is before or shortly after planting, while fertilization should be completed before the jointing stage. In fact, fertilizing strategies in the last months before the harvest may even be counterproductive and lead to irreversible yield loss.[15] Whereas some endogenous response might be present, this should be meager relative to the variation induced by other factors, for example, weather.[16]

Figure 4 shows the time series of the 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 this 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 U.S. production, and an index of global production yields. Both indicators are used below in a sensitivity analysis of the benchmark results (subsection II.D). The production yield is defined as the ratio of food production to the area harvested, which is also obtained from the FAO database (see footnote 9). The upward trend in this variable is flatter than the production volume, implying that part of the food production

15. The bottom line is that fertilization strategies (for example, 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, for example, by destroying crops or an insufficient treatment of diseases during the harvesting season, but that is not likely to happen at a large scale.

16. 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 three months.

Figure 4. Global Food Commodity Production Index, 1961–2014[a]



Source: Authors' calculations.

a. The production index aggregates the production of corn, wheat, rice, and soybeans on a calorie-weighted basis.

b. Variables are measured as 100 times the natural log of the global food commodity production index (see the text).

c. The production yield is defined as the ratio of food production to the area harvested.

expansion is driven by an increase in the amount of land that is used in crop production.

I.D. Other Variables

For the baseline estimations, we use the broad food commodity price index from the International Monetary Fund. The index is a trade-weighted average of different benchmark food prices in U.S. dollars for cereals, vegetable oils, meat, seafood, sugar, bananas, and oranges. These benchmark prices are representative of the global market and are determined by the largest exporter of each commodity. The nominal price index has been deflated by the U.S. CPI. The time series is shown in figure 1 above. 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 afterward. 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, and in 1983, 1987–88, 1995–96, 2002–04, 2007–08, 2010, and 2012. Overall, the standard deviation of the quarter-on-quarter change in real food commodity prices is 5.7 percent.[17]

Because our production index is limited to the four major staples, we have also constructed an alternative composite cereal price index containing only the prices of corn, wheat, rice, and soybeans. This index, which is also shown in figure 1 above, is based on the trend production weights of the four commodities and is used below in another sensitivity check of the benchmark results. As observed in figure 1, the correlation with the International Monetary Fund's broad index 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 price index, with a quarterly standard deviation of 7.8 percent.

The volume of seeds from harvests 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 subsection I.C for the production index. Other data are standard. Global oil production is obtained from the *Oil & Gas Journal* for the period before 1973, and from the U.S. Energy Information Administration afterward, following Christiane Baumeister and Peersman (2013b). Similar to Kilian (2009), among others, the real oil price series is the refiner acquisition cost of imported crude oil, deflated by the U.S. CPI. To proxy global economic activity, we follow Baumeister and Peersman (2013a) by using the world industrial production index from the Netherlands 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, U.S. macroeconomic data are obtained from the Federal Reserve Bank of St. Louis's FRED database.

II. VAR Results

In this section we describe the estimation of the VAR model. We show the identified shocks and their contribution to real food commodity prices, and discuss the dynamic effects on the U.S. economy. In subsection II.D, we examine the sensitivity and robustness of the results.

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

II.A. Inference

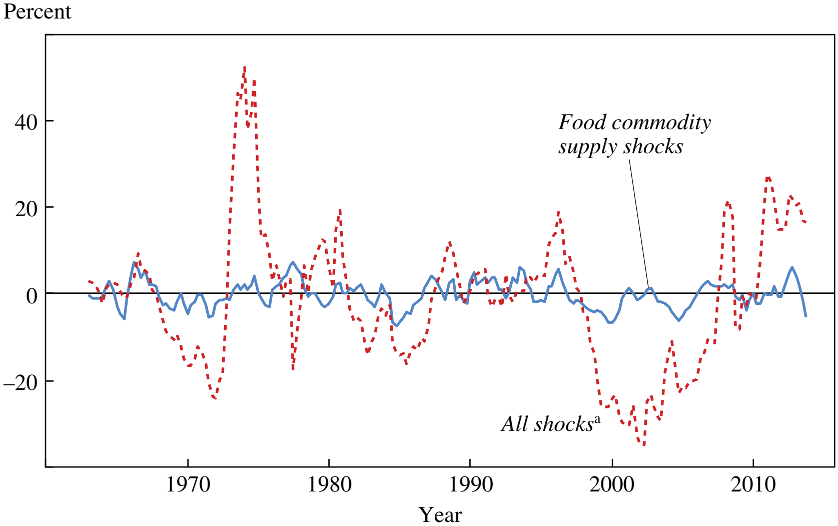
The benchmark VAR model for the global food commodity market and the U.S. economy has been estimated over the sample period 1963:Q1–2013:Q4. All variables are seasonally adjusted natural logarithms (multiplied by 100), except for the federal funds rate, which is measured in percent. Estimation in log levels gives consistent estimates and allows for implicit cointegrating relationships in the data.[18] Based on the Akaike information criterion, we include five lags of the endogenous variables. However, the qualitative results are not sensitive to the lag order choice. In subsection II.D, we examine the robustness of the results across subsamples. In the figures, we show the median estimates of the impulse responses, together with percentile error bands based on 10,000 draws. These are constructed as proposed by Sims and Tao Zha (1999).

II.B. 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 (solid line), as well as the contribution of all shocks implied by the VAR model (dashed line). Overall, the shocks explain approximately 10 percent of food commodity price volatility. The contribution of the shocks to real food commodity prices corroborates 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 during the periods or years 1967–72, the mid-1980s, 1992, 1994, 1996–2000, and 2004–05. In contrast, shocks to the global food production index have been unfavorable in the periods or years 1972–77, 1985–88, 1996, 2000–03, 2005–07, and 2009–12. Almost all these episodes have been characterized by significantly falling or rising food commodity prices and correlate with many spikes discussed in subsection I.D.

18. See Sims, Stock, and Watson (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 (or quadratic) time trend.

Figure 5. Historical Contribution of Identified Shocks to Real Food Commodity Prices, 1963–2013



Source: Authors' calculations.
a. Calculated as the actual data minus the baseline of the VAR.

The cumulative contribution of the identified food commodity supply shocks to the surges in food commodity prices between 2005–07 and 2009–12 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 is in line with common perceptions 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—for example, renewable fuel standard 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, Hurt, and Tyner 2011). For instance, the share of U.S. 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).[19] Examples of other shocks mentioned in the literature are the strong income growth in the BRIC countries (Brazil, Russia, India, and China) during that period—which allowed citizens of 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 U.S. 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.

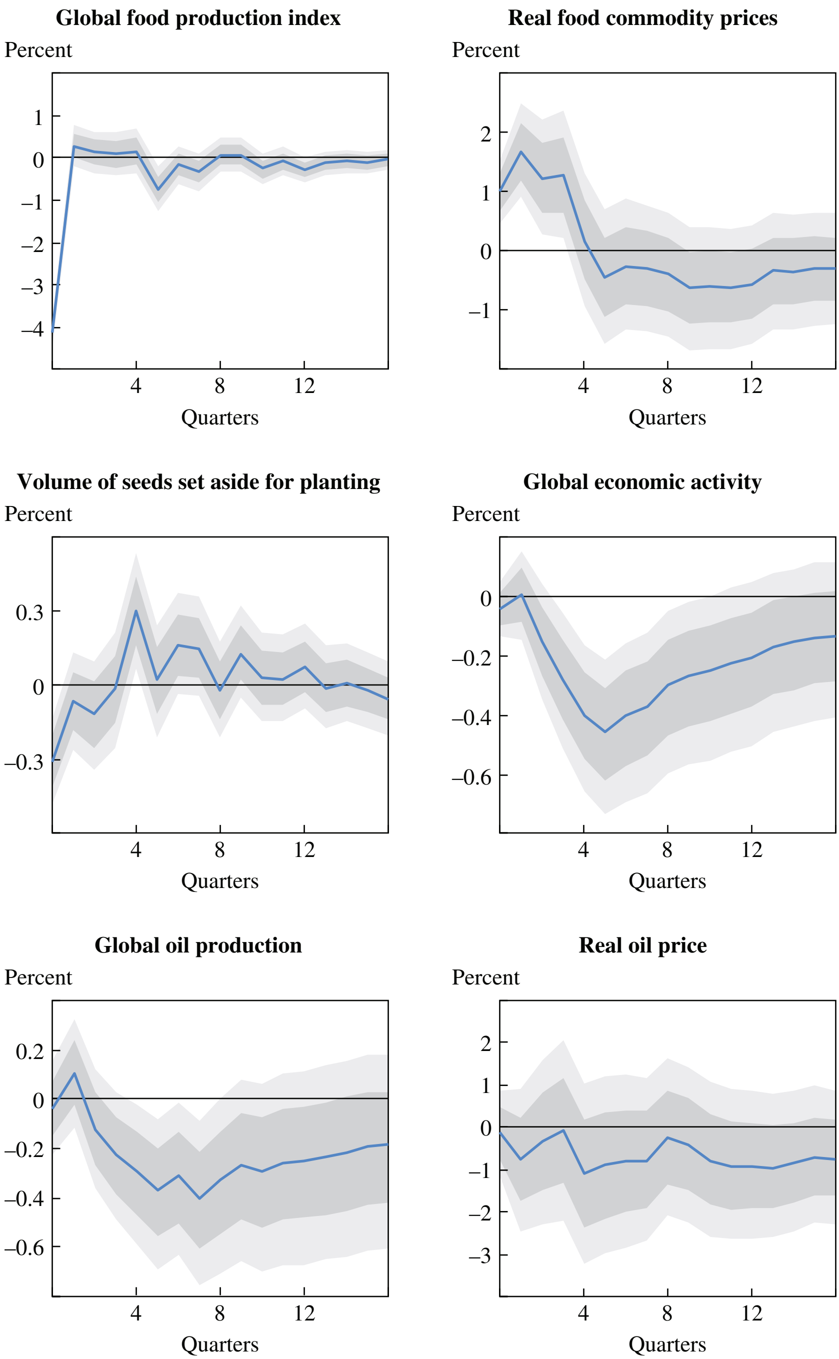
II.C. Impact of Food Market Disruptions on the U.S. Economy

The impulse responses to a shock of 1 standard deviation 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 decline in the food production index of 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 decline in global economic activity. Global oil production starts to decrease after approximately two quarters, which is in line with the pattern of the decline in global economic activity, while the impact on the real price of oil is insignificant at all horizons.

Global food commodity production returns to the baseline after one quarter. This pattern, together with the persistent response of food commodity prices, is consistent with John Muth's (1961) rational expectations model for commodity markets with speculation, and is at odds with the so-called cobweb theorem. Specifically, Muth (1961) shows that the introduction of rational expectations into 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

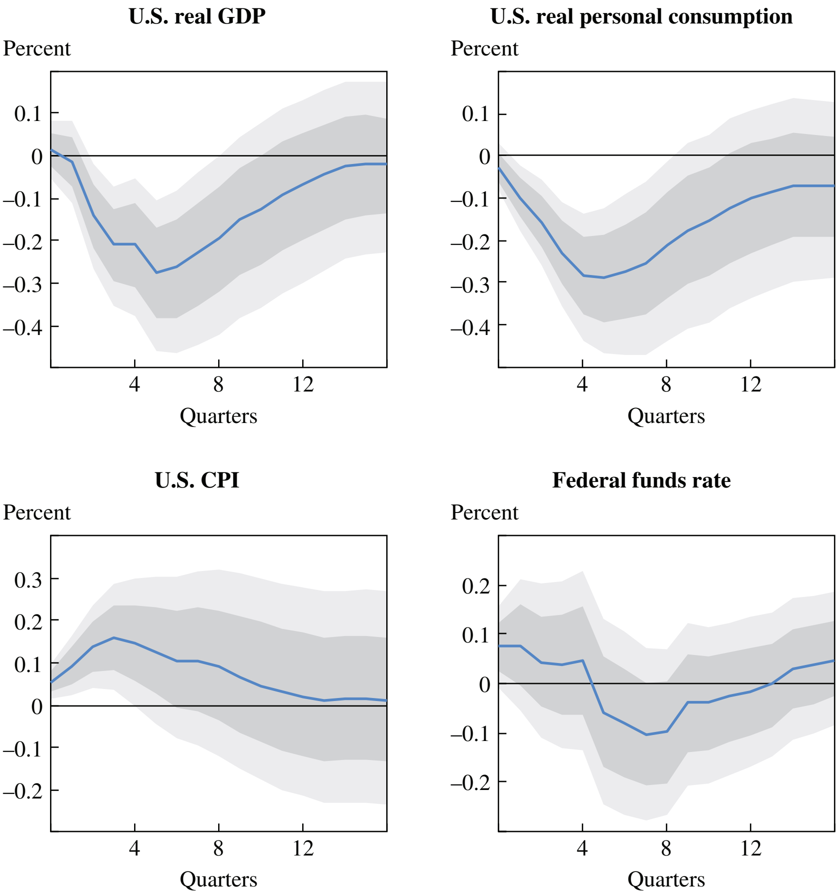
19. Notice that biofuels demand did not only strongly account for corn price increases during that period but also price increases in other staples. For example, the rapid expansion of the U.S. corn area by 23 percent in 2007 resulted in a 16 percent decline in the soybean area, which reduced soybean 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 the wheat area by oilseeds and hence higher wheat prices.

Figure 6. Impulse Responses to Global Food Commodity Supply Shocks: Benchmark VAR Results[a]



(*continued*)

Figure 6. Impulse Responses to Global Food Commodity Supply Shocks: Benchmark VAR Results[a] (*Continued*)



Source: Authors' calculations.

a. The sample period is 1963:Q1–2013:Q4. The darker shading indicates the 16th and 84th percentile error bands; the lighter shading indicates the 5th and 95th percentile error bands.

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.

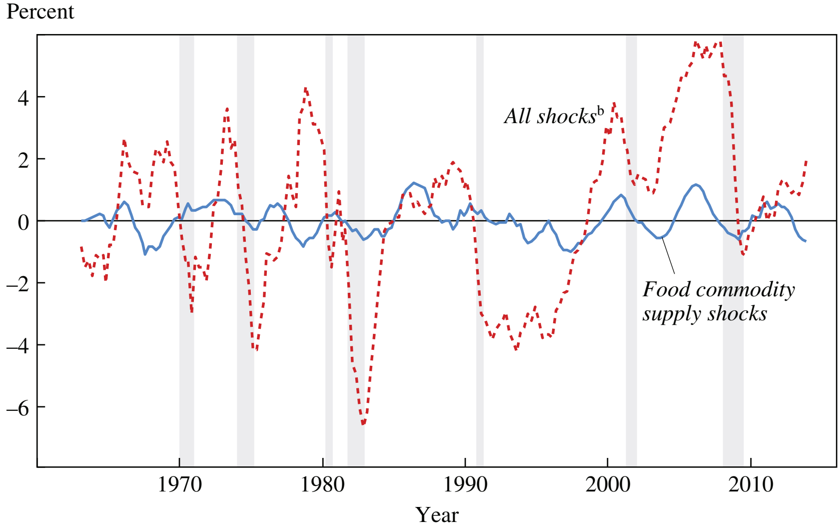
The influence of global food market disruptions on the U.S. economy is considerable. In particular, real GDP starts to decrease after two quarters, reaching a maximum decline of 0.28 percent after five to six quarters, and then gradually returns to the baseline. Although the rise in real food commodity prices lasts for only four quarters, the decline in real GDP is still significant after two years. The macroeconomic consequences are thus very persistent. A similar pattern appears for the response of households' real personal consumption expenditures. 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 CPI 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 to 0.05 percent.[20] This suggests that indirect effects are important in magnifying the macroeconomic repercussions; that is, not only food prices but also other components of the CPI should increase after a surge in food commodity prices, while the decline in consumption cannot solely be the consequence of a discretionary income effect. In section IV, we analyze this in more detail.

Whereas disturbances in food commodity markets have obviously not been the main driver of the U.S. business cycle, the identified global food market shocks did contribute to several post–World War II recessions. This can be observed in figure 7, which shows the cumulative contribution of the identified shocks to real GDP over time (solid line), the contribution of all shocks to real GDP implied by the benchmark VAR model (dashed line),

20. 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.

Figure 7. Historical Contribution of Identified Shocks to U.S. Real GDP, 1963–2013[a]



Source: Authors' calculations.
a. Gray areas indicate recessions.
b. Calculated as the actual data minus the baseline of the VAR.

and the National Bureau of Economic Research's 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 contribution to the decline in real GDP), 1982 (0.6 percent), the early 1990s (0.2 percent), 2001 (0.7 percent), and the Great Recession of 2008–09 (0.5 percent). In nonrecessionary 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 1967–72, by 1.7 percent in the mid-1980s, by 1.8 percent in 1997–2000, and by 1.7 percent between 2003 and 2005. In sum, the macroeconomic repercussions of food market disturbances have been important for the U.S. economy.

II.D. The Sensitivity and Robustness of Benchmark Results

In section III, 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. But before doing this, we consider a set of alternative VAR specifications to assess the sensitivity of the results that are based on the production index. We also investigate whether the estimations are picking up other effects and the stability of the results across subsamples.

DID WE IDENTIFY EXOGENOUS FOOD COMMODITY MARKET SHOCKS? Due to the time lag between the planting and the harvesting seasons, shocks to the global food commodity production index should in principle be exogenous with respect to the macroeconomy. In subsection I.C, we also argued that farmers cannot influence grain yields any more in the harvesting quarter, for example, by raising fertilization activity. As noted above, fertilizer applications must 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 U.S. weather conditions may simultaneously affect food production and economic activity.[21] Michael Boldin and Jonathan Wright (2015) find that unusual temperatures have a statistically significant effect on U.S. real GDP growth in the first and second quarters. For example, several panel studies find significant negative effects of hotter temperatures on agricultural output, and also on labor productivity and labor supply at the spatial level (Dell, Jones, and Olken 2014).[22] Additionally, storms may distort the estimations and exaggerate the role of food commodity markets in macroeconomic developments.

Overall, we do not find compelling support for the hypothesis that the innovations are picking up other shocks or are having meaningful direct effects on economic activity, other than through food commodity markets, for several reasons. First, a closer inspection of the impulse responses

21. This evidence is usually only found for poor countries; several papers have found that temperature shocks have little effect on per capita income or industrial value-added output at the spatial level in rich countries (Dell, Jones, and Olken 2014).

22. 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 1990:Q1. The series also 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.

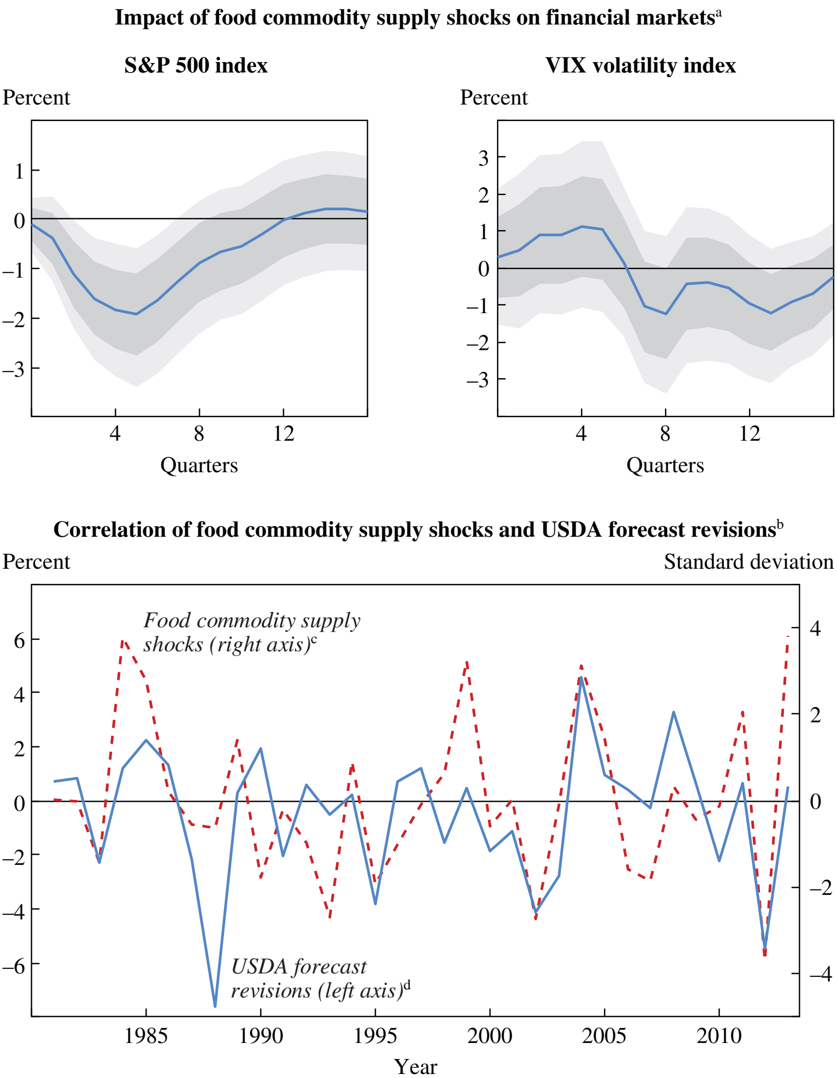
shown in figure 6 conveys the perception that both issues probably do not have an important influence on the results. Specifically, global economic activity and U.S. real GDP only start to decline with a delay of at least two quarters after the identified food market disruptions. Put differently, the shocks are not reflected in economic activity on impact, which implies that the innovations are not aggregate demand shocks and that the direct effects of the underlying global weather conditions on the U.S. economy cannot be large.[23] Similarly, global oil production only decreases after approximately three quarters, whereas the response of crude oil prices is never significant and is even slightly negative at longer horizons.

In addition, the return to the 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 the top panel of figure 8. The panel shows the dynamic effects of food commodity supply shocks on equity prices (as measured by the S&P 500 index) and implied stock market volatility (as measured by the VIX volatility index). 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 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 the global food commodity market variables in the benchmark VAR are statistically significant. The patterns of the impulse response functions—that is, food production and prices shifting

23. We also find no correlation between the series of the annualized food commodity supply shocks and the annual occurrence (–.09), the total number of deaths (.11), or the total dollar damage estimate (.07) of U.S. natural disasters reported in the EM-DAT database (http://www.emdat.be/database).

Figure 8. Did We Identify Exogenous Food Commodity Market Shocks?



Sources: Authors' calculations; USDA.

a. Shows the impulse response function of the S&P 500 index and the VIX stock market volatility index by adding these variables to the benchmark VAR. The darker shading indicates the 16th and 84th percentile error bands; the lighter shading indicates the 5th and 95th percentile error bands.

b. Shows the annual USDA forecast revisions for world grains output and annual food commodity supply shocks.

c. Food commodity supply shocks are calorie-weighted aggregates of corn, wheat, rice, and soybeans. Annual shocks are the sum of the four quarters.

d. USDA forecasts are millions of metric tons of wheat, coarse grains (corn, sorghum, barley, oats, rye, millet, and mixed grains), and milled rice. Forecast revisions are the sum of forecast revisions for the periods May–December and December–April.

in opposite directions—are also consistent with food supply shocks and are hard to reconcile with other types of disturbances. Moreover, as can be observed in the bottom panel of figure 8, the estimated innovations coincide quite well with the U.S. Department of Agriculture's (USDA's) forecast revisions. Since the early 1980s, the USDA's World Agricultural Outlook Board has regularly published projections of world annual grains production.[24] These projections are always for the period May–April (known as the marketing year), and are an aggregate (millions of metric 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's forecast revisions for the periods May–December and December–April. 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 (.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 other important effects or endogenous responses to the macroeconomy.

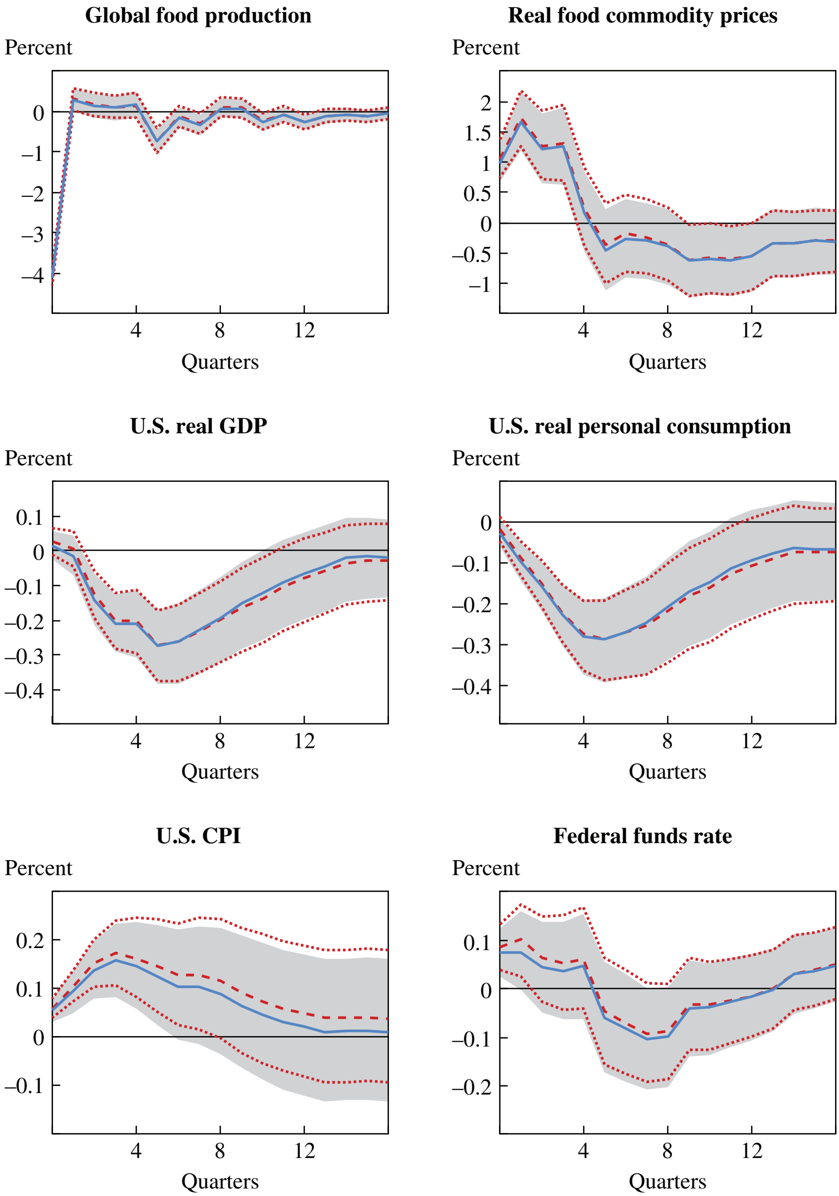
This reasoning is also confirmed by the first sensitivity check reported in figure 9, which shows the results of several alternative VAR models. The first sensitivity check orders the global food production index after global oil production, the real price of oil, and global economic activity in the 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 U.S. food commodity production from the global production index and reestimate 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

24. An archive of these World Agricultural Supply and Demand Estimates can be found at http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1194.

Figure 9. Effects of Global Food Commodity Supply Shocks on Key Variables: Sensitivity Analysis[a]

Panel A. Alternative ordering of food production in VAR



(continued)

Figure 9. Effects of Global Food Commodity Supply Shocks on Key Variables: Sensitivity Analysis[a] (*Continued*)

Panel B. Global food production index, excluding U.S. food production, as a measure of food production

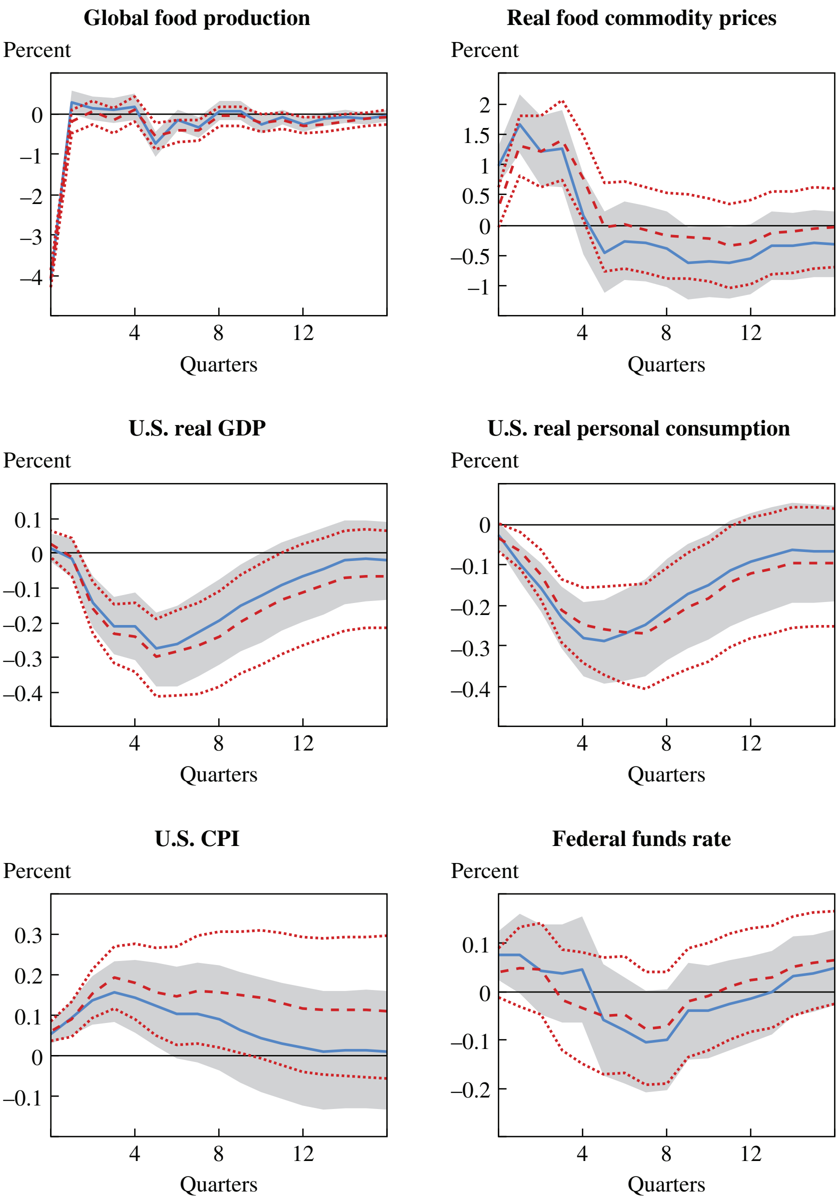


Figure 9. Effects of Global Food Commodity Supply Shocks on Key Variables: Sensitivity Analysis[a] (*Continued*)

Panel C. Real cereal prices as a measure of the food commodity price

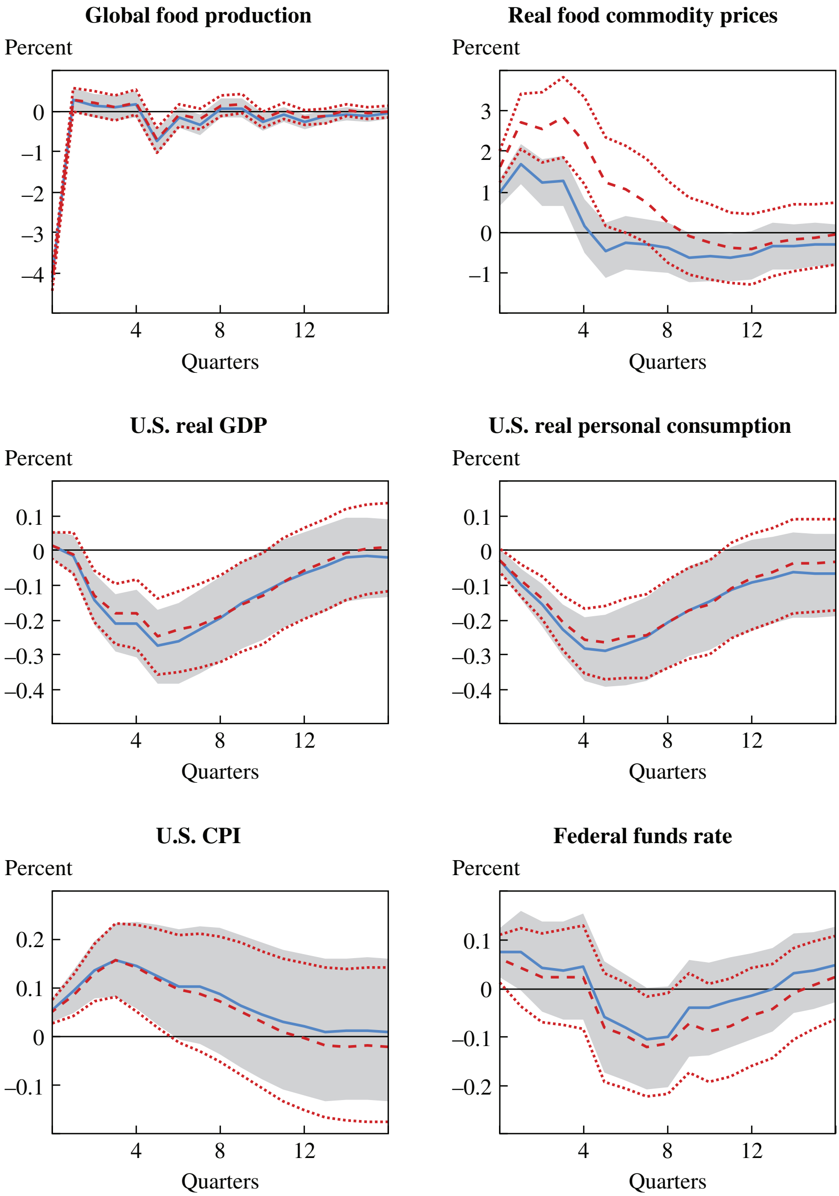


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Figure 9. Effects of Global Food Commodity Supply Shocks on Key Variables: Sensitivity Analysis[a] (*Continued*)

Panel D. Global food production yields as a measure of food production

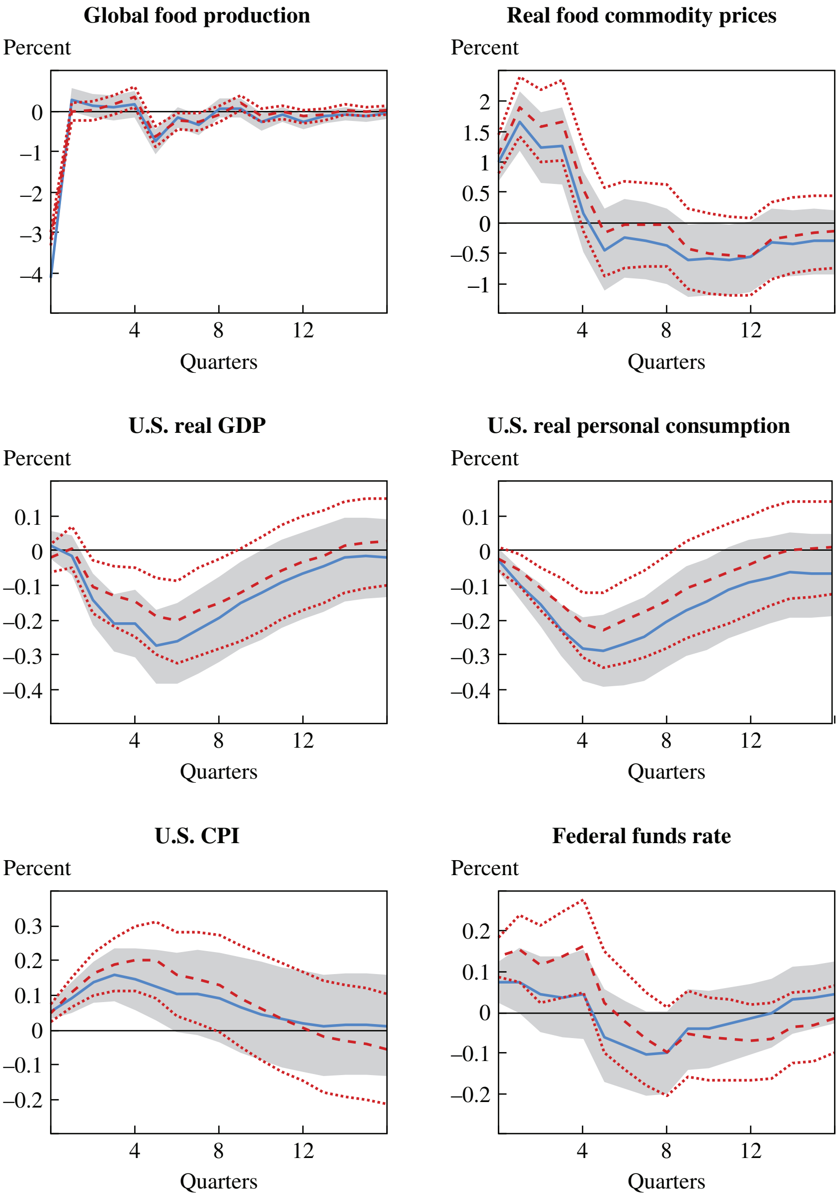
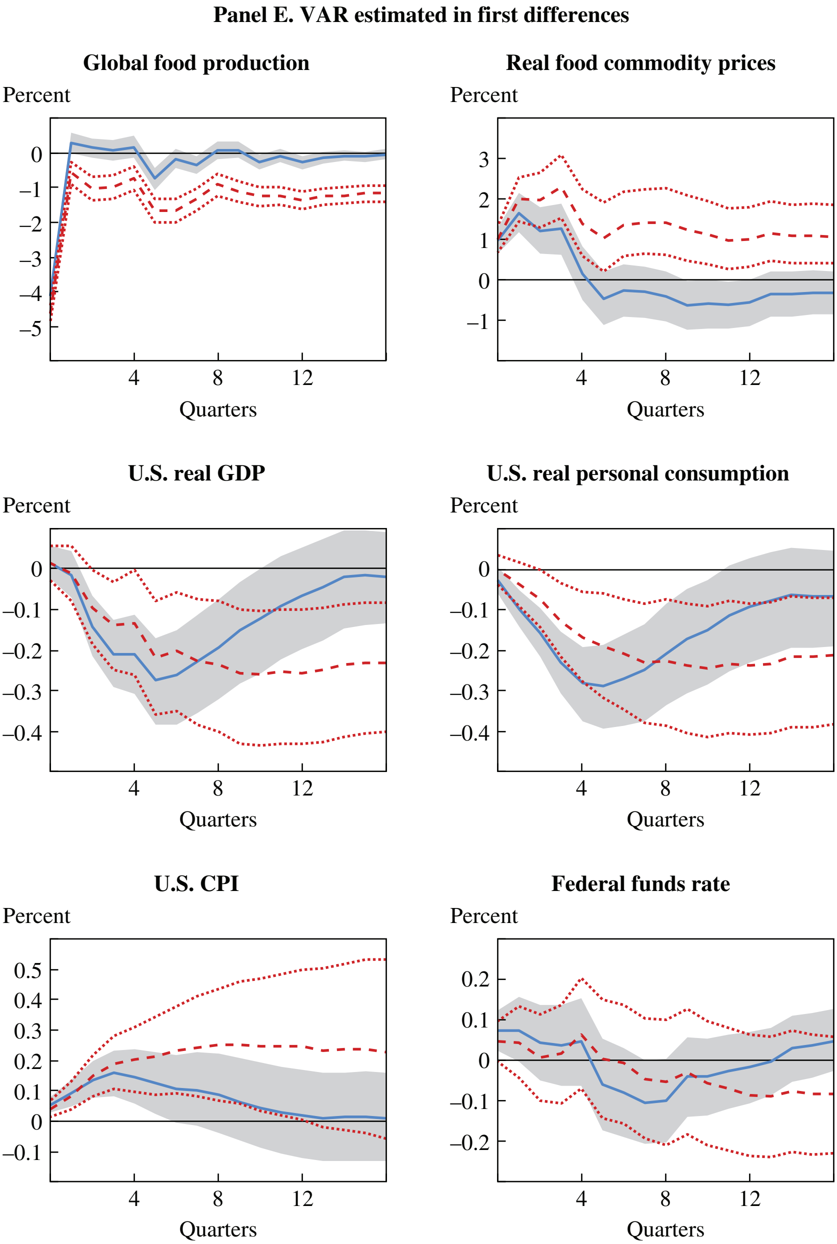


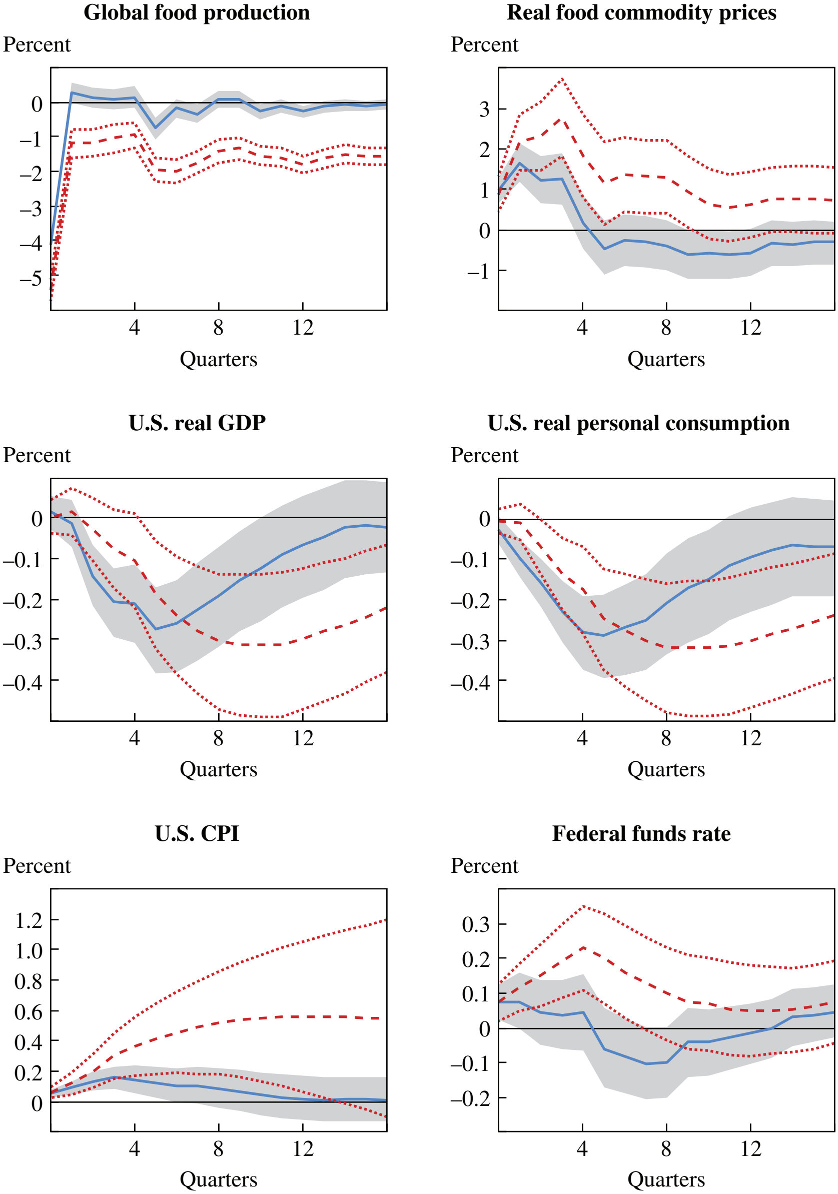
Figure 9. Effects of Global Food Commodity Supply Shocks on Key Variables: Sensitivity Analysis[a] (*Continued*)



(*continued*)

Figure 9. Effects of Global Food Commodity Supply Shocks on Key Variables: Sensitivity Analysis[a] (*Continued*)

Panel F. FAVAR with six unobserved macroeconomic factors, global food production, and real food commodity prices



Source: Authors' calculations.

a. The range shown around estimates are the 16th and 84th percentile error bands. The solid line and shaded area are the results of the benchmark VAR (same as in figure 6); the dashed and dotted lines are results of the alternative VAR specification.

U.S. real GDP.[25] The results, which are shown in panel B of figure 9, 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 are available upon request. In sum, it is unlikely that the identified innovations are picking up other shocks, or that there are significant direct effects of weather variation on the U.S. economy.

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 shock of 1 standard deviation 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

25. External food commodity supply shocks would not have a direct effect on U.S. real GDP unless there is a systematic correlation of non-U.S. food production shocks and U.S. food production. If this is the case, the correlation is probably small given the global level of our analysis. For example, the correlation between the estimated global food supply innovations and the Multivariate El Niño Southern Oscillation Index, the Oceanic Niño Index, and a dummy variable based on the U.S. National Oceanic and Atmospheric Administration's definition of El Niños varies between −.10 and −.11. The correlation between food production shocks excluding U.S. production and the El Niño variables varies between −.14 and −.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 U.S. economy via trade. In section IV, however, we document that trade effects are relatively small and that export is not an important driver of the output consequences.

the benchmark VAR model estimated in first differences, while panel F depicts the impulse responses of the key variables estimated with a factor-augmented vector autoregression (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.[26] 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 James Stock and Mark Watson (2016) have used to estimate the effects of oil market shocks. The FAVAR is estimated with five lags of two observed factors (that is, the global food production index and real food commodity prices) and six unobserved factors.[27]

The impulse responses of the alternative models in panels E and F of figure 9 have been accumulated and are shown in levels. Five interesting observations, which mostly apply to both models, are worth mentioning. First, the contemporaneous decline in global food production is somewhat greater than in the benchmark VAR. Second, there is a permanent decline in global food production, along with 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 among 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 with the VARs estimated in log levels.

26. VARs estimated with ordinary least squares 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's discussion of our paper. Also see Sims (2000) for a discussion on the role of initial conditions for the low-frequency variation in observed time series.

27. This model has also been used by Mark Watson for the discussion of our paper. We are grateful to him for sharing the code and data sets. The 207-variable time series consists of real activity, prices, productivity, earnings, interest rates, spreads, money, credit, assets, wealth, and oil market variables, as well as variables representing international activity. All variables are transformed to a stationary form. See Stock and Watson (2016) for details.

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. Fifth and finally, the federal funds rate also rises more strongly 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.[28]

SUBSAMPLE ANALYSIS We now assess the robustness of the results across subsamples. A constraint on 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 reestimate the benchmark VAR model for the sample periods 1963:Q1–1999:Q4 and 1985:Q1–2013:Q4, respectively. The former sample period does not take into account the global food crisis of the 2000s and the subsequent collapse of food commodity prices, or 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 are 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 declining 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

28. By estimating food production equations (with all lagged VAR variables as independent 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 macroeconomic consequences are different (i) when we allow food production to react differently to increases and decreases of the lagged independent 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.

Figure 10. Subsample Analysis Based on Benchmark VAR: 1963–99 versus 1985–2013[a]

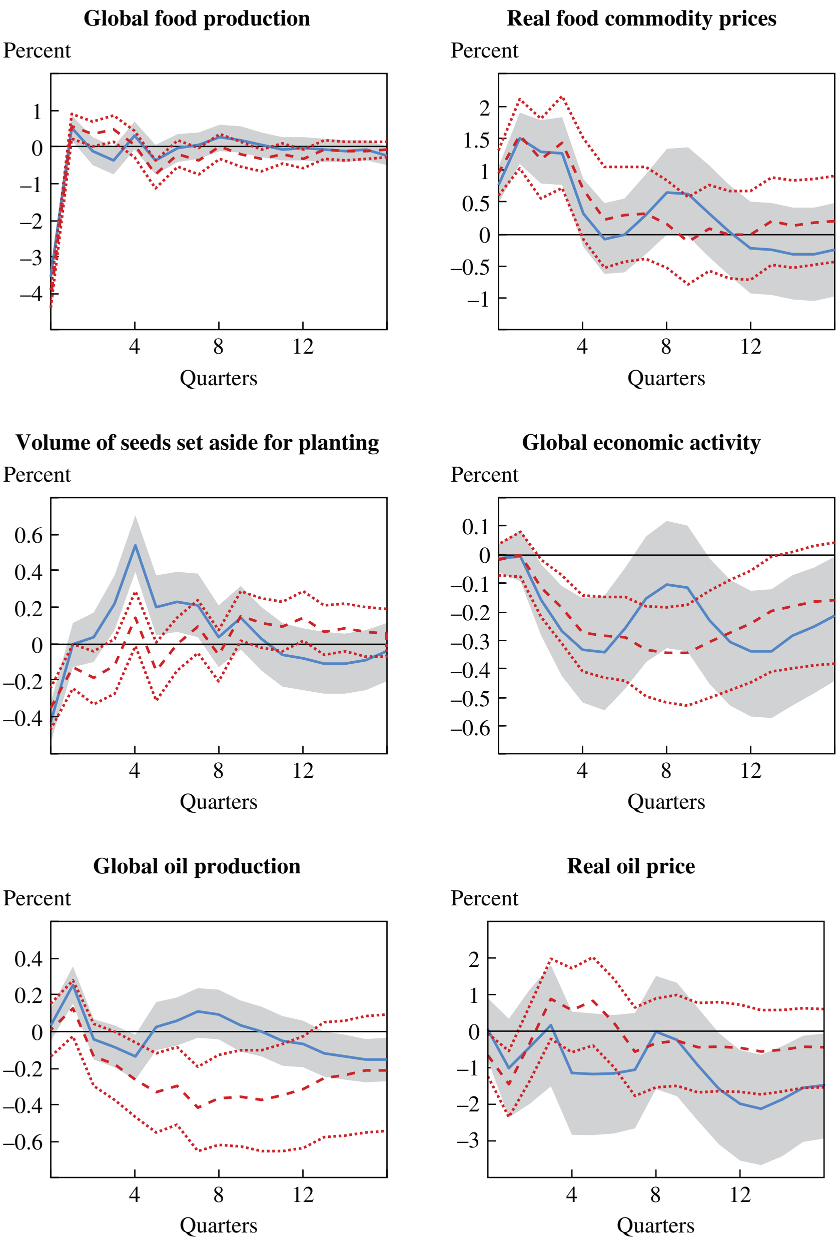
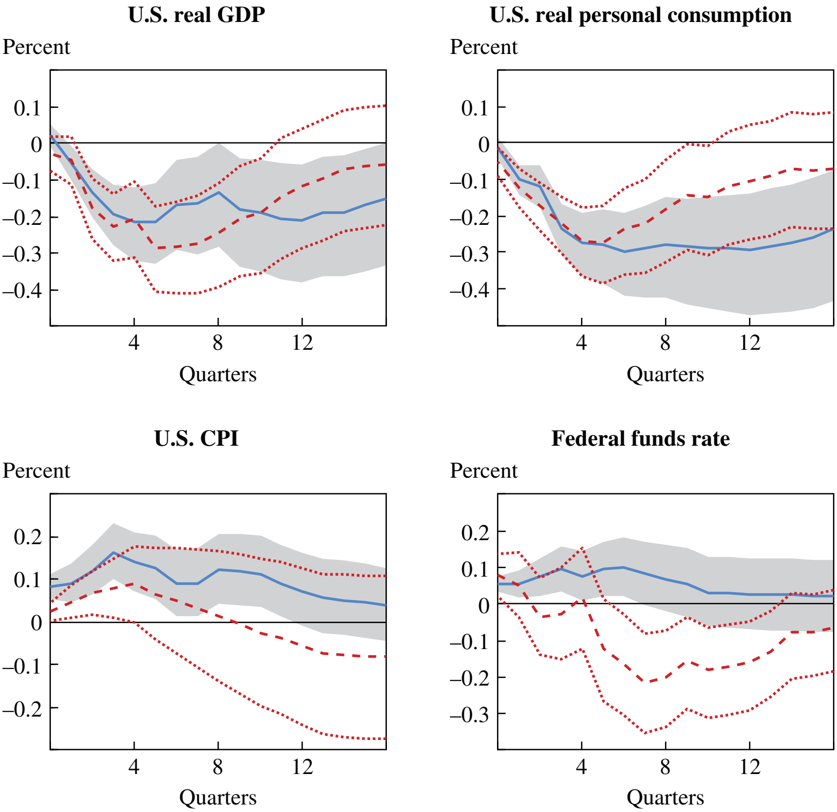


Figure 10. Subsample Analysis Based on Benchmark VAR: 1963–99 versus 1985–2013[a] (*Continued*)



Source: Authors' calculations.

a. The range shown around estimates are the 16th and 84th percentile error bands. The solid line and shaded area are the results for the period 1985:Q1–2013:Q4; the dashed and dotted lines are the results for the period 1963:Q1–1999:Q4.

tighter link between agricultural and energy prices, magnifying the consequences of food commodity market disruptions for the U.S. economy at the end of the sample.

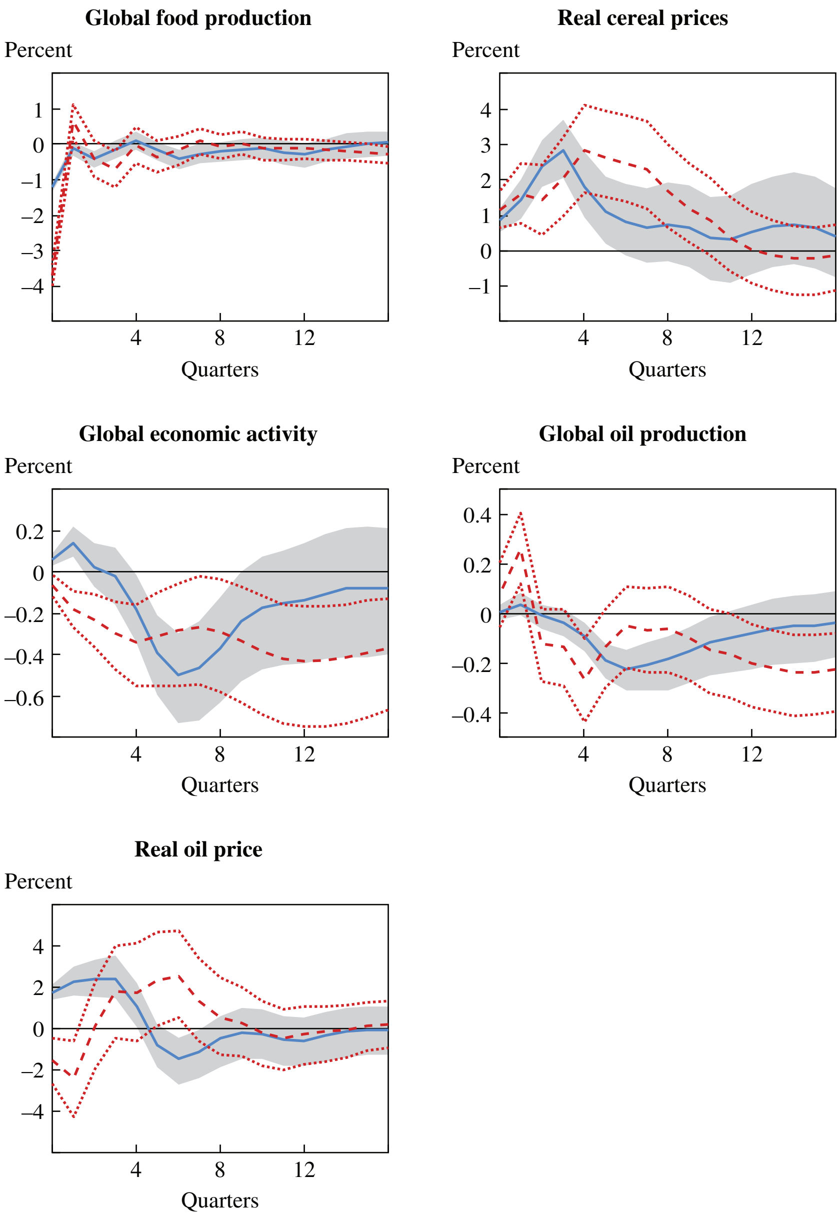
An enhanced link between food commodity markets and energy prices is confirmed by the second exercise to assess time variation. For this exercise, we borrow results from Peersman, Sebastian Rüth, and Wouter Van der Veken (2016). More specifically, elaborating on the present study, Peersman, Rüth, and Van der Veken (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 Giorgio Primiceri (2005)—to examine whether crude oil and food commodities have become more closely linked in recent periods. The VAR used by Peersman, Rüth, and Van der Veken (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 their impact starts to gradually rise over time. A similar story emerges for oil supply shocks; that is, oil supply shocks have no significant effects 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 the first panel of figure 11, we reproduce Peersman, Rüth, and Van der Veken's (2016) results for the sample periods 1985:Q1–2002:Q4 and 2003:Q1–2014:Q4 for global food commodity supply shocks.[29] As can be observed in the figure, a food market disturbance that raises real cereal prices also triggers an immediate shift of crude oil prices in the post-2003 period. In the second panel, we show the macroeconomic consequences of the shocks in both periods by adding a set of U.S. variables one by one to the five-variable 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 for real GDP, personal consumption, and consumer prices have not dramatically changed over time. But this is 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.

29. Notice that the VARs given by Peersman, Rüth, and Van der Veken (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 subsection II.D. 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.

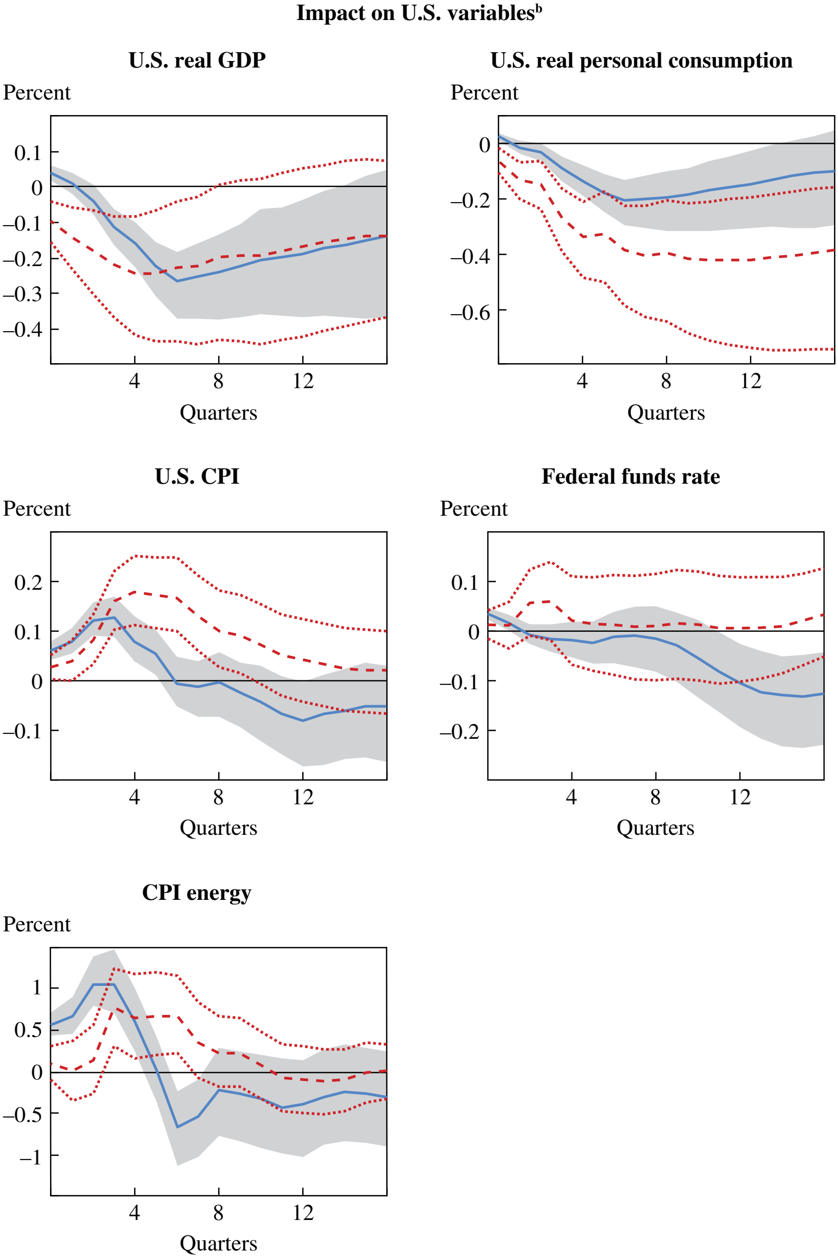
Figure 11. Subsample Analysis Based on Smaller VAR: 1985–2002 versus 2003–14[a]

Results of five-variable VAR model from Peersman, Rüth, and Van der Veken (2016)



(continued)

Figure 11. Subsample Analysis Based on Smaller VAR: 1985–2002 versus 2003–14[a] (*Continued*)



Sources: Authors' calculations; Peersman, Rüth, and Van der Veken (2016).

a. The range shown around estimates are the 16th and 84th percentile error bands. The solid line and shaded area are the results for the period 2003:Q1–2014:Q4; the dashed and dotted lines are the results for the period 1985:Q1–2002:Q4.

b. Variables are added one by one to the global VAR model.

III. A Narrative Approach to Identifying Food Market Disturbances

As an alternative approach to examine the consequences of food commodity market disruptions for the U.S. 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. For example, they were used by Romer and Romer (1989) to estimate the effects of monetary policy changes. By examining the minutes of the Federal Open Market Committee's 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 *Bloomberg Businessweek,* 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 when changes in oil prices were almost solely driven by exogenous disturbances to supply that had little to do with macroeconomic conditions—for example, 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 fewer assumptions, and there is no need to identify 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 subsection III.A, we describe the narrative approach to identify exogenous food commodity market shocks. Subsection III.B discusses the estimation method, and subsection III.C presents the results.

III.A. 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—that is, movements for which the proximate causes are disturbances in global food commodity markets. We rely on FAO reports, newspaper articles, disaster databases, and several other online sources to identify historical episodes of such movements. The task is daunting, given the global level of the analysis. Continuous, and many times even conflicting, events affect food commodity markets somewhere in the world. We therefore only include episodes that fulfill these criteria:

—There needs 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 (for example, a sizable revision of expected agricultural production by the USDA).

—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 by at least 1 standard deviation from the sample mean.[30]

—There should be no developments in the macroeconomy, alternative events, or macroeconomic news that could 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 (1 standard deviation from its sample mean) or in economic activity (for example, a U.S. or global recession). Put differently, we eliminate or minimize possible endogenous movements in food commodity prices to current or future fluctuations in the business cycle; that is, the event in food commodity markets must be the proximate cause of the price shift.[31] No ambiguous cases are selected as episodes.

A narrative approach to identifying exogenous shocks involves judgment calls, which is a concern we acknowledge. However, we believe that we have identified 13 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

30. 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.

31. 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.

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 southeast Asia) in the summer of 1972 and the more recent Russian and Ukrainian droughts of 2010 and 2012. Conversely, a number of unanticipated significant upward revisions in the expected harvest volume (for example, in 1975, 1996, and 2004) can clearly be classified as episodes of favorable food market shocks. The dates, as well as brief descriptions of all global food commodity market events, are reported in table 1. A detailed motivation for the selected quarters can be found in the online appendix to the paper. In every case, we attempt to give explanations and quotations so other researchers can see our reasoning for classifying the episodes as food commodity market disruptions. To give an idea of our approach, the appendix at the end of this paper reproduces the motivation for the most recent shock that we identified in 2012:Q3.

III.B. Estimation Method

There is no one-to-one mapping between the true structural shocks and the observed changes in food commodity prices in these 13 episodes. We therefore first construct a dummy variable, which is equal to 1 for the unfavorable food market disturbances that we have identified and is equal to −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, Karel Mertens and Morten Ravn (2013) show that a series based on narrative evidence is robust to many types of measurement problems and is a valid instrument, as long as the series is contemporaneously correlated with the structural shock and is contemporaneously uncorrelated with all other structural shocks in the economy.

In the next step, we examine the dynamic effects of shocks to global food commodity prices on the U.S. economy using Jordà's (2005) local projection method for estimating impulse responses.[32] The advantage of the local projection method is that it is more robust to misspecification than

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

Table 1. Overview of Narrative Food Commodity Market Shocks, 1972–2012

		Cumulative change in food commodity prices (percent)		
Period	*Type*	*On impact*	*After one quarter*	*Food commodity market event*
1972:Q3	Unfavorable	1.4	18.3	**Russian Wheat Deal and failed monsoon in southeast Asia** Wheat production in the USSR declined by 13 percent 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 and onward. The negative consequences of the bad weather conditions in the USSR were only known very late, and were perceived as a considerable shock worldwide, because only a few months earlier there had been reports of heavy surplus stocks building. The sales involved a series of subsidized transactions following an agreement whereby the United States made credit available to the USSR for the purchases (known as the Russian Wheat Deal). The rise in wheat prices was further accelerated by the United States' decision 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 the summer, which was followed by extremely dry weather throughout autumn and early winter. Rice production decreased in Cambodia, India, Malaysia, and Thailand by 29 percent, 9 percent, 13 percent, and 10 percent, respectively. In 1972:Q3 and 1972:Q4, real cereal prices rose by 9.7 percent and 16.5 percent, respectively. Overall, annual global cereal production declined by 1.6 percent in 1972, compared with a rise of 9.2 percent and 7.4 percent in 1971 and 1973, respectively.

1975:Q2	Favorable	–10.9	–9.9	**Significantly 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 and demand balance of the previous two years. Furthermore, in May 1975, the USDA increased its U.S. 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 percent relative to the previous year.
1975:Q4	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 onward which is the start of the harvesting season. Real cereal prices fell by 19 percent 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 relative to 1974 by 23 percent, 7 percent, and 14 percent, respectively.
1977:Q3	Favorable	–20.9	–12.9	**Predictions of record U.S. and Soviet harvests** Several favorable food production forecasts were published throughout July and August 1977: predictions of record U.S. 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 U.S. soybeans crops (August 1977).
1977:Q4	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 the 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 percent below the latest estimate predicted by the USDA. In addition, the International Grains Council lowered its estimate of world wheat output by 2 to 3 percent. In retrospect, Soviet wheat production decreased by 5 percent compared with the previous year. Chinese wheat production declined by 18 percent; and in the United States, wheat production declined by 5 percent. It is clear that this came as an unexpected shock in 1977:Q4, given the extremely optimistic forecasts in 1977:Q3.

(*continued*)

Table 1. Overview of Narrative Food Commodity Market Shocks, 1972–2012 (*Continued*)

		Cumulative change in food commodity prices (percent)		
Period	*Type*	*On impact*	*After one quarter*	*Food commodity market event*
1984:Q3	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 U.S. 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, U.S. maize production rose considerably, by about 84 percent. Furthermore, wheat production increased in China, India, and France by 8 percent, 33 percent, and 6 percent, respectively. Overall, global cereal production increased by 11.4 percent in 1984, which was the largest annual rise since the 1960s.
1988:Q4	Favorable	−4.5	−9.4	**Expectations of a global surge in wheat production** In December 1988, it was announced by the International Grains Council that worldwide wheat production was expected to rise considerably in 1989, because, among other factors, there was a reduction in the requirement for the U.S. set-aside of arable land, from 27.5 percent to only 10 percent of the wheat acreage in the next year, which was a farm policy response to the 1988 drought in the United States (codified in the Disaster Relief and Emergency Assistance Act of 1988). In response to drought-shortened crop inventories, the 1989 version of the farm bill was expected to encourage more crop planting. Wheat production in 1989 increased in all large wheat-producing countries (China, 6 percent; France, 10 percent; India, 17 percent; the United States, 12 percent; the USSR, 11 percent). Ex post, annual global cereal production increased by more than 10 percent in 1989.

1995:Q3	Unfavorable	6.6	7.8	**Significant downward revision of world cereal estimates** In 1995:Q3, there were large downward revisions of 1995 world cereal production. This was especially the case for wheat and coarse grains production in the United States (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 of the country. In retrospect, wheat production declined in the United States and Russia by 6 percent, and in Argentina by 16 percent. Mexican corn production stagnated in 1995, but U.S. corn production decreased by 26 percent. Annual global production of the four major staples ultimately declined by 2.6 percent in 1995.
1996:Q3	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 percent 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 with 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.

(*continued*)

Table 1. Overview of Narrative Food Commodity Market Shocks, 1972–2012 (*Continued*)

Period	*Type*	*Cumulative change in food commodity prices (percent)*		*Food commodity market event*
		On impact	*After one quarter*	
2002:Q3	Unfavorable	9.4	10.7	**Significant downward revised global cereal estimates** The FAO's July 2002 forecast pointed to a global cereal output which was 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 downward since the last report mainly because of dry weather conditions in Russia. In September, the Australian Bureau of Agricultural and Resource Economics and Sciences announced that drought would slash the country's winter grain production. Australia is one of the top five wheat exporters. In retrospect, U.S. wheat production decreased by 18 percent in 2002, and Australian wheat production decreased by 60 percent.
2004:Q3	Favorable	–6.9	–10.9	**Significantly improved forecast of world cereal output** Favorable weather conditions triggered expectations of significantly higher cereal production in Europe, China, Brazil, and the United States. In July 2004, the International Grains Council announced an expected rise in the global volume of coarse grain. In September 2004, the FAO raised its forecast for world cereal output after the previous report in June. Annual global cereal production increased by more than 9 percent in 2004.

2010:Q3	Unfavorable	8.6	22.1	**Droughts in Russia and Eastern Europe** The 2010 cereal output in Moldova, Russia, Kazakhstan, and Ukraine was seriously affected by adverse weather conditions. Russia, Kazakhstan, and Ukraine (all three among the world's top 10 wheat exporters) suffered the worst heat wave and drought in more than a century, and Moldova was struck by floods and hailstorms. In Russia, the country that was most severely affected by adverse conditions, the 2010 cereal crop was 33 percent lower than the previous year. In Ukraine, the wheat harvest decreased by 19 percent. Accordingly, in July 2010, wheat prices saw the biggest one-month jump in more than three decades, a rise of nearly 50 percent since late June. In September, wheat prices were even 60 to 80 percent higher due to a decision by Russia to ban exports.
2012:Q3	Unfavorable	7.9	6.9	**Droughts around the globe** Due to droughts in Russia, Eastern Europe, Asia, and the United States, there was a significant decline in global cereal production. In retrospect, annual global cereal production contracted by 2.4 percent. In July 2012, the USDA decreased its June estimate for U.S. corn by 12 percent because of the worst midwestern drought in a quarter century. Heat waves 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 negatively affecting the rice harvest in Asia. According to the International Food Policy Research Institute, production of food grains in southern Asia was expected to decline by 12 percent compared with a year earlier. Also in August, the Russian grain harvest forecasts were reduced because of a drought. In October 2012, wheat output in Russia was estimated to be about 30 percent down from 2011; in Ukraine, a decrease of about 33 percent was expected; and in Kazakhstan, output was reported to be just half of the previous year's good level. The wheat harvest indeed declined in 2012, by 33 percent, 29 percent, and 57 percent in Russia, Ukraine, and Kazakhstan, respectively.

Source: A detailed motivation and description of the episodes in this table can be found in the online appendix.

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.[33]

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

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

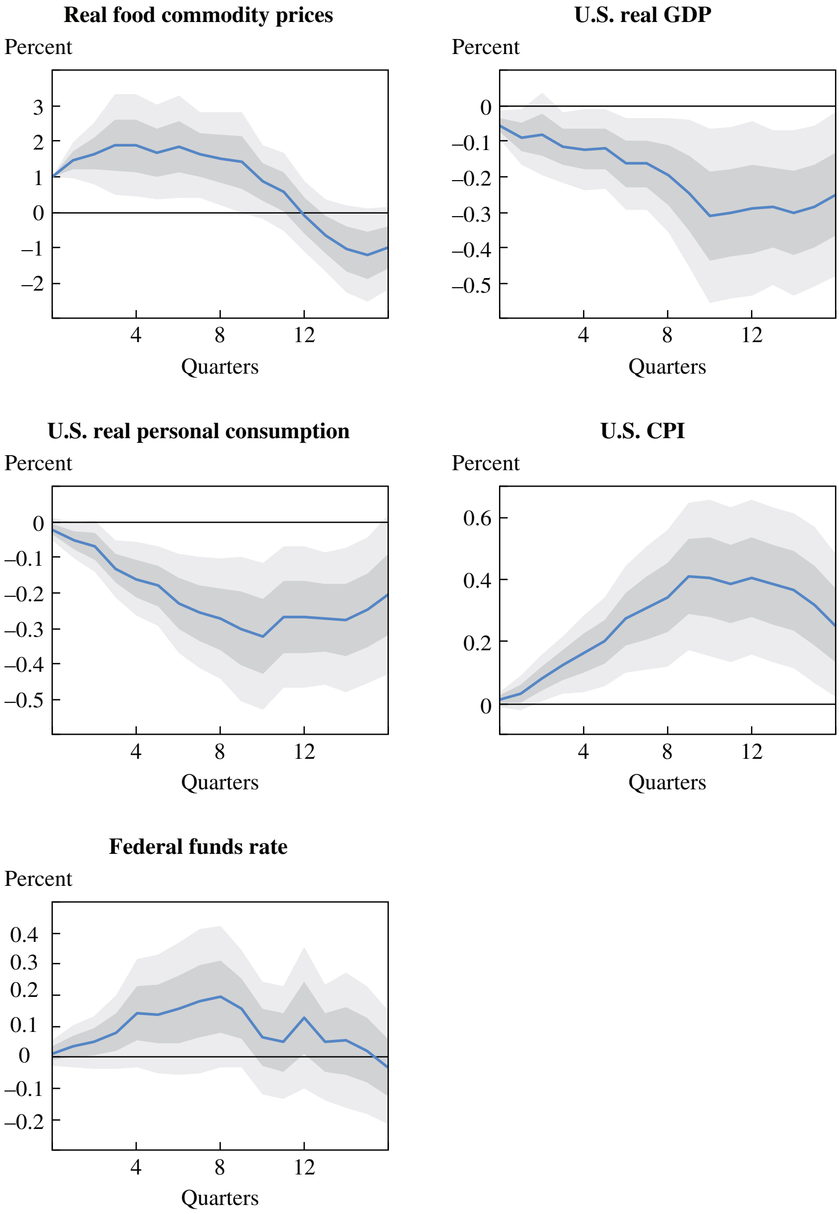
where z is the variable of interest at horizon h. We consider real food commodity prices and a set of variables representing the U.S. economy: real GDP, real personal consumption, CPI, and the federal funds rate. The term α_h is a vector of deterministic terms—a constant, linear, and quadratic time trend—$\lambda_h(L)$ 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 U.S. economy, we estimate equation 2 with the narrative dummy and the 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 the online appendix). The F statistic of the instruments (dummy and lagged dummy) is 12.6. The t statistics of the dummy and the lagged dummy are 4.9 and 1.9, respectively.

III.C. 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

33. 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 one hand, we have embedded the episodes as dummy variables in a standard VAR to estimate the macroeconomic effects, an approach similar to that taken by 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.

Figure 12. Impulse Responses to Narrative Food Commodity Supply Shocks: Local Projections[a]



Source: Authors' calculations.
a. The darker shading indicates 1 Newey–West standard error; the lighter shading indicates 2 Newey–West standard errors.

some form of a moving-average structure, with an order that is a function of 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 3 to 4 quarters. This corresponds to a rise in nominal food commodity prices of 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 the baseline after approximately 12 quarters, compared with 4 quarters in the benchmark VAR.

The persistent rise in real food commodity prices is also reflected in more persistent effects on the U.S. economy relative to the benchmark VAR results. Real GDP and real personal consumption decrease by approximately 0.3 percent, reaching their peak after 10 quarters. Taking into account the more persistent and slightly greater rise in global food commodity prices, the magnitudes of the consequences for the real economy are comparable to the VAR results reported in section II. In contrast, the impact on consumer prices and the 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 for the U.S. economy are compelling. In the next section, we examine the pass-through in more detail.

IV. The Pass-Through to Consumer Prices and Economic Activity

In subsection II.C, we 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 CPI should increase after a surge in food commodity prices, while the decline 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.[34]

To do this, we extend the VAR analysis of section I 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 U.S. economy that is disproportionately large compared with 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 by Peersman and Ine Van Robays (2009) and by Baumeister and Peersman (2013a). Specifically, unfavorable oil supply shocks are identified as innovations that are orthogonal to the identified food commodity supply shocks and are characterized by a decline in global oil production and a rise in the real price of oil, while world economic activity does not expand.[35] Second, we reestimate 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.

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

35. Since the sign restrictions are based on competitive market forces and the oil price was regulated before 1974, the results for oil supply shocks are based on VARs that have been estimated over the sample period 1974:Q1–2013:Q4. 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 nonuniform 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.

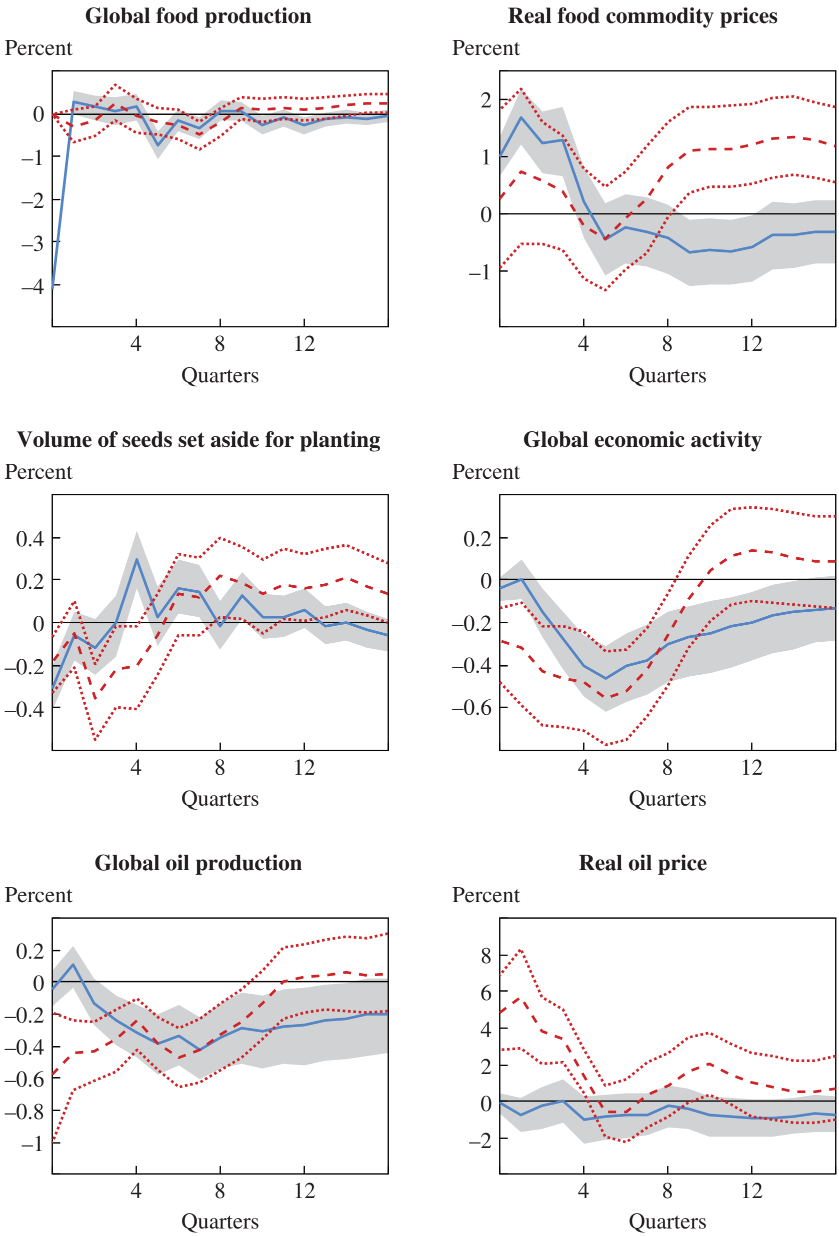
IV.A. Comparison with Oil Shocks

Figure 13 compares the impulse responses of the benchmark variables to a commodity supply shock of 1 standard deviation for crude oil and food. Some interesting facts are worth mentioning. First, an oil supply shock of 1 standard deviation 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 the 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 supply shock, although the magnitude is approximately three times larger. Second, with a peak effect of −0.39, the consequences of an oil supply shock of 1 standard deviation for 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; that is, 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 by 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 for economic activity, while partly stabilizing the real effects of oil supply shocks. This is relevant for interpreting 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 of 10 basis points leads to a decline in real GDP of between 0.05 and 0.1 percent.[36] If we take these values seriously, this implies that the contemporaneous monetary policy response to food

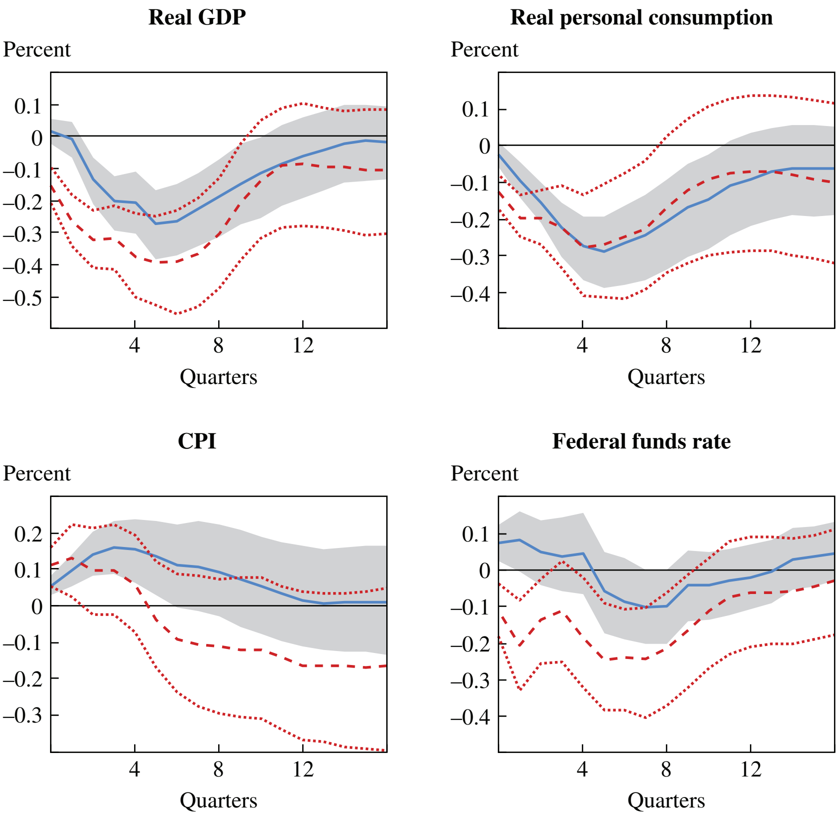
36. Christiano, Eichenbaum, and Evans (1999) find that an interest rate innovation of 60 basis points reduces real GDP by 0.5 percent. Bernanke and Mihov (1998) find that a monetary policy shock that raises the federal funds rate by 0.4 percent leads to a decline of real GDP by 0.3 percent. When we also identify a monetary policy shock within the benchmark VAR model (by ordering the federal funds rate last in the Cholesky decomposition), as discussed in subsection IV.B, 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.

Figure 13. Comparing Food Supply and Oil Supply Shocks[a]



(*continued*)

Figure 13. Comparing Food Supply and Oil Supply Shocks[a] (*Continued*)



Source: Authors' calculations.

a. The range shown around estimates are the 16th and 84th percentile error bands. The solid line and shaded area are the results of the food commodity supply shocks (same as in figure 6); the dashed and dotted lines are the results of the oil supply shocks.

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 Edelstein and Kilian's (2009) results are representative for oil supply shocks—that is, 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 indirect (nonmonetary policy) effects of food commodity and oil supply shocks on consumption are probably in the same neighborhood.[37]

IV.B. Consumer Prices

The CPI is calculated as a weighted average of prices of different types of goods and services, which can be divided into food (17 percent), energy (6 percent), and core (77 percent) CPI. A rise in food commodity prices can affect these components via several channels. First, there is a direct effect on the CPI's food component. 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—from home heating to vehicle fuels, which are a source of energy. Third, if energy prices rise, production costs for firms could also rise. If firms pass these costs through to their selling prices, the consumer prices of nonenergy goods may also rise. Finally, higher inflation or inflation expectations could trigger so-called second-round effects that could 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 in order 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 figure 14. Not surprisingly, a rise in food commodity prices has a strong and significant effect 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 through to food consumer prices. Furthermore, the effects of food commodity market disturbances on CPI energy are positive, but are not statistically significant at the 10 percent

37. 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 expenditures, and take into account that about half of gasoline prices is 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.

Figure 14. The Pass-Through to Consumer Prices[a]

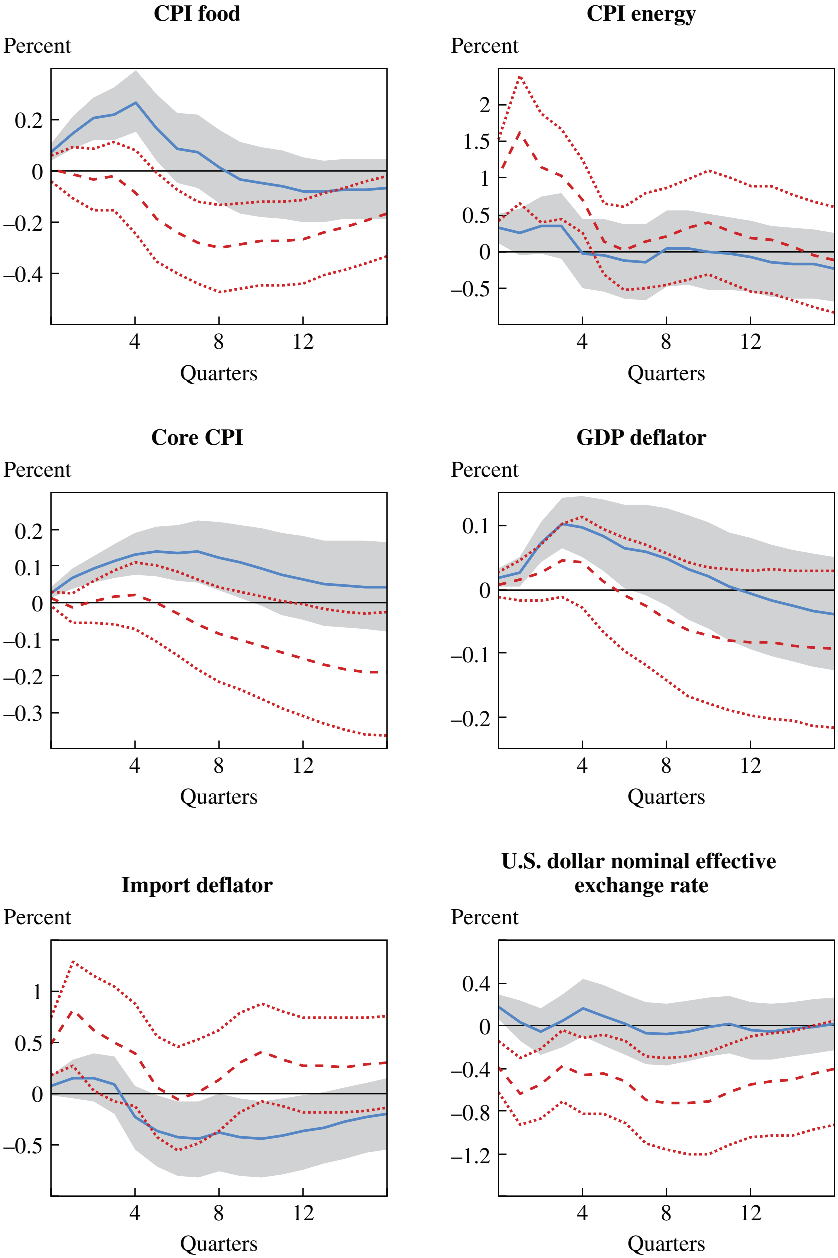
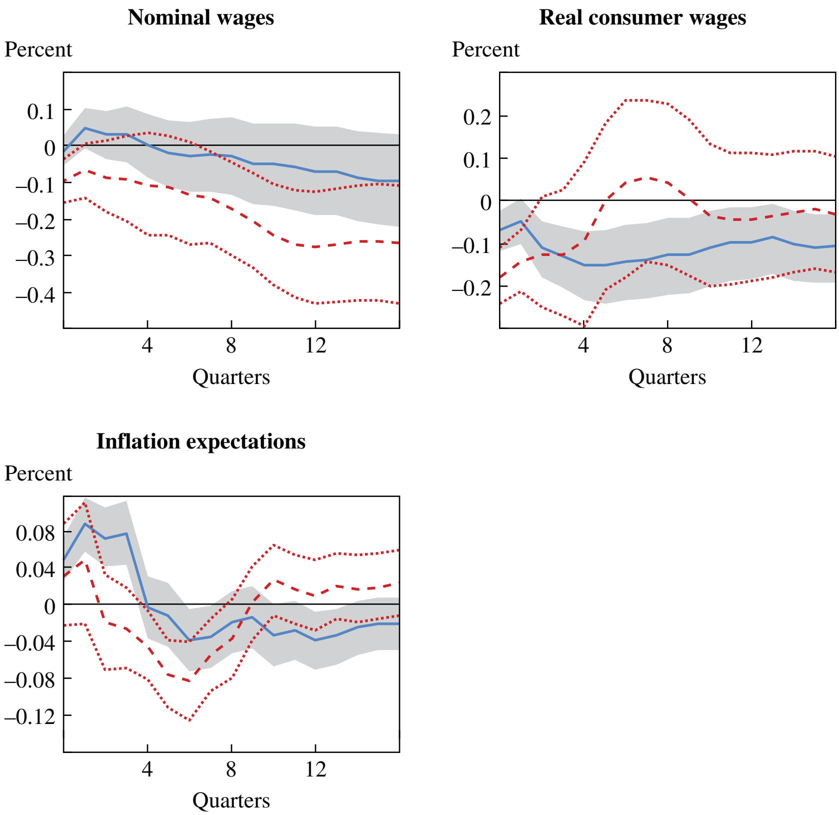


Figure 14. The Pass-Through to Consumer Prices[a] (*Continued*)



Source: Authors' calculations.

a. The range shown around estimates are the 16th and 84th percentile error bands. The solid line and shaded area are the results of the food commodity supply shocks; the dashed and dotted lines are the results of the oil supply shocks.

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 was shown in subsection II.D (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.[38] Finally, there is a significant rise of core CPI after an unfavorable food market disturbance, which reaches a peak of 0.14 percent after seven quarters. Given the share of core CPI in the overall CPI, this accounts for 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.[39]

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 U.S. 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 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 with oil supply shocks. This hypothesis is confirmed by the impulse responses of inflation expectations shown in figure 14. We observe a persistent and significant rise in 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 to the prices of nonfood and nonenergy goods and services. Furthermore, higher inflation expectations augment the demand for nominal wages in the wage-bargaining process, which further increases firms' costs and the prices of nonfood and nonenergy goods and services. The presence

38. Notice also that the error bands of the effects on CPI energy in figure 14 are relatively large, while the magnitudes of the effects are quite strong, that is, CPI energy increases by 0.31 percent on impact and 0.37 percent at its peak. In contrast, when we reestimate the VAR over a sample period that ends in 2002:Q4, the effects on CPI energy are essentially zero. The difference between the point estimates also suggests that the pass-through to energy prices has become an important channel in recent periods.

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

of second-round effects and the greater impact of food market disruptions on inflation expectations and core inflation probably also explain the Federal Reserve's tightening of monetary policy after such shocks, in contrast to a policy easing following oil supply shocks.[40]

IV.C. 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 decline in expenditures. In subsection II.C, we argued that the upper bound of such a discretionary income effect is 0.04 to 0.05 percent, while personal consumption declines by almost 0.3 percent after a food commodity supply shock of 1 standard deviation. 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 subsection IV.A, the monetary policy response can at most explain 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 subsection IV.A, the magnitudes of the indirect (nonmonetary policy) effects of both shocks are within the same neighborhood. Most important, the dynamic effects of both shocks on the components of household expenditures are also 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—that is, food and beverages for off-premises consumption—while oil supply shocks reduce the consumption of energy goods and services, not the other way around.[41] However, all other impulse responses

40. The finding that inflation expectations (and core inflation) respond more to food prices than energy prices has also been documented by Clark and Davig (2008), among 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 (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.

41. 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.

Figure 15. The Pass-Through to Household Expenditures[a]

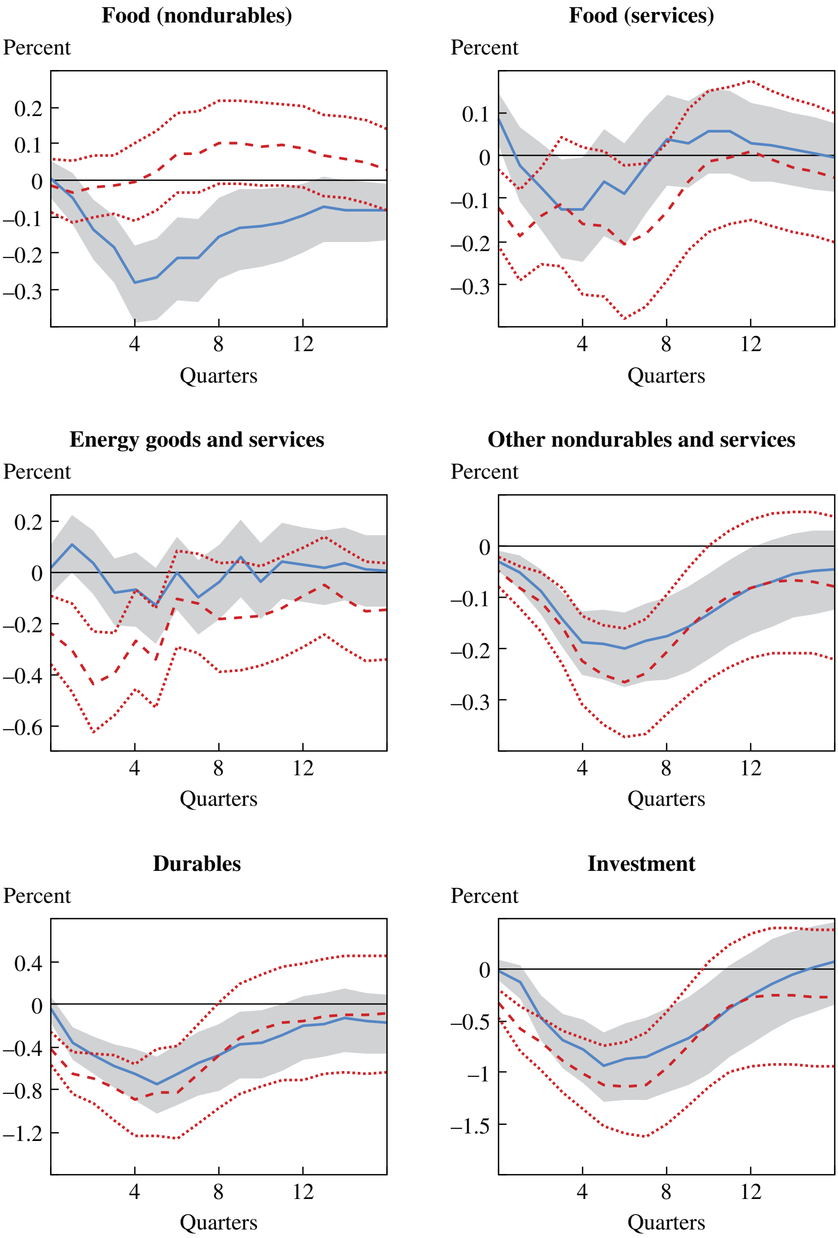
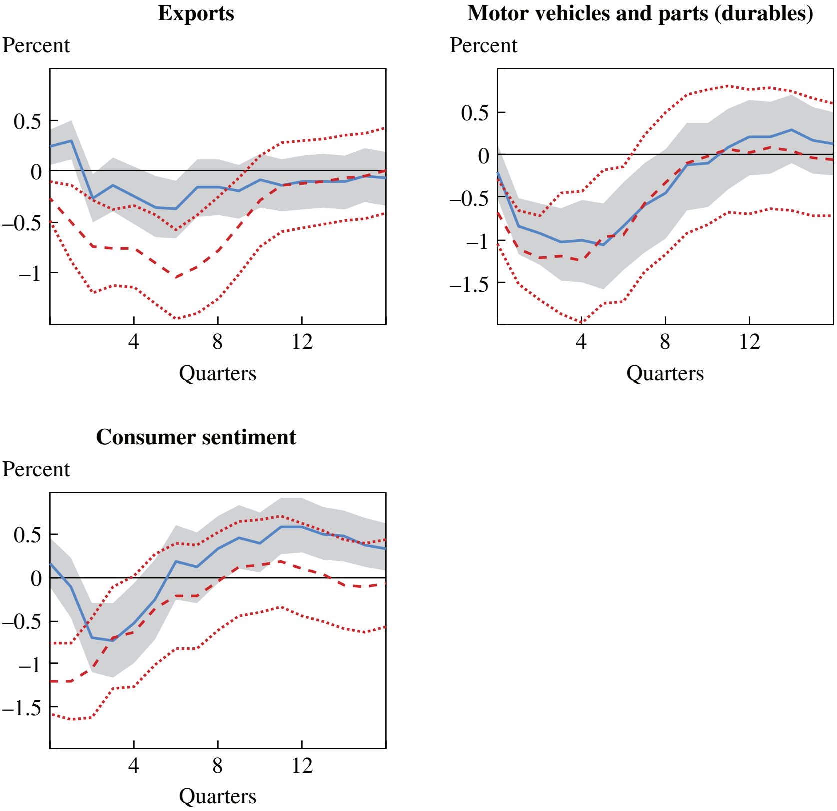


Figure 15. The Pass-Through to Household Expenditures[a] (*Continued*)



Source: Authors' calculations.
a. The range shown around estimates are the 16th and 84th percentile error bands. The solid line and shaded area are the results of the food commodity supply shocks; the dashed and dotted lines are the results of the oil supply shocks.

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 is 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 nonfood and nonenergy nondurables and services, and also purchases of durable consumption goods, are quite similar.

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 more than the overall decline in personal consumption. Likewise, there is a reduction in investment of 0.93 percent. The relevance of both output components for explaining the consequences of food market disruptions is illustrated in table 2. The table's first two columns show the maximum effects of both shocks on all the components of figure 15, while the third and fourth columns list the relative responses of the components to the response of total personal consumption. The fifth and sixth columns show the weighted effects of the components, with the weights calculated as the ratio of each component to GDP. 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.[42]

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 are driven by the monetary policy response rather than other mechanisms, because both aggregates are typically much more sensitive to interest rate changes. Though this is true, we believe that it does not change our conclusion. To illustrate this, we identify a monetary policy shock within the VAR model.[43] The maximum effects of a shift in the federal funds rate of 8 basis points—that is, the estimated contemporaneous monetary policy response to a food commodity supply shock—on all components are reported in the last 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 table's first two columns. 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 with other categories of goods

42. There is also a decline in the volume of exports 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 exports that matters for the overall output effects.

43. For simplicity, we use Christiano, Eichenbaum, and Evans's (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.

Table 2. Maximum Effects on Household Expenditures and Economic Activity

	Shock of 1 standard deviation[a]		*Ratio to total consumption*[b]		*Weighted impact*[c]		*Monetary shock of 8 basis points*[d]
	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*
Food (nondurables)	–0.28*	–0.03	0.97	0.11	–0.02*	0.00	–0.01
Food (services)	–0.13	–0.21	0.45	0.75	0.00	–0.01	–0.04*
Other nondurables and services	–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*
Exports	–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*

Source: Authors' calculations.

a. The maximum impact of a shock of 1 standard deviation on the food commodity supply and oil supply. Statistical significance is indicated at the *10 percent level.

b. The ratio of the maximum impact on the variable to the maximum impact on total consumption.

c. The maximum impact times the ratio of the component to real GDP. Statistical significance is indicated at the *10 percent level.

d. The maximum impact of a monetary policy shock of 8 basis points. Statistical significance is indicated at the *10 percent level.

and services 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.

IV.D. Potential Explanations for Magnitude and Composition of Output Effects

The remaining question is which nonmonetary policy mechanisms could magnify the consequences of both shocks for 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 the consumption of durables that are complementary in use with energy (Edelstein and Kilian 2009; Hamilton 2008). However, it is not likely that the postponement of irreversible purchases applies to food prices. Furthermore, because the purchases of motor vehicles react in a similar way to food and oil shocks, complementary effects also cannot be dominant.[44]

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, Julio Rotemberg and Michael Woodford (1996) demonstrate that imperfect competition considerably amplifies the effects of shocks on factor prices. With 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 for U.S. output. Mary Finn (2000) shows that variable capital utilization also greatly intensifies the repercussions of shifts in factor prices for the real economy, even in perfectly 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 focuses on frictions in reallocating capital and labor across sectors that may be differently influenced by oil price shifts (Davis and Haltiwanger 2001; Hamilton 1988). Such frictions lead to higher unemployment and lower capacity utilization in

44. 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.

affected sectors that can magnify the effects on economic activity.[45] A popular example in the oil literature is a reallocation of capital and labor away from the automobile sector when consumers purchase fewer cars, or a reallocation of resources within the automobile sector when consumers switch toward more energy-efficient cars in response to oil price hikes. However, food market shocks could also lead to a changed composition of aggregate demand, which could result in a costly reallocation of capital and labor across sectors that would reduce 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 important, the results given in figure 15 show that food price shocks lead to a considerably greater decline in expenditures on durable goods compared with nondurables and services, which could trigger sectoral shifts throughout the economy that further amplify the macroeconomic consequences.[46]

In fact, a stronger response of durable consumption to shocks in households' purchasing power, and possible reallocation effects that protract the macroeconomic consequences, may be a plausible mechanism to explain our empirical results—both the amplification and composition of the output effects—as well as the similarity to 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, Martin Browning and Thomas Crossley (2009) demonstrate that households can significantly reduce their total expenditures without a significant decline in welfare if they concentrate their budget reductions on durables. The reason is that a substantial reduction in expenditures on durables can be realized with only a modest decline in the consumption of durables because existing stocks of durables could continue to provide a flow of services.[47] Such a mechanism

45. These additional effects can be very large. For example, Acemoglu, Akcigit, and Kerr (2016) show that small shocks can cause sizable aggregate fluctuations due to their propagation through the production network.

46. Notice that the presence of significant reallocation effects implies that the consequences of food price increases for household expenditures should be stronger than food price decreases because such effects amplify the former, while dampening the latter. As mentioned in footnote 28, we find support for this prediction in the data.

47. Hamermesh (1982), Parker (1999), and Browning and Crossley (2000) also discuss mechanisms for 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 U.S. data for 57 types of consumer goods. Dynarski and Gruber (1997) find that the elasticity of durables to changes in income in the United States is eight times larger than for nondurables.

can explain why purchases of motor vehicles respond considerably more strongly 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 their existing car for a while, rather than buying a new car. Although the welfare losses from this behavior might be small at the individual household level, 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 U.S. Bureau of Labor Statistics' Consumer Expenditure Survey, the share of food and beverages consumption in total expenditures of the lowest income quintile was 16.2 percent in 2014, compared with 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 dramatic: 35.8 and 9.1 percent for food consumption, and 23.6 and 4.8 percent for energy consumption. Because food and energy are basic necessities, and low-income households typically also have borrowing constraints and no liquid assets to smooth consumption over time, they thus have few other options than reducing expenditures on durables.

Finally, when food prices increase, households may decide to consume less and to increase their precautionary savings because of a rise in uncertainty or a greater perceived likelihood of future unemployment and income loss. According to John Cochrane (2016), precautionary savings and risk aversion are prominent ingredients of 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's 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.

V. 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 the linkages between food commodity market fluctuations and the macroeconomy are important for designing policies that can ameliorate the consequences of these swings, these linkages are poorly understood. With global temperatures expected to rise substantially during the next decades, understanding these relationships will become even more important. In this paper, we have estimated the consequences of disruptions in global food commodity markets for the U.S. economy during the past 50 years. Because food markets also respond to developments in the macroeconomy, the main challenge in doing this is to identify 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 U.S. 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 our second, alternative identification strategy, we relied on narratives—from FAO reports, newspaper articles, disaster databases, and several other sources—to identify 13 historical episodes when significant changes in food commodity prices were mainly caused by exogenous food market events.

The structural VAR analysis and the narrative approach lead to similar conclusions. We find a considerable impact of fluctuations in food commodity markets on the U.S. economy. On 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 decline 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 CPI 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 tightening of monetary policy in order to stabilize the shocks' inflationary consequences. A better understanding of these indirect effects' exact mechanisms remains complex and is an interesting topic for future research. The construction of dynamic general equilibrium models for food markets may be useful to answer this question. Other avenues for future research are analyses of cross-country differences and consideration of the question of whether policies, such as public food security programs or monetary policy, could dampen the macroeconomic consequences of food market disruptions.

APPENDIX

Example of a Narratively Identified Global Food Commodity Market Shock: Droughts around the Globe in 2012:Q3

Type of shock: Unfavorable.

Food commodity market event:

Due to droughts in Russia, Eastern Europe, Asia, and the United States, there was a significant decline in global cereal production. In retrospect, annual global cereal production contracted by 2.4 percent. In July 2012, the USDA decreased its June estimate for U.S. corn by 12 percent because of the worst midwestern drought in a quarter century. Heat waves 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 negatively affecting the rice harvest in Asia. According to the International Food Policy Research Institute, production of food grains in southern Asia was expected to decline by 12 percent compared with a year earlier. Also in August, the Russian grain harvest forecasts were reduced because of a drought. In October 2012, wheat output in Russia was estimated to be about 30 percent down from 2011; in Ukraine, a decrease of about 33 percent was expected; and in Kazakhstan, output was reported to be just half of the previous year's good level. The wheat harvest indeed declined in 2012, by 33 percent, 29 percent, and 57 percent in Russia, Ukraine, and Kazakhstan, respectively. The EM-DAT database of international disasters lists droughts in Ukraine (April 15, 2012 to July 31, 2012), Russia

(June 2012 to September 2012), and the United States (June 2012 to December 2012).

We allocate the shock to 2012:Q3 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 percent in that quarter, whereas oil prices decreased by 1.6 percent. The same comment about the Greek debt crisis reported for the 2010:Q3 shock applies for 2012:Q3 (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:

Charles Abbott, "Midwest Drought Slashes Corn Estimate, Jolts Market," *Reuters* (July 12, 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. *The 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.

Rudy Ruitenberg, "Europe Heat Wave Wilting Corn Adds to U.S. Drought," *Bloomberg* (July 24, 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.

Prabhudatta Mishra, "Rice Harvest in India Set to Drop as Drought Curbs Sowing," *Bloomberg* (August 16, 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.

Polina Devitt, "Russia Harvest Forecasts Cut as Drought Hits Crop in East," *Reuters* (August 20, 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.

Global Information and Early Warning System, "Crop Prospects and Food Situation," no. 3 (October 2012), Rome: United Nations, Food and Agricultural Organization.

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.

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Comments and Discussion

COMMENT BY

WOLFRAM SCHLENKER This paper by Jasmien De Winne and Gert Peersman presents an innovative analysis of whether food commodity price shocks have ramifications throughout the larger economy. There is a large body of literature discussing how oil price fluctuations might have an impact on the economy, yet very little work has been done examining the effects of food commodity price fluctuations.

The authors address this question in two ways: empirically, by estimating a vector autoregression (VAR) model; and narratively, by examining the economic response to 13 episodes of significant commodity market surprises. The VAR cleverly extends a previous analysis that used annual commodity yield shocks of the four staple commodities—corn, wheat, rice, and soybeans—as instruments for commodity prices. The authors utilize calendars for the various crops to define the quarters for which production shocks should show up as news. The analysis concentrates on crops and countries where the harvest time falls in a different quarter than the planting time. Farmers endogenously choose how much to plant; but, conditional on the planted area, production shocks at harvest time are predominantly exogenously determined by the effect of weather on yields. The authors find a large effect of commodity price shocks on U.S. GDP. There is even a surprisingly large positive effect on durables like cars.

The VAR is discussed in more detail in Mark Watson's comment. Here, I focus on a puzzle in the mechanism behind the discovered relationship and a reduced-form sensitivity check.

COMMODITY PRICES VERSUS FOOD PRICES When talking about prices, it is important to separate the raw *commodity* prices that farmers receive for their products from the *food* prices that consumers pay at the store. Though the latter accounted for, on average, 17 percent of households' expenditures in the 1960–2015 period, the fraction that falls on the pure commodity cost is rather minor. Michael Roberts and I (2013) estimate that for a 2,000-calorie daily diet of raw, unprocessed rice, the annual commodity cost fell in real terms during the 20th century, and is currently less than $100. Because nobody eats raw, unprocessed rice and nothing else, this is of course a hypothetical example. A meat-based diet would have higher commodity costs; 1 calorie of meat requires more than 1 calorie of feedstock, as a large fraction of the feedstock is used to sustain the animal. But the largest component of the final food price consumers end up paying at the store is the processing and distribution cost. There is a big difference between changes in the price of raw commodities—which can easily double in response to production shocks due to the inelastic demand for commodities—and the change in food prices at the supermarket.

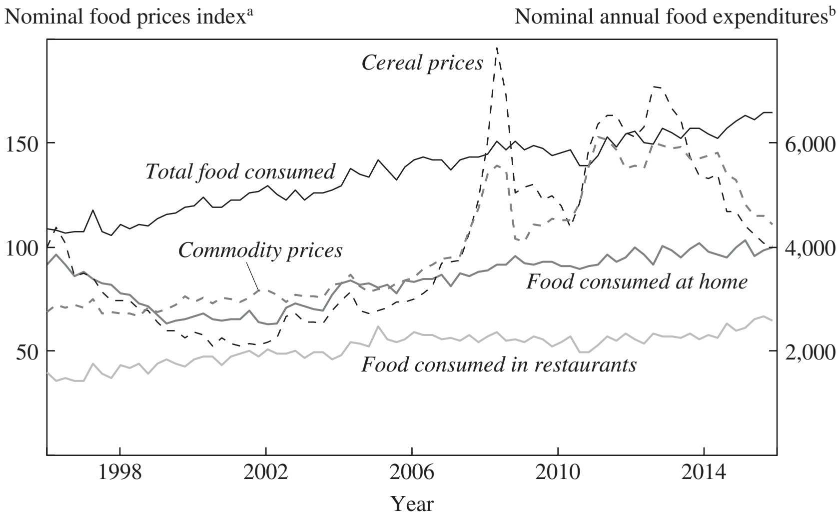
This point has been made by Christiane Baumeister and Lutz Kilian (2014), who show that fluctuations in oil prices do not translate into changes in the food prices consumers pay at the store. They emphasize,

> The distinction between retail food prices and the prices received by farmers for grain crops and livestock is important. . . . The discrepancy between the slow growth in real consumer food prices and the more rapid growth in the crop prices received by farmers is explained by the small cost share of agricultural products in the food prices paid by U.S. consumers. For example, the farm value of wheat in the price of bread is only about 5 percent, so even substantial wheat price increases are associated with only small increases in the price of bread. (Baumeister and Kilian 2014, p. 736)

This raises a question about the possible mechanism between commodity prices that farmers receive and overall economic fluctuations in the United States: Are the observed commodity price swings large enough to change how much consumers pay at the store? If not, how would higher commodity prices affect consumer spending, and possibly make an impact on the larger economy?

My figure 1 plots the quarterly commodity price index for both the large basket of commodities and the narrower cereal price index from De Winne and Peersman for the years 1996–2015. The dashed lines show the large rise between 2005 and 2008, especially for the cereal index, where prices roughly tripled. The figure also shows food expenditures taken from the diary files of the U.S. Bureau of Labor Statistics' Consumer Expenditure Survey. Weekly expenditures are aggregated to the quarterly level to match De Winne and Peersman's time scale, and are then multiplied by four to get the corresponding annual cost in nominal dollars, as shown on the right vertical axis. The solid black line shows total expenditures, which increase

Figure 1. Commodity Prices versus Food Price Expenditures, 1996–2015



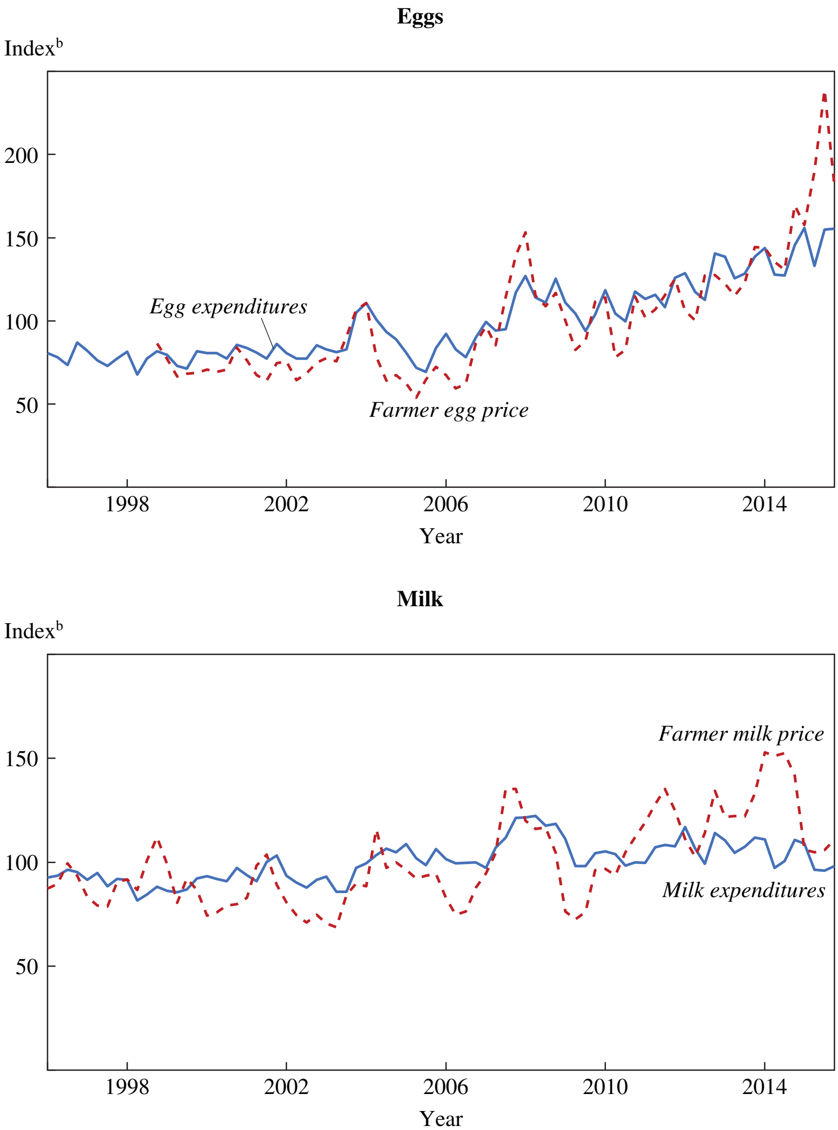
Sources: De Winne and Peersman; U.S. Bureau of Labor Statistics, Consumer Expenditure Survey.
a. The values are indexed so that the average nominal food price equals 100.
b. Weekly nominal food expenditures are aggregated to the quarterly level, and are multiplied by 4 to give the annual cost.

smoothly over time, from roughly $4,500 in 1996 to $6,500 in 2015. The solid gray lines separate total expenditures into ones for food consumed at home and in restaurants. These lines rise smoothly over time as well.

The disconnect between commodity prices and food expenditures is apparent. The former roughly tripled, yet the latter hardly budged at all. There might be differences between farmers' commodity prices and consumers' food expenditures. Stores might choose not to pass on all fluctuations. Alternatively, an increase in prices might be offset by a decrease in the quantity consumed, though the complete unresponsiveness in expenditures when commodity prices triple seems odd, given the highly inelastic demand. For comparison, my figure 2 plots prices for eggs and milk as well as food expenditures from the diary files from the Consumer Expenditure Survey. Both eggs and milk are much harder to store than raw commodities, so farmer prices fluctuate more wildly because shocks cannot be smoothed across time; yet, the two series of farmer prices and store prices appear to be very much linked.

The most likely reason why consumers' food expenditures do not respond to farmers' commodity prices for the four basic staples—corn, wheat, rice,

Figure 2. Food Prices versus Food Expenditures for Eggs and Milk, 1996–2015[a]



Sources: U.S. Department of Agriculture, National Agricultural Statistics Service; U.S. Bureau of Labor Statistics, Consumer Expenditure Survey.

a. For food prices, monthly data are averaged over the three months of each quarter; for consumer expenditures, weekly data are aggregated to the quarterly level.

b. The values are indexed so that the average nominal food price equals 100.

and soybeans—is that the latter are a small fraction of the former. If food expenditures do not respond to commodity prices, is the observed significant relationship between commodity prices and the economy at large real? The next section presents an alternative reduced-form sensitivity check.

REDUCED-FORM ANALYSIS USING CALORIC SHOCKS De Winne and Peersman's VAR uses production in the harvest quarter as a variable. Not all changes in total production are news, given that some are anticipated and endogenous, such as changes in the growing area. This is accounted for in the VAR by incorporating commodity prices, which should reflect all information the market knew at the time of the harvest. However, the linearity in the VAR model might be inadequate to model all nonlinear responses to changes in expectations and prices.

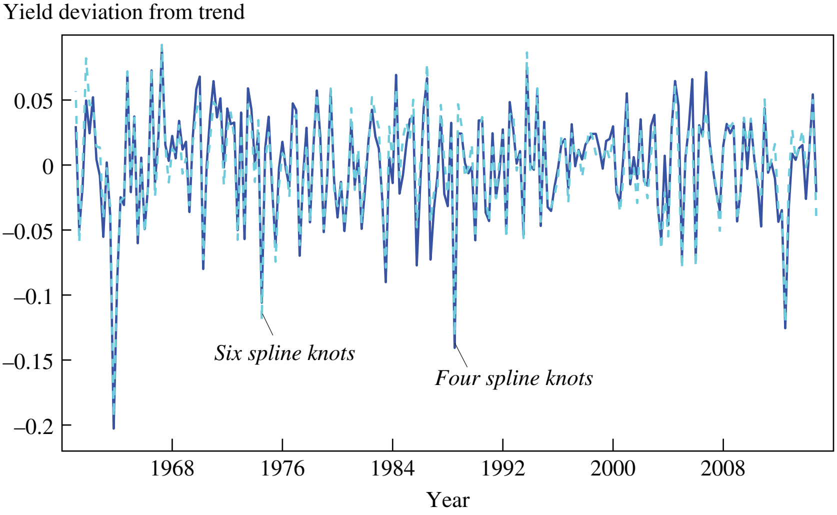
An alternative to including total production as a variable is to construct shocks that are unexpected news. My figure 3 shows such unexpected quarterly caloric shocks, which are constructed as residuals from a regression of log yields to country- and crop-specific time trends. They are then summed over all countries and crops using predicted production weights and the caloric content of each crop. For a detailed description of how these shocks are derived, see Roberts and Schlenker (2013, p. 2271). The only difference between my figure 3 and Roberts and Schlenker's (2013) methodology is that my shocks are aggregated to the quarterly level, whereas Roberts and Schlenker aggregate to the annual level. The harvest starts as defined by De Winne and Peersman's crop calendar. My figure 3 shows the results when the time trend is modeled as a restricted cubic spline with either four or six knots. The number of knots has a negligible effect on the shocks, because yields have been trending upward very smoothly over time. The shocks (deviations from a country- and crop-specific trend) are exogenous and random in time, making them ideal as an instrument.

My table 1 presents the results of a simple reduced-form regression when various quarterly dependent variables, y_t, are regressed on the caloric production shocks that are due to yield anomalies w_t (both a contemporaneous term and five lags to match the lag structure of De Winne and Peersman), quarterly fixed effects $\alpha_{q(t)}$, and a time trend $f(t)$, which is again flexibly modeled as a restricted cubic spline with either four or six knots:

$$y_t = \alpha_{q(t)} + \sum_{k=0}^{5} \beta_k w_{t-k} + f(t) + \varepsilon_t.$$

Various variables used by De Winne and Peersman are used as the dependent variable: Columns 1 and 2 use their real commodity price index; columns 3 and 4 use the real cereal price index; columns 5 and 6 use real

Figure 3. Caloric Shocks, 1960–2015[a]



Sources: Author's calculations; Roberts and Schlenker (2013).

a. This figure shows caloric shocks in the harvesting quarter, following the crop calendar used by De Winne and Peersman. The model regresses log yields on time trends for each crop and country, and derives the residuals. The log deviations are aggregated over all crops and countries for the harvesting quarter using the predicted production (yield trend × actual area), multiplied by a caloric conversion factor as weight. Time trends are modeled as restricted cubic splines with four or six knots.

U.S. GDP; and columns 7 and 8 use real global production. The odd-numbered columns use a restricted cubic spline time trend with four knots, while the even-numbered columns use six knots. The top panel estimates the model in first differences of the log variables, while the bottom panel estimates the model in log levels.

Focus on the differenced results in the top panel: The results for commodity price in columns 1 and 2 are highly significant; an unexpected caloric shock in production leads to a large, significant change in prices of the opposite sign. The large magnitude is due to the extremely inelastic demand for the good, and supply usually requires a full year (four quarters) to respond during the next annual cropping cycle. The timing also seems intuitive; prices move in the two quarters after new production shocks are revealed. The second quarter might be an artifact of the classification scheme, where harvesting periods that span two quarters are assigned to the first. Shocks might not be fully revealed until quarter $t + 1$. The coefficients a year later in quarters $t + 4$ and $t + 5$ are significant and of the opposite sign, as production shortfalls can be counterbalanced in the next growing season by increasing the growing area. The combined effect—the sum of

Table 1. Reduced-Form Effects of Unexpected Production Shocks[a]

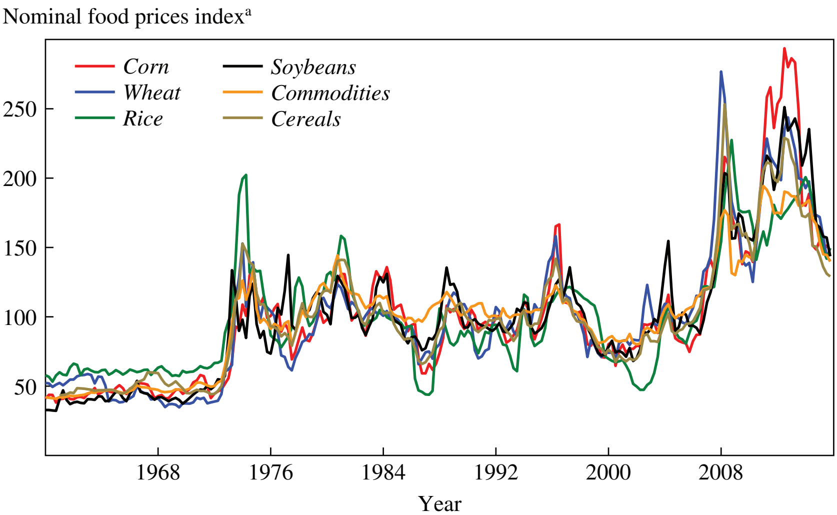
	Commodity price		*Cereal price*		*GDP*		*Global production*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Regression in first differences of log dependent variables								
Shock in t	−4.92***	−5.48***	−5.64**	−6.33**	−0.00	0.00	0.01	0.00
	(1.68)	(1.69)	(2.69)	(2.87)	(0.01)	(0.01)	(0.02)	(0.02)
Shock in $t-1$	−3.85**	−4.30**	−3.96*	−4.67*	−0.01	−0.01	−0.01	−0.02
	(1.87)	(1.95)	(2.23)	(2.39)	(0.01)	(0.02)	(0.02)	(0.02)
Shock in $t-2$	1.71	1.52	0.89	−0.05	−0.00	0.00	−0.01	−0.01
	(2.15)	(2.46)	(2.47)	(2.69)	(0.01)	(0.01)	(0.02)	(0.02)
Shock in $t-3$	−0.16	−0.64	−0.52	−0.66	−0.00	−0.00	−0.00	−0.00
	(1.77)	(1.87)	(2.29)	(2.42)	(0.01)	(0.01)	(0.02)	(0.02)
Shock in $t-4$	6.81***	6.24***	6.33***	5.42**	−0.01	−0.00	0.02	0.02
	(1.75)	(1.80)	(2.41)	(2.38)	(0.01)	(0.01)	(0.02)	(0.02)
Shock in $t-5$	4.92***	4.32	7.11***	6.05**	0.02	0.02	0.03*	0.03*
	(1.70)	(1.59)	(2.32)	(2.34)	(0.02)	(0.02)	(0.02)	(0.02)
Combined effect	4.52	1.67	4.22	−0.24	−0.01	0.01	0.03	0.02
	(3.77)	(4.09)	(5.04)	(5.71)	(0.03)	(0.03)	(0.03)	(0.04)

Regression in levels of log dependent variables								
Shock in t	−9.05*	−10.33**	−9.87	12.13	0.13***	0.03	0.09*	−0.02
	(4.66)	(4.89)	(7.20)	(7.62)	(0.05)	(0.04)	(0.06)	(0.05)
Shock in $t-1$	−13.08**	−14.44***	−14.31*	−17.06**	0.12**	0.02	0.08	−0.04
	(5.35)	(5.49)	(7.63)	(7.72)	(0.05)	(0.04)	(0.05)	(0.05)
Shock in $t-2$	−11.24**	−11.62**	−12.75*	−15.00**	0.13***	0.02	0.08	−0.04
	(4.88)	(4.75)	(7.56)	(7.43)	(0.05)	(0.04)	(0.05)	(0.05)
Shock in $t-3$	−11.72**	−12.13***	−13.41*	−15.38**	0.13***	0.01	0.07	−0.05
	(4.74)	(4.66)	(7.77)	(7.49)	(0.05)	(0.04)	(0.05)	(0.05)
Shock in $t-4$	−5.46	−6.58	−7.78*	−10.62	0.12**	0.01	0.08	−0.03
	(4.56)	(4.37)	(7.44)	(7.11)	(0.05)	(0.04)	(0.05)	(0.04)
Shock in $t-5$	−0.26	−0.93	−0.22	−2.73	0.12***	0.02	0.11**	0.00
	(4.43)	(4.29)	(7.00)	(6.69)	(0.05)	(0.04)	(0.05)	(0.05)
Combined effect	−50.81***	−56.03***	−58.33***	−72.92***	0.74***	0.13	0.51***	−0.19**
	(9.76)	(11.69)	(16.50)	(19.18)	(0.09)	(0.10)	(0.09)	(0.09)
Time trend	4 knots	6 knots	4 knots	6 knots	4 knots	6 knots	4 knots	6 knots

Source: Author's calculations.

a. Regressions include quarterly fixed effects and cubic splines as time trends, with either four or six spline knots. Standard errors are in parentheses. Statistical significance is indicated at the ***1 percent, **5 percent, and *10 percent levels.

Figure 4. Comparison of Various Commodity Prices, 1960–2015



Sources: De Winne and Peersman; U.S. Department of Agriculture, National Agricultural Statistics Service.
a. Monthly data are averaged over the three months of each quarter. The values are indexed so that the average nominal food price equals 100.

the six individual coefficients—is given at the bottom of each panel. They are insignificant because temporary price spikes disappear in the next growing season, when production responses can take place. My figure 4 shows that commodity prices move very closely together; the figure compares De Winne and Peersman's price indexes with data for the four commodities, corn, wheat, rice, and soybeans. Correlations of the price deviations from a time trend are given in my table 2; they are generally very high, on average about .80.

Conversely, the results for GDP and global production in the last four columns of my table 1 suggest no significant effects of production shocks on GDP or global production in any of the following five quarters. The combined effect is very small in magnitude and not significantly different from 0.

The bottom panel of my table 1 uses levels as a sensitivity check, which might be questionable for variables that are not stationary but is shown for comparison purposes. Price effects are again significant and of a large magnitude, while the effects on GDP and global production are sometimes significant, but can have the opposite sign found by De Winne and Peersman. The results are highly sensitive to whether one includes four or six spline

Table 2. Correlation of Price Deviations from a Trend

	Corn price		*Wheat price*		*Rice price*		*Soybean price*		*Commodity price index*		*Cereal price index*	
	4 knots	*6 knots*	*4 knots*	*6 knots*	*4 knots*	*6 knots*	*4 knots*	*6 knots*	*4 knots*	*6 knots*	*4 knots*	*6 knots*
Corn price: 4 knots	1.0000											
Corn price: 6 knots	0.9911	1.0000										
Wheat price: 4 knots	0.8009	0.8116	1.0000									
Wheat price: 6 knots	0.8106	0.8208	0.9882	1.0000								
Rice price: 4 knots	0.7595	0.7530	0.7000	0.7099	1.0000							
Rice price: 6 knots	0.7468	0.7567	0.7094	0.7165	0.9923	1.0000						
Soybean price: 4 knots	0.6360	0.6344	0.6201	0.6551	0.6389	0.6331	1.0000					
Soybean price: 6 knots	0.6397	0.6457	0.6616	0.6695	0.6472	0.6504	0.9824	1.0000				
Commodity price index: 4 knots	0.7609	0.7553	0.8531	0.8624	0.8317	0.8251	0.6847	0.6969	1.0000			
Commodity price index: 6 knots	0.7471	0.7580	0.8556	0.8686	0.8229	0.8311	0.6846	0.6993	0.9920	1.0000		
Cereal price index: 4 knots	0.8434	0.8448	0.8590	0.8811	0.7754	0.7729	0.7942	0.7944	0.8975	0.8972	1.0000	
Cereal price index: 6 knots	0.8360	0.8465	0.8764	0.8856	0.7721	0.7792	0.7766	0.7955	0.8962	0.9022	0.99441	1.0000

knots. The more flexible specification using six knots gives insignificant results or significant results that have a counterintuitive sign.

In summary, the reduced-form regression linking U.S. GDP and global production to unexpected food price shocks does not corroborate the finding that food price shocks have an impact on the economy at large. So why do the authors find them? One explanation might be that the effects are real but small enough that the reduced-form analysis does not pick them up. A lack of evidence does not necessarily show the lack of an effect, although the standard errors are fairly small.

An alternative explanation might be that instead of food prices affecting GDP, there are omitted confounders. An emerging literature shows that weather has strong influences on GDP growth (Dell, Jones, and Olken 2012; Boldin and Wright 2015; Burke, Hsiang, and Miguel 2015) and conflict (Hsiang, Meng, and Cane 2011; Hsiang, Burke, and Miguel 2013). If detrimental weather shocks cause both agricultural and other sectors to decline while commodity prices spike, there might be an induced correlation that is not causal. The authors address this by only using agricultural shocks outside the United States, but the spurious correlation might even be at work if countries' GDPs are linked through international trade. On top of this, the VAR structure might be too restrictive to force the identification to rest on unexpected shocks. This empirical puzzle—that the VAR detects a relationship that the reduced-form analysis fails to pick up—needs to be addressed by future research.

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COMMENT BY

MARK W. WATSON This paper by Jasmien De Winne and Gert Peersman is an ambitious and careful analysis of the effects of global food supply shocks on the U.S. macroeconomy. The authors use a familiar framework—structural vector autoregression (SVAR)—and related distributed lag models. Their key challenge is to identify exogenous variation in global food production that can be used to estimate the dynamic causal effects of global food shocks on the U.S. macroeconomy. They do this in two complementary ways, both involving the construction of new data series.

For their first approach, they construct a quarterly index of crop harvests for four staple food commodities using data covering nearly 200 countries. They argue that much of the unforecastable variation in harvests is exogenous because planting decisions are made in the quarters before the harvest. Using this logic, 1-quarter-ahead forecast errors in their production index are exogenous food supply shocks. The dynamic causal effects of food shocks can be identified by ordering their global food production index as the first variable in an SVAR identified by a Wold causal ordering.

For their second approach, they construct a time series of narrative shocks that isolate quarters in which major changes in food production were caused by judgmentally determined exogenous factors. The authors find 13 such quarters during their 1963–2013 sample period. They use the resulting set of indicator variables as instruments to estimate dynamic causal effects in a series of distributed lag models.

Both approaches yield similar conclusions; an unexpected increase in global food supply leads to (i) a reduction in global food prices, (ii) an increase in U.S. GDP, (iii) a decrease in both overall and core prices, (iv) a decrease in interest rates, and (v) a relatively large increase in expenditures on durable consumption goods. The authors argue that part of the channel from food production shocks to expenditures on consumer durables runs through interest rates—that is, Federal Reserve easing as inflation falls following a favorable food supply shock.[1] But their estimates suggest that this interest rate channel is responsible for only one-third of the total effect. The channel (or channels) explaining the remaining two-thirds remains a mystery, although the authors provide several interesting conjectures.

Here, I use an alternative econometric framework—a structural dynamic factor model (SDFM)—to estimate the causal effect of global food shocks

1. See Bernanke, Gertler, and Watson (1997) for a related analysis of the monetary policy channel for oil shocks.

on the U.S. macroeconomy. I have two goals: first, to gauge the robustness of the authors' conclusions; and second, to see if the alternative framework provides additional clues as to why global food supply shocks have such a large effect of expenditures for consumer durables. To preview the results, I find the authors' main empirical conclusions are robust to this alternative framework, but the SDFM suggests that the interest rate channel may be more important than is suggested by the authors' SVAR.

I begin by briefly reviewing the SDFM and how it (usefully, in my mind) extends the authors' SVAR analysis.[2] A key feature of the SDFM is that it easily scales up to incorporate more variables. In a standard n-variable SVAR, the number of parameters to be estimated is of the order n^2; in an SDFM, the number of parameters is of the order n. This makes it possible to include many more variables in an SDFM than would be feasible in an SVAR. For example, I use more than 200 macroeconomic variables in the SDFM to estimate the effect of global food supply shocks. The large number of variables in the SDFM gives it two distinct advantages over an SVAR: First, it attenuates omitted variable and measurement error biases in estimates of the unobserved structural shocks; and second, it provides a coherent framework for estimating the effect of shocks on a large number of macroeconomic variables. The general SDFM has the form

$$X_t = \Lambda F_t + e_t, \tag{1}$$

$$F_t = \Phi(\mathrm{L}) F_{t-1} + G\eta_t, \tag{2}$$

where X_t is an $n \times 1$ vector of observed variables ($n > 200$ in this application), F_t is a $k \times 1$ vector of unobserved factors where k is relatively small ($k = 8$ here), e_t is a vector of idiosyncratic errors, and η_t is a vector of the model's structural shocks. My interest is in global food shocks, so they are an element of η_t.

When interest focuses on a structural shock that has only a small effect on most of the variables in the model, its factor needs to be tightly connected to an observed series (Stock and Watson 2016). As De Winne and Peersman show, this is the case for food supply shocks, as they explain

2. Stock and Watson (2016) provide a comprehensive survey of dynamic factor models and how the structural versions of these models, SDFMs, are related to SVARs. The empirical results presented here use this framework, and are closely related to the analysis of oil supply shocks appearing in Stock and Watson's (2016) survey.

only a small amount of the variability in U.S. macroeconomic variables. This leads me to specify equation 1 of the SDFM as

$$(3) \qquad X_t = \begin{bmatrix} Q_t^{Food} \\ P_t^{Food} \\ Y_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ \lambda_{F^{Q-Food}} & \lambda_{F^{P-Food}} & \lambda_{F^{Other}} \end{bmatrix} \begin{bmatrix} F_t^{Q-Food} \\ F_t^{P-Food} \\ F_t^{Other} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ e_t^{TY} \end{bmatrix},$$

where Q_t^{Food} is the logarithm of the global food supply index constructed by De Winne and Peersman, P_t^{Food} is the logarithm of the food commodity price index constructed by De Winne and Peersman, and Y_t is a vector of more than 200 macroeconomic variables, as described by Stock and Watson (2016). From equation 3, the first factor, F_t^{Q-Food}, is the global food index and the second factor, F_t^{P-Food}, is the food commodity price index. The other factors, F_t^{Other}, are not directly observed, and they correspond to macroeconomic factors beyond food supply and food prices that cause common variation in the macroeconomic variables included in Y_t. Finally, using the same timing assumption as the authors' SVAR, I set the first row of G in equation 2 as (1 0 . . . 0), so that the first element of η_t is the global food supply shock. I estimate the model using six factors in F_t^{Other} and four lags of F in the VAR in equation 2.

My table 1 shows the estimated impulse effects, $\partial X_{i,t+h}/\partial\eta_t^{Q-Food}$, computed using the SDFM model along with the fraction of forecast error variance associated with the food supply shock, η^{Q-Food}. The first row shows that the food shock has a unit impact effect on the logarithm of global food production and an R^2 of 1, which follow from the identifying assumptions that the shock yields a 1 log point increase in food production, and this shock explains all of the 1-quarter-ahead forecast error. The next row shows the estimated effect of this shock on the logarithm of the food commodity price index after $h = 1$ quarter. Food prices fall by 0.39 log points, and food supply shocks explain just 7 percent of the variance in food prices at this horizon. The SDFM includes more than 200 variables, and the remaining rows of the table show impulse responses for a subset of these variables after $h = 5$ quarters.

The SDFM's estimates suggest many of the same conclusions as the SVAR used by the authors. An exogenous 1 log point increase in global food supply leads to (i) a nearly identical fall in global food prices (0.39 in the SDFM versus 0.41 in the SVAR); (ii) an increase in U.S. GDP; (iii) decreases in both overall and core prices, both measured by personal

Table 1. Estimated Effect of Global Food Supply Shocks on Selected Variables from a Structural Dynamic Factor Model[a]

Variable	*Impulse response at horizon* h	$R^2(h)$
Global food production ($h = 0$)	1.000 (0.000)	1.00
Food commodity price index ($h = 1$)	–0.390 (0.110)	0.07
Other variables ($h = 5$)		
GDP	0.037 (0.021)	0.01
Consumption	0.050 (0.020)	0.04
Consumption: durables	0.153 (0.070)	0.03
Consumption: nondurables	0.044 (0.019)	0.03
Consumption: services	0.027 (0.010)	0.03
Investment	0.046 (0.082)	0.00
Investment: fixed nonresidential	–0.002 (0.062)	0.01
Investment: fixed residential	0.340 (0.120)	0.04
Industrial production	0.023 (0.040)	0.01
Industrial production: consumer durables	0.128 (0.075)	0.01
Industrial production: automobiles	0.190 (0.107)	0.01
Employment	0.009 (0.016)	0.00
Unemployment rate	–0.810 (0.951)	0.01
Labor productivity	0.034 (0.017)	0.02
Housing permits	0.656 (0.226)	0.04
Retail sales	0.097 (0.039)	0.04
PCE prices	–0.063 (0.028)	0.04
PCE prices: core	–0.029 (0.014)	0.02
PCE prices: food and beverages	–0.137 (0.058)	0.05
PCE prices: durable goods	–0.038 (0.027)	0.01
PCE prices: services	–0.028 (0.015)	0.03
Federal funds rate	–4.310 (2.140)	0.04
10-year Treasury bond rate	–2.440 (0.880)	0.03
30-year mortgage rate	–3.000 (1.130)	0.04
Senior Loan Officer Opinion Survey[b]	3.730 (1.300)	0.06
Excess bond premium[c]	–0.660 (0.305)	0.01
S&P 500 Index	0.293 (0.183)	0.01
Housing prices	0.068 (0.034)	0.02
Exchange rates	–0.114 (0.059)	0.02
Consumer expectations	2.460 (0.850)	0.04
Oil production	0.062 (0.026)	0.01
Oil prices	–0.483 (0.260)	0.03
CPI gasoline	–0.259 (0.141)	0.03

Sources: Author's calculations; Stock and Watson (2016).

a. $R^2(h)$ is the fraction of the (h + 1)-quarter-ahead forecast error associated with the global supply shock. Standard errors (computed using parametric bootstrap simulations) are in parentheses.

b. The Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices is a quarterly survey of large banks that seeks qualitative information with respect to changes in bank lending practices in the previous quarter.

c. The excess bond premium measure comes from Gilchrist and Zakrajšek (2012).

consumption expenditures (PCE) in the SDFM; (iv) a decrease in interest rates; and (v) a relatively large increase in expenditures on consumer durables.

That said, there are interesting quantitative differences in the estimated effects of the SDFM and SVAR that, when coupled with the information from other variables, suggest a more important role for interest rates in the transmission of food shocks to the macroeconomy. For example, in addition to large effects on consumer durable expenditures and automobile production, food shocks have large effects on residential investment and new housing permits. Evidently, sectors that are sensitive to the interest rate are particularly affected by food shocks. The SDFM suggests a somewhat smaller effect of the shocks on GDP (roughly 60 percent of the size of the SVAR effect), and a larger and more persistent effect on the federal funds rates (consistent with the results for the authors' FAVAR model in their figure 11). Longer-term interest rates (10-year Treasury bonds and 30-year mortgage rates) fall significantly following a favorable food supply shock. Other financial variables also move in ways consistent with an easing of monetary policy: Stock prices rise, the dollar falls relative to other currencies, the Federal Reserve's Senior Loan Officer Opinion Survey indicates an easing of credit, and the excess bond premium described by Simon Gilchrist and Egon Zakrajšek (2012) falls.

The SDFM results suggest that interest rates are an important, perhaps dominant, channel for the effect of food shocks on the macroeconomy. The size of the effect of food shocks on sectors that are sensitive to the interest rate (residential investment, expenditures on consumer durables) appears to be roughly what would be predicted by the effect of these shocks on interest rates (Bernanke and Gertler 1995; McCarthy and Peach 2002).

Of course, this SDFM exercise is merely a single robustness check that should be viewed in the context of the large number of careful exercises reported by De Winne and Peersman. Their paper raises a novel and interesting question, and I have no doubt that it will be investigated in future papers using other methods and data. I look forward to following this research.

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GENERAL DISCUSSION Lutz Kilian observed that the paper's primary story that food supply shocks raise the price of food and lower the discretionary income of consumers, given that households spend a relatively large proportion of their budget on food, is a sensible starting point for the analysis, but that this view is not supported by the evidence. The first problem is how to define "food prices." On one hand, there are food commodity prices in the global economy; on the other hand, there are U.S. retail food prices. In a recent paper, Kilian and Christiane Baumeister show that, despite large fluctuations in global food commodity prices, there was virtually no change in U.S. retail food prices.[1] One explanation is that most of the prices of final goods are determined by factors other than commodity prices; for example, data from the U.S. Department of Agriculture suggest that only about 5 percent of the cost of producing bread comes from the cost of wheat. According to this logic, it is easy to see why a fluctuation in the global price of wheat would have very little effect on the retail price of bread. Hence, if there is a channel of transmission from food commodity prices to the macroeconomy, as the authors conjectured, that channel must be about something entirely different, something that links food commodity prices to real GDP.

The interesting part of the paper, Kilian contended, is not the impulse responses and variance compositions; it is the historical decompositions that quantify the cumulative effect of food supply shocks. Kilian stressed that these historical decompositions reveal a puzzle. This puzzle is how food supply shocks that explain little of the evolution of global food commodity prices can explain much of the variation in U.S. real GDP growth and its components at the same time. A good example is the apparently large effect of food supply shocks on automobile purchases by consumers. One potential explanation for this finding might seem to be the discretion-

1. Christiane Baumeister and Lutz Kilian, "Do Oil Price Increases Cause Higher Food Prices?" *Economic Policy* 29, no. 80 (2014): 691–747.

ary incomes as food prices change; but as Kilian had just observed, there is little variation in discretionary incomes because retail food prices do not move much. A second possible explanation is that there might be a direct link between crude oil prices, biofuel prices, and food commodity prices; but as Kilian had mentioned, he and Baumeister had found no support for such a link. Yet another possible explanation is that monetary policymakers might have responded to changes in inflation driven by changes in retail food prices, Kilian explained; but there have been no large changes in retail food price inflation, so this explanation does not seem plausible. Finally, Kilian expressed skepticism about the paper's attempt to explain its findings based on other channels of the transmission of food supply shocks (such as reallocation effects or food price uncertainty effects). The latter channels, Kilian pointed out, all require the use of nonlinear models, and hence cannot be used to rationalize the authors' estimates obtained from linear models.

Kilian concluded that, rather than there being some mystery explanation yet to be discovered, the paper likely has a problem identifying food supply shocks. A properly identified model, he contended, would include data on global food prices and quantities, but would also include changes in income that ultimately drive the demand for food. It would also include things like inventories of food commodities, which are difficult to measure. Kilian argued that the paper's model might also have omitted variables as well as measurement problems, pointing to a mismatch between the prices and quantity data for food commodities. For example, the Soviet Union is included in constructing the quality measure, but the Soviet Union only very intermittently participated in global food commodity markets, meaning that the price data do not match the quantity data, invalidating the identification.

Kilian had one final comment related to the paper's results on the effects of the oil supply shocks. He noted that the way the paper identified these shocks was not state of the art; rather, it was done in a way that, according to recent research, is known to be misleading because it does not impose all relevant identifying restrictions.[2] He suggested discarding that particular

2. See, for example, Lutz Kilian and Daniel P. Murphy, "Why Agnostic Sign Restrictions Are Not Enough: Understanding the Dynamics of Oil Market VAR Models," *Journal of the European Economic Association* 10, no. 5 (2012): 1166–88; Christiane Baumeister and Gert Peersman, "The Role of Time-Varying Price Elasticities in Accounting for Volatility Changes in the Crude Oil Market," *Journal of Applied Econometrics* 28, no. 7 (2013): 1087–1109; and Juan Antolin-Diaz and Juan Francisco Rubio Ramírez, "Narrative Sign Restrictions for SVARs," Discussion Paper no. 11517, London: Centre for Economic Policy Research.

evidence; but more important, he failed to see why that evidence was included in the paper in the first place, given that it is not related to the paper's central question of what the effects of food supply shocks are.

As Mark Watson's discussion had emphasized, Christopher Sims noted that it is hard to reliably estimate the effects of food prices because the contribution to the shocks' variance is small. Sims took issue with Watson's approach in his presentation of taking the first difference of the data, noting that the cointegration literature finds that this is a bad idea because it throws away too much information. It is always possible to get different results with a worse model, he noted. If the authors could show that altering their model to produce a better fit would give different results, this would be a legitimate criticism; but Watson's presentation simply presented a handful of other models, some of which may fit much worse. Sims hoped that the authors would do more to analyze their model's fit.

Sims was surprised that the authors were able to show big impulse responses with good estimates of the error bands. It is hard to know what kind of model would explain the error bands, he noted; but the effects are certainly there, and are statistically significant. To undermine this, one would need to produce a better model showing that the error bands are wrong or that the impulse responses come out in a different way.

Sims mentioned a few possible econometric issues. Specifically, when it comes to food prices, seasonality is extremely important. Seasonality is pervasive in price and output data for commodities, particularly food commodities. The authors' model, as he understands it, includes seasonal dummies *and* uses seasonally adjusted data. He noted a bit of danger in doing this, because seasonally adjusted data always use future data as part of the adjustment. Unraveling this adjustment using a multivariable vector autoregression could be cause for worry, and so Sims suggested that the authors check for robustness there, by testing whether the seasonal dummies matter or by replacing some series with series that are not seasonally adjusted and by leaving in the dummies. He noted that commodity prices notoriously produce nonnormal residuals due to large outliers. According to the authors' current framework, it would not be too difficult to construct a model that allowed for t-distributed errors, which would indicate whether the results were being driven by a few large outliers.

Justin Wolfers noted that what the authors do with the global food index seems to make sense; once a crop is planted, conditional on what is planted, what ends up getting harvested seems exogenous. In the regression context, if one were to include harvests and control for planting, then other exogenous effects would be identified. But the authors did not seem to include planting in their model, so he was not sure how harvests turned out to be exogenous.

Looking at the authors' results at face value, Robert Hall thought they seemed totally implausible, which is always interesting, he noted. A big wave in macroeconomic theory, pioneered by Robert Shiller, deals with a concept variously termed *confidence, sentiment, ambiguity aversion,* or *animal spirits.* Models that have these features tend to generate the pattern observed by the authors, which is changes in a wide variety of macroeconomic variables that are similar in magnitude and are highly correlated. Within this framework, the price of basic cereals should be profoundly and primordially important for the present paper. It seems sensible, he noted, that they could perhaps trigger changes in confidence; if so, this is interesting because most research in this area has taken it to be totally unobservable and not triggered by some natural phenomenon. He suggested that the present paper could constitute a new branch of this line of thinking.

Martin Eichenbaum bet that a typical consumer has no clue about what is happening in commodity markets, and that the real question consumers face is about the price they are actually paying at the grocery store, not the price of cereals on the commodity market. Hall contended that, in fact, people are well informed through the media about commodity prices, which Eichenbaum stated was possible.

Eichenbaum also commented on variance being small and yet things being estimated precisely. There is an analogue in the literature on monetary policy shocks: When models are estimated in log levels, they explain very little of the variance in output identified with fund shocks, and yet standard errors are generally estimated quite precisely. He suggested that this might be something for the authors to consider.

Building on Hall's comments, James Stock added that there is a lot of evidence that consumer sentiment tends to move with prices that are highly salient, such as those for gasoline and meat. An empirical question is whether this salience—even though it turns out not to be a big deal in bottom-line expenditures—might be a feature.

Narayana Kocherlakota suggested that since commodities have a durable aspect, movements in discount factors could actually have an effect on their prices. He proposed that perhaps the authors' food prices were picking up a spurious correlation, and that discount factors are moving in relation to many other important things in the economy. He suggested that adding stock prices to their model might avoid some of this spurious correlation.

Gerald Cohen noted that there is a nontrivial lag between the effect of input costs for types of feed—like corn and wheat—and the cost of meat.

He recalled a glut of meat production in the middle to late 2000s, following the increase in corn prices, and suggested that the authors might look into this phenomenon. A related phenomenon is observed in the pig industry, called the corn–hog cycle. This cycle consists of massive fluctuations in pig production caused by overreactions to changes in the market prices of pigs and their feed. In pig rearing, feedstuffs are a large proportion of the economic market cost of a pig, so a change in feedstuff price has an immediate effect on farmers' profits; conversely, cattle primarily eat grass, and specialty feed is normally only a small proportion of total feed costs.

Echoing Sims, Peersman was critical of Watson's stability argument because estimating the model in first differences does not take into account potential cointegration relationships between the data. This approach was also the only one of which he was aware that produced somewhat weaker effects and different dynamics. He noted that estimating several variants of the level specifications for the full sample produces results that are quantitatively and qualitatively very similar.

Regarding variance decompositions, though it is true that the shocks explain only about 10 percent of U.S. GDP variation, Peersman asked, "Did you expect more?" Food prices are obviously not the main driver of the U.S. business cycle, so it is good that the authors did not find big effects, he contended. Notwithstanding, the contribution of food commodity market shocks to GDP variation turns out to be approximately the same as monetary policy or oil supply shocks, which are two shocks that receive a lot of attention in the literature. Peersman agreed with Eichenbaum that the macroeconomic consequences could be estimated quite precisely, even when they explain a relatively small proportion of the variance.

In response to questions of omitted variable bias, he noted that the authors' VAR model does not include global income measures, and that they had tested their model for robustness by including both more and fewer variables. The authors believed that the final model, which includes 10 variables, was sufficient to counter omitted variable bias. This is also confirmed by the FAVAR analysis reported in the paper. Furthermore, the narrative analysis revealed that food commodity market events in the Soviet Union did have an important influence on global commodity prices, even in the 1970s. However, as Kilian had suggested, Peersman noted that data on inventories do not exist at the required quarterly frequency.

Looking at subsamples, Peersman noted that, taking into account the error bands, the results are stable if two decades of observations are excluded at the beginning or the end of the sample period. The results become less stable for shorter sample periods but this should not be a surprise, because the authors are working with 10 variables and thus many observations are needed to make proper estimates. For more parsimonious versions of the VAR—for example, by including fewer variables or lags—the results are also stable for shorter sample periods. In general, much variation in the variables is needed to capture the shocks of global food prices and food production, which is why Peersman is not a fan of these types of subsample analysis.

Schlenker was surprised to find that people spend about the same amount on food each year. He stated that a natural question to ask, then, is why there are any effects of food shocks at all. Peersman asserted that this is exactly the point, and might be the mechanism: When people keep on consuming equally as much food because they need to eat every day, they must cut expenditures on some other components of their budgets. The data suggest that households in the lowest quintile of the income distribution spend about 36 percent of their income on food; furthermore, low-income households are typically liquidity constrained, so food price fluctuations might have big effects on these households' other types of spending. There also seems to be a significant decline in consumer confidence, which is a natural amplifier of the macroeconomic consequences.

Peersman disagreed with Kilian's assertion that there is no pass-through from global food prices to domestic retail prices. Peersman argued that there is, in fact, a one-to-one pass-through of global food commodity prices to U.S. food commodity prices, and a pass-through to the food component of the consumer price index proportional to the share of food commodities in final food products. He also stressed that this share has been about 14 percent on average, which is much larger than the share Kilian was insinuating. Regarding the authors' identification strategy for oil supply shocks, Peersman noted that this strategy followed that used in a recent paper he and Baumeister published in the *American Economic Journal.*[3] Furthermore, he asserted that imposing the kind of restrictions on the elasticities that Kilian had suggested produces the same results, noting that these restrictions only matter to identify demand shocks in the oil market, not supply shocks.

Peersman conceded that Sims's point about seasonality was a good one. There is indeed much seasonality in the food production index. He noted that they had run specifications without seasonal dummies, and this had no

3. Christiane Baumeister and Gert Peersman, "Time-Varying Effects of Oil Supply Shocks on the U.S. Economy," *American Economic Journal: Macroeconomics* 5, no. 4 (2013): 1–28.

influence on the results. The authors also found similar macroeconomic consequences using data that were not seasonally adjusted, as Sims had also suggested. All in all, the authors found that the effects are similar across the various specifications.

Regarding Wolfers's comment about why the authors do not include data on crop planting, Peersman noted that planting data are actually not needed because what is being identified are quarterly shocks, that is, shocks within the harvesting quarter. Everything that happens before this quarter should already be included in the information of the model's other variables. Food commodity prices, for instance, should contain all the relevant information about planting that is in principle reflected in the price just before the harvesting quarter.

Regarding Kocherlakota's suggestions that there could be a common shock to commodities that is basically driven by rates of returns and discount factors, Peersman noted that this was indeed one of the authors' concerns, and they did a lot of work to figure out whether this was the case. For example, in the paper they show that only food commodity market variables react on impact. Similarly, GDP and other variables only start to decline after a couple of quarters, meaning that on impact, there is no shock directly affecting GDP. More importantly, equity prices also do not shift on impact.

Finally, Peersman noted that estimating the impact of food prices on exports shows that the effects are not strong. Even though there is a decline in global economic activity, exports do not appear to be the culprit; they decline a bit, but the effect is not statistically significant. He concluded that domestic consumption is what really seems to drive the output effect.

CHAPTER 2: AGRICULTURAL PRICE SHOCKS AND BUSINESS CYCLES

A GLOBAL WARNING FOR ADVANCED ECONOMIES

Agricultural Price Shocks and Business Cycles*

A Global Warning for Advanced Economies

Jasmien De Winne
Ghent University

Gert Peersman
Ghent University

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Abstract

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

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

Keywords: Agricultural commodity prices, economic activity, climate change

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1 Introduction

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

An element that has not been considered so far is the possible impact of climate change on economic performance of countries through a rise in the volatility of global agricultural (food) commodity prices. More specifically, disruptions in agricultural markets around the globe that are the result of extreme weather conditions could lead to substantial changes in the prices of agricultural commodities. For example, the extreme droughts in Russia and Eastern Europe were the primary reason for the rise in global real food commodity prices by more than 20% in the summer of 2010 (De Winne and Peersman 2016, henceforth DWP 2016). Real cereal prices increased even by almost 30% (see Figure 1). These changes in agricultural prices could, in turn, curtail economic activity of countries that are not directly exposed to the extreme weather conditions, for example, through an impact on consumer spending. Given the high proportion of food consumption in household expenditures, this could augment the costs of global climate change for poor countries. Moreover, these indirect effects may as well affect rich economies, which also have non-negligible shares of food expenditures. DWP (2016) demonstrate that this is the case for the United States, where the macroeconomic effects of increases in global food commodity prices turn out to be a multiple of the share of food commodities in household consumption.[1]

In this paper we provide empirical evidence on the impact of (non-domestic) fluctuations in global agricultural markets on economic activity of 75 advanced and developing countries. In

[1] Between 1960 and 2015, food commodity expenditures per capita per year measured in constant 2015 dollar values amounted to approximately $900 in the United States (DWP 2016). As a reference, crude oil expenditures over this period were on average roughly $750 per capita per year. DWP (2016) document that the effects of a rise in global food commodity prices on real GDP are approximately twice as large as a rise in global crude oil prices. We are not aware of other studies that have estimated the effects of changes in agricultural prices on economic activity of advanced economies.

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

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

The first instrument is a quarterly series of unanticipated foreign harvest shocks. The shocks are estimated as prediction errors of composite production indices that aggregate the harvests of the world's four most important staple food commodities: corn, wheat, rice and soybeans. Overall, these commodities make up approximately 75% of the caloric content of food production worldwide (Roberts and Schlenker 2013). We use harvest data of 192 countries, and systematically exclude the harvests of the country itself, the entire sub-region in which the country is located and the harvests in the neighboring sub-regions. We also orthogonalize the shocks to domestic weather conditions. As a second instrument, we use the 13 episodes of major global agricultural commodity market disruptions that have been identified with narrative methods in DWP (2016). The episodes that did not directly affect the harvests of a country are converted to an instrumental variable series for that country. In the next step,

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

we use both instruments to estimate the dynamic effects of a rise in global cereal prices on real GDP per capita. We apply two methods that are popular in empirical macroeconomics. As the baseline, we estimate panel (and individual-country) structural vector autoregression models with external instruments (SVAR-IV). As an alternative, we conduct direct panel IV regressions of the effects with local projection methods (LP-IV).

According to the SVAR-IV estimations, an exogenous rise in global cereal prices by 1% on impact (which further increases to 1.5% after one quarter) ultimately reduces average real GDP per capita across countries by 0.10%. The effects are statistically significant, but also economically important if one considers that the quarterly standard deviation of changes in real cereal prices has been 7.3% over the past five decades, and 8.7% since the start of the millennium (see Figure 1). The results of the LP-IV estimations turn out to be very similar. Furthermore, we show that the use of external instruments matters. In particular, when we estimate the effects of "average" global cereal price shocks (that is, a recursively identified SVAR with cereal prices ordered first), we find much milder effects on economic activity. Notably, the latter also applies to small economies.

The estimation of panel SVAR-IVs for country groups reveal that the effects are significantly larger in high-income countries; that is, the decline of real GDP is 0.11% for the top income-tertile of the countries, compared to only 0.03% for the lowest income-tertile. This difference is surprising given the fact that high-income economies have much lower shares of food in household expenditures. Moreover, high-income countries usually have more advanced government institutions and better developed financial markets to absorb food price volatility.

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

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

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

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

2 Methodology

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

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

2.1 Baseline SVAR Model with External Instruments

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

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

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

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

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

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

The coefficients of α_i and $A_i(L)$ in equation (1) can simply be estimated by OLS. Also the variance-covariance matrix of the reduced form VAR can be estimated; that is, $E\left[u_{i,t}u_{i,t}^{'}\right] = B_iB_i^{'}$, which provides six independent identifying restrictions to obtain the coefficients of B_i. Because we are only interested in one of the structural shocks; that is, exogenous shifts in real cereal prices, we do not have to identify all the coefficients of B_i. Only the elements of the first column of B_i have to be identified, which nevertheless requires additional restrictions. To do this, we follow Stock and Watson (2012) and Mertens and Ravn (2013) by using external instruments. Specifically, let $Z_{i,t}$ be a vector of external instrumental variables for country i. These variables can be used for identification of the first column of B_i if the following

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

conditions are satisfied:

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

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

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

2.2 Unanticipated Foreign Harvest Shocks

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

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

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

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

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

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

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

Census X-13 ARIMA-SEATS Seasonal Adjustment Program (method X-11). The result of this exercise are 75 indicators of foreign harvest volumes.

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

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

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

For all 75 countries, we estimate equation (5) over the sample period 1975Q1-2014Q4. The start of the sample period is determined by the availability of the precipitation series, while harvest data are made available by the FAO until 2014. If we assume that the information sets of local farmers are no greater than equation (5), the residuals $\nu_{i,t}$ of this equation can be considered as unanticipated harvest shocks. Notice that anticipated harvest innovations before the harvesting quarter should be reflected in the control variables, in particular cereal prices, because an arbitrage condition ensures that changes in futures prices also shift sport

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

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

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

2.3 Narrative Global Agricultural Market Shocks

As a second external instrument, we use the series of major exogenous global food commodity market disruptions that have been identified with narrative methods in DWP (2016). More precisely, DWP (2016) rely on newspaper articles, FAO reports, disaster databases and other online sources to identify 13 historical episodes of substantial movements in food commodity prices that are unambiguously caused by disturbances in global food commodity markets and unrelated to the state of the economy. An overview and brief description of these episodes is reported in Table 1. For more details, we refer to the online appendix of DWP (2016). Six episodes are unfavorable shocks that have augmented food prices, while seven episodes have been characterized by a meaningful decline in food commodity prices. These episodes are converted to a dummy variable series, which is equal to 1 and -1 for unfavorable and favorable shocks respectively, and can be used as an external instrument to identify the VAR. However, to minimize correlation of the shocks with domestic agricultural conditions, for each individual country, we exclude the episodes when domestic annual cereal production growth deviated more than one standard deviation from its mean over the period 1965-2014. Accordingly, about 30 percent of the episodes are excluded.

3 Effects of Global Agricultural Market Shocks

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

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

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

To check the validity and strength of the instruments for the baseline estimations, Table A1 shows the first-stage F-statistics and robust F-statistics allowing for heteroskedasticity. With very few exceptions, the values for each country turn out to be much higher than the threshold suggested by Stock and Yogo (2005) for having possible weak instrument problems. The F-statistic of the instruments at the panel level (based on a Mean Group estimation of the first stage) that is robust for clustering by time is 28.1, while the corresponding clustered t-statistics of the harvest and narrative shocks are 4.8 and 5.4, respectively. Put differently, our instruments can be considered as strong, which fulfills the relevance condition posited in equation (3).

In the figures, we always show the estimated impulse responses for a global agricultural market shock that raises real cereal prices by 1% on impact. We construct one- and two-standard error confidence intervals using a recursive-design wild bootstrap procedure. Specifically, following Mertens and Ravn (2013), we generate bootstrap draws of $Y_{i,t}^b$ recursively by using the estimated coefficients of the VAR denoted in equation (1), where the residuals of all countries are (simultaneously) multiplied by a random variable e_t^b taking on values of -1 or 1 with probability 0.5. We also generate a draw for the instruments $Z_{i,t}^b = Z_{i,t}e_t^b$. The reduced

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

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

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

3.1 Baseline Panel VAR Results

The estimated impulse responses of the panel VAR are shown in Figure 2. An exogenous shock to global agricultural markets that raises real cereal prices by 1% on impact reaches a peak of approximately 1.5% after one quarter, in order to gradually decline to roughly 0.4% at longer horizons. The rise in cereal prices leads to a fall in the global economic activity index, as well as average real GDP per capita of the 75 countries in our panel. The decline in output is sluggish and very persistent. In particular, the effects on real GDP are only statistically significant after 3-4 quarters and reach a maximal decline of approximately 0.10% after about 8 quarters.[13] Beyond this horizon, output remains permanently lower at this level.

The macroeconomic effects of changes in agricultural prices are not only statistically significant, but also economically important. Notice, for example, that the standard deviation of quarterly changes in real cereal prices has been 7.3% since the 1960s, and even 8.7% since the start of the millennium. Furthermore, as shown in Figure 1, swings in agricultural prices can be very persistent. For example, global real cereal prices increased by 112% between 2002 and 2011, followed by a collapse of 77% afterwards. These fluctuations are obviously only partly

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

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

driven by agricultural supply disruptions; that is, the consequences of endogenous shifts in cereal prices may be different, but the magnitudes suggest that developments in agricultural markets matter for business cycle fluctuations.

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

3.2 Sensitivity of Panel VAR Results

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

As can be observed in Figure 3, the effects on real GDP are much smaller for the recursive identification. The impact is even significantly positive in the short run, while the long-run decline is approximately 0.06%, compared to 0.10% in the benchmark estimations. As shown

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

in the right panel of the figure, the difference between both impulse response functions is also statistically significant. Since both identification methods rely on the same reduced form VAR system, this can formally be tested by calculating the difference between the impulse responses for each replication of the bootstrapping procedure. This finding suggests that the reduced form innovations to cereal prices are a mixture of exogenous agricultural market shocks and endogenous responses to other macroeconomic shocks (e.g. global demand shocks), which could bias the estimated effects considerably. A rise in cereal prices caused by a disruption in global agricultural markets is clearly different from a surge that is consequence of increased worldwide economic activity. In fact, we find that this also applies to most small countries that could not influence global agricultural prices. It is hence important to isolate shifts in commodity prices that are truly exogenous to estimate the macroeconomic effects properly.

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

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

[15]The clustered panel VAR F-statistic of both instruments independently are 25.2 and 37.3 for the foreign harvest and narrative shocks, respectively. Notice, however, that the robust F-statistics are below 10 for 17 countries if only the foreign harvest shocks are used for the identification of the shocks. For the narrative shocks, this is only the case for two countries. For this reason, we excluded Mexico, Jamaica, Belize, Costa Rica, Egypt, Guatemala and Tanzania from the estimations that are solely based on the foreign harvest shocks. The first-stage robust F-statistics for these countries are less than 1, resulting in explosive error bands of the panel VARs. The exclusion of these countries, however, has a negligible influence on the point estimates of the impulse responses. Overall, it appears that there is value added by using both instruments jointly to identify the shocks. As documented in Table A1, the (joint) robust F-statistics are lower than 10 for only four countries and always higher than 6.5.

[16]The impulse responses of inflation and the exchange rate are not shown, but available upon request. The temporary depreciation of the real USD exchange rate may be the consequence of the relative strong decline of US real GDP compared to the majority of the other countries, which is shown in Figure A1.

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

Finally, panel (F) shows the estimated impulse responses when we use the broad food commodity price index of the IMF instead of cereal prices, which was also shown in Figure 1. Panel (F) reveals that the effects of a rise in food commodity prices by 1% are stronger than an equal rise in cereal prices. In particular, real GDP decreases by 0.14% in the long run. This finding is not very surprising since this index covers a larger share of food commodities.[17] Overall, we can conclude that the panel VAR results are generally robust to several perturbations of the VAR model.

3.3 Comparison with a Panel LP-IV Approach

If the SVAR model adequately captures the data generating process, this method is most efficient to estimate the dynamic effects of agricultural shocks at all horizons. However, if the SVAR is not a correct representation of the dynamics of the variables in the system, the specification errors will be compounded at each horizon resulting in impulse responses that are potentially biased (Ramey 2016). To further check the robustness of the results, we therefore also estimate the impulse responses directly with panel LP-IV methods. The advantage compared to VARs is that LP methods are more robust to misspecification (Jordà 2005; Stock and Watson 2017).[18] Another advantage is that it will be able to estimate the relationship between the dynamic effects and several country characteristics simultaneously in section 4, which is not possible with panel VARs. A disadvantage of this method, however, is a loss of efficiency and hence less precisely estimated effects that are often quite erratic at longer horizons.

[17] The panel F-statistic of the instruments is 19.7 for the broad food commodity price index. However, the robust F-statistics for 17 individual countries are lower than 10, which suggests that it is better to use real cereal prices as the price variable in the estimations.

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

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

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

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

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

As expected, the precision of the LP-IV estimates is less accurate than the SVAR-IV results due to the loss of efficiency. The effects on real GDP around the peak are still significant at 5% level for the PMG estimator, but the MG estimations are only significant at 10% level. The point estimates are, however, very similar to the SVAR-IV estimates. The peak declines of real GDP based on the PMG and MG estimator are respectively 0.14% and 0.12%, which is only moderately larger than the SVAR-IV estimates. We can thus conclude that the panel results are robust to the estimation method.

3.4 Individual Country Results

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

4 Exploring Cross-Country Heterogeneity

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

The analysis in this section is mainly based on the effects of agricultural shocks across country groups. The composition of the groups is based on the averages of a selection of country characteristics over the period 2000-2015 (annual data). More precisely, we use the baseline panel SVAR-IV model and calculate the Mean Group impulse responses of respectively the top and bottom tertile of the countries according to a specific country characteristic, as well as the differences between both tertiles.[19] The groups hence always contain respectively the 25 highest and lowest ranked countries for a characteristic. The period to compose the groups overlaps but does not correspond one-to-one with the SVAR-IV sample periods of all countries due to the unbalanced nature and availability of the data. However, since we use the underlying data only to compose the groups and the middle tertile is excluded to conduct the estimations, this should have little or no impact on the results. Notice also that the results are qualitatively robust to alternative sizes of the groups, e.g. top/bottom

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

half or quintiles of the countries. As a special case, in section 4.3 we will also estimate an LP-IV specification that is based on the country averages directly. Details about the data sources can be found in the appendix. Table A1 reports for each country the averages of the characteristics between 2000 and 2015, as well as the country's rankings that have been used to construct the groups between parentheses.

4.1 Are the Effects Different between Rich and Poor Countries?

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

The results are shown in Figure 6. A remarkable observation is that high-income countries appear to be much more affected by exogenous global agricultural price shocks. For the group of high-income countries, a rise in global cereal prices induces a gradual and persistent decline in economic activity; that is, real GDP per capita declines by 0.11% in the long run. In contrast, low-income countries experience a temporary increase of real GDP during the first year after the shock, which reaches a statistically significant peak of 0.05% after two quarters. Subsequently, the effects on real GDP start to decrease and become negative after one year. The peak decline, however, is only 0.03% and statistically insignificant. Furthermore, as shown in the right panel of the figure, the differences between the impulse responses of both country groups are clearly significant at all horizons.

The stronger output effects in rich countries turn out to be very robust. Figure 7 summarizes a battery of robustness checks. We only show the estimated differences between both groups. First, the results do not depend on the way the groups are constructed. As shown in panels (A) and (B), we also find significant differences between the top and bottom half or quintiles of the countries. We also find it when we estimate the SVAR-IV model solely for the post 1990 sample period, which implies that this result is e.g. not driven by the longer sample periods that most high-income countries have (panel (C)). Furthermore, the results are similar when we estimate the effects of changes in global real cereal prices measured in domestic currency. The results are thus also not the consequence of exchange rate movements that are different between high and low-income countries (panel (D)).[20] Finally, as can be observed in panels (E) and (F), we find stronger effects when we estimate the difference between both groups with panel LP-IV techniques or when we identify average agricultural price shocks using a simple recursive (Cholesky) decomposition of the variance-covariance matrix of the VAR residuals.[21]

The finding of significantly larger effects on economic activity of high-income countries is surprising. In fact, there are several reasons why real GDP of high-income countries is expected to be less affected by changes in global agricultural commodity prices. First, the share of food (commodities) consumption in total household expenditures is much lower compared to low-income countries. For example, the share of food and non-alcoholic beverages consumed at home in total household expenditures over the period 2000-2015 has been respectively 12% and 33% for the top and bottom income-tertile, while the elementary correlation with average income per capita across all countries has been -0.76. Although such data does not exist, this is likely also the case for the share of (raw) food commodities in household expenditures. Second, high-income countries typically have more effective government institutions. It is hence less likely that increases in food prices trigger conflicts such as food riots which, in turn, could have an impact on real GDP. Finally, high-income countries are financially more developed than low-income countries, which should allow households to smooth consumption and firms to smooth production when they experience income shocks.[22] In sum, there must be other important mechanisms that explain why rich countries are more vulnerable to exogenous changes in global agricultural prices.

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

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

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

4.2 Alternative Country Characteristics

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

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

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

Furthermore, food commodity price increases do not only affect the terms of trade, it also involves redistribution of income within countries, which could magnify or dampen the consequences on economic activity if food producers have different propensities to consume (or invest) out of changes in disposable income than food consumers.[23] Since low-income

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

households usually have higher marginal propensities to consume, such effects may be different between rich and poor countries. In particular, the revenues of higher food prices in rich countries are typically concentrated to a relatively small group of people, while the bulk of poor people are urban with limited access to land that spend large portions of their income on food. For example, households belonging to the lowest income quintile in the United States spend 35.8% of their income after taxes on food consumption. For the highest quintile, this is only 9.1%.[24] Since low-income households have no access to capital markets to smooth consumption and food is a basic necessity, they have no other options than reducing their non-food expenditures. For example, DWP (2016) find that changes in food prices in the United States trigger a significant decline in durable consumption of households, which magnifies the repercussions on economic activity considerably.

On the other hand, food consumers typically have higher average incomes than food sellers in low developed countries (Aksoy and Isik-Dikmelik 2008), while many impoverished people in low-income countries depend upon food production for their livelihood (Headey and Fan 2008). Although poor households in these countries spend higher shares of their budgets on food, their incomes are likely more responsive to agricultural prices. Poor countries may thus also benefit from higher agricultural prices as a result of redistribution of income that, in turn, stimulates aggregate spending.[25] Overall, favorable redistribution effects are likely greater when the share of agriculture in the economy is larger; that is, more households benefit from higher food prices. For example, Jacoby (2016) constructs a simple general equilibrium model and finds that countries with large shares of agricultural employment could ultimately benefit from higher food prices because this has a positive impact on rural wages.[26]

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

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

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

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

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

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

Trade tariffs for agricultural goods Finally, agricultural import barriers may mitigate the consequences of global agricultural shocks on the domestic economy because retail prices might be more decoupled from international prices. Anderson and Nelgen (2012) find that the pass-through of changes in global cereal prices to domestic prices is on average only about 0.5. Gouel (2014) argues that the incomplete transmission is likely the result of trade policies.[27] To evaluate whether countries that have tighter import barriers are differently affected by global agricultural shocks, we group the countries according to the effectively applied rate for agricultural goods calculated with the UNCTAD method based on Trade Analysis Information System (TRAINS) data. There seems to be a moderate positive correlation between import barriers and the wealth of nations (see Table 2).

4.3 Estimation Results

Panel SVAR-IV for country groups Figure 8 shows the impulse responses estimated with the panel SVAR-IV approach for the top and bottom tertiles of the countries according to each characteristic. The results confirm several hypotheses that have been postulated in section 4.2. More specifically, we find weaker average effects of unfavorable global agricultural price shocks on the economies of countries that are large net exporters of primary food and beverages, as well as countries that have a higher share of agriculture in GDP. Both features may thus be a possible explanation for the stronger effects on high-income countries. This also applies to the degree of trade integration. Figure 8 reveals that the decline in real GDP is on average greater in countries with higher shares of trade in GDP. Specifically, real GDP decreases by 0.16% in the top-tertile of the countries, compared to only 0.06% in the lowest

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

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

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

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

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

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

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

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

5 Conclusions

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

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

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

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

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

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Appendix: Data

Baseline SVAR-model

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

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

- **Real GDP per capita** (country-specific): As the preferred source we use the seasonally adjusted real GDP index from the OECD Main Economic Indicators database. This series is available for 37 countries for varying sample periods. For Greece this series still contains seasonality, so we perform additional seasonal adjustment. For the remaining countries we download real GDP from the IMF International Financial Statistics (IFS) database. In order to obtain longer time series we backcast the OECD and IMF series using various other sources: 1) We use GDP series from the Bank for International Settlements (BIS) for Argentina, Brazil, China, Chile, Colombia, Czech Republic, Estonia, Hungary, Indonesia, India, Latvia, Poland, South Korea and Hong Kong. 2) We use GDP series from Oxford Economics (downloaded via Datastream) for Argentina, Bulgaria, China, Croatia, Malaysia, Romania, Russia and Thailand. 3) We use GDP series provided by the respective national statistical office for Belize, Iran, Morocco and Uruguay. 4) For Costa Rica and Iceland we backcast using a GDP series from the OECD

Quarterly National Accounts database. 5) For Kyrgyzstan we use the GDP series from the World Development Indicators Database (quarterly series, downloaded via Datastream). 6) For Colombia, Cyprus, Hungary, Indonesia, Israel, Macedonia, Malaysia, Poland, Slovakia we backcast using annual GDP, Chow-Lin interpolated with quarterly industrial production from the IMF IFS database. Additional details are available on request.

Unanticipated foreign harvest shocks

- **Foreign harvest volume** (country-specific): These indices are based on annual food production data downloaded from the Food and Agriculture Organization (FAO). For a more detailed description of the construction of the index, see main text.
- **Real crude oil prices**: The refiner acquisition cost of imported crude oil, deflated by the U.S. CPI.
- **Multivariate El Niño Southern Oscillation Index**: Index provided by the Earth System Research Laboratory (https://www.esrl.noaa.gov/psd/enso/mei/, accessed August 2016). The index is based on six different variables in order to measure El Niño/Southern Oscillation (ENSO).
- **Oceanic Niño Index**: Index made available by the Earth System Research Laboratory (https://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Data/nino34.long.anom.data, accessed August 2016). This index is calculated by averaging sea surface temperature anomalies in an area of the east-central equatorial Pacific Ocean (the Nino-3.4 region).
- **European Drought Observatory (EDO) index of domestic precipitation (country-specific)**: The Standardized Precipitation Index 3 (SPI 3) measures the observed rainfall in mm. over 3 months minus the average over 3 months divided by the standard deviation of 3 months. The country average of half minute cells is made available by the European Drought Observatory (EDO).
  Data downloaded from http://edo.jrc.ec.europa.eu/edov2/php/index.php?id=1140 in March 2017.
- **Temperature anomaly index**: This index measures quarterly averages of monthly deviations from long-term (1901-2015) average national temperatures. Data was downloaded from the World Bank Climate Change Data Portal

(http://sdwebx.worldbank.org/climateportal, accessed September 2017). The underlying dataset was produced by the Climatic Research Unit (CRU) of University of East Anglia (UEA).) Missing values for Romania and Hong Kong were replaced by anomaly data from Berkeley Earth (http://berkeleyearth.lbl.gov/country-list/, accessed September 2017).

Sensitivity of SVAR-Model

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

Cross-country heterogeneity

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

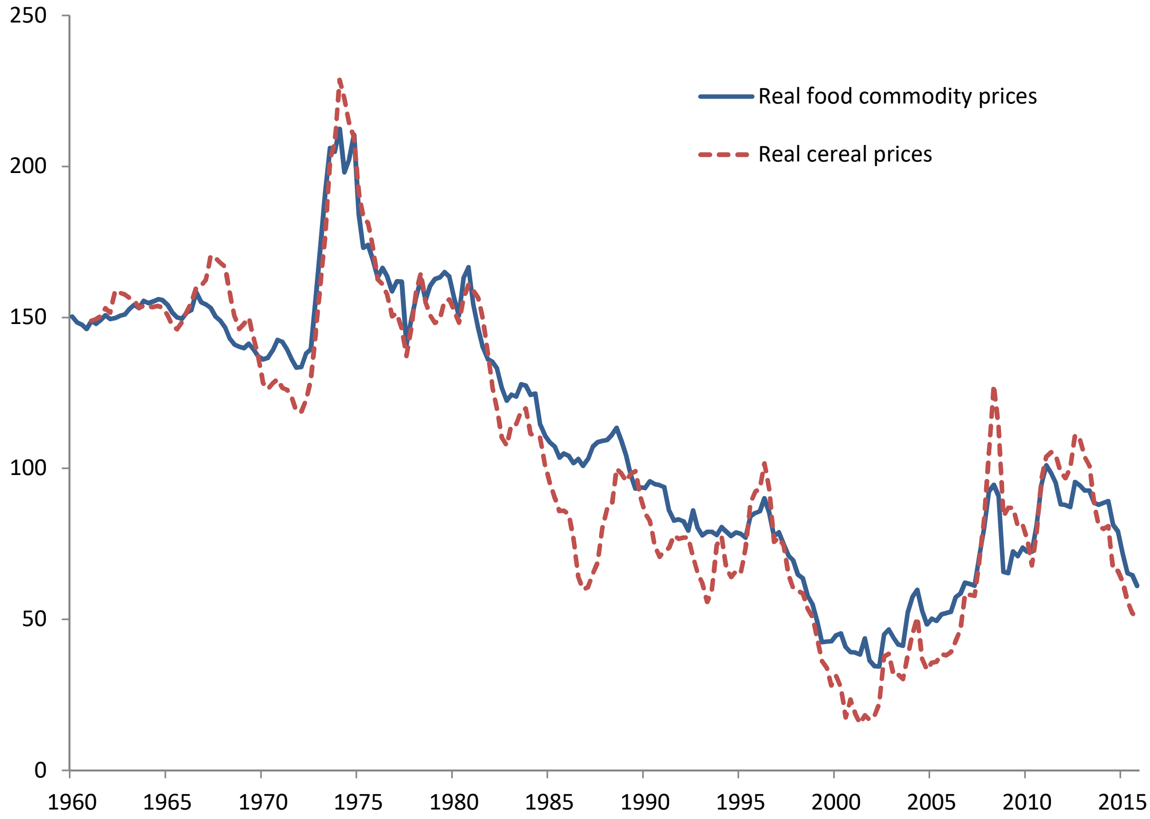
- **Net exports of primary food and beverages** (country-specific, annual frequency): Share in GDP of primary food and beverages net exports. Trade data in U.S. dollar downloaded from the UN Comtrade database. Primary food and beverages corresponds with Broad Economic Categories (BEC) Classification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

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

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

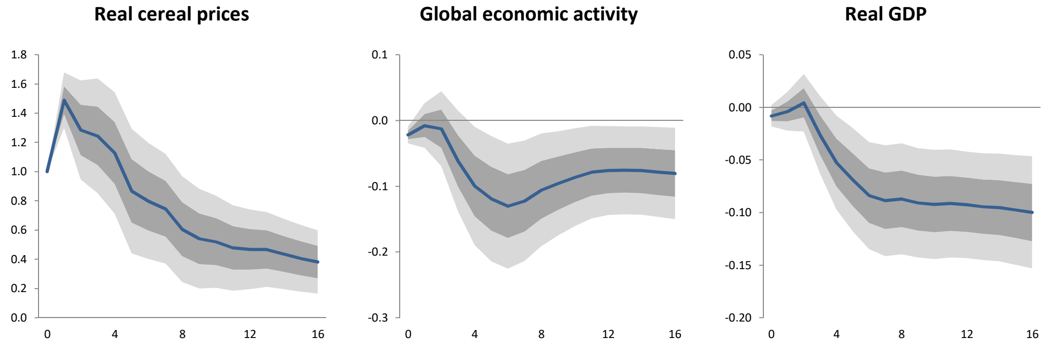
- **Trade tariffs for agricultural goods** (country-specific, annual frequency): Effectively Applied Rate for Agricultural Goods (HS classification), including ad-valorem-equivalents (AVEs) calculated with UNCTAD method based on Trade Analysis Information System (TRAINS) data. Downloaded using World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

Figure 1 - Evolution of food commodity prices over time



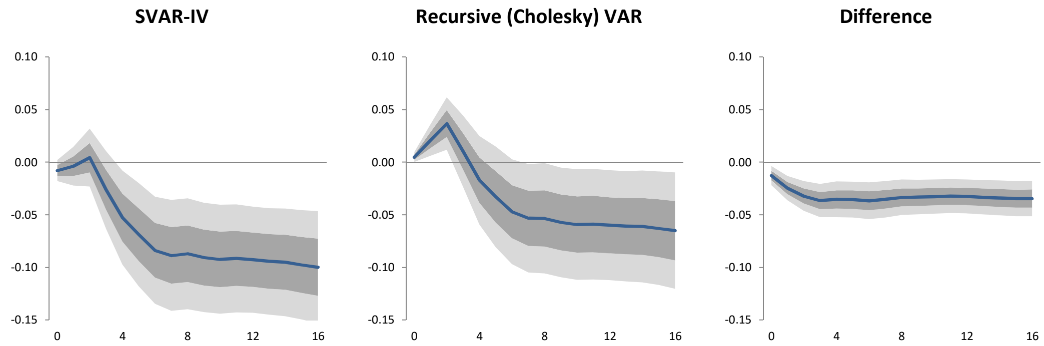
Note: variables are measured as 100*log of index deflated by US CPI. Real food commodity prices is a trade-weighted average of benchmark food prices in US dollars for cereals, vegetable oils, meat, seafood, sugar, bananas and oranges. Cereal prices aggregates the prices of corn, wheat, rice and soybeans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

Figure 2 - Effects of 1 percent increase in global real cereal prices: panel SVAR-IV estimations



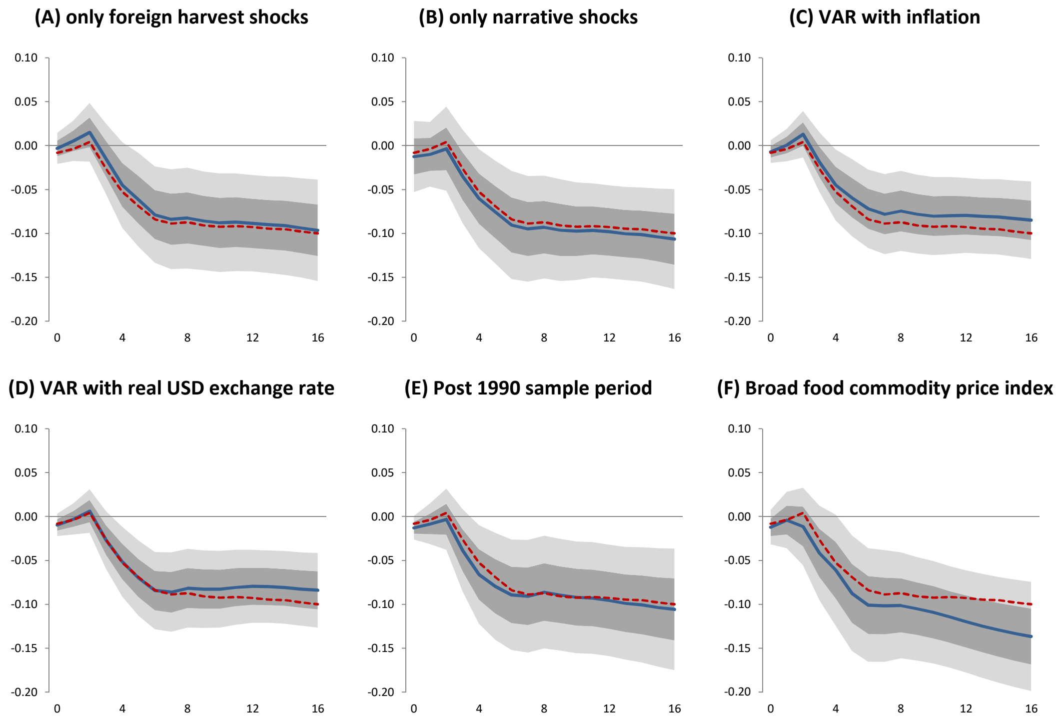
Note: Mean Group impulse responses with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly

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



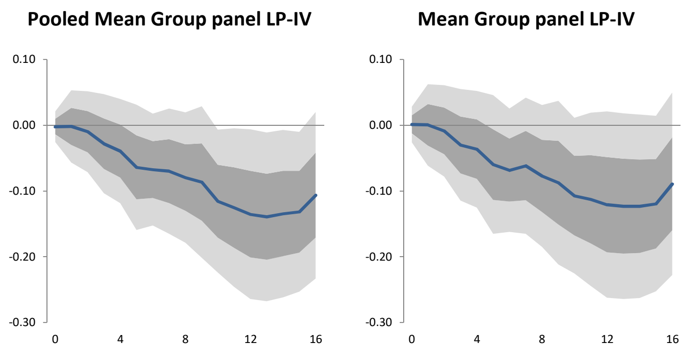
Note: Mean Group impulse responses with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly

Figure 4 - Effects on real GDP: alternative panel SVAR-IV estimations



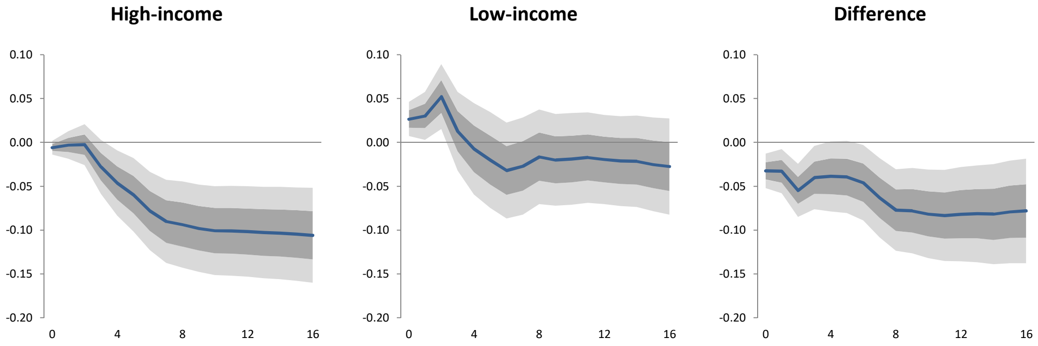
Note: Mean Group impulse responses with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly; red dashed lines are the responses of the benchmark panel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

Figure 5 - Effects of 1 percent increase in global real cereal prices: panel LP-IV estimations



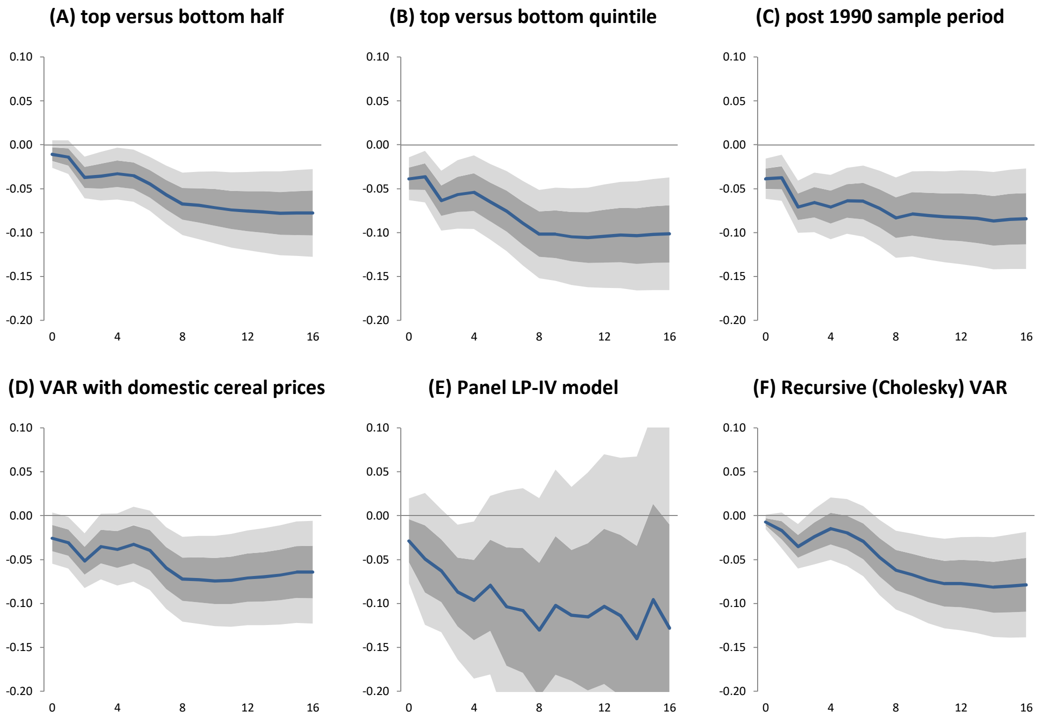
Note: Impulse responses with one- and two-standard error bands; the confidence intervals are adjusted for correlations between the residuals across countries, as well as serial correlation between the residuals over time; horizon is quarterly

Figure 6 - Effects of 1 percent increase in global real cereal prices on high-income versus low-income countries



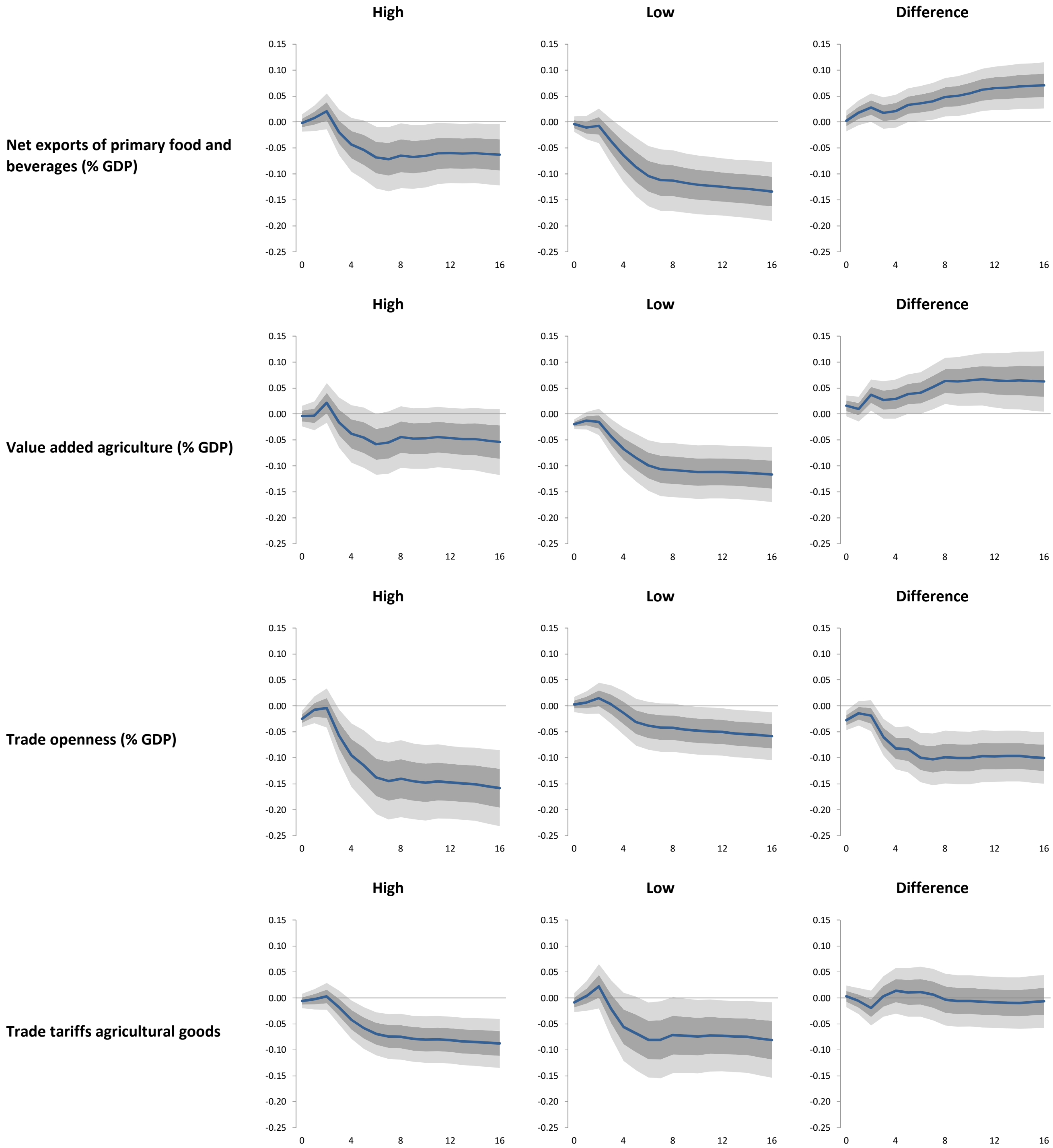
Note: Mean Group impulse responses for top and bottom tertiles of the countries with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly

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



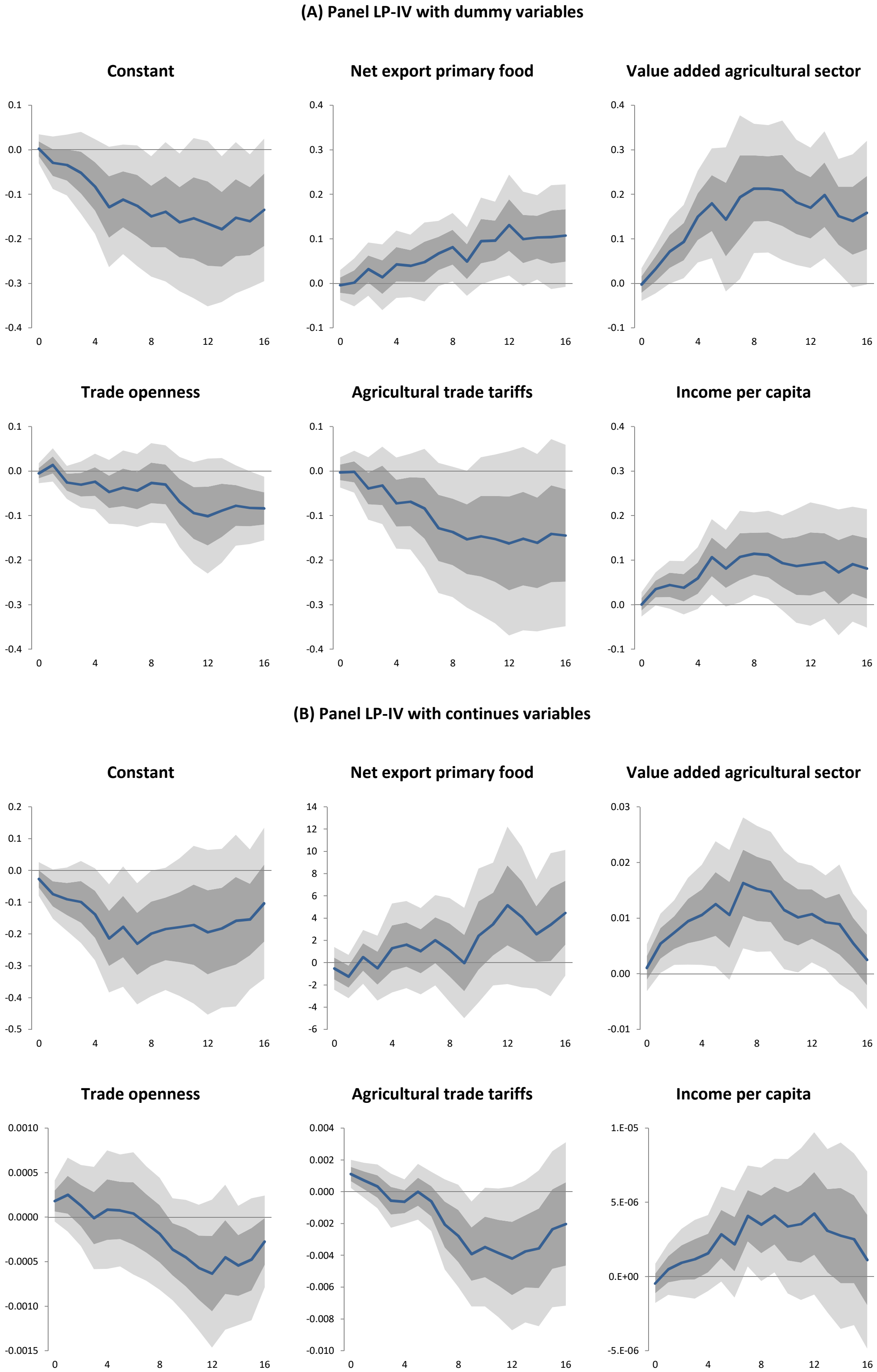
Note: Differences between impulse responses of high-income versus low-income countries with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly

Figure 8 - Effects of 1 percent increase in global real cereal prices on country groups: alternative characteristics



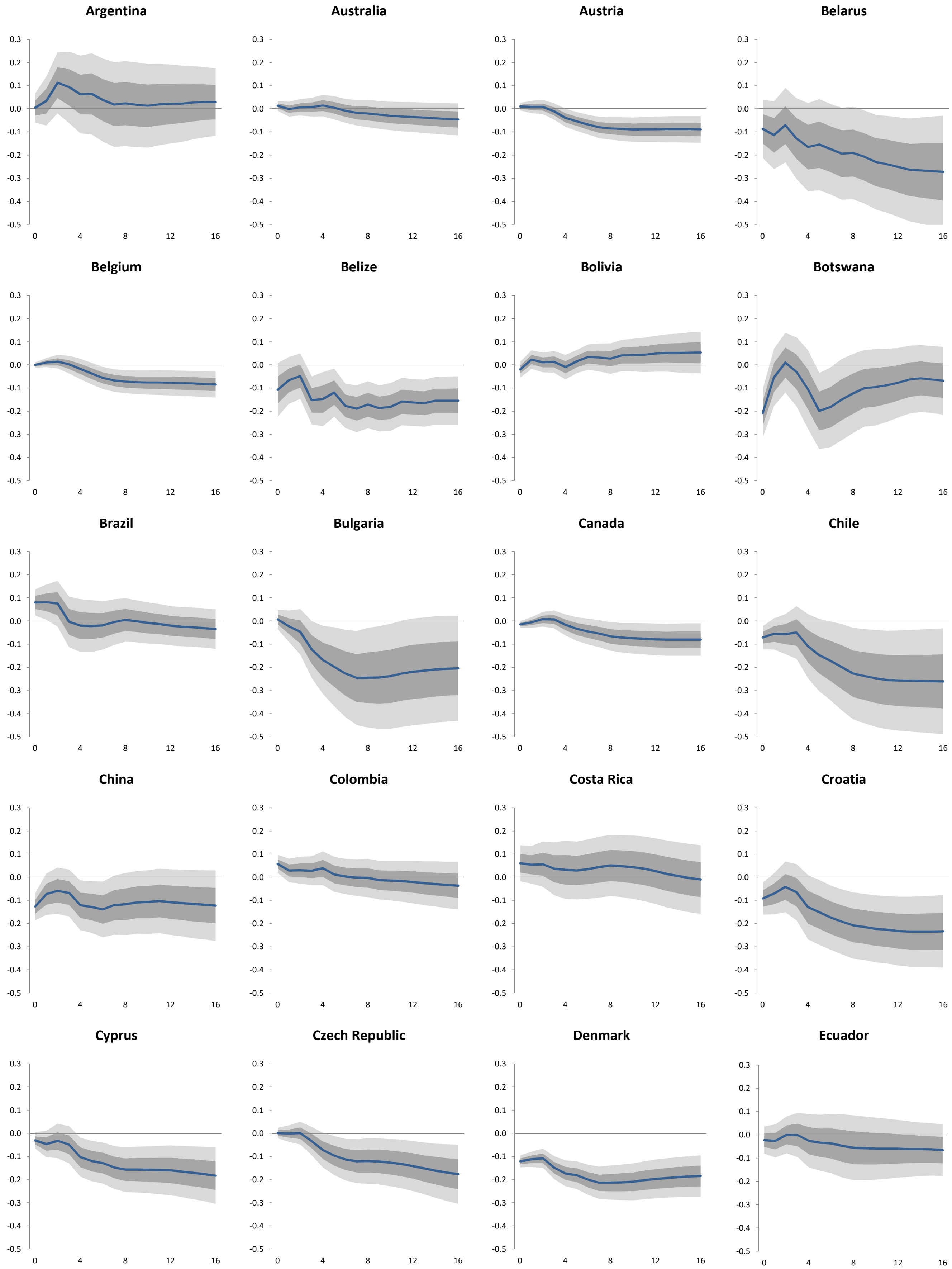
Note: Mean Group impulse responses for top and bottom tertiles of the countries with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap that accounts for correlation of the VAR residuals across countries; horizon is quarterly

Figure 9 - Simultaneous analysis of country characteristics



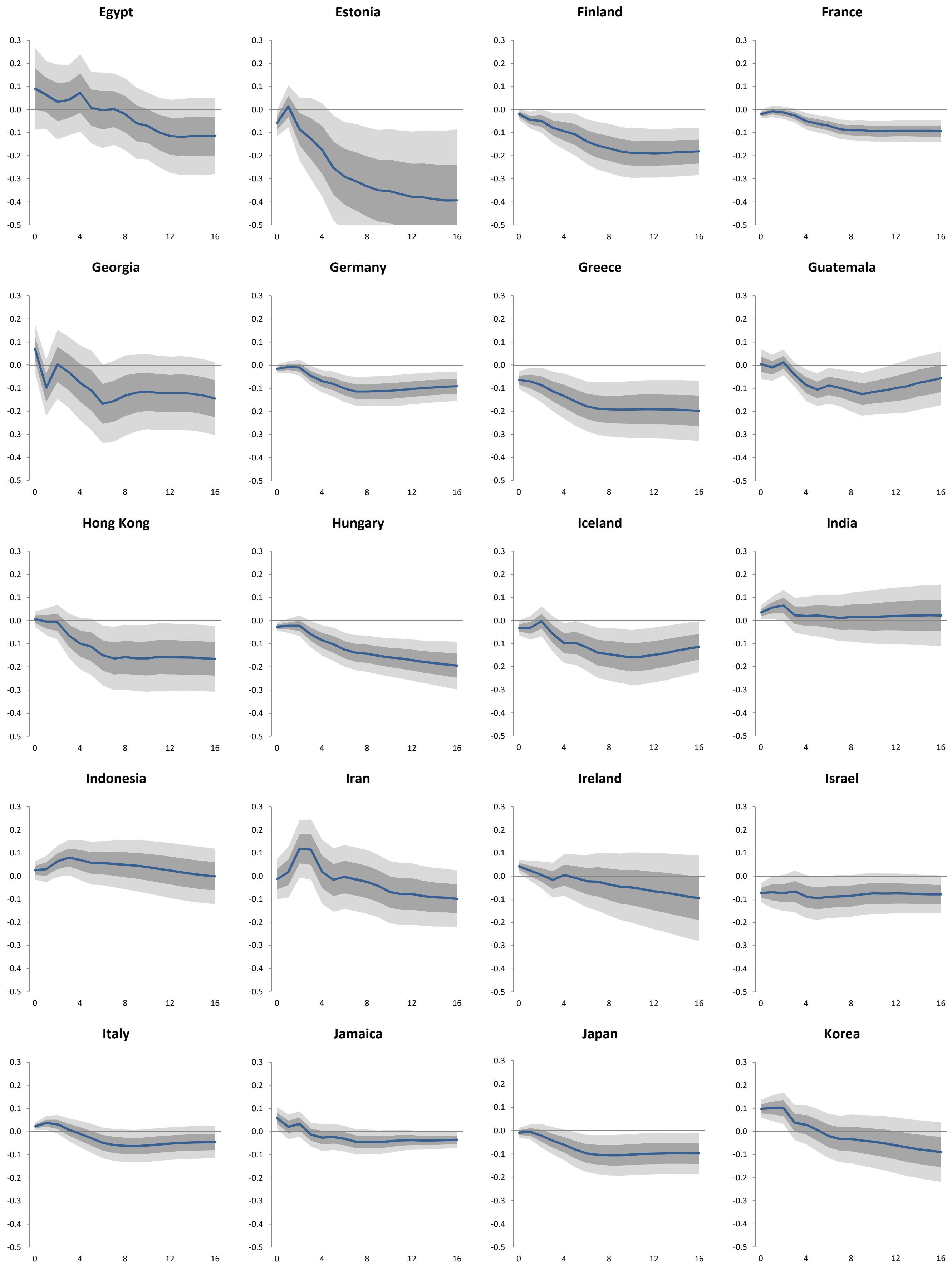
Note: Impulse responses with one- and two-standard error bands; the confidence intervals are adjusted for correlations between the residuals across countries, as well as serial correlation between the residuals over time; horizon is quarterly
(A) dummy variables if countries belong to top-tertile of characteristics; (B) based on average values of characteristics over period 2000-2015

Figure A1 - Effects of 1 percent increase in global cereal prices on individual countries



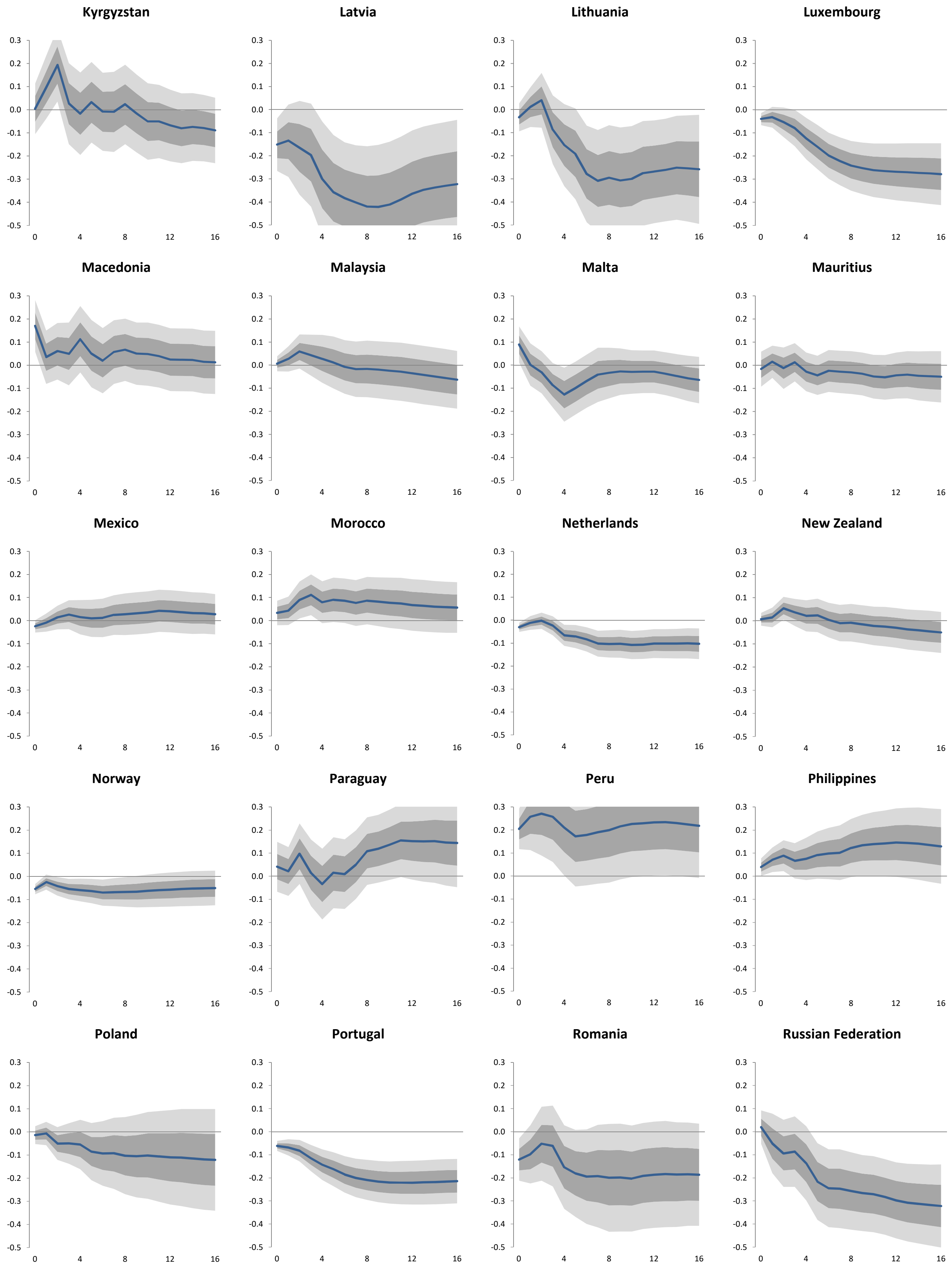
Note: Impulse responses with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap; horizon is quarterly

Figure A1 (continued) - Effects of 1 percent increase in global cereal prices on individual countries



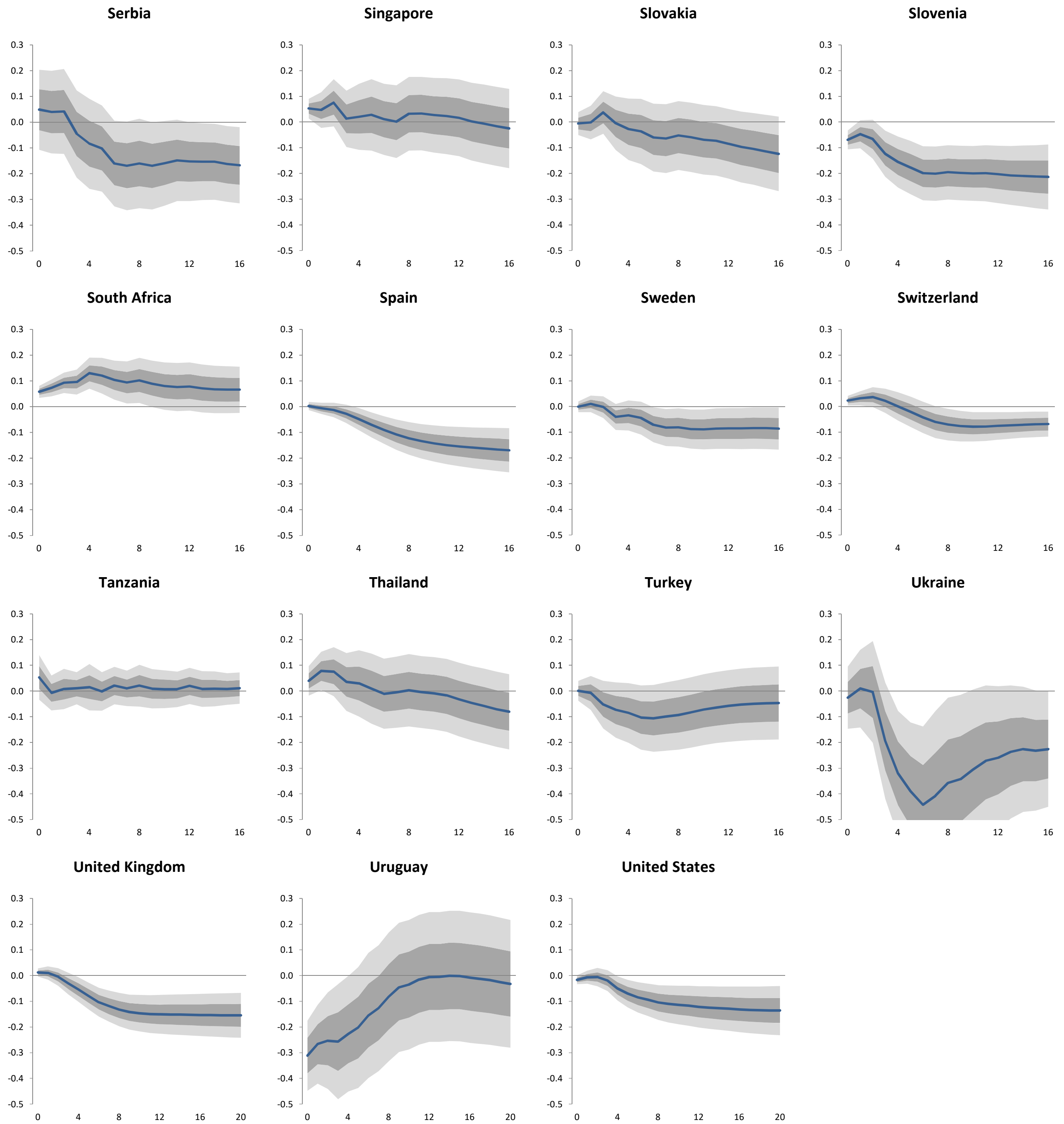
Note: Impulse responses with one- and two-standard error bands; the confidence intervals are constructed using a recursive-design wil bootstrap; horizon is quarterly

Figure A1 (continued) - Effects of 1 percent increase in global cereal prices on individual countries



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

Figure A1 (continued) - Effects of 1 percent increase in global cereal prices on individual countries



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

Table 1 - Overview of narrative global agricultural commodity market shocks

Date	Type	(Cumulative) change in food commodity prices: Impact	(Cumulative) change in food commodity prices: 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 De Winne and Peersman (2016).

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

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

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

Table A1 - Country characteristics

	Sample period	F-statistics instruments	Robust F-statistics instruments	Country characteristics: average values 2000-2015 (ranking between brackets)									
				Income per capita		Net export primary food & beverages (%GDP)		Value added agriculture (%GDP)		Trade (%GDP)		Agricultural tariffs (%)	
Argentina	1968Q1-2014Q4	12.6	14.7	16031	(41)	2.16	(6)	8.0	(25)	34	(72)	5.1	(66)
Australia	1965Q1-2014Q4	15.9	21.1	41353	(9)	0.77	(18)	2.9	(48)	41	(70)	2.9	(72)
Austria	1965Q1-2014Q4	15.5	19.7	39429	(13)	-0.28	(50)	1.6	(65)	96	(26)	10.3	(43)
Belarus	1992Q1-2014Q4	10.4	15.3	13327	(48)	-0.73	(67)	10.1	(18)	131	(12)	6.4	(60)
Belgium	1965Q1-2014Q4	16.4	18.4	36218	(18)	-0.58	(66)	0.9	(69)	149	(8)	10.3	(35)
Belize	1994Q1-2014Q4	8.4	12.6	6952	(64)	4.84	(3)	14.8	(5)	125	(16)	13.4	(18)
Bolivia	1990Q1-2014Q4	11.7	19.8	4182	(72)	0.72	(19)	13.9	(9)	69	(47)	5.6	(65)
Botswana	1994Q1-2014Q4	14.0	30.1	11940	(51)	-1.27	(74)	2.7	(52)	97	(25)	0.6	(74)
Brazil	1980Q1-2014Q4	11.1	15.6	11018	(52)	0.84	(15)	5.5	(33)	26	(75)	6.9	(58)
Bulgaria	1980Q1-2014Q4	13.7	29.7	12983	(50)	1.43	(11)	7.5	(29)	106	(22)	14.1	(17)
Canada	1965Q1-2014Q4	10.9	16.9	40379	(10)	0.60	(22)	1.7	(61)	68	(49)	11.1	(25)
Chile	1965Q1-2014Q4	14.3	14.1	15523	(42)	2.07	(8)	4.2	(40)	68	(48)	3.6	(70)
China	1980Q1-2014Q4	18.5	31.1	7771	(61)	-0.20	(48)	11.0	(16)	50	(64)	16.6	(12)
Colombia	1980Q1-2014Q4	10.7	14.3	9263	(58)	0.80	(16)	7.7	(27)	36	(71)	11.1	(26)
Costa Rica	1991Q1-2014Q4	2.7	8.4	10951	(53)	4.87	(2)	8.0	(24)	78	(38)	7.9	(54)
Croatia	1988Q3-2014Q4	10.3	18.6	17788	(35)	-0.49	(63)	5.1	(35)	84	(35)	7.2	(56)
Cyprus	1988Q1-2014Q4	14.4	50.7	26383	(26)	-0.32	(52)	2.9	(49)	116	(19)	15.6	(15)
Czech Republic	1988Q3-2014Q4	14.7	20.4	24538	(29)	-0.07	(45)	2.5	(54)	125	(15)	9.4	(48)
Denmark	1965Q1-2014Q4	15.9	19.6	40161	(11)	0.00	(38)	1.6	(62)	93	(29)	10.3	(40)
Ecuador	1991Q1-2014Q4	6.8	41.0	8035	(59)	4.62	(4)	10.7	(17)	57	(55)	9.8	(45)
Egypt	2002Q1-2014Q4	4.4	33.5	7502	(63)	-1.17	(73)	14.0	(8)	49	(65)	13.4	(19)
Estonia	1988Q3-2014Q4	12.3	16.0	18690	(34)	-0.21	(49)	3.6	(43)	141	(10)	8.7	(51)
Finland	1965Q1-2014Q4	15.2	17.7	36705	(16)	-0.41	(58)	2.8	(51)	76	(40)	10.3	(29)
France	1965Q1-2014Q4	15.2	18.8	34735	(19)	0.08	(34)	1.9	(60)	55	(58)	10.3	(36)
Georgia	1996Q1-2014Q4	8.2	19.5	6388	(66)	-0.30	(51)	13.5	(10)	86	(31)	7.0	(57)
Germany	1965Q1-2014Q4	12.4	18.1	39353	(14)	-0.44	(61)	0.9	(71)	75	(42)	10.3	(41)
Greece	1965Q1-2014Q4	15.4	17.9	25916	(27)	0.01	(37)	4.2	(39)	56	(56)	10.3	(32)
Guatemala	2001Q1-2014Q4	3.8	21.2	5887	(69)	3.27	(5)	12.6	(11)	62	(50)	6.4	(61)
Hong Kong	1966Q1-2014Q4	20.1	33.4	45664	(7)	-1.67	(75)	0.1	(74)	381	(1)	0.0	(75)
Hungary	1979Q1-2014Q4	14.6	26.8	18842	(33)	0.78	(17)	4.5	(37)	148	(9)	12.9	(21)
Iceland	1965Q1-2014Q4	17.6	22.9	37044	(15)	1.86	(9)	7.1	(30)	85	(32)	19.2	(9)
India	1965Q1-2014Q4	17.5	25.4	3519	(73)	0.28	(28)	19.2	(4)	43	(69)	46.2	(2)
Indonesia	1970Q1-2014Q4	20.1	25.3	5891	(68)	0.18	(33)	14.2	(6)	55	(59)	4.4	(67)
Iran	1988Q1-2014Q4	15.6	24.3	13893	(45)	0.26	(30)	7.6	(28)	48	(66)	17.5	(10)
Ireland	1965Q1-2014Q4	12.9	12.3	48326	(6)	-0.20	(47)	1.4	(66)	174	(6)	10.3	(42)
Israel	1965Q1-2014Q4	17.4	23.1	29501	(24)	-0.16	(46)	1.9	(58)	71	(44)	11.9	(22)
Italy	1965Q1-2014Q4	11.7	16.1	34094	(21)	-0.42	(59)	2.3	(56)	52	(61)	10.3	(34)

	Sample period	F-statistics instruments	Robust F-statistics instruments	Country characteristics: average values 2000-2015 (ranking between brackets)									
				Income (2011 USD per capita)		Net export primary food & beverages (%)		Share agriculture in GDP (%)		Trade openness (%)		Agriculture tariffs (%)	
Jamaica	1996Q1-2014Q4	4.9	13.7	6432	(65)	-0.54	(65)	6.4	(32)	88	(30)	16.1	(13)
Japan	1965Q1-2014Q4	16.9	28.9	34659	(20)	-0.33	(54)	1.2	(67)	28	(73)	22.8	(6)
Korea	1965Q1-2014Q4	11.3	26.8	29413	(25)	-0.36	(55)	3.0	(46)	84	(34)	96.1	(1)
Kyrgyzstan	1986Q2-2014Q4	10.7	16.7	3093	(74)	-0.04	(43)	27.1	(2)	115	(20)	4.0	(69)
Latvia	1988Q3-2014Q4	17.5	40.2	16240	(39)	-0.03	(41)	4.1	(41)	102	(24)	9.6	(47)
Lithuania	1993Q1-2014Q4	16.1	31.2	17310	(37)	0.51	(25)	4.3	(38)	124	(17)	7.9	(53)
Luxembourg	1965Q1-2014Q4	17.7	49.4	57796	(2)	-0.42	(60)	0.4	(73)	318	(3)	10.3	(37)
Macedonia	1993Q1-2014Q4	9.0	37.8	9966	(57)	0.02	(36)	11.7	(14)	95	(28)	10.9	(27)
Malaysia	1970Q1-2014Q4	17.1	20.5	16233	(40)	-0.78	(68)	9.2	(21)	178	(5)	10.5	(28)
Malta	1996Q1-2014Q4	9.0	17.4	22973	(31)	-0.95	(70)	1.9	(59)	265	(4)	8.1	(52)
Mauritius	2000Q1-2014Q4	5.4	9.6	14932	(43)	-1.08	(71)	5.1	(34)	117	(18)	5.7	(64)
Mexico	1965Q1-2014Q4	15.3	25.7	13587	(46)	0.27	(29)	3.5	(44)	58	(53)	15.2	(16)
Morocco	1966Q2-2014Q4	11.9	12.4	5681	(70)	0.32	(26)	14.1	(7)	72	(43)	25.9	(5)
Netherlands	1965Q1-2014Q4	18.8	23.8	43794	(8)	-0.02	(40)	2.0	(57)	133	(11)	10.3	(39)
New Zealand	1965Q1-2014Q4	18.5	22.5	29511	(23)	1.22	(12)	6.4	(31)	60	(51)	8.7	(50)
Norway	1965Q1-2014Q4	15.9	17.6	69450	(1)	0.61	(21)	1.6	(63)	70	(45)	40.4	(3)
Paraguay	1994Q1-2014Q4	8.9	18.8	5976	(67)	7.27	(1)	19.4	(3)	96	(27)	6.0	(63)
Peru	1979Q1-2014Q4	9.0	13.2	7645	(62)	0.93	(14)	7.8	(26)	47	(67)	6.5	(59)
Philippines	1981Q1-2014Q4	15.3	19.0	4919	(71)	-0.04	(42)	12.5	(12)	83	(36)	11.3	(24)
Poland	1982Q1-2014Q4	15.3	36.1	17712	(36)	-0.05	(44)	3.1	(45)	78	(37)	13.4	(20)
Portugal	1965Q1-2014Q4	14.3	15.6	23873	(30)	-1.12	(72)	2.6	(53)	69	(46)	10.3	(31)
Romania	1980Q1-2014Q4	12.0	28.5	13484	(47)	0.22	(32)	8.6	(23)	75	(41)	15.9	(14)
Russian Federation	1990Q1-2014Q4	12.3	22.6	16493	(38)	-0.32	(53)	4.9	(36)	54	(60)	11.6	(23)
Serbia	1995Q1-2014Q4	5.6	6.6	10478	(56)	0.57	(23)	12.0	(13)	76	(39)	10.3	(30)
Singapore	1975Q1-2014Q4	19.8	25.2	51756	(3)	-0.78	(69)	0.1	(75)	380	(2)	1.5	(73)
Slovakia	1992Q1-2014Q4	13.0	30.6	19373	(32)	-0.02	(39)	4.0	(42)	154	(7)	8.8	(49)
Slovenia	1992Q1-2014Q4	7.6	43.9	24864	(28)	-0.49	(64)	2.4	(55)	125	(14)	9.6	(46)
South Africa	1965Q1-2014Q4	14.7	14.9	10674	(54)	0.52	(24)	2.9	(50)	59	(52)	6.1	(62)
Spain	1965Q1-2014Q4	14.0	13.2	30484	(22)	0.24	(31)	3.0	(47)	57	(54)	10.3	(33)
Sweden	1965Q1-2014Q4	18.2	19.7	39603	(12)	-0.41	(57)	1.6	(64)	85	(33)	10.3	(38)
Switzerland	1965Q1-2014Q4	14.6	23.4	51248	(4)	-0.47	(62)	0.9	(70)	109	(21)	31.4	(4)
Tanzania	2001Q1-2014Q4	5.4	7.5	1722	(75)	1.05	(13)	31.9	(1)	45	(68)	20.1	(8)
Thailand	1980Q1-2014Q4	17.5	20.1	10615	(55)	0.62	(20)	9.8	(19)	129	(13)	16.6	(11)
Turkey	1965Q1-2014Q4	20.0	33.0	14466	(44)	0.32	(27)	9.6	(20)	52	(63)	20.6	(7)
Ukraine	2001Q1-2014Q4	10.0	16.4	7963	(60)	1.45	(10)	11.1	(15)	103	(23)	7.5	(55)
United Kingdom	1965Q1-2014Q4	16.2	17.1	36294	(17)	-0.37	(56)	0.7	(72)	55	(57)	10.3	(44)
Uruguay	1988Q1-2014Q4	5.6	13.7	13216	(49)	2.16	(7)	9.2	(22)	52	(62)	4.3	(68)
United States	1965Q1-2014Q4	12.8	24.5	49020	(5)	0.03	(35)	1.2	(68)	27	(74)	2.9	(71)

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

CHAPTER 3: THE IMPACT OF FOOD PRICES ON CONFLICT REVISITED

The Impact of Food Prices on Conflict Revisited*

Jasmien De Winne
Ghent University

Gert Peersman
Ghent University

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Abstract

We study the link between international food commodity prices and conflict in Africa. In contrast to existing studies, we identify truly exogenous food price changes by using data on global food production. Using geo-referenced conflict data at a quarterly frequency, we show that an exogenous increase in international food prices raises conflict incidence and intensity considerably. The bulk of the effect takes place beyond one year, and the effect is larger and more persistent for smaller-scale conflict types such as riots and protests. This contrasts with the results from a "naive" regression of conflict on food prices showing an inverse relationship. Additionally, we find that higher food prices lead to even more conflict in areas with more agriculture. We show that the traditional approach in the literature to evaluate this effect wipes out the positive baseline effects for areas with and without agriculture.

JEL classification: C23, D74, F44, Q11, Q34
Keywords: Food commodity prices, Economic shocks, Conflict

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1 Introduction

"Bread, freedom, social justice!"
(Slogan shouted in Cairo, 2011—Mittermaier, 2014)

Throughout history, various violent events occurred in times of high food prices. A surge in food prices in 2008 and again in 2010–2011 spurred interest in the investigation of this relationship: a large number of recent papers feature food commodities and conflict incidence.[1] However, theory provides arguments for both a negative and a positive relationship, and also the empirical evidence is mixed. For example, Brückner and Ciccone (2010), Berman and Couttenier (2015) and Fjelde (2015) show that higher prices decrease the risk of violent events. Bazzi and Blattman (2014) find no evidence of a robust, significant link, while Smith (2014), Bellemare (2015), Hendrix and Haggard (2015) and Raleigh et al. (2015) show that higher prices correspond with more conflict.

The existing food price-conflict literature has a few shortcomings. Notably because the measurement of a causal effect of food prices on conflict is complicated by two important issues. The first issue concerns the possible endogeneity of food prices. A potential source of endogeneity is reverse causality. Most papers merely assume that conflict does not affect global food prices, but Raleigh et al. (2015) find a positive feedback loop between food prices and violence. Another – and probably more important – source of endogeneity arises if both conflict incidence and food prices are determined by a third variable such as global economic activity. A booming global economy can result in higher food prices, but it can also affect conflict incidence through increased global trade, investment, remittances or aid flows. The consequences of higher food prices because of strong economic growth might be very different from the consequences of higher prices due to supply shocks such as failed harvests. Failing to take into account this heterogeneity might lead to the inability to reject the null hypothesis.

A second issue arises because many papers focus exclusively on the relative effect for producers or exporters by including time fixed effects in their analysis (see for example Brückner and Ciccone, 2010, Bazzi and Blattman, 2014, Berman and Couttenier, 2015 and Fjelde, 2015). These time fixed effects are included to capture for example the global business cycle. However, this results in the omission of any effect that is common for all areas. These common effects, which we label baseline effects, could be non-negligible, for example, because food prices likely affect consumers in all areas. These baseline effects could offset or even

[1] In this paper we consider a broad range of violent events, ranging from riots to civil wars, whereas many existing papers have focused on more narrowly defined types of conflict. In section 5 we will pay particular attention to different types of conflict.

reverse the partial, differential effect for producers. In essence, these studies including time fixed effects do not tell us anything about the total effect of food prices on conflict in a given area.

In this paper we want to deal with these two shortcomings in the existing literature in order to shed more light on the existence, direction and size of a causal effect of changes in food commodity prices on conflict in Africa. To do so, we identify truly exogenous changes in food prices by instrumenting international food commodity prices with two exogenous instruments as proposed by De Winne and Peersman (2016).[2] The first external instrument captures unexpected changes in global food production outside Africa. Our method ensures that these production shocks are only the result of changing supply conditions. As a second external instrument we use a narrative dummy indicator of exogenous food supply shocks, constructed based on FAO reports, newspaper articles, and several other sources. This identification strategy deals with the issues in the literature as follows. First, we can easily ensure that the shock did not occur in Africa, thereby avoiding any possibility of reverse causality. Second, the source of the price change is unambiguously a supply shock. Since these shocks are not the result of changing demand conditions, we do not need to include time fixed effects in order to control for the global business cycle or other common shocks as in most papers. This allows us to study both the baseline effects and the differential effect for producers of exogenous food price changes.

We follow the existing literature as much as possible and in line with the most recent advances in this literature we use geo-referenced, sub-national conflict data. Just as McGuirk and Burke (2017) we study two different types of conflicts: factor conflict (large-scale battles for territory) using the Uppsala Conflict Data Program (UCDP) database and output conflict (smaller-scale conflict such as riots and protests) using the Armed Conflict Location and Event Data Project (ACLED) dataset. These geo-coded violent events are converted to a panel of 10678 African equally sized cells (around 55×55 km at the equator) between 1997Q1 and 2014Q4. However, in contrast to the existing literature, we aggregate the data to a quarterly frequency instead of an annual frequency.[3] The existing food-conflict papers using grid-level data only consider the annual frequency, which is surprising given the very detailed, almost daily, information on conflict incidence. The higher frequency allows to pay more attention

[2]In the benchmark analysis we use a narrow production-weighted average of only four crop types as an indicator of global food prices. These four crops account nevertheless for 75 percent of worldwide calorie production (Roberts and Schlenker, 2013). In the robustness section we show that the results are robust to using a broader index of food commodity prices.

[3]We could also aggregate the conflict data to a monthly frequency, but the external instruments used in this paper are only available at the quarterly frequency.

to the dynamics of the food-conflict nexus. In order to study the dynamic effect of food price changes on conflict, we apply the local projections method proposed by Jordà (2005).

The main findings are the following. First, we show that an exogenous rise in international food commodity prices increases both types of conflict. This contrasts with the results from a "naive" regression of conflict on food prices showing an inverse relationship. Hence, it is important to isolate exogenous changes in food prices. Second, for both conflict types the bulk of the effect takes place beyond one year after the price increase, and the effect is larger and more persistent for output conflict than for factor conflict. Third, we find that in areas with more agriculture, an exogenous price increase will result in more output conflict. This is in line with the deprivation hypothesis: in food-producing cells, higher food prices increase the income gap between net consumers and producers *and* there is food production available to prey upon. Again we show that when failing to account for an exogenous price change the results exhibit a downward bias. Fourth, we show that the inclusion of time fixed effects, as is commonly done in the literature to evaluate the effect on food producers, results in an underestimation of the true effect for producers, because there are positive baseline effects for all cells. For cells with an average amount of agriculture, the inclusion of time fixed effects results in an underestimation of the effect of food prices on conflict by almost 50 percent.

In the next section we describe the main theories and findings put forward in the existing literature, and we discuss the caveats in this literature. In section 3 we outline how we provide a solution for these caveats by identifying exogenous food price changes. Section 4 gives an overview of the conflict data used in this study. In section 5 we estimate the effect of exogenous food price changes on conflict and we compare these results with those from a "naive" regression. In section 6 we focus on the baseline effects and the differential effect for producers. Finally, section 7 concludes.

2 Existing Literature

In this section we first discuss the main theoretical reasons why higher food prices could affect conflict, next we outline the existing empirical findings, and finally we highlight the main caveats in the current literature. Note that we limit this literature review to the link between food prices and conflict. This rather specific food price-conflict literature fits within a broader literature focusing on the causes of civil war and other forms of conflict. Blattman and Miguel (2010) survey the vast literature on civil war and conclude that there is a robust link between civil war, low per capita income and slow economic growth, but that the direction of causality remains contested. Various empirical studies have continuously searched for better identification strategies. The papers discussed in this section fit within this literature, because they have (implicitly) used international food prices as an instrument for local economic conditions, thereby aiming to achieve causal identification.[4]

2.1 Theories

According to theory, the impact of food prices on conflict is not unambiguously negative or positive. There are two main reasons why higher food prices can reduce conflict. First, if food prices increase, there is a higher opportunity cost of insurrection for farmers. A higher wage makes it less appealing to abandon work (assuming higher food prices translate into a net increase in real farm wages). This interpretation has been the most popular one in the food-conflict literature, see e.g. Besley and Persson (2008), Dube and Vargas (2013), Bazzi and Blattman (2014), Berman and Couttenier (2015) and Fjelde (2015), but it is also a leading theory in a broader literature on the origins of civil war or conflict (e.g. Grossman, 1991, Collier and Hoeffler, 1998, 2004). Second, higher commodity prices can increase state revenues and hence also the capacity of the state to prevent, curb or resolve conflict (Fearon and Laitin, 2003, Besley and Persson, 2010). For food commodities this channel is probably less important than for higher-valued and more easily taxable commodities such as mined products, petroleum, rubber, coffee and cocoa (Bazzi and Blattman, 2014).[5]

Conversely, there are three reasons why higher food prices can result in more violent events. To begin with, food is a basic necessity. If higher food prices make food unaffordable, and if there is no legal way to obtain (money for) food, food price hikes will result into stealing or other criminal activities. We label this the absolute deprivation hypothesis. Second, even if there is legal way to purchase food (use up savings, borrow money, work more), consumers can feel relatively deprived. Deprivation can arise from comparisons over time or with other groups or individuals. According to the relative deprivation hypothesis, unfulfilled material expectations cause anger, ultimately leading to public unrest (Hendrix and Haggard, 2015).[6] Arezki and Brückner (2014), for example, find that higher food prices increase the

[4]Another group of studies has focused on weather variables as an instrument for economic conditions (e.g. Miguel et al., 2004). This is in turn related to an emerging literature linking climate and conflict. For a survey, see Burke et al. (2015).

[5]Nunn and Qian (2014) have shown that an increase in U.S. food aid due to changes in U.S. wheat production increases the incidence and duration of civil conflict. Qualitative accounts point to aid stealing as one of the key ways in which humanitarian aid fuels conflict. If this result can be extrapolated to global food aid, food aid could constitute another channel through which higher food prices reduce conflict: i.e. lower food production (corresponding with higher prices) entails less food aid and hence also less conflict.

[6]See Hendrix and Haggard (2015) for a discussion of the related psychological and behavioral economics

income gap in low-income countries, thereby increasing relative deprivation for consumers. This hypothesis is not often mentioned in the literature, but it is in line with a long list of episodes of high food prices coinciding with public unrest, ranging from ancient Rome, when "bread and circuses" were needed to appease the people (Juvenal, Satire 10.77–81), to the French Revolution (Doyle, 1989), flour riots in the 19th century in the U.S. (McPherson, 1988, Burrows and Wallace, 1999), and food riots in 2007–2008 in West and North Africa and in the Middle East (Bush, 2010, Berazneva and Lee, 2013). See for example Bellemare (2015) for an overview of food riots in modern and contemporary history. A third reason could be that higher prices increase the value of the appropriable surplus, the "state prize" (Besley and Persson, 2008, Dube and Vargas, 2013, McGuirk and Burke, 2017). However, this "rapacity effect" is probably less applicable for food commodities and more relevant for commodities that bring large rents, such as extractive commodities and tree crops (Bazzi and Blattman, 2014).[7]

To sum up, the most important channels through which food price shocks can affect violent events are the opportunity cost channel for farmers (predicting higher food prices to cause less conflict) and the absolute and relative deprivation channel for consumers (predicting higher food prices to result in more violent events). Our analysis is limited to food commodities. This will allow us to focus on a more limited number of theoretical mechanisms in the interpretation of the results. Several papers have shown that the findings can be opposite for different types of commodities. Dube and Vargas (2013) for example find opposite effects for agricultural goods and natural resources.

2.2 Empirical Evidence

A first glance at the existing empirical literature gives the impression that no consensus at all exists whether higher food prices result in conflict. Table 1 offers a schematic overview of thirteen recent studies in which the relationship between food prices and conflict plays a major

literature. Note that this relative deprivation effect is not the same as an inverse opportunity cost effect for consumers. Higher food prices will not decrease the opportunity cost of engaging in violent events for consumers, as higher food prices will decrease both the real wage of workers and the real "wage" (or any source of income that is used to buy groceries) for protesters/fighters. In fact, if protesting or engaging in violent events does not yield an income, liquidity-constrained consumers will have to work *more* to buy the same amount of food. On the other hand, there can be an inverse relative deprivation effect for farmers (i.e. they feel less relatively deprived when food prices are high). It is hard to discern this effect from the opportunity cost effect for farmers described earlier.

[7] A fourth reason is mentioned in the literature, namely that higher commodity prices can fund conflict, but it is also less likely that this applies to food crops. For example, Klare (2001) discusses several examples of natural resource extortion, such as diamonds in West Africa, timber in Cambodia, and cocaine in Colombia.

role. Some of these papers also focus on other commodity types besides food commodities or on other outcome variables besides conflict, but all of these papers estimate a variant of a (panel) model with a measure of violent events as the dependent variable and (among others) food prices as an explanatory variable. Four studies find that higher food prices lead to less conflict, whereas six studies show that higher food prices cause more conflict. Two papers find a mixed effect and one paper finds no significant link.

However, these seemingly opposing findings make more sense when grouped in a particular way. On the one hand, the papers that do not distinguish between the effect on producers and consumers, as well as the studies focusing on the effect for consumers find that higher food prices result in more conflict (Smith, 2014, Bellemare, 2015, Hendrix and Haggard, 2015, Janus and Riera-Crichton, 2015, Raleigh et al., 2015, McGuirk and Burke, 2017). On the other hand, there are studies that consider only the effect for producers. These studies construct an independent variable for which international food prices are multiplied with export or production shares. Most of these papers conclude that higher food prices reduce conflict (Brückner and Ciccone, 2010, Dube and Vargas, 2013, Berman and Couttenier, 2015, Fjelde, 2015, Janus and Riera-Crichton, 2015).[8] However, this finding is not entirely robust: Besley and Persson (2008) and Arezki and Brückner (2014) find that even when focusing on (net) export-weighted prices, higher food prices cause more conflict. McGuirk and Burke (2017) show that in food-producing cells higher prices result in more output conflict (e.g. riots and protests), but less factor conflict (large-scale battles). Bazzi and Blattman (2014) find no significant link between food prices and conflict incidence. To sum up, most studies find that higher food prices lead to more conflict, except some — but not all — papers focusing on the effect for producers find the opposite.

Some of the papers in table 1 have also investigated whether the link between food price changes and conflict depends on other characteristics. Various sources of heterogeneity are considered: the inclusiveness of the political institutions (Besley and Persson, 2008), the remoteness of the area (Berman and Couttenier, 2015), regime type (Hendrix and Haggard, 2015), ethnic composition (Janus and Riera-Crichton, 2015) and economic development (McGuirk and Burke, 2017). We will analyze whether heterogeneity influences our results in section 6.

[8] Janus and Riera-Crichton (2015) and McGuirk and Burke (2017) consider the effect for both consumers and producers. Janus and Riera-Crichton (2015) also look at the joint estimate by analyzing terms of trade changes.

2.3 Caveats in Existing Studies

Despite the recent surge in empirical studies on food and conflict, there are two important caveats in the existing literature: endogeneity and the omission of baseline effects when focusing on the differential effect for producers. First, when studying the effect of food prices on conflict, there are two sources of endogeneity. There could be reverse causality running from conflict to food prices. For this reason, most papers study international food commodity prices and they assume there is no causal effect of African conflict on global prices, because most African countries are small food producers (for example Smith, 2014; Hendrix and Haggard, 2015; Raleigh et al., 2015 and McGuirk and Burke, 2017). Some papers perform a robustness check where they exclude countries with levels of production above a certain threshold (Brückner and Ciccone, 2010, Arezki and Brückner, 2014, Bazzi and Blattman, 2014, Berman and Couttenier, 2015, Fjelde, 2015, Janus and Riera-Crichton, 2015). However, local conflict can also have an impact on global food prices through changing demand conditions. Bellemare (2015) addresses the issue of reverse causality by using data on natural disasters to identify the causal effect of food prices on social unrest. However, the exclusion criterion might not be met, as natural disasters could affect conflict incidence through other channels besides food prices.[9]

A second endogeneity problem arises if both international food prices and conflict are determined by a third variable such as global economic activity. To address this problem most papers in table 1 include time fixed effects to control for changes in conflict incidence related to the global business cycle or other common shocks.[10] The inclusion of time fixed effects wipes out any effect that is common for all countries. These studies resort to a difference-in-differences strategy: they multiply international food prices with time-invariant local food production, export or import shares. The estimated coefficient corresponds with the differential effect of higher food prices in cells with more production, exports or imports. However, this differential effect does not tell us anything about the overall effect of food prices on conflict. For example, if an increase in global commodity prices causes more conflict in all African countries, but slightly less so in food-producing countries, the difference-in-difference estimator will *only* provide us with the latter piece of information. These common effects,

[9] In another related paper Buhaug et al. (2015) estimate the effect on various conflict measures of local food production shocks instrumented by weather and they find no consistent link. The same concern with regards to the exclusion criterion applies. For the case of coffee Dube and Vargas (2013) address the reverse causality issue by instrumenting coffee prices with export volumes of the three major coffee exporters.

[10] See for example Besley and Persson (2008), Brückner and Ciccone (2010), Dube and Vargas (2013), Arezki and Brückner (2014), Bazzi and Blattman (2014), Smith (2014), Berman and Couttenier (2015), Fjelde (2015), Janus and Riera-Crichton (2015) and McGuirk and Burke (2017).

which we label baseline effects, can take place directly, via consumption, but also indirectly via trade or aid if global food supply shocks affect the global economy. We will illustrate the importance of these baseline effects explicitly in section 6.[11]

3 Exogenous Food Price Changes

In the previous section we have discussed the main problems that arise when estimating the effects of food prices on conflict. In this section we explain how we can address those caveats by identifying exogenous food price changes. To do so, we use two different shock variables which will later on serve as external instruments for changes in international food commodity prices: a series of unexpected food production shocks and a series of narrative shocks.

3.1 Food Production Shocks

The first external instrument is a quarterly series of unexpected changes in global food production. The underlying idea is that unexpected variations in harvests that are sufficiently large to affect global supply of cereals likely trigger significant shifts in international food commodity prices (fulfilling the instrument relevance condition). On the other hand, harvest volumes can in principle not (endogenously) respond to changes in the state of the economy within one quarter (fulfilling the exogeneity condition). More specifically, for the staple food commodities that we consider, there is a time lag of at least one quarter between the planting and harvesting seasons (De Winne and Peersman, 2016). If farmers adjust their planting volumes in response to changing economic conditions this could only have an impact on the harvest volumes in subsequent quarters. In any case, the possible influence of food producers on the volumes during the quarter of the harvest itself is probably meager relative to variation induced by other factors such as weather conditions, pests or diseases affecting crops. For example, it is not realistic that farmers increase food production significantly by raising fertilization activity during the harvesting quarter in response to an improvement of economic conditions. In fact, several studies have shown that in-season fertilization strategies are inefficient and often even counterproductive for the staples that we consider (see De Winne and Peersman, 2016 for a more elaborate discussion).

[11] The time fixed effects do not only wipe out the effects of a common demand shock, but also of a common supply shock. This channel is non-negligible: in De Winne and Peersman (2016) we have shown that global food supply disruptions have a large effect on the global economy. Another solution could be to include global economic activity as a control variable, but again, this would also eliminate the impact of a food supply shock that affects both global economic activity and conflict simultaneously.

To derive the instrument, in a first step, we construct a quarterly index of global food production. To do so, we elaborate on De Winne and Peersman (2016). More precisely, the Food and Agriculture Organization (FAO) of the United Nations publishes annual harvest data for each of the four major staples for 192 countries over the period 1961-2014.[12] In De Winne and Peersman (2016) we combined the annual harvest data of each individual country with that country's planting and harvesting calendars for each of the four crops, in order to allocate the harvest volumes to a specific quarter. Harvests were only allocated if the planting season was at least one quarter earlier. Since most countries have only one relatively short harvest season for each crop, i.e. a few months, and the delay between planting and harvesting varies between 3 and 10 months, we could assign two-thirds of world harvests to a specific quarter. In line with Roberts and Schlenker (2013) we then aggregated all crops and countries using calorie weights into one global quarterly index. In this paper we follow the same approach, but we exclude African production from the production index to ensure that the shock originates elsewhere. By doing so, we rule out changes in food production that are the result of conflict, or changes in food production that are the result of local weather conditions affecting both food production and conflict simultaneously.

In a next step, we use this index to obtain unexpected changes in global food production (ε_t). In essence, the shocks are prediction errors of the harvest volumes conditional on past harvests and a set of relevant information variables that may influence harvests. Specifically, we estimate the following equation:

$$Fq_t = \beta_0 + \beta_1(L)X_{t-1} + \varepsilon_t \tag{1}$$

Fq_t is the seasonally adjusted quarterly index of global food commodity production excluding Africa. X_{t-1} is a vector of control variables that may affect global food commodity markets and hence also harvest volumes with a lag of one or more quarters: an index of real food commodity prices (based on the same four crops), real oil prices, world industrial production and lagged values of the food production index. We include five lags of the control variables ($L = 5$). These variables should adequately capture global demand. Oil prices are included to make sure that we are not picking up a response to oil prices, because food commodities

[12]Note that the global food production index is based on only four crop types: wheat, maize, rice and soybeans. Limiting our analysis to these four commodities facilitates the construction of the global food production index needed for the identification of the quarterly shocks. These four crops account nevertheless for 75 percent of worldwide calorie production (Roberts and Schlenker, 2013), so the identified shocks should characterize developments in global food markets reasonably well. In De Winne and Peersman (2016) we have shown that exogenous food supply shocks based on the quarterly index of food production have a large and significant effect on global food commodity prices.

can be considered as a substitute for crude oil to produce refined energy products, while oil is used in the production, processing and distribution of food commodities. All variables enter in log-levels. A detailed description of the data used can be found in appendix A. Equation 1 is estimated for the largest time sample as possible (1962Q2–2014Q4).[13] If we assume that the information sets of local farmers are no greater than equation 1, the residuals (ε_t) of this equation can be considered as unanticipated harvest shocks. Figure 1 displays these residuals (ε_t), which we will use as our first instrument, together with the index of real food commodity prices.

To sum up, by excluding African production from the production index, the issue of reverse causality is addressed: any shock to food production should by construction originate elsewhere. As a consequence, we can make strong causal claims about the link between food market events and conflict. The second endogeneity issue is also addressed, because any unexpected change in the food production index that is not captured by the control variables are food supply shocks. This is the case because food production cannot react to demand conditions within a quarter, given the time lag between planting and harvesting of at least one quarter. Thus, any demand-induced production change should be captured by the lags of food prices or world industrial production.[14] Typically the unexpected changes in food production will be the result of harvest failure in the producing areas due to bad weather or a pest.

A worry could be that these external production changes are systematically correlated with global weather phenomena such as El Niño, and these weather phenomena might also affect conflict directly (Burke et al., 2015). In that case we would be measuring the effect of local weather on conflict instead of food price changes on conflict. Therefore we will include different local weather variables as control variables in a robustness check (see section 5). An additional concern could be that conflict elsewhere in the world has an effect on food production and at the same time influences conflict in Africa. If we include two different measures of international conflict (excluding Africa) between 1960 and 2014 and their (annual) lag in equation 1, the results remain unchanged (available on request).[15]

[13]If we instead restrict the sample for the estimation of equation 1 to 1997 Q1–2014 Q4, the results remain largely unchanged (results available on request).

[14]Note that these residuals are also exogenous with respect to *expected* demand conditions, because expectations of higher demand for food should be reflected in food prices, and food prices are included in equation 1.

[15]The first measure counts the number of events per year in the annual UCDP/PRIO Armed Conflict Dataset (version 4-2016). The second measure counts the number of deaths per year in the Systemic Peace Major Episodes of Political Violence Dataset.

3.2 Narrative Shocks

Alongside the unexpected food production shocks, we consider a second external instrument. This alternative instrument, which is borrowed from De Winne and Peersman (2016), is based on a narrative approach in the spirit of Hamilton (1983), Romer and Romer (1989, 2010), Ramey and Shapiro (1998) and Ramey (2011). Based on newspaper articles, FAO reports and disaster databases, a number of historical episodes have been identified that can be considered as major exogenous food commodity market disturbances. For each episode we made sure that the change in food prices is unambiguously driven by an exogenous commodity market shock, and not by another macroeconomic event, such as oil shocks.

A short motivation and description of these events — three unfavorable shocks in 2002, 2010 and 2012 and one favorable shock in 2004 — is listed in table 2. In the summer of 2002 droughts in major wheat and coarse grain producing countries, especially Russia and Australia, led to large drops in production. In that period real food commodity prices rose by 9.4%. In the third quarter of 2004, favorable weather conditions led to better-than-expected cereal harvests in Europe, China, Brazil and the U.S.. Real food prices declined by 6.9%. In the summer of 2010, droughts in Russia and Eastern Europe led to a surge in real food prices of 8.6% and 13.5% in the subsequent quarter. Two years later, in the third quarter of 2012, droughts in Russia, Eastern Europe, Asia and the U.S. caused a decline in global cereal production of 2.4%. Real food commodity prices increased by 7.9% in that quarter. A more detailed description, and excerpts from the newspaper articles and reports can be found in the online appendix of De Winne and Peersman (2016).

The instrument we use is a dummy variable equal to one for unfavorable food market disturbances and equal to minus one for the favorable event. The narrative shocks are also displayed in figure 1. The correlation between the food production shocks and the narrative shocks is 0.18. The advantage of the narrative method compared to the food production shocks is that we can incorporate a large amount of information. We can ensure for example that these shocks are not the result of conflict in Africa or anywhere else in the world. The downside is that it requires judgment from the researcher. In the benchmark analysis we will use both the food production shocks and the narrative shocks as external instruments to identify exogenous changes in food prices. In the robustness section we will also study the effect of using only one instrument. Section 5 outlines how we will use these external instruments in a dynamic panel model.

4 Conflict Data

In line with McGuirk and Burke (2017) we consider two different types of conflict: large-scale factor conflict and smaller-scale output conflict. For both types of conflict we rely on two highly disaggregated datasets, listing individual events that can (almost always) be allocated to a specific day and a specific geographical location (down to the level of individual villages). These two datasets have been often used in the literature. Both datasets are constructed based on information from various sources: local and international media sources, reports from NGOs and international organizations, research articles etc.

Factor conflict is defined as armed conflict over the control of land (McGuirk and Burke, 2017). As in McGuirk and Burke (2017) we use the Uppsala Conflict Data Program (UCDP) Georeferenced Event Dataset version 4 (Sundberg and Melander, 2013, Croicu and Sundberg, 2015) to measure factor conflict. The scope of this dataset is rather narrow, because the events are restricted to incidents of lethal violence committed by an organized actor.[16] Additionally, only those dyads (pair of conflicting parties) are included if during at least one year the conflict resulted in at least 25 battle deaths. Given that this variable measures larger conflicts, it is deemed appropriate to capture conflicts associated with the permanent control of land.[17]

The second conflict type, output conflict, is defined as conflict over the appropriation of surplus. To measure output conflict we use the Armed Conflict Location and Event Data Project (ACLED) database version 6 (Raleigh and Dowd, 2016). The scope of the database is wide, including various sub-types of conflict. In line with McGuirk and Burke (2017) we retain only two event types: riots and protests, and violence against civilians.[18] These events are more transitory and more likely to capture appropriation of surplus. The UCDP dataset covers the globe between 1989 and 2014 and the ACLED dataset covers only African

[16] An event is defined as: "An incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least one direct death at a specific location and a specific date".

[17] Note that also the ACLED database contains data on battles, however the threshold for inclusion is much lower in the ACLED database. By including these ACLED battle types we might run the risk of including events that fall within the scope of smaller-scale output conflict.

[18] Riots and protests include demonstrations against a political entity (or against businesses or other private institutions), and spontaneous acts of violence by disorganized groups, which may target property, businesses, or other disorganized groups. Violence against civilians is defined as deliberate violent acts perpetrated by an organized political group such as a rebel, militia or government force against unarmed non-combatants (Raleigh and Dowd, 2016). For example, the database includes an event classified as violence against civilians in October 2013, in Timiaouine (Algeria) with the following description: "A trader informed the gendarmerie force in Timiaouine that his truck which was carrying food had been looted and carjacked at a point 10km north of Timiaouine after having been attacked by an armed group consisting of four to five men." Additionally, note that the results are similar if we consider both types of smaller-scale conflict separately (results available on request).

countries between 1997 and 2015. In order to make useful comparisons between the two types of conflict we look at the overlapping sample for our benchmark analysis: Africa between 1997 and 2014.[19]

As in Berman and Couttenier (2015), Fjelde (2015), McGuirk and Burke (2017) we consider sub-national units of analysis, defined by a standardized grid structure covering all 54 African countries. The grid has a spatial resolution of 0.5 decimal degrees latitude/longitude (approximately 55×55 km at the equator), dividing the continent into 10678 equally sized cells (Tollefsen et al., 2012). Because of the large inter-annual variability in food prices and conflict incidence, we consider the quarterly frequency, so the cell-quarter is our unit of analysis. We recode the available conflict information into two different dependent variables. First, the events are transformed into a set of dummy variables indicating whether or not an event took place in a given cell-quarter. This approach is commonly used in the literature.[20] As a second dependent variable we consider conflict intensity. Smith (2014) argues that measuring the intensity of unrest is subjective and counting events requires distinguishing between events that may be related. On the other hand, the binary approach does discard a lot of potentially valuable information concerning the intensity of the conflict. Besides, in the ACLED database each event is recorded only once (in contrast, double-counting can occur when using a search and count of news stories approach as in Bellemare, 2015). Therefore we use the number of total events in a cell in a given quarter as a proxy for conflict intensity.[21]

Table 3 lists some descriptive statistics for each of these variables. ACLED output conflict is twice as common as UCDP factor conflict. The unconditional probability of any event taking place in a given quarter is 2.36 percent for ACLED output conflict versus 1.18 percent for UCDP factor conflict. Figure 2 shows the evolution of events over time. The number of ACLED events rises steeply as of 2010. This increase is driven by a large number of events between 2010 and 2014 in Egypt (3846), South Africa (4025), Somalia (2990) and Nigeria (2839). In contrast, the amount of UCDP events remains constant over time, with around 1000 to 2000 events per year.

[19]Most other papers in the food-conflict literature also focus on Africa (Brückner and Ciccone, 2010, Smith, 2014, Berman and Couttenier, 2015, Fjelde, 2015, Raleigh et al., 2015, McGuirk and Burke, 2017).

[20]See for example Besley and Persson, 2008, Smith, 2014, Berman and Couttenier, 2015, Fjelde, 2015, McGuirk and Burke, 2017.

[21]Dube and Vargas (2013), Arezki and Brückner (2014), Bellemare (2015), Hendrix and Haggard (2015), Raleigh et al. (2015) also include the total number of events in their analysis.

5 The Impact of Food Prices on Conflict: Price Changes versus Exogenous Price Changes

5.1 Estimation Framework

Bazzi and Blattman (2014) have raised the issue that a binary indicator of conflict incidence constrains shocks to have the same effect on conflict onset as on conflict continuation or ending. Moreover, they state that there is a serious econometric concern, as conflict is a persistent variable and ignoring dynamics biases the estimated effect of shocks on conflict. They suggest two solutions. One is to use a dynamic model, another solution is to model onset and ending separately. Whereas Bazzi and Blattman (2014) and also Berman and Couttenier (2015) and McGuirk and Burke (2017) opt for the latter option, we choose the first option.[22] We use the local projections method pioneered by Jordà (2005) to estimate impulse response functions. The local projections method easily allows us to study the dynamic effects of food price changes on conflict incidence in a panel set-up. This local projections method has become an increasingly popular method to study the dynamic effects of shocks, especially in a panel set-up.[23] Essentially, a local projections estimate of the impulse response function of the dependent variable y to a shock in an exogenous regressor x in period h after the shock, corresponds with the coefficient on x in the regression of y_{t+h}on the regressors measured at time t (Teulings and Zubanov, 2014). The intermediate values realized between t and $t+h$ are not included.

In our case, this local projections method entails estimating the following panel model for different horizons h:

$$c_{it+h} = \alpha_{ih} + \beta_h fp_t + \lambda_h(L)\, c_{it-1} + \psi_h(L)\, fp_{t-1} + \delta_{ch} \times y_{ct-1} + \gamma_{ih} \times trend_t + \mu_{it+h} \qquad (2)$$

where c_{it+h} is either a dummy variable indicating whether conflict took place in cell i in a given quarter (conflict incidence) or a variable counting the number of events (conflict intensity). α_{ih} are cell fixed effects. In the benchmark analysis we use a (production-weighted) index of international prices of only four crop types (fp_t). These four crops (wheat, maize, rice and soybeans) correspond with the instruments (see subsection 3.1). These crop prices, made available by the IMF, are representative for the global market and determined by the largest

[22] Nickell (1981) has shown that the fixed effects panel estimation of dynamic models is biased when the time dimension of the panel is small. We assume this bias is small in our set-up given that $T = 72$.

[23] The local projections method has been used to estimate, for example, government spending multipliers (Owyang et al., 2013), the effect of a banking crisis on GDP (Teulings and Zubanov, 2014) and the effect of household debt on the business cycle (Mian et al., 2017).

exporter of each commodity. In the robustness section we show that the results are robust to using a broader index of food commodity prices. Note that this variable is common for all cells.[24] As control variables we include five lags of the conflict variable and five lags of the price variable ($\lambda_h(L)$ and $\psi_h(L)$ are polynomials in the lag operator, with $L = 5$). We also include a country-specific coefficient for the natural logarithm of annual national GDP ($\delta_{ch} \times y_{ct}$) lagged by one year, in order to control for any local demand effects. Finally, we include a cell-specific trend ($\gamma_{ih} \times trend_t$) to capture any time-varying factor exhibiting an analogous trend to conflict in cell i. The conflict variables were discussed in the previous section, a description of the other data can be found in appendix A.

We estimate equation 2 in two ways. On the one hand we obtain "naive" results by estimating equation 2 using Ordinary Least Squares (OLS). On the other hand we deal with the endogeneity issues raised in subsection 2.3 by using the food production shocks and the narrative dummy variable as two external instruments for fp_t.[25] We assess the strength of the instrument set by evaluating the cluster-robust Kleibergen-Paap F-statistic. The values of the F-statistic range between 50 and 90 for the different horizons, which exceeds the relevant Stock and Yogo (2005) critical value. The first-stage t-statistics vary between -2.22 and -3.31 for the different horizons for the production shocks, and between 4.82 and 6.86 for the narrative shocks. When the dependent variable is the binary indicator of conflict this corresponds with estimating a linear probability model. This model is most commonly used in the literature owing to the straightforward interpretation of the coefficients.[26]

Equation 2 is estimated for horizons $h = 0, 1, ..., 12$. The coefficient β_h measures the effect of a change in food prices on conflict at each horizon h, controlling for past incidences of conflict and lagged values of food prices. By using a cell fixed effects model we study the

[24] Note that unlike some papers in table 1, we do not construct country or cell-specific food price indices by multiplying international price series with local production, consumption or trade weights. First, the choice of weights is not neutral: the resulting price index will lean closer to either consumers, producers or exporters. We will explicitly zoom in on the differential effect for producers in section 6. Second, the prices of these four crops (wheat, maize, rice, soybeans) are highly correlated anyway. For example, the correlation between the monthly change in the price of maize and the monthly change in the price of soybeans is 0.65 (between 1997 and 2014). Third, the instrument capturing production shocks is only based on these four crops (the construction of crop calendars is only feasible for a limited number of crops). By including more commodity types in the price index the instruments become weaker.

[25] Specifically, we use the Stata command *reghdfe* (Correia, 2017) which easily accommodates the large amount of fixed effects, the use of instrumental variables and clustered standard errors.

[26] An alternative approach is a model that explicitly takes into account the binary nature of the dependent variable. Most papers present these limited dependent variable results as a robustness check (see for example Besley and Persson, 2008; Brückner and Ciccone, 2010; Arezki and Brückner, 2014; Bazzi and Blattman, 2014; Berman and Couttenier, 2015; Janus and Riera-Crichton, 2015; Hendrix and Haggard, 2015 and McGuirk and Burke, 2017). We also find that when using an IV probit estimation with country fixed effects, the food supply shock has a significant positive effect on conflict incidence (results available on request).

variation in conflict within cells. The cell fixed effects control for any time-invariant effect on conflict incidence. For example, the fact that poor countries are more often involved in civil war (Besley and Persson, 2008) should be captured, at least to the extent that this is time-invariant. Notice that, since the international food commodity price index (fp_t) does not vary across cells, we cannot include time fixed effects. In contrast with the existing studies, we do not have to include these time fixed effects to control for global demand shocks, given that our identification strategy already ensures the exogeneity of food prices. Since we estimate the effect of a common shock, the errors may exhibit time effects, meaning that the errors may have arbitrary correlation across cells at a moment in time. We correct for this time effect by calculating Driscoll-Kraay standard errors. These standard errors also correct for persistent common shocks, with the degree of persistence increasing with horizon h (see Thompson, 2011, for an elaborate discussion).[27]

5.2 Results

It has been common practice in the conflict literature to show the estimation results in a table, but because we study the dynamic effects on conflict over time, we think it is more useful to show the results in the form of impulse response functions. This approach is common in the macroeconomic literature and various other fields of economics (see for example Jordà, 2005; Beaudry and Portier, 2006; Romer and Romer, 2010 and Galí, 1999). Results in tabular format are reported in the appendix table A1 (for space considerations we only include the peak effect). The impulse responses are shown in figure 3. In particular we show the estimated coefficient β_h of equation 2 for horizons $h = 0, 1, ..., 12$, both for UCDP factor conflict and ACLED output conflict. These impulse responses hence show the evolution over time – until 12 quarters after the initial shock – of the effect of a one percent increase in real food prices. We show both the effect on conflict incidence (part A) and intensity (part B) together with one and two standard error bands. The left column (red graphs) shows the results for the "naive" OLS estimations and the right column (blue graphs) shows the results for the IV estimation with the food production shocks and the narrative dummy as external instruments.

Figure 3 shows that for the OLS estimations an increase in food prices only has a significant impact on conflict incidence and intensity at a few horizons. Moreover, if significant (at the 5 percent level), this effect is negative. In contrast, when looking at the IV results, an exogenous increase in food prices has a significant positive effect on conflict. We can conclude that it

[27] By not including time fixed effects the estimates could be biased if there are omitted persistent common factors. In the robustness section in appendix B we show that an IV estimator with demeaned variables in order to capture these unobserved common factors yields very similar results.

matters to study exogenous changes in food prices. A potential explanation could be that a price increase can be the result of higher global economic activity. Higher global demand might coincide with increased trade flows, aid flows, remittances etc., which can (more than) offset the negative consequences of food price increases.

Our approach allows to study the dynamics of the effect of food shocks on conflict. On impact and within the first year after the shock the effect on conflict is much smaller and often not significantly different from zero. The effects peak around six quarters after the price increase, and for ACLED output conflict there is even a significant, though diminishing, effect in the third year after the shock. To get a better understanding of these dynamics we re-estimate equation 2 with the food commodity price index as the dependent variable. This allows us to assess the dynamic effects of a food production shock on food prices themselves. The result is shown in figure 4. We can see that after a food production shock, food prices keep on increasing for three quarters after the shock. Prices only return to baseline in the second year after the shock. It seems reasonably that if food prices increase, people do not immediately engage in conflict, since they probably have some reserves. However, if prices remain elevated, as is apparently the case after food production shocks, the relative and absolute deprivation become more pressing.

How large are the effects? A one percent exogenous increase in food prices augments UCDP factor conflict incidence with 0.03 percentage points after six quarters. The unconditional probability of such a large-scale event taking place in a given cell-quarter is 1.18 percent, so a ten percent exogenous increase in food prices leads to a relative increase in factor conflict probability of 25 percent.[28] For ACLED output conflict, a one percent exogenous increase in food prices increases conflict incidence with 0.092 percentage points after eight quarters. The unconditional probability of such a smaller-scale event taking place in a given cell-quarter is 2.36 percent, so a ten percent exogenous increase in food prices leads to an increase in factor conflict probability of 39 percent. This finding is in line with Arezki and Brückner (2014) who also show that increases in international food prices have a stronger positive effect on the incidence of demonstrations and riots than on civil conflict. The graphs for conflict intensity show that an increase in production has a similar effect on the total number of events. A one percent increase in real food prices leads to an increase in the absolute number of events at horizon six by 0.001 and 0.003 for factor and output conflict respectively.

In appendix B we present and discuss various robustness checks. A major concern of the approach proposed in subsection 5.1 is that we assume homogeneous slope coefficients

[28]This number is calculated as follows: 0.03 (increase in absolute probability for a 1 percent price increase) is multiplied with 10 (size of the price increase) and divided by 1.18 (unconditional probability).

for all cells. In the next section we investigate whether the coefficient β_h is different for cells with more agriculture. However, the literature has shown that various other sources of heterogeneity can exist (see subsection 2.2 for some examples). Pesaran and Smith (1995) propose a mean group panel estimator where separate regressions are estimated for each cross-sectional unit and panel estimates are obtained by means of taking cross-sectional averages of the estimation results. Appendix figure A1 shows that this mean group estimator yields very similar results. Furthermore, we show that the results of figure 3 are quantitatively robust to changing the set of external instruments, the inclusion of local weather variables, using a broad index of food commodity prices instead of a narrow index and including only precisely measured events.

6 Baseline Effects versus Relative Effects for Food-Producers

One of the caveats in the literature highlighted in subsection 2.3 is that most existing studies include time fixed effects to control for changes in conflict incidence related to the global business cycle. Therefore these studies have to resort to a difference-in-differences strategy: they multiply international food prices with, for example, time-invariant food production shares. The estimated coefficient corresponds with the differential effect of higher food prices on conflict in cells with more production. Given our identification strategy, we do not have to include these time fixed effects. This allows us to estimate both the baseline effect, which is common for cells with and without agriculture, as well as the relative effect for producers.

6.1 Estimation Framework

To measure the relative or differential effect for producers we build our case step by step. We run three types of estimations. As a starting point we follow the approach commonly used in the literature. We multiply food prices with a measure of agricultural specialization (s_{it}) to create a "producer price index". We estimate the following equation using OLS:

$$c_{it+h} = \alpha_{ih} + \beta_h^p fp_t \times s_{it} + \lambda_h(L)\, c_{it-1} + \psi_h^p(L)\, fp_{t-1} \times s_{it-1} + \gamma_{cth} + \mu_{it+h} \qquad (3)$$

In line with the literature we include time fixed effects (γ_{cth}).[29] We allow the time fixed effects to differ by country as is also done in McGuirk and Burke (2017). This strategy corresponds

[29] See for example Besley and Persson (2008), Brückner and Ciccone (2010), Dube and Vargas (2013), Arezki and Brückner (2014), Bazzi and Blattman (2014), Smith (2014), Berman and Couttenier (2015), Fjelde (2015), Janus and Riera-Crichton (2015) and McGuirk and Burke (2017).

with a difference-in-differences estimator: the coefficient β_h^p measures the effect of an increase in food prices on conflict for cells with an additional unit of agricultural specialization.

In a second step we can compare the OLS estimation of equation 3 with an IV approach in order to assess again the importance of dealing with endogeneity. As external instruments we now multiply the food production shocks and the narrative shocks with the measure of agricultural specialization. This approach still has some drawbacks. The difference-in-differences estimator only shows the *differential* effect for areas with more agriculture. Due to the inclusion of time fixed effects, the coefficient β_h^p does not tell us anything about the effect that is common for all producing cells.[30] For example, if higher food prices increase conflict in all producing cells, but slightly less in areas with more production, the difference-in-difference estimator would only give us the latter information, but it would not tell us anything about the total or absolute effects. There could be common effects for all cells via consumption, but also via spill-overs or via trade, investment, aid flows and remittances (if exogenous food price changes affect the global business cycle).

Given this shortcoming, as a third strategy, we also estimate the following equation, where we replace the time fixed effects by the food price index:

$$\begin{aligned} c_{it+h} = \alpha_{ih} + \beta_h^C fp_t + \beta_h^{\tilde{p}} fp_t \times s_{it} + \lambda_h(L)\, c_{it-1} + \psi_h^c(L)\, fp_{t-1} + \\ \psi_h^{\tilde{p}}(L)\, fp_{t-1} \times s_{it-1} + \tau_h s_{it} + \delta_{ch} \times y_{ct-1} + \gamma_{ih} \times trend_t + \mu_{it+h} \quad (4) \end{aligned}$$

We estimate equation 4 using an IV approach. The coefficient β_h^C measures the baseline effects of a food price increase for all cells (with and without agriculture) and the coefficient $\beta_h^{\tilde{p}}$ measures how this effect is different for cells with an additional unit of agricultural specialization.[31]

In line with McGuirk and Burke (2017) we use cell-specific land-use data to measure agricultural specialization. More specifically, we use the share of the area of a cell dedicated to agriculture provided by the PRIO-GRID.[32] Data are available for 1990, 2000 and 2010. We interpolate and extrapolate missing values.[33] The agricultural land share ranges between

[30] A similar remark on the use of time fixed effects has been made by Dupor and Guerrero (2016) in the context of estimating the effect of fiscal spending on U.S. states.

[31] Given the comment of Brambor et al. (2006) with regards to the omission of constitutive terms (i.e. the elements that constitute the interaction term) potentially leading to an omitted variable bias, we also include agricultural specialization (s_{it}) by itself in equation 4. However, this does not affect the results.

[32] The underlying dataset is the ISAM-HYDE land-use dataset.

[33] Using constant values instead of interpolated values has little effect on the results. Results available on request.

0 and 99 percent, and is 7 percent on average.

6.2 Results

In figure 5 we compare three sets of results: (i) equation 3 estimated with OLS; (ii) equation 3 estimated with IV; (iii) equation 4 estimated with IV. We show the results for both UCDP and ACLED conflict, and for conflict incidence (part A) and conflict intensity (part B). The peak effects are also reported in appendix table A2.

First, when comparing column (i) and column (ii), notice that there is again a large difference between the OLS estimates and the IV estimates. The impulse responses show the effect of an increase in food prices on conflict for cells with an additional unit of agricultural specialization. This means that for the OLS estimates, the impulse responses show the differential effect on conflict of an increase in food prices due to any type of shock (e.g. a demand shock) for cells with more agriculture. The IV estimates only show the differential effect on conflict of an increase in food prices due to a supply shock. Overall, we can conclude that including time fixed effects is not an adequate way to filter out demand effects.

Looking at the effects of the exogenous price changes, column (ii), we can see that for UCDP factor conflict the sign of the effect changes over time. First there is a positive effect on factor conflict, but in the third year after the shock there is a negative effect (only significant for conflict incidence). This means that for factor conflict, which typically includes larger conflicts, in the long-run the opportunity cost effect for farmers surpasses the absolute and relative deprivation effect for consumers.[34]

For ACLED output conflict, an increase in real food prices has a significant positive effect on conflict incidence and intensity in cells with one percentage point more agricultural land. This means that higher food prices result in more output conflict in food producing cells. From a theoretical point of view this means that the relative and absolute deprivation effect for consumers more than offset the opportunity cost effect for producers. When food prices rise, the income gap between net consumers and net producers will increase, which can result into anger and protest according to the relative deprivation hypothesis. Additionally, the presence of producers facilitates theft or looting. These results are consistent with the

[34] McGuirk and Burke (2017) also find a negative effect on UCDP factor conflict in food-producing cells. According to their theoretical model, in food-producing cells, higher food prices will reduce factor conflict, as rural groups choose to farm rather than to attack neighboring territory. Factor conflict is concerned with the permanent control of the land, and an increase in prices will have a comparatively weaker effect on the present value of victory than on the opportunity cost of fighting. However, this theoretical prediction rests on the assumption of stationary prices.

findings of McGuirk and Burke (2017): they also show that higher food prices cause more ACLED output conflict in food-producing cells. Furthermore, in a robustness check with Afrobarometer survey data, they show that higher food prices increase the probability that commercial farmers report incidences of theft and violence in food-producing areas.

Next, we focus on column (iii) showing the IV estimations of equation 4. The blue impulse responses (first row) show the additional effect for one percentage point more agricultural land (coefficient $\beta_h^{\tilde{p}}$ in equation 4). The additional effect for producers is more or less similar to the IV results in column (ii), although the effect for UCDP factor conflict is less significant. The green impulse responses (second row) correspond with the baseline effects (coefficient β_h^C in equation 4), i.e. the effects that are common for all cells, regardless their level of agricultural production. For both conflict types there are significant positive baseline effects of food price changes on conflict. For example, for ACLED output conflict incidence, a one percent rise in real food prices leads to a common increase in the absolute probability of conflict of 0.034 percentage points after two years. For a 10 percent food price increase, this corresponds with a relative increase in the probability of 15 percent. Each additional percentage point of land devoted to agriculture increases the absolute probability with 0.005 percentage points. For cells with an average share of agricultural land of 7 percent, a 10 percent increase in prices will increase the relative probability of output conflict additionally with 15 percent.[35] In total, the probability of conflict occurring in those cells will thus increase by 29 percent.[36] Omitting the baseline effects would lead us to understate the effect in those cells by 50 percent. Note that the positive baseline effects also apply to cells with no food production at all. The effect is consistent with the hypothesis of relative deprivation: even in cells with no production, higher food prices make consumers poorer, which causes grievances and can lead to riots and protests.

In appendix B we present various robustness checks. We perform the same robustness

[35]We assume a linear effect: each additional unit of agricultural specialization has the same effect. If we instead estimate equation 4 with the interaction of food prices and a dummy variable indicating if agricultural production is larger than a certain threshold, we observe again that more agriculture leads to more conflict, but as the share of agricultural land increases the extra effect on conflict becomes smaller. For example, for ACLED output conflict, a one percent increase in real food prices leads to a maximal increase in the absolute probability of conflict incidence of 0.21 percentage points for cells with a share of agricultural land of more than 1.56 percent (the median). For cells with a share of agricultural land of more than 7.19 percent (75 percentile) and 21.27 (90 percentile) there is an increase in conflict incidence of respectively 0.37 and 0.44 percentage points.

[36]These numbers are calculated as follows: 0.0344 is multiplied with 10 (size of the price increase) and divided by 2.36 (unconditional probability of conflict), which results in a relative increase in the probability of 15 percent. 0.005 is also multiplied with 10 (size of the price increase) and divided by 2.36 (unconditional probability of conflict), this number is then multiplied by 7 (average agricultural land share) which results in 15 percent.

checks as in the previous section: controlling for local weather conditions, changing the set of external instruments, using a broader index of food commodity prices, and including only precisely measured events. Additionally, we also alter the measure of agricultural specialization by using the share of cereal net exports in GDP instead of the agricultural land share. This variable is only available at the country-level and the additional effect for cereal net exporters is never significant at the 5 percent confidence level. However, the large, positive baseline effect remains significant. Next, agricultural specialization could be correlated with other characteristics. For example, there is a positive correlation between the share of agricultural land in a cell and the population of a cell. A higher population density could be a breeding ground for certain types of conflict. Therefore, as a robustness check we include interaction terms of food prices with other characteristics that could be correlated with agricultural specialization and/or that have been found to play an important role in the literature. We include interactions with population, travel time, the polity2 index for democracy, and an ethnic diversity dummy. Overall, for both factor and output conflict incidence, the positive effect for cells with more agriculture remains significantly positive when including these interactions. We also find that more populous, and less distant cells experience more output conflict when food prices increase.

6.3 Why Is There More (Output) Conflict in Cells With More Agriculture?

Our finding that in cells with more agriculture, higher food prices have a stronger positive effect on (mainly) output conflict incidence might seem somewhat counter-intuitive. Figure 6 sheds more light on this matter. The left histogram in figure 6 shows how much of the household budget is spent on food and beverages in Africa and the right histogram shows the share of the budget spent on grains. These figures are based on household survey data from 2010 provided by the World Bank.

In the majority of the countries more than fifty percent of the household budget is spent on food and beverages (left histogram). The total numbers (black bars) mask a divergence between the urban population (gray bars) on the one hand, and the rural population (white bars) and the population belonging to the lowest income group (blue bars) on the other hand. In the majority of the countries, these latter two groups spend more than sixty percent on food and beverages. It is remarkable that even in rural areas, where we expect households to be more self-sufficient, more money is spent on food and beverages than in urban areas. Grains take up a smaller part of the household budget, but they are again more important for rural and low income households than for urban households (right histogram). Knowing that in rural areas more money is spent on food and grains than in urban areas, it is less surprising that in cells with more agriculture a food price increase leads to more output conflict.

7 Conclusion

Since 1997 political violence in Africa has resulted in more than 600.000 deaths.[37] A plethora of studies has tried to analyze which factors cause such havoc. A large strand of this literature has focused on the link between income shocks and conflict. A subset of this literature has focused on changes in international food prices as the source of income shocks. We extend this literature by estimating the dynamic effects of exogenous food supply shocks rather than a potentially endogenous food price change.

Our findings are the following: 1) Exogenous food price increases raise conflict incidence and intensity in Africa. "Naive" estimates find the opposite effect, so identifying exogenous price changes is non-trivial. 2) The effect is more pronounced for output conflict types such as riots and protests (39 percent higher probability after a 10 percent real food price increase), than for battles over land control (25 percent higher probability). Because we estimate a dynamic model, we can see that the bulk of the effect only takes place beyond one year after the price increase. Especially for output conflict the effect is persistent: also in the third year after the shock there is still a significant effect on output conflict. 3) The effect on output conflict is more pronounced in areas with more agricultural land. 4) Additionally, we show that the inclusion of time fixed effects as is commonly done in the literature to evaluate the effect for food producers wipes out the positive baseline effects for areas with and without agriculture. As a result, the total effect for food producers is in fact much larger.

Overall, our results confirm that income shocks are a likely source for violent events. Although most violent events probably do not occur because of higher food prices, but due to broader economic conditions or political grievances such as injustice, inequality and political repression (Bush, 2010, Berazneva and Lee, 2013), these income shocks can be a trigger to engage in violent events. It is unlikely that the implications of these results will become less important in the future. The demand for cereals in sub-Saharan Africa will approximately triple by 2050 and unless there is significant agricultural intensification and massive cropland expansion sub-Saharan Africa will depend much more on imports of cereals than it already does today (Ittersum et al., 2016).

[37] Based on ACLED dataset, sum of estimated fatalities for all conflict types between 1997 and 2015.

Consequently, our results support the type of policy recommendations oriented at insuring poor societies against negative income shocks in order to avoid violent events (Blattman and Miguel, 2010). However, our results also suggest that these insurance schemes should not only be targeted towards farmers, but also — and perhaps more importantly — towards the consumers. Measures targeting only the poorest consumers are easier to maintain than broader consumer subsidies (Egyptian government food and fuel subsidies increased from 1.4 percent in 2002 to 8 percent of GDP in 2011 according to Hendrix and Haggard, 2015) and cause less international turmoil than export bans or restrictions (a strategy followed by China and India in 2008).

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Appendix A: Data

- **Food production index excluding Africa**: The construction of this index is based on annual food production data downloaded from the Food and Agriculture Organization (FAO). Annual production data for wheat, rice, soybeans and maize are allocated to a specific quarter using country-specific harvest calendars. The four crops are then aggregated into a global index using calorie weights. For a more detailed description of the construction of the index, see De Winne and Peersman (2016). The index is seasonally adjusted using Census X-13 (X-11 option).

- **Real food commodity price index:** The real food commodity price index is a (trend) production-weighted aggregate of the price series of corn, wheat, rice and soybeans made available by the IMF. These benchmark prices are representative for the global market and determined by the largest exporter of each commodity. Seasonally adjusted using Census X-13 (X-11 option). The nominal price index has been deflated by U.S. CPI.

- **World industrial production:** World industrial production is the world industrial production index from the Dutch Bureau for Economic Policy Analysis backcasted for the period before 1991 using the growth rate of industrial production from the United Nations.

- **Oil price:** The real oil price series is the refiner acquisition cost of imported crude oil. Seasonally adjusted using Census X-13 (X-11 option). The nominal price index has been deflated by U.S. CPI.

- **Domestic GDP:** National GDP in current U.S. dollars made available by the World Bank at an annual frequency (code: NY.GDP.MKTP.CD).

- **Share of agricultural land in total:** We use the share of the area of a cell used as agricultural land provided by the PRIO-GRID. The underlying dataset is the ISAM-HYDE land-use dataset. Data are available for 1990, 2000 and 2010. We interpolate and extrapolate missing values.

Appendix B: Robustness

B.1 Robustness of Figure 3

We perform a number of checks to evaluate the robustness of the baseline results of section 5. The point estimates are shown in figures A1 and A2, together with the two standard error confidence bands of the benchmark estimations of figure 3. A complete overview of the robustness checks, including error bands, is available on request.

- **Mean Group estimator:** A major concern of the approach proposed in subsection 5.1 is that we assume homogeneous slope coefficients for all cells. In section 6 we investigated explicitly whether the slope coefficient is different for cells with more agriculture. However, the literature has shown that various other sources of heterogeneity can exist (see subsection 2.2 for some examples). Pesaran and Smith (1995) have shown that if slope heterogeneity is present, a fixed-effects model is fundamentally misspecified and will yield biased results. Pesaran and Smith (1995) propose a mean group panel estimator where separate regressions are estimated for each cross-sectional unit and panel estimates are obtained by means of taking cross-sectional averages of the estimation results. Appendix figure A1 (dotted black line) shows that this mean group estimator yields very similar results.

- **Addressing potential omitted common factors problem:** Everaert and De Groote (2016) have shown that omitting common factors in a dynamic panel model implies inconsistent estimators when the omitted common factor shows persistence. The inconsistency spills over even to the exogenous variables (in our case the instrumented fp_t) if these are correlated with the lagged dependent variable (in our case c_{it-1}). In order to deal with this potential bias we use an IV approach in order to eliminate any time fixed effect, except for the effect of an exogenous food shock. Specifically, we instrument all variables in equation 2 that could be correlated with the omitted common factors: we instrument fp_t (and its lags) with the two external instruments (and their lags) and we instrument c_{it-1} (and its lags) with the demeaned variable (across cross-sections). Appendix figure A1 (dashed-dotted green line) shows that following this approach yields very similar results, indicating that the bias due to persistent omitted common factors is small. However, instrumenting 11 variables with 17 instruments renders the Kleibergen-Paap F-statistic very small and it becomes hard to assess the strength of the instruments. Therefore we do not follow this approach as our benchmark approach.[38]

[38] Note that the natural logarithm of annual national GDP ($\delta_{ch} \times y_{ct}$) could also be correlated with the

- **Different external instruments:** For the baseline results we included two external instruments. As a robustness check we include only one external instrument. The size of the effect is very similar when including only the food production shocks as external instrument (figure A1, full blue line), but the results are less significant. The Kleibergen-Paap F-statistics (tables available on request) are now much lower: between 6.7 and 16.7, so our instrument is a borderline weak instrument. The dummy variable on the other hand is a much stronger instrument and the results are also significantly positive when using only this variable as external instrument (figure A1, red dashed line).

- **Including weather variables:** As mentioned above, if the changes in the food production index are the result of weather phenomena that also affect Africa, and weather has a direct effect on conflict, the results in figure 3 might be showing the effect of global weather patterns on conflict. For example, the Intergovernmental Panel on Climate Change (2001) lists the El Niño-Southern Oscillation (ENSO) and the the North Atlantic Oscillation (NAO) as key factors influencing African inter-annual variability of climate. Burke et al. (2015) survey an emerging literature linking climate and conflict. In order to control for local weather conditions we include three different local weather variables as a robustness check. These weather variables are made available at the cell-year level by the PRIO-GRID project.[39] We include the average temperature in a cell, the total precipitation in a cell and the proportion of the year that experienced drought. We include both the contemporaneous values and the one year lag of the weather variables. The underlying sources for these variables are respectively: the GHCN_CAMS dataset for temperature, the GPCP Version 2.3 Combined Precipitation Data Set (both provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, U.S.) and the SPEI Global drought monitor. This latter variable captures deviations from normal conditions and it takes into account both temperature and precipitation. Figure A2 (black dotted line) shows that the results are very similar when including these weather variables.

- **Broader index of food commodity prices:** The size of the effect is slightly larger when using the food commodity price index from the International Monetary Fund (figure A2, full blue line). This index is a trade-weighted average of different benchmark food prices in U.S. dollars for cereals, vegetable oils, meat, seafood, sugar, bananas,

omitted common factors. However, these country-specific coefficients are absorbed as fixed effects when using the function reghdfe. Using the demeaned variable (across countries) also does not alter the results.

[39] These datasets can be downloaded at http://grid.prio.org/#/download.

and oranges. These benchmark prices are representative of the global market and are determined by the largest exporter of each commodity. A one percent increase in real food commodity prices increases the probability of ACLED output after two years with 0.16 percentage points, compared to 0.097 for a one percent increase in the narrow index of food commodity prices. However, the two external instruments are less strong when using this broad index.

- **Only precise events:** Both the UCDP and the ACLED dataset include information on the spatial and temporal precision level of the event. Events are attributed the highest level of precision if the actual date is provided by the source and if a particular town and coordinates for that town are provided. Lower levels of precision are assigned if only the week or month, or (a part of) the region of the event are provided. We re-run the estimations, but we include only events when the exact month of the event is know (temporal precision level lower than 5 for UCDP factor conflict and all ACLED events - ACLED does not include events with less temporal information) and the exact location or 25 km radius is known (spatial precision level lower than or equal to 2 for UCDP events and equal to 1 for ACLED events). The results (figure A2, red dotted line) remain largely unchanged.

The results are also qualitatively robust to changing the time period (using the full sample for both conflict types — 1989Q1 until 2014Q4 for UCDP factor conflict and 1997Q1 until 2015Q4 for ACLED output conflict — or restricting the sample period to the pre-crisis period 1997Q1 until 2006Q4. These results are available on request.

B.2 Robustness of Figure 5

First of all, we perform the same robustness checks as for figure 3. These results are available on request. Again, the results are quantitatively robust to including weather variables, changing the external instruments, using a broader index of food commodity prices, and including only precise events.

Second, we perform a number of additional robustness checks. Here we focus on the robustness of the results in column (iii), the IV estimations of equation 4.

- **Cereal Net Exports:** Instead of the land share devoted to agriculture we can also use the share of cereal net exports in GDP as a measure of agricultural specialization. The use of the share of cereal net exports in GDP is more in line with the country-year panel papers that have constructed country-specific food price indices by multiplying international commodity prices with (net) export shares (see for example (Besley and Persson, 2008, Brückner and Ciccone, 2010, Arezki and Brückner, 2014, Bazzi and Blattman, 2014) and Janus and Riera-Crichton, 2015). However, the share of cereal net exports in GDP is only available at the country level.[40] Figure A3 shows that countries with (one standard deviation) more cereal net exports experience more factor and output conflict after an increase in food prices, but the effect is not very significant. Importantly, the green impulse responses show that there is a significant baseline effect on conflict incidence and intensity for both types of conflict.

- **Controlling for other interactions:** Agricultural specialization might be correlated with other characteristics. For example, there is a positive correlation between the share of agricultural land in a cell and the population of a cell. A higher population density could increase certain types of conflict. Therefore, as a robustness check we include interaction terms of food prices with other characteristics that could be correlated with agricultural specialization and/or that have been found to play an important role in the literature. We include interactions with population, travel time, the polity2 index for democracy and an ethnic diversity dummy. Population at the cell level is made available by the PRIO-GRID at five-year intervals.[41] Berman and Couttenier (2015) find that the relationship between income shocks and conflict is significantly weaker for more remote cells, because these cells are less likely to be affected by international shocks. Therefore we also include the interaction with a variable measuring the travel time to the nearest urban center. This time-invariant variable is also provided by the PRIO-GRID.[42] Next, Hendrix and Haggard (2015) find a positive relationship between food prices on urban unrest, but only for democracies. Therefore we also include the interaction with the annual Polity2 index, which scores countries between -10 (strongly autocratic) and +10 (strongly democratic).[43] Finally, Janus and Riera-Crichton (2015) find that commodity terms of trade declines cause civil war only in countries with intermediate ethnic diversity. In line with their approach we construct a dummy variable equal to one for countries with intermediate ethnic diversity: this corresponds with a population share

[40]Cereal export and import data is downloaded from the UN Comtrade Database (SITC Rev. 2, Cereals and cereals preparations). GDP is made available by the World Bank.

[41]The underlying source is the Gridded Population of the World dataset, made available by the Socioeconomic Data and Applications Center.

[42]The underlying global map of accessibility was developed by the European Commission and the World Bank.

[43]This index is part of the Polity IV project, and it is produced by the Center for Systemic Peace.

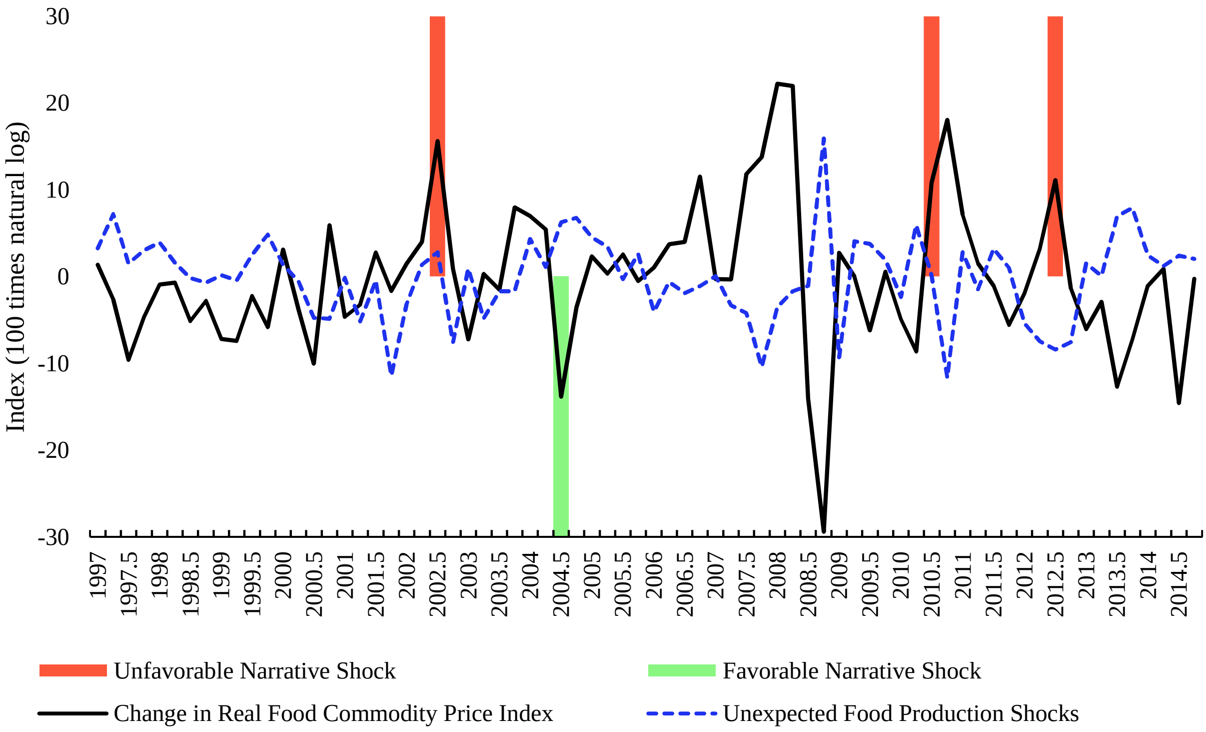
of the largest ethnic group between 50% and 85%, based on data from Fearon (2003). Figures A4 and A5 show the results for the interaction with these characteristics. The full set of results, including the baseline effect and additional effect for cells with more agriculture, are available on request. The estimates are scaled so that they show the effect of an additional standard deviation of the characteristic. Overall, for both factor and output conflict incidence, the effect for cells with more agriculture remains significantly positive. For conflict intensity the positive effect largely disappears when including the interaction with population. Additionally, we can see that more populous cells experience less factor conflict and more output conflict after a food price increase. More remote cells experience less output conflict. There is no significant impact of the interaction with regime type. Finally, cells with intermediate ethnic diversity will experience more factor conflict (in the short term), which is in line with finding by Janus and Riera-Crichton (2015). The long term effect (mainly for output conflict) is opposite.

Table 1: Literature on Food Prices and Conflict

Paper	Set-up & Sample	Independent	Dependent	Distinction	Controls	Finding [i]
McGuirk and Burke (2017)	Grid cell - Year Africa '89-'13	Producer prices: $\sum$(World Prices$_t$*Trade Share$_{country}$*Crop Land Share$_{cell}$) Consumer prices: $\sum$(World Prices$_t$*Trade Share$_{country}$*Crop Calorie Share$_{country}$)	Conflict (UCDP GED, ACLED & Afrobarometer Survey) (dummy for incidence, onset, offset)	Type of conflict Food vs. cash crops, Interaction with luminosity, urbanization.	Control for weather, for interaction with population, distance to lights and capital, mountain terrain, precolonial hierarchy.	Mixed: - (P) & + (C) for factor conflict[ii] + (P&C) for output conflict
Raleigh et al. (2015)	Regional - Month Africa '97-'10	Local Commodity Prices$_{rt}$ (IV: International Prices$_t$)	Violent Conflict (ACLED) (count)	Interaction with climate, feedback from conflict to prices	Democracy, economic growth (t)	+
Janus and Riera-Crichton (2015)	Country - Year Global '70-'09	Commodity Terms of Trade: $\Delta\ln(\prod(Pt\hat{}\text{Export Share}_c)/\prod(P_t\hat{}\text{Import Share}_c))$	Civil war onset (UCDP, COW) (dummy for onset)	Interaction with ethnic diversity	Income, population, trade openness, government expenditure, foreign aid, democracy (t-5)	Mixed: - (P) & + (C)
Hendrix and Haggard (2015)	City - Year Asia & Africa '61-'10	International Food Prices$_t$	Urban protests and riots (PRIO Urban Social Disturbance database) (count)	Interaction with regime type	GDP per capita, GDP growth, trade openness (t-1)	+
Fjelde (2015)	Grid cell - Year Africa '90-'10	Δ($\sum$Export Prices$_{t-1}$ * Production$_c$)	Conflict (UCDP GED) (dummy for incidence)	Asymmetries	Local income, population, excluded ethnic group, time since conflict, spatial dependence, drought, oil or diamond extraction. (t-1)	- (P)
Berman and Couttenier (2015)	Grid cell - Year sub-Saharan Africa '80-'06	World Import Value$_{country,t}$*Production$_{region}$	Conflict (UCDP GED, ACLED) (dummy for incidence, intensity, onset and ending)	Interaction with remoteness (distance to seaport)	Interaction with distance to capital, distance to natural resources, distance to border, population, GDP (time-invariant)	- (P) [iii]
Bellemare (2015)	Month Global '90-'11	Food Prices$_t$ (IV: Natural Disasters$_t$)	Social Unrest (search of news stories and SCAD) (count)			+
Smith (2014)	Country - Month Africa '90-'12	Domestic Food Prices$_{ct}$ (IV: International Prices$_{ct}$ & Rainfall$_{ct}$)	Urban unrest (SCAD) (dummy for incidence)	Type of unrest	Election time, democracy, civil conflict, size of youth population, urban population, income, life expectancy, mortality	+ (C)
Bazzi and Blattman (2014)	Country - Year Developing countries '57-'07	($\Delta\ln(\prod$Commodity Export Prices$_t\hat{}$Export Share$_{c,t-2}$))*Commodity Exports/GDP$_c$	Civil wars, battle deaths, coups (UCDP, COW and others) (dummy for onset and ending, count of deaths)	Various crop types	Consumption shock (t, t-1, t-2)	No link
Arezki and Brückner (2014)	Country - Year Low-income countries '70-'07	$\Delta\ln(\prod$International Food Prices$_t$ ^ Food Net Export Share$_c$)	Demonstrations, Riots, Civil Conflict (UCDP and others) (count)		Weather conditions (t)	+ (P-C)
Dube and Vargas (2013)	Municipality - Year Columbia '88-'05	$\sum\ln$(International Commodity Prices$_t$)* Production$_m$	Armed Conflict (count)	Various types of attacks, Various types of commodities	Coca production, population (t)	- (P) for agricultural commodities, which are labour intensive
Brückner and Ciccone (2010)	Country - Year sub-Saharan Africa '80-'06	Δ($\sum$International Commodity Prices$_t$ * Export Share$_c$)	Civil War (UCDP) (dummy for onset)		Rainfall (t, t-1, t-2)	- (P)
Besley and Persson (2008)	Country - Year Global '60-'05	$\sum$International Commodity Prices$_t$ * Export Share$_c$ $\sum$International Commodity Prices$_t$ * Import Share$_c$	Civil War (COW, UCDP) (dummy for occurence)	Interaction with political institutions	Controls: Income, Democracy, Natural Disasters (t)	+ (P&C)

Notes: (i) "-" means higher food prices lead to less conflict. "+" means higher food prices lead to more conflict. "P" and "C" stand for focus on the effect for respectively producers and consumers. "P-C" means that the paper looks at a net effect, producers minus consumers, e.g. terms of trade. (ii) The authors define factor conflict as conflict over the permanent control of land and output conflict as as conflict over the appropriation of surplus. (iii) The authors shows that when using country level data no significant effect is found.

Figure 1: Real Food Price Index, Unexpected Food Production Shocks and Narrative Shocks



Notes: The real food commodity price index is a (trend) production-weighted aggregate of the price series of corn, wheat, rice and soybeans made available by the IMF, deflated with U.S. consumer prices. The construction of the unexpected food production shocks and the narrative shocks is explained in section 3.

Table 2: Overview of Narrative Food Shocks

Period	Type	(Cumulative) change in food commodity prices		Food commodity market event
		Impact	After 1Q	
2002Q3	Unfavorable	9.4%	10.7%	**Significant downward revised global cereal estimates** The FAO's July 2002 forecast pointed to a global cereal output which was 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 Russia. In September, the Australian Bureau of Agricultural and Resource Economics and Sciences announced that drought would slash the country's winter grain production. Australia is one of the top five wheat exporters. In retrospect, U.S. wheat production decreased by 18 percent in 2002, and Australian wheat production decreased by 60 percent.
2004Q3	Favorable	-6.9%	-10.9%	**Significantly improved forecast of world cereal output** Favorable weather conditions triggered expectations of significantly higher cereal production in Europe, China, Brazil, and the United States. In July 2004, the International Grains Council announced an expected rise in the global volume of coarse grain. In September 2004, the FAO raised its forecast for world cereal output after the previous report in June. Annual global cereal production increased by more than 9 percent in 2004.
2010Q3	Unfavorable	8.6%	22.1%	**Droughts in Russia and Eastern Europe** The 2010 cereal output in Moldova, Russia, Kazakhstan, and Ukraine was seriously affected by adverse weather conditions. Russia, Kazakhstan, and Ukraine (all three among the world's top 10 wheat exporters) suffered the worst heat wave and drought in more than a century, and Moldova was struck by floods and hail storms. In Russia, the country that was most severely affected by adverse conditions, the 2010 cereal crop was 33 percent lower than the previous year. In Ukraine, the wheat harvest decreased by 19 percent. Accordingly, in July 2010, wheat prices saw the biggest one-month jump in more than three decades, a rise of nearly 50 percent. since late June. In September, wheat prices were even 60 to 80 percent higher due to a decision by Russia to ban exports.
2012Q3	Unfavorable	7.9%	6.9%	**Droughts around the globe** Due to droughts in Russia, eastern Europe, Asia, and the United States, there was a signifcant decline in global cereal production. In retrospect, annual global cereal production contracted by 2.4 percent. In July 2012, the USDA decreased its June estimate for U.S. corn by 12 percent because of the worst midwestern drought in a quarter century. Heat waves 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 negatively affecting the rice harvest in Asia. According to the International Food Policy Research Institute, production of food grains in southern Asia was expected to decline by 12 percent compared with a year earlier. Also in August, the Russian grain harvest forecasts were reduced because of a drought. In October 2012, wheat output in Russia was estimated to be about 30 percent down from 2011; in Ukraine, a decrease of about 33 percent was expected; and in Kazakhstan, output was reported to be just half of the previous year's good level. The wheat harvest indeed declined in 2012, by 33 percent, 29 percent, and 57 percent in Russia, Ukraine, and Kazakhstan, respectively.

Note: Table based on De Winne and Peersman (2016) - Online Appendix.

Figure 2: Conflict Events in Africa

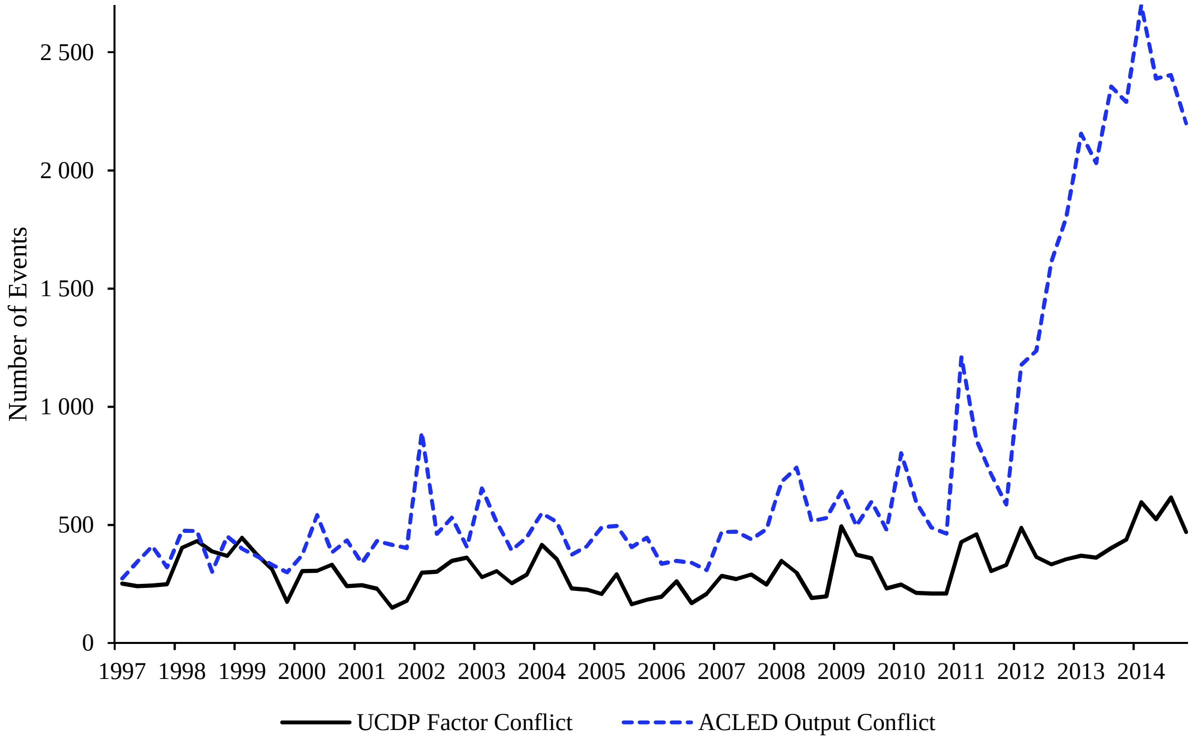


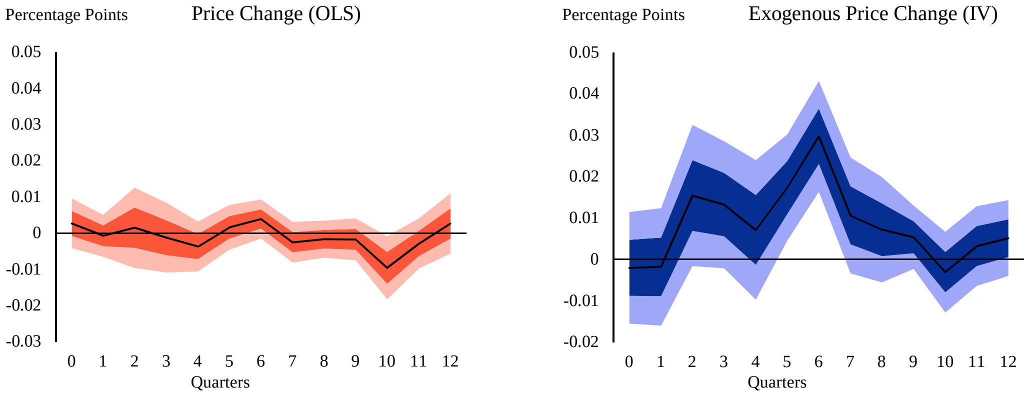
Table 3: Descriptives

Variable	Mean	Std. Dev.	Sample	Observations
UCDP Factor Conflict Dummy (%)	1.18	10.82	1997Q1-2014Q4	768816
UCDP Factor Conflict Total Events	0.03	0.56	1997Q1-2014Q4	768816
ACLED Output Conflict Dummy (%)	2.36	15.18	1997Q1-2014Q4	768816
ACLED Output Conflict Total Events	0.07	1.06	1997Q1-2014Q4	768816

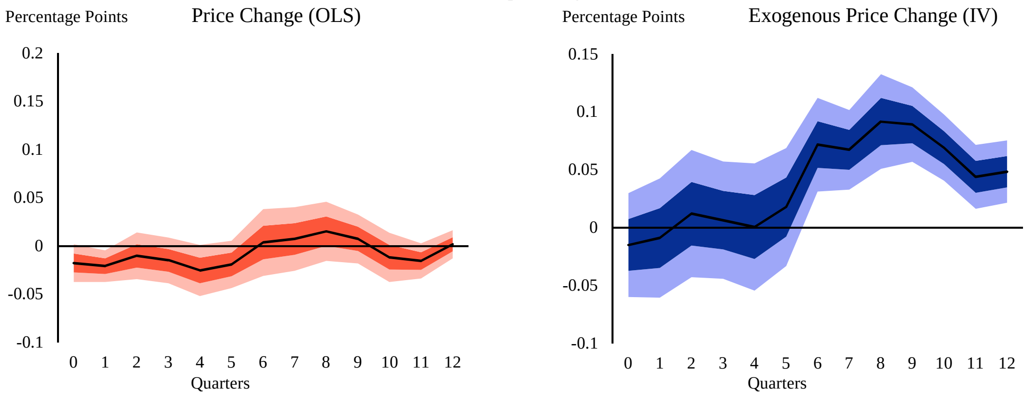
Figure 3: Effects of a 1 Percent Increase in Food Prices on Conflict

(A) Conflict Incidence

(1) UCDP Factor Conflict

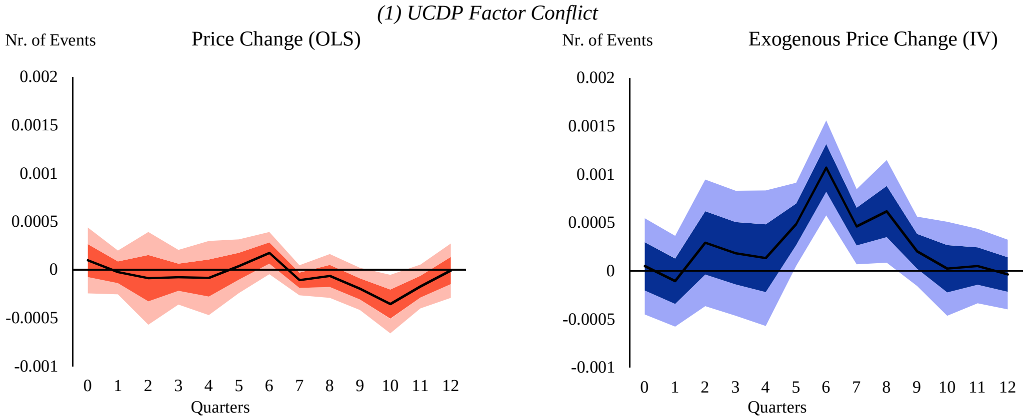


(2) ACLED Output Conflict

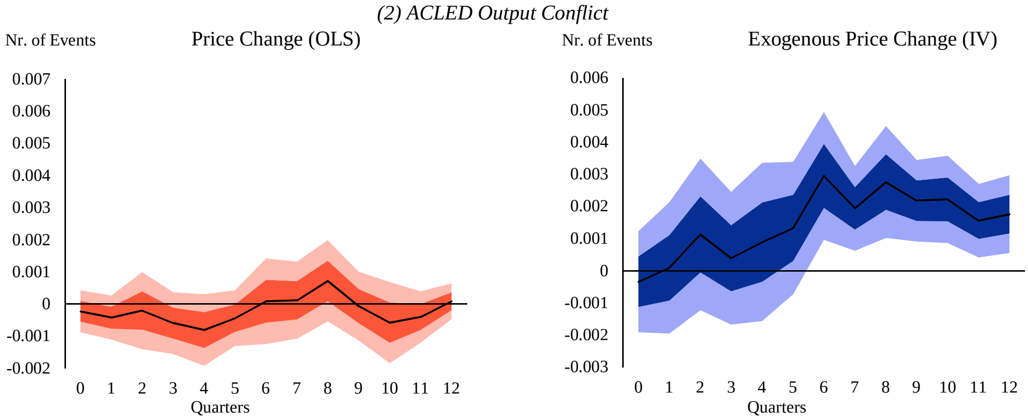


(B) Conflict Intensity

(1) UCDP Factor Conflict

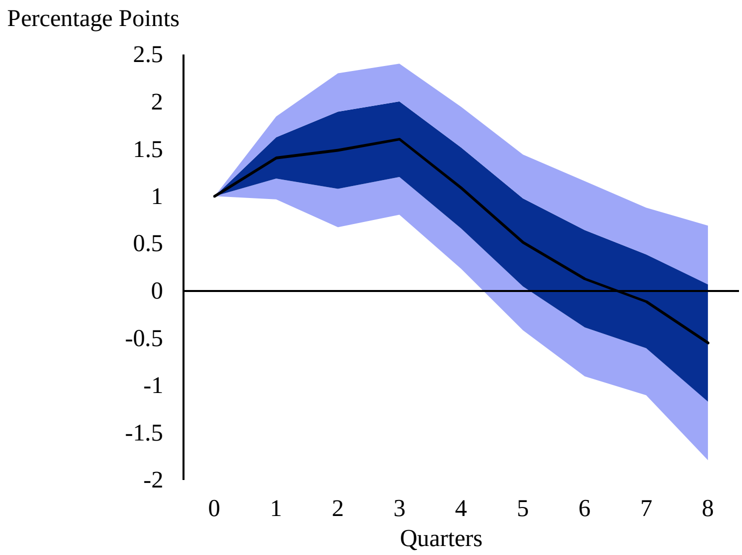


(2) ACLED Output Conflict



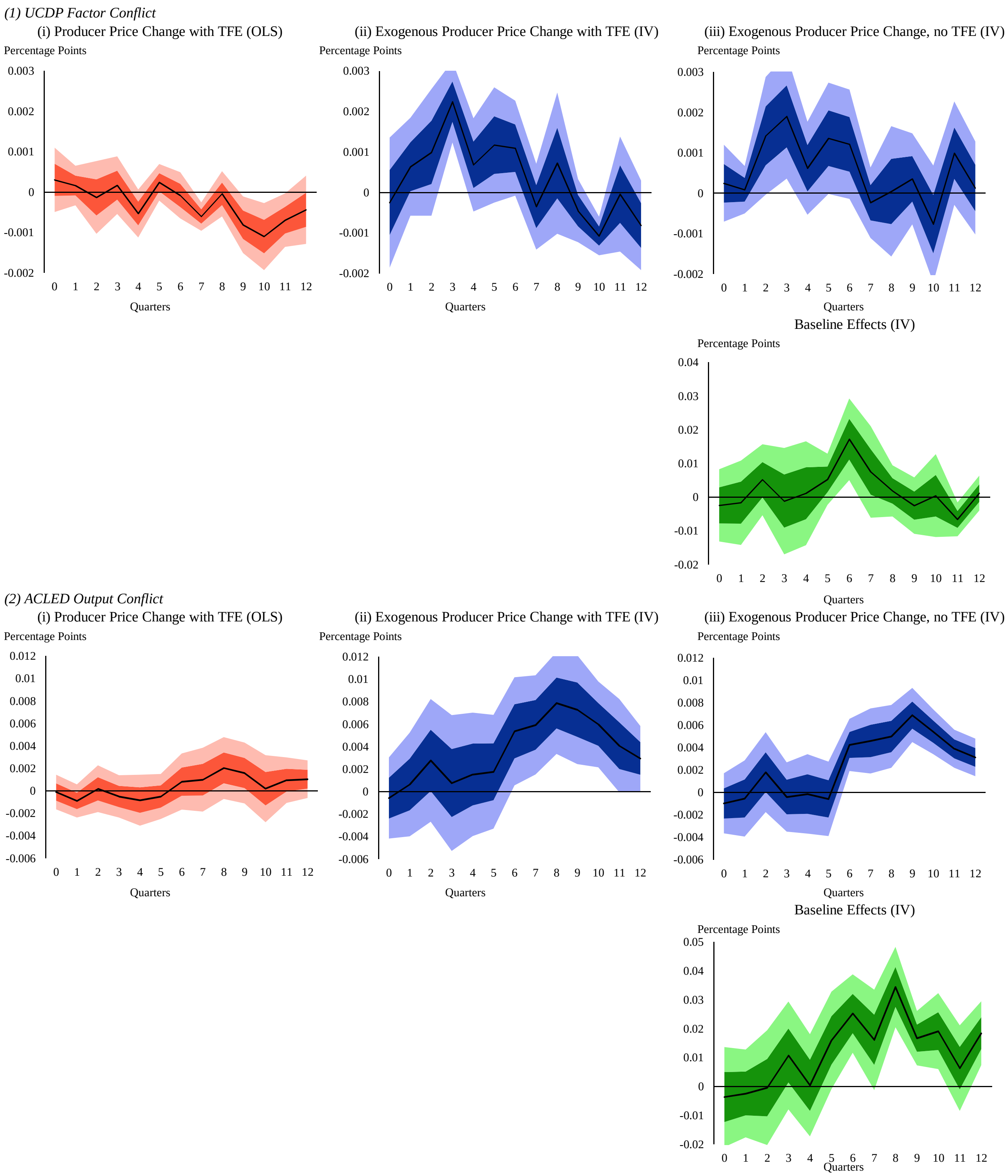
Note: Cell fixed effects, cell-specific time trends, 5 lags of the conflict variable, 5 lags of food prices, and country-specific annual lags of national GDP are always included. External instrumental variables: residual from production function and narrative dummy. One and two standard error confidence bands based on Driscoll-Kraay standard errors.

Figure 4: Effects of an Exogenous Food Production Shock on Food Prices



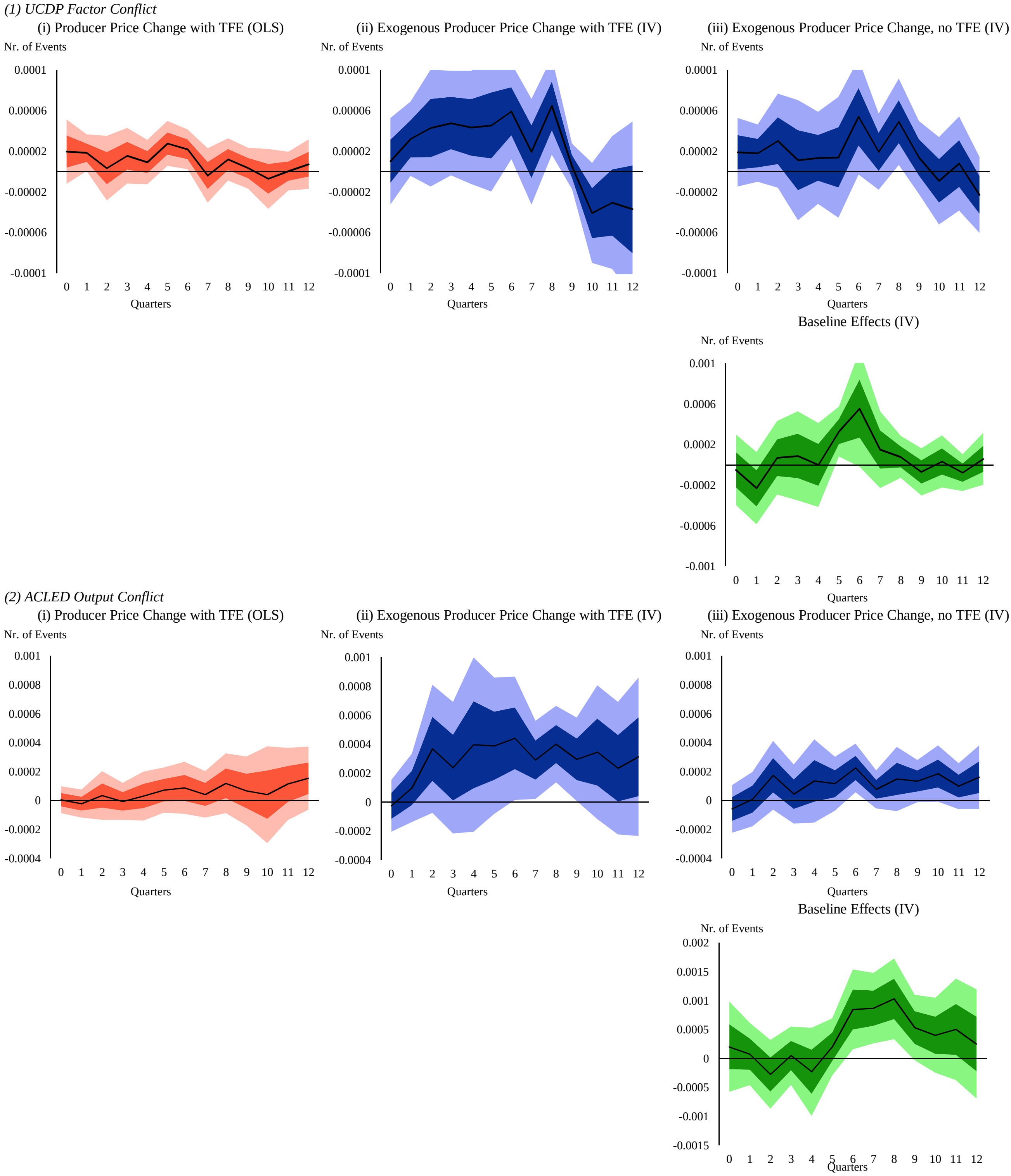
Note: Cell fixed effects, cell-specific time trends, 5 lags of food prices, and country-specific annual lags of national GDP are included. External instrumental variables: residual from production function and narrative dummy. One and two standard error confidence bands based on Driscoll-Kraay standard errors.

Figure 5A: Effects of a 1 Percent Increase in Food Prices and Food "Producer" Prices on Conflict Incidence



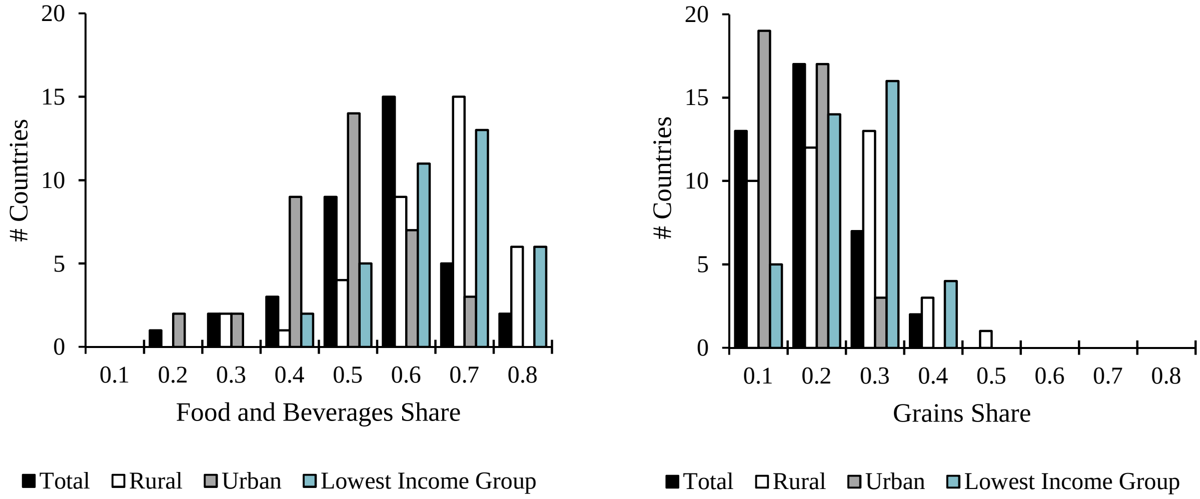
Note: Cell fixed effects, 5 lags of the conflict variable and 5 lags of food "producer" prices are always included. Estimations of equation 3 include country-specific time fixed effects (TFE). Estimations of equation 4 also include 5 lags of food prices and the measure of agricultural specialization, and the country-specific annual lag of national GDP. External instrumental variables: residual from production function and narrative dummy. One and two standard error confidence bands based on Driscoll-Kraay standard errors.

Figure 5B: Effects of a 1 Percent Increase in Food Prices and Food "Producer" Prices on Conflict Intensity



Note: Cell fixed effects, 5 lags of the conflict variable and 5 lags of food "producer" prices are always included. Estimations of equation 3 include country-specific time fixed effects (TFE). Estimations of equation 4 also include 5 lags of food prices and the measure of agricultural specialization, and the country-specific annual lag of national GDP. External instrumental variables: residual from production function and narrative dummy. One and two standard error confidence bands based on Driscoll-Kraay standard errors.

Figure 6: Histogram of Food and Grains Shares in Household Expenditures



Source: World Bank Global Consumption Database (based on survey data, 2010 values) for consumption data. The lowest income group corresponds with an income below $2.97 per capita a day.

Appendix Table A1: Maximal Effect of a 1 Percent Increase in Food Prices on Conflict

	(A) Conflict Incidence				(B) Conflict Intensity			
VARIABLES	UCDP Factor		ACLED Output		UCDP Factor		ACLED Output	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
Horizon	6	6	8	8	6	6	6	6
Food Prices	0.004	0.030***	0.015	0.092***	0.0002	0.001***	0.0001	0.003***
S.E.	(-0.003)	(-0.007)	(-0.015)	(-0.020)	(0.000)	(0.000)	(-0.001)	(-0.001)
P-value	0.158	0.000	0.322	0.000	0.117	0.000	0.896	0.004
L1.Conflict Variable	-0.021	-0.021	-0.023**	-0.022**	0.026	0.026	-0.012	-0.012
S.E.	(-0.013)	(-0.013)	(-0.009)	(-0.009)	(-0.040)	(-0.040)	(-0.064)	(-0.064)
P-value	0.113	0.113	0.014	0.015	0.516	0.517	0.851	0.853
L2.Conflict Variable	-0.008	-0.008	-0.026***	-0.026***	-0.046***	-0.046***	0.063**	0.063**
S.E.	(-0.011)	(-0.011)	(-0.009)	(-0.009)	(-0.016)	(-0.016)	(-0.031)	(-0.031)
P-value	0.453	0.454	0.007	0.009	0.006	0.006	0.047	0.047
L3.Conflict Variable	-0.016	-0.016	-0.023***	-0.023***	-0.034***	-0.034***	0.027	0.027
S.E.	(-0.010)	(-0.010)	(-0.007)	(-0.007)	(-0.011)	(-0.011)	(-0.020)	(-0.020)
P-value	0.127	0.128	0.001	0.001	0.003	0.003	0.193	0.190
L4.Conflict Variable	-0.015*	-0.015*	-0.018***	-0.018***	-0.016	-0.016	0.072	0.072
S.E.	(-0.008)	(-0.008)	(-0.005)	(-0.005)	(-0.017)	(-0.017)	(-0.094)	(-0.094)
P-value	0.058	0.057	0.001	0.001	0.348	0.349	0.446	0.446
L5.Conflict Variable	-0.026***	-0.026***	-0.032***	-0.032***	-0.054***	-0.054***	0.063	0.063
S.E.	(-0.007)	(-0.007)	(-0.005)	(-0.005)	(-0.015)	(-0.015)	(-0.039)	(-0.039)
P-value	0.000	0.000	0.000	0.000	0.001	0.001	0.113	0.113
L1.Food Prices	-0.006	-0.040***	-0.008	-0.109***	-0.000**	-0.001***	0.000	-0.004***
S.E.	(-0.004)	(-0.008)	(-0.013)	(-0.027)	(0.000)	(0.000)	(-0.001)	(-0.001)
P-value	0.168	0.000	0.545	0.000	0.044	0.000	0.790	0.007
L2.Food Prices	0.003	0.025***	-0.010	0.054**	0.000	0.001***	0.000	0.003**
S.E.	(-0.005)	(-0.006)	(-0.012)	(-0.024)	(0.000)	(0.000)	(-0.001)	(-0.001)
P-value	0.522	0.000	0.394	0.029	0.175	0.000	0.545	0.016
L3.Food Prices	0.003	-0.011	0.007	-0.034	0.000	-0.001**	0.000	-0.002
S.E.	(-0.005)	(-0.008)	(-0.013)	(-0.023)	(0.000)	(0.000)	(-0.001)	(-0.001)
P-value	0.619	0.187	0.614	0.145	0.393	0.028	0.552	0.123
L4.Food Prices	-0.011**	-0.002	0.013	0.042*	0.000	0.000	0.000	0.001
S.E.	(-0.005)	(-0.007)	(-0.017)	(-0.022)	(0.000)	(0.000)	(-0.001)	(-0.001)
P-value	0.024	0.775	0.450	0.057	0.304	0.429	0.447	0.426
L5.Food Prices	0.017***	0.012***	0.008	-0.007	0.000***	0.000*	0.001	0.000
S.E.	(-0.003)	(-0.004)	(-0.018)	(-0.017)	(0.000)	(0.000)	(-0.001)	(-0.001)
P-value	0.000	0.002	0.671	0.704	0.001	0.094	0.125	0.432
Observations	636,098	636,098	615,738	615,738	636,098	636,098	636,098	636,098
Adjusted R-squared	0.254	0.254	0.333	0.332	0.278	0.278	0.489	0.488
Kleibergen-Paap F-statistic		60.82		51.43		60.81		60.76
Hansen J-statistic		0.353		1.41		0.149		0.873
p-value		0.552		0.235		0.7		0.35

Note: Cell fixed effects, cell-specific time trends, and country-specific annual lags of national GDP are always included. External instrumental variables: residual from production function and narrative dummy. Driscoll-Kraay standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table A2: Maximal Effects of a 1 Percent Increase in Food Prices and Food "Producer" Prices on Conflict

	(A) Conflict Incidence						(B) Conflict Intensity					
VARIABLES	UCDP Factor			ACLED Output			UCDP Factor			ACLED Output		
	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV	(6) IV	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV	(6) IV
Horizon	6	6	6	8	8	8	6	6	6	8	8	8
Producer Prices (= Food Prices * Agricultural Specialization)	-0.0001	0.001*	0.001*	0.002	0.008***	0.005***	0.00002**	0.0001**	0.0001*	0.0001	0.0004***	0.0001
S.E.	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
P-value	0.770	0.068	0.078	0.146	0.001	0.001	0.029	0.015	0.063	0.250	0.004	0.184
Baseline Effect (=Food Prices)			0.017***			0.034***			0.001*			0.001***
S.E.			(0.006)			(0.007)			(0.000)			(0.000)
P-value			0.006			0.000			0.058			0.005
L1.Conflict Variable	0.039***	0.039***	-0.021	0.030**	0.030**	-0.024***	0.172***	0.172***	0.028	0.182**	0.181**	0.017
S.E.	(0.011)	(0.011)	(0.013)	(0.014)	(0.014)	(0.008)	(0.041)	(0.041)	(0.042)	(0.077)	(0.077)	(0.016)
P-value	0.001	0.000	0.113	0.038	0.038	0.006	0.000	0.000	0.507	0.022	0.022	0.299
L2.Conflict Variable	0.039***	0.039***	-0.009	0.019	0.019	-0.025***	0.035	0.035	-0.049***	0.174	0.174	0.066
S.E.	(0.013)	(0.013)	(0.011)	(0.014)	(0.014)	(0.009)	(0.027)	(0.027)	(0.017)	(0.144)	(0.144)	(0.099)
P-value	0.005	0.004	0.417	0.195	0.191	0.008	0.197	0.197	0.005	0.232	0.232	0.509
L3.Conflict Variable	0.023**	0.023**	-0.016	0.017	0.017	-0.024***	0.047*	0.047*	-0.036***	0.125*	0.125*	0.042
S.E.	(0.011)	(0.011)	(0.010)	(0.012)	(0.012)	(0.006)	(0.027)	(0.027)	(0.011)	(0.073)	(0.073)	(0.036)
P-value	0.043	0.042	0.130	0.152	0.149	0.000	0.087	0.087	0.002	0.091	0.090	0.242
L4.Conflict Variable	0.017**	0.017**	-0.016**	0.018	0.018	-0.019***	0.062***	0.062***	-0.016	0.126**	0.126**	0.027
S.E.	(0.008)	(0.008)	(0.007)	(0.013)	(0.013)	(0.005)	(0.021)	(0.021)	(0.018)	(0.055)	(0.055)	(0.027)
P-value	0.030	0.030	0.037	0.172	0.173	0.000	0.005	0.005	0.358	0.026	0.026	0.322
L5.Conflict Variable	0.008	0.008	-0.026***	0.008	0.008	-0.031***	0.044	0.044	-0.057***	0.075**	0.075**	-0.014
S.E.	(0.008)	(0.008)	(0.007)	(0.013)	(0.013)	(0.005)	(0.033)	(0.033)	(0.015)	(0.030)	(0.030)	(0.037)
P-value	0.353	0.350	0.000	0.563	0.556	0.000	0.194	0.193	0.000	0.016	0.016	0.702
L1.Producer Prices	-0.000	-0.002***	-0.002**	-0.001	-0.010***	-0.005***	-0.000***	-0.000***	-0.000**	-0.000	-0.001**	-0.000
S.E.	(0.000)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
P-value	0.411	0.008	0.018	0.405	0.002	0.002	0.001	0.002	0.013	0.325	0.024	0.240
L2.Producer Prices	0.001	0.002***	0.001*	0.000	0.006**	0.002*	0.000**	0.000***	0.000***	0.000	0.000**	0.000
S.E.	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
P-value	0.174	0.004	0.061	0.916	0.047	0.077	0.014	0.000	0.004	0.561	0.044	0.307
L3.Producer Prices	-0.001*	-0.002**	-0.001	0.001	-0.003	-0.001	-0.000	-0.000**	-0.000**	0.000	-0.000	0.000
S.E.	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
P-value	0.060	0.015	0.383	0.715	0.166	0.438	0.137	0.025	0.030	0.663	0.250	0.911
L4.Producer Prices	-0.000	0.000	-0.001	0.000	0.003	0.002	-0.000	0.000	0.000	0.000	0.000	0.000
S.E.	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
P-value	0.764	0.640	0.371	0.744	0.167	0.291	0.481	0.767	0.619	0.794	0.202	0.607
L5.Producer Prices	0.001**	0.001*	0.001**	-0.000	-0.001	-0.000	0.000**	0.000	0.000**	-0.000	-0.000	-0.000
S.E.	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
P-value	0.011	0.057	0.021	0.846	0.313	0.804	0.031	0.186	0.021	0.616	0.274	0.814
L1.Food Prices			-0.021***			-0.043***			-0.001**			-0.001**
S.E.			(0.007)			(0.010)			(0.000)			(0.001)
P-value			0.004			0.000			0.038			0.017
L2.Food Prices			0.014***			0.023**			0.000**			0.001*
S.E.			(0.004)			(0.009)			(0.000)			(0.000)
P-value			0.001			0.012			0.018			0.072
L3.Food Prices			-0.006			-0.017**			-0.000			-0.001**
S.E.			(0.004)			(0.008)			(0.000)			(0.000)
P-value			0.205			0.028			0.135			0.049
L4.Food Prices			0.002			0.022***			0.000			0.001**
S.E.			(0.004)			(0.007)			(0.000)			(0.000)
P-value			0.592			0.002			0.459			0.017
L5.Food Prices			0.003			-0.002			0.000			0.000
S.E.			(0.002)			(0.003)			(0.000)			(0.000)
P-value			0.199			0.526			0.781			0.852
Agricultural Specialization			-1.835***			-8.375***			-0.069***			-0.226***
S.E.			(0.438)			(0.969)			(0.015)			(0.016)
P-value			0.000			0.000			0.000			0.000
TFE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Observations	628,117	628,117	614,504	607,523	607,523	594,838	628,117	628,117	614,504	607,523	607,523	594,838
Adjusted R-squared	0.220	0.220	0.256	0.297	0.296	0.325	0.354	0.354	0.279	0.332	0.332	0.507
Kleibergen-Paap F-statistic		57.37	30.63		55.56	25.87		57.34	30.63		55.49	25.87
Hansen J-statistic		2.331	0.340		0.770	2.644		4.149	0.0282		0.659	2.933
p-value		0.127	0.843		0.380	0.267		0.0417	0.986		0.417	0.231

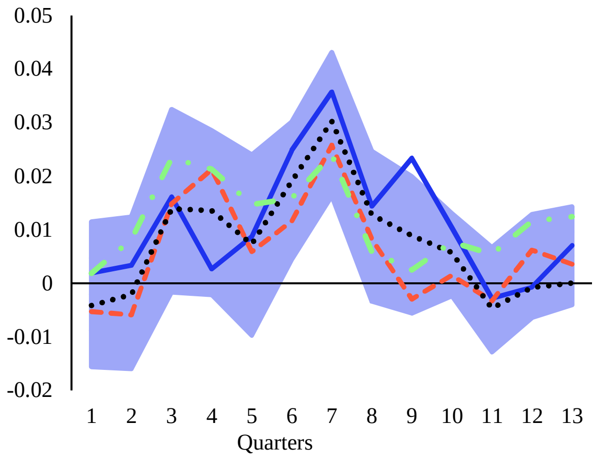
Note: Cell fixed effects are always included. Estimations of equation 3 include country-specific time fixed effects (TFE). Estimations of equation 4 also include the country-specific annual lag of national GDP. External instrumental variables: residual from production function and narrative dummy. Driscoll-Kraay standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Appendix Figure A1: Robustness of Figure 3

(A) Conflict Incidence

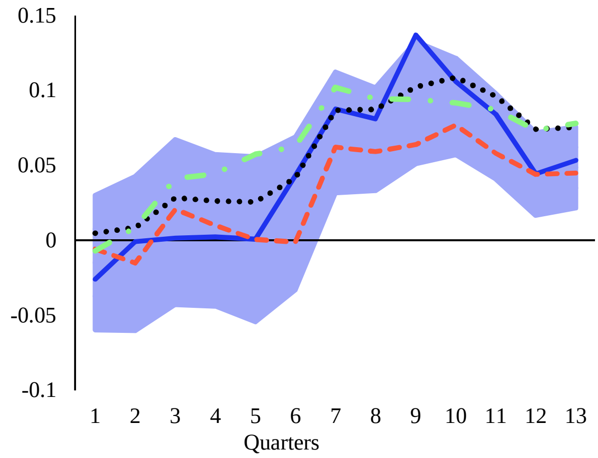
(1) UCDP Factor Conflict

Percentage Points



(2) ACLED Output Conflict

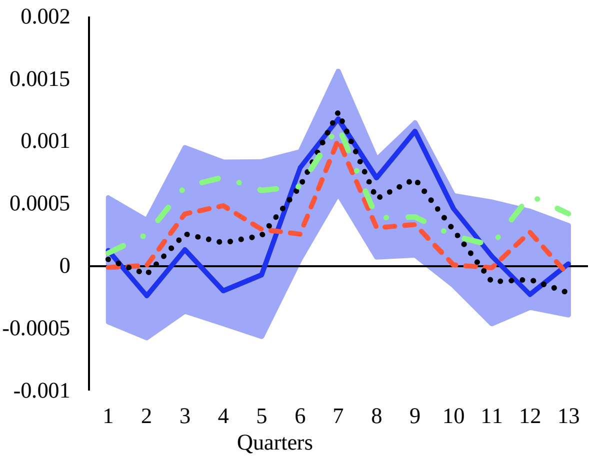
Percentage Points



(B) Conflict Intensity

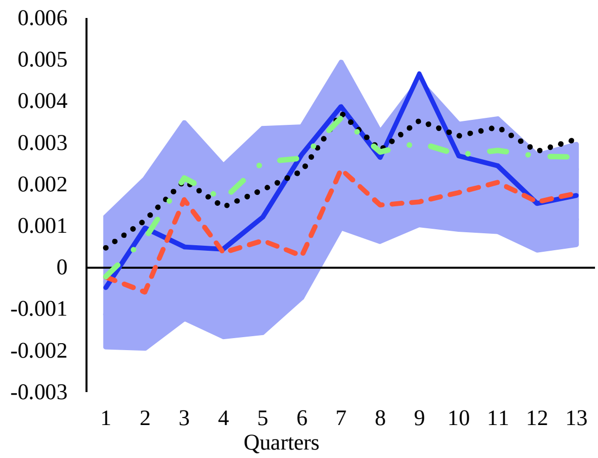
(1) UCDP Factor Conflict

Nr. of Events



(2) ACLED Output Conflict

Nr. of Events

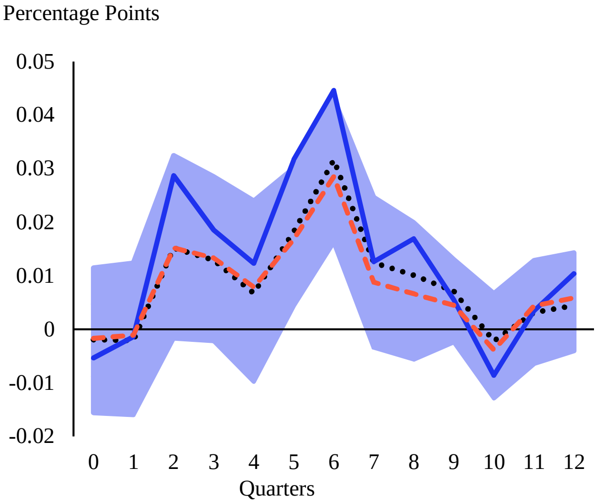


Two standard error confidence bands of benchmark estimations (Figure 3)
Mean Group estimator
Residual as Only External Instrument
Dummy as Only External Instrument
Addressing potential omitted common factors problem

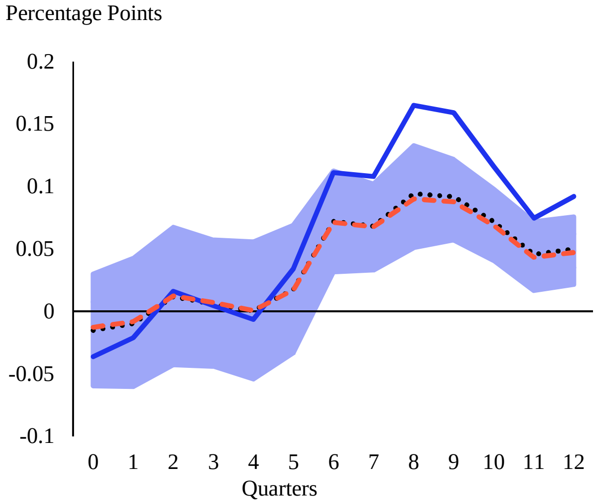
Appendix Figure A2: Robustness of Figure 3 (continued)

(A) Conflict Incidence

(1) UCDP Factor Conflict

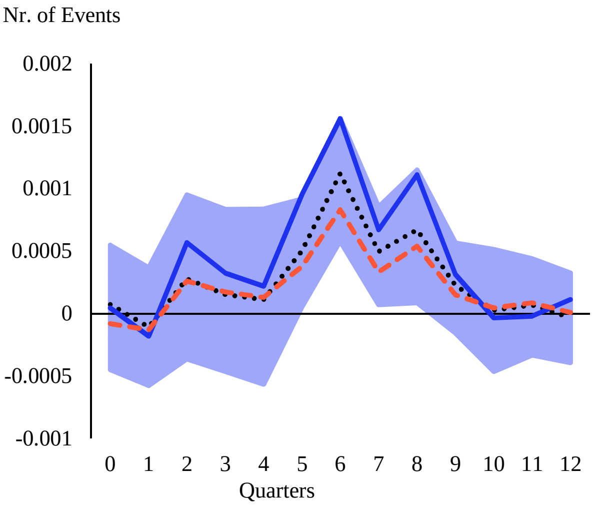


(2) ACLED Output Conflict

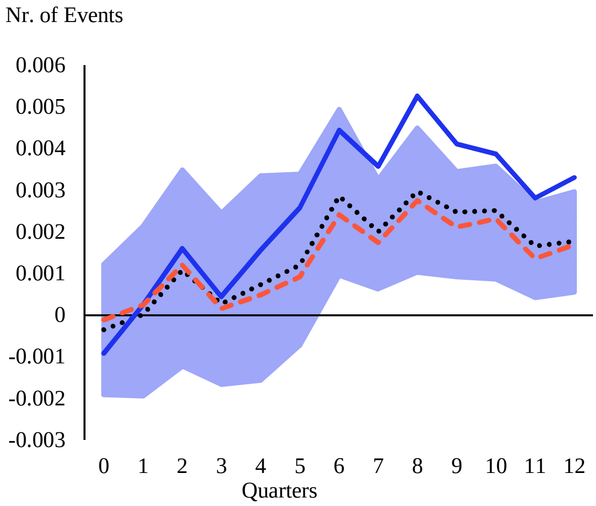


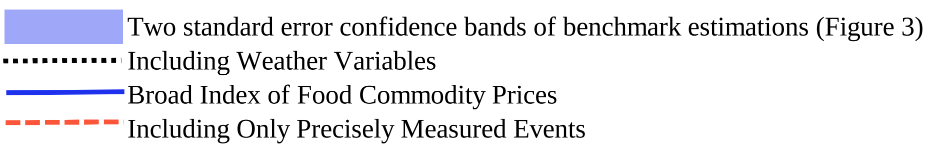
(B) Conflict Intensity

(1) UCDP Factor Conflict



(2) ACLED Output Conflict

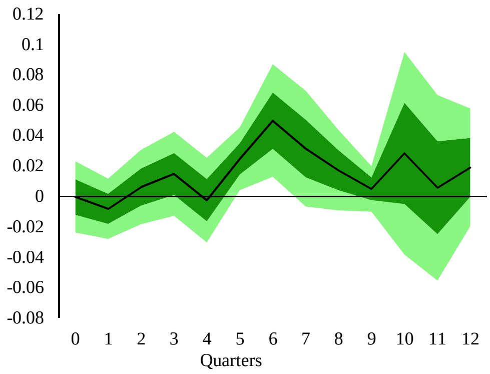


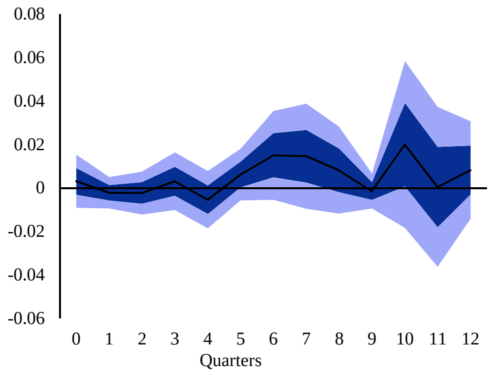


Appendix Figure A3: Robustness of Figure 4 - Using Cereal Net Exports
(A) Conflict Incidence

(1) UCDP Factor Conflict

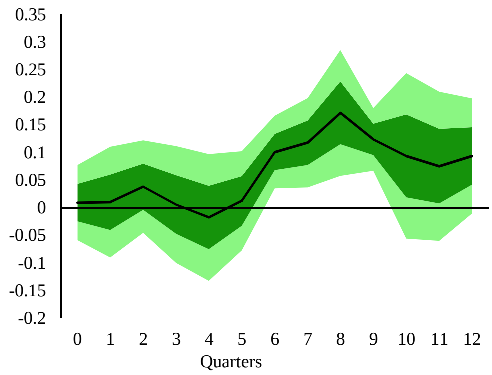
Percentage Points — Baseline Effect — Additional Effect for Cereal Net Exporters

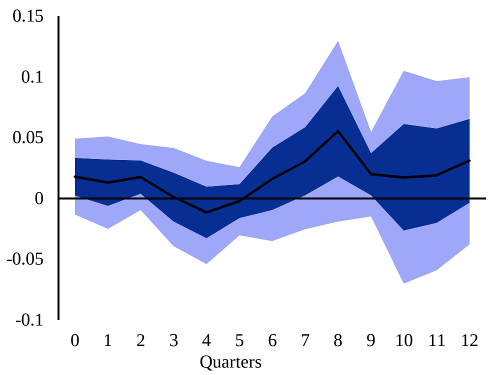




(2) ACLED Output Conflict

Percentage Points — Baseline Effect — Additional Effect for Cereal Net Exporters

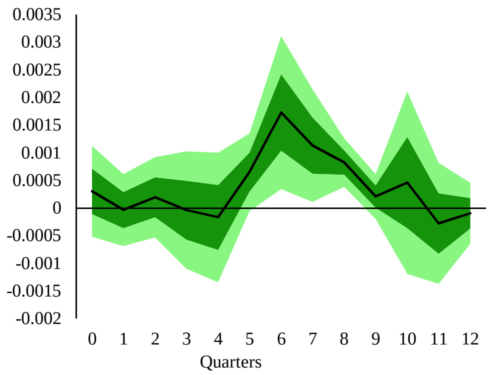


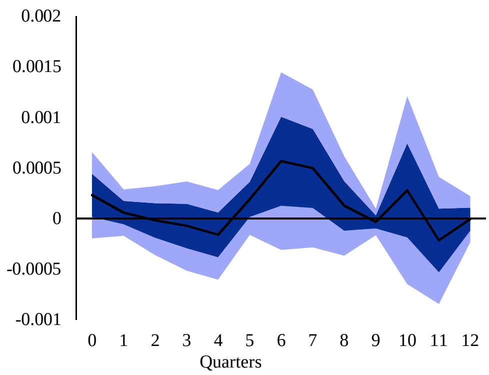


(B) Conflict Intensity

(1) UCDP Factor Conflict

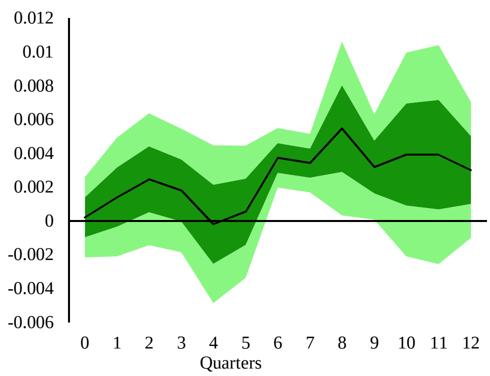
Nr. of Events — Baseline Effect — Additional Effect for Cereal Net Exporters

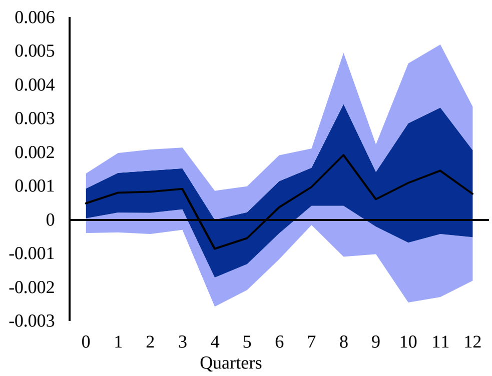




(2) ACLED Output Conflict

Nr. of Events — Baseline Effect — Additional Effect for Cereal Net Exporters





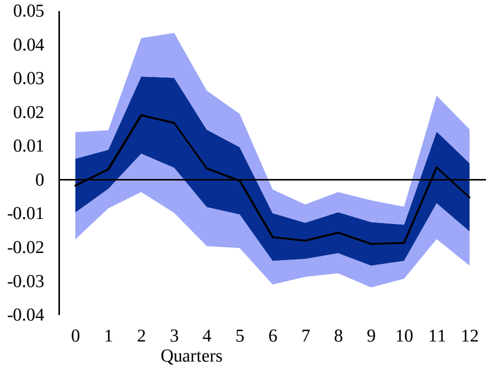
Note: Cell fixed effect, cell-specific time trend, 5 lags of the conflict variable, 5 lags of food prices, 5 lags of the interaction, the measure of agricultural specialization, and the country-specific annual lag of national GDP are always included. External instrumental variables: residual from production function and narrative dummy. One and two standard error confidence bands based on Driscoll-Kraay standard errors.

Appendix Figure A4: Robustness of Figure 4 - Controlling for Interaction with Extra Characteristic

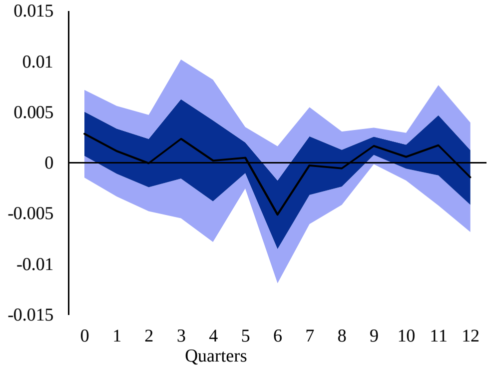
(A) Conflict Incidence

(1) UCDP Factor Conflict

Percentage Points Population

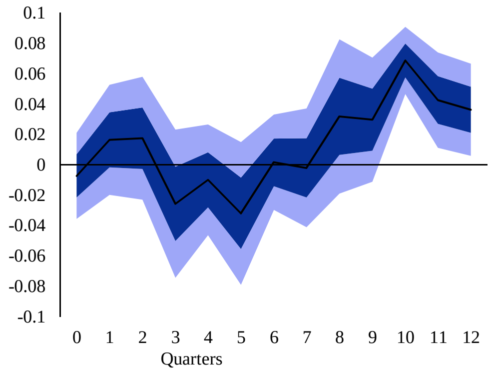


Travel Time

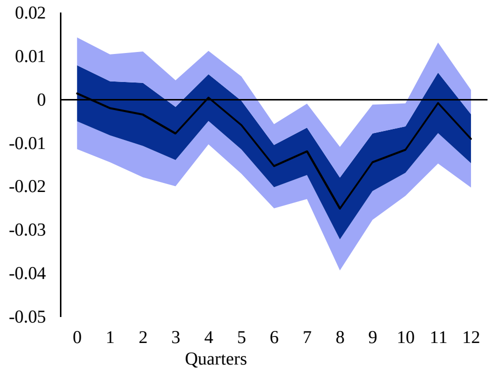


(2) ACLED Output Conflict

Percentage Points Population



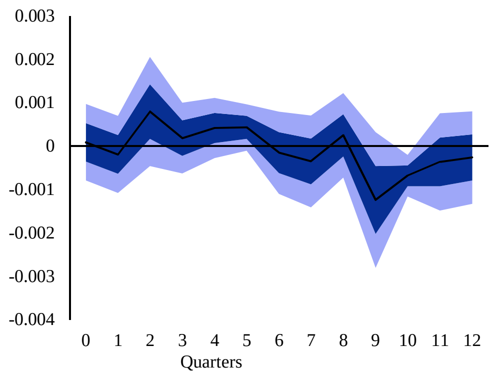
Travel Time



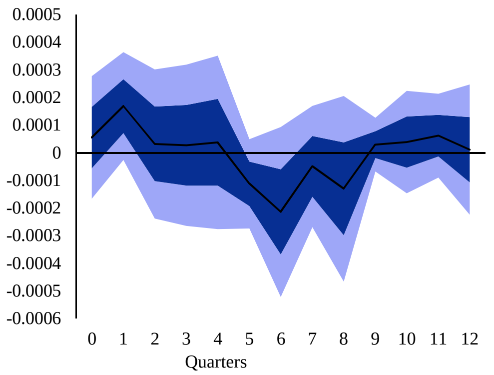
(B) Conflict Intensity

(1) UCDP Factor Conflict

Nr. of Events Population

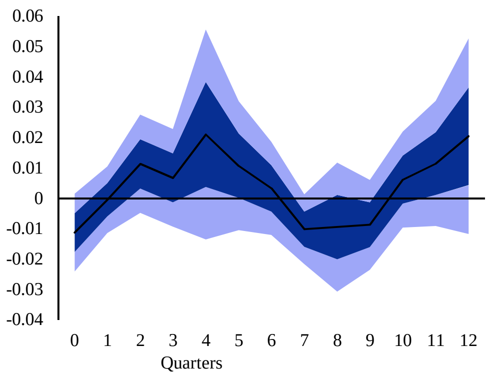


Travel Time

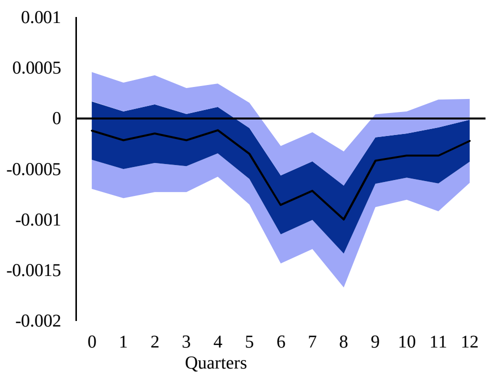


(2) ACLED Output Conflict

Nr. of Events Population



Travel Time



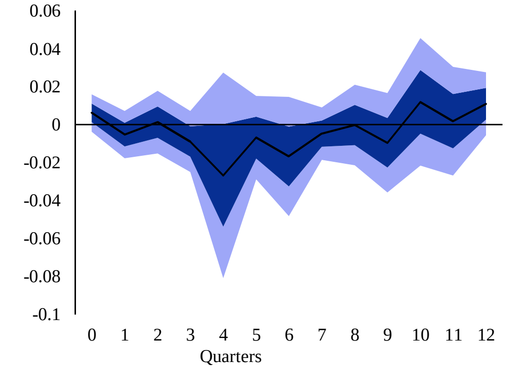
Note: Cell fixed effect, cell-specific time trend, 5 lags of the conflict variable, 5 lags of food prices, 5 lags of food "producer" prices, the measure of agricultural specialization, and the country-specific annual lag of national GDP are always included. External instrumental variables: residual from production function and narrative dummy. One and two standard error confidence bands based on Driscoll-Kraay standard errors.

Appendix Figure A5: Robustness of Figure 4 - Controlling for Interaction with Extra Characteristic (continued)

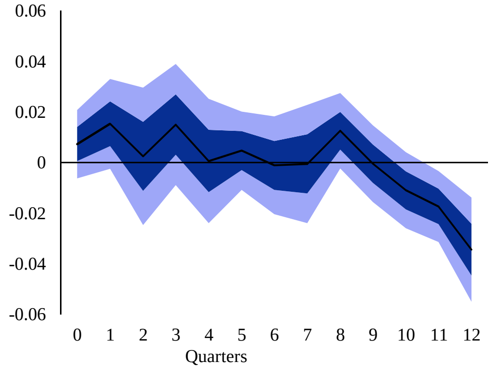
(A) Conflict Incidence

(1) UCDP Factor Conflict

Percentage Points — Regime Type

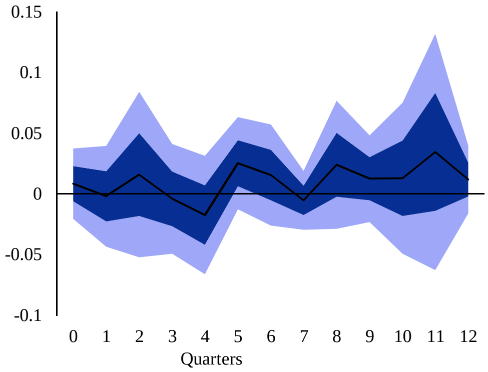


Dummy for Intermediate Ethnic Diversity

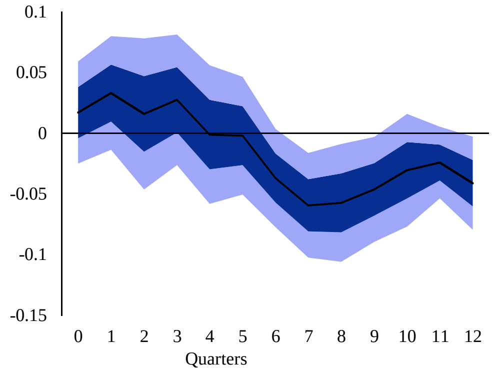


(2) ACLED Output Conflict

Percentage Points — Regime Type



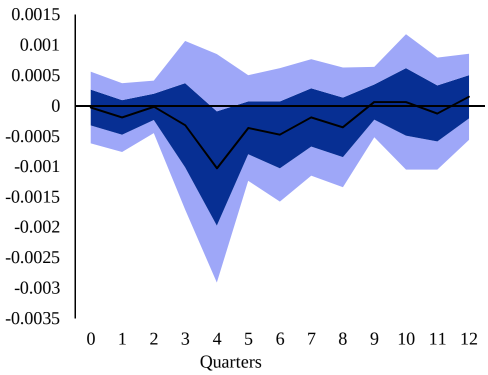
Dummy for Intermediate Ethnic Diversity



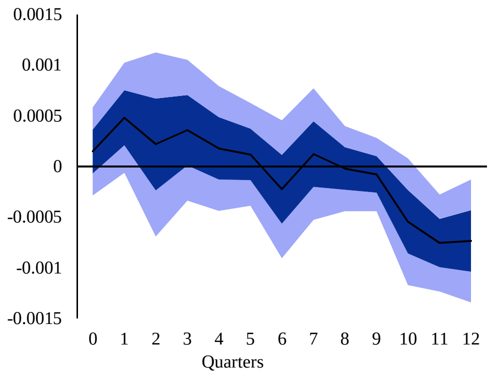
(B) Conflict Intensity

(1) UCDP Factor Conflict

Nr. of Events — Regime Type

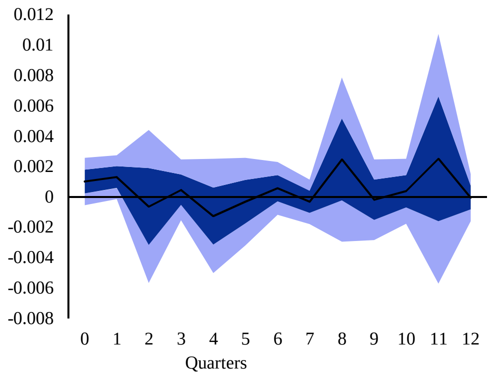


Dummy for Intermediate Ethnic Diversity

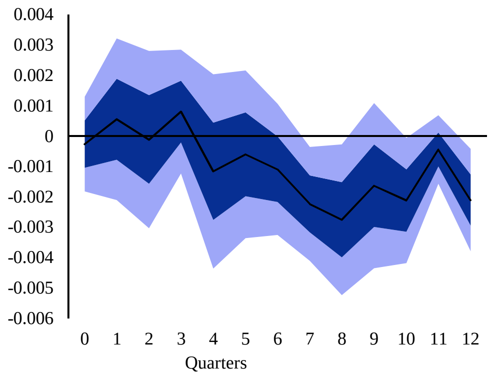


(2) ACLED Output Conflict

Nr. of Events — Regime Type



Dummy for Intermediate Ethnic Diversity



Note: Cell fixed effect, cell-specific time trend, 5 lags of the conflict variable, 5 lags of food prices, 5 lags of food "producer" prices, the measure of agricultural specialization, and the country-specific annual lag of national GDP are always included. External instrumental variables: residual from production function and narrative dummy. One and two standard error confidence bands based on Driscoll-Kraay standard errors.