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Drivers and triggers of international food price spikes and volatility

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ABSTRACT

The objective of this study is to explore empirical evidence on the quantitative importance of supply, demand, and market shocks for price changes in international food commodity markets. To this end, it distinguishes between root, conditional, and internal drivers of price changes using three empirical models: (1) a price spike model where monthly food price returns (spikes) are estimated against oil prices, supply and demand shocks, and excessive speculative activity; (2) a volatility model where annualized monthly variability of food prices is estimated against the same set of variables plus a financial crises index; and (3) a trigger model that estimates extreme values of price spikes and volatility using quantile regressions. The results point to the increasing linkages among food, energy, and financial markets, which explain much of the observed food price spikes and volatility. While financial speculation amplifies short-term price spikes, oil price volatility intensifies medium-term price volatility.

Introduction

The global food system recently showed exceptional international commodity price developments. In 2007–2008, the nominal prices of almost all food commodities increased by more than 50%. Three years after the 2007–2008 global food price spikes, food prices surged again in 2010–2011 (Fig. 1). Though the two events were different in terms of affected commodities,[4] a strong correlation among most food prices was registered. More important, prices of all food commodities soared above the long-term average, with an adverse impact on poor people in poor countries (Conforti, 2004; Dawe, 2008; Dorosh et al., 2009; Hernandez et al., 2011). Indeed, the sudden increase in international food prices and its transmission to domestic prices led to rising inflation rates, which mainly hurt the poor, who spend large shares of their income on staple foods. Volatility causes economic uncertainty and may result in lower investment, especially in small businesses lacking access to credit. Although on global markets food grains are viewed mainly as commodities, they constitute the basic food of the poor and the "currency" of the poorest 2 billion people.

Faced with rising food insecurity, social unrest, and accelerated inflation driven by food prices, developing and advanced countries as well as international governmental and nongovernmental organizations began to respond with a new sense of urgency. For instance, the G20 agenda of 2011 addressed food security. Nonetheless, although the price crises of 2007–2008 and 2010–2011 have led to some policy changes, the sense of urgency about preventing human suffering has not yet translated into comprehensive actions related to world food supply and demand.

Unstable food prices at national and regional levels are not a new phenomenon. Some consider the 2007–2008 price spike part of normal price instability caused by temporary shocks (Díaz-Bonilla and Ron, 2010). In fact, average price volatility did not differ significantly between the 1970s and the late 2000s, but the nature of the volatility and its causes are different. Traditional market fundamentals—that is, demand and supply factors—were found inadequate to explain the extreme price spikes in 2007–2008 and 2010–2011.

In the past few years, many studies have been carried out to investigate the causes of and solutions to soaring food prices (Abbott et al., 2009, 2011; Gilbert, 2010; Roache, 2010). They have identified a set of drivers of food price upsurges including biofuel

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4 The sugar price index was lower than its historical average during the first food price crisis (2007–08) but reached a historic high in 2010–11. Rice prices were the highest during the first high price episode but were lower than most other cereals during the second crisis.

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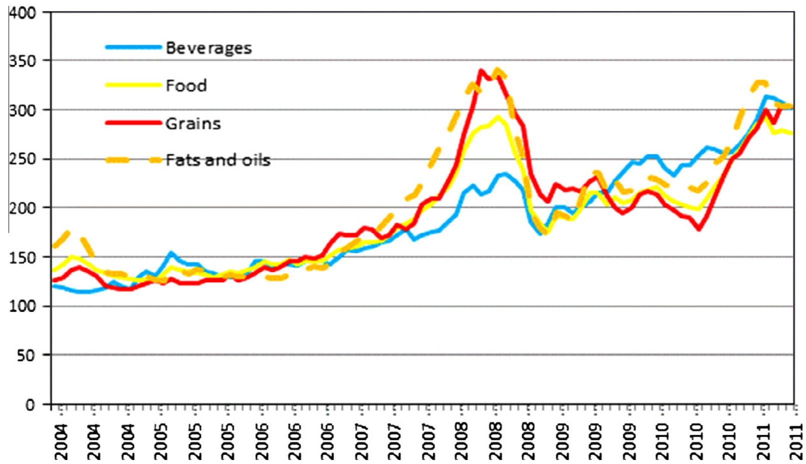

Fig. 1. FAO food price indices from January 2004 to November 2011. *Source*: FAO (2011).

demand, speculation in commodity futures markets, countries' aggressive stockpiling policies, trade restrictions, macroeconomic shocks to money supply, exchange rates, and economic growth. The relative importance and actual impact of these causes have been widely discussed. While there is a certain consensus regarding the effects of weather, biofuel production, and export restrictions on food commodity markets, the dispute surrounding speculation is far from settled. Most of the empirical studies focus primarily on Granger causality tests to explain the role of speculation in price returns or volatility (Irwin et al., 2009; Robles et al., 2009; Gilbert, 2010). Another strand of research seeks to identify bubble behavior—that is, explosive increases in prices—in commodity markets during 2007–2008 (Gilbert, 2009; Phillips and Yu, 2011; Shi and Arora, 2012). Granger causality tests, however, are criticized for presuming a time-lag structure that might be too long to allow for observing any reaction of liquid financial markets (Gilbert and Pfuderer, 2012; Grosche, 2012). Analysis of bubbles can identify abnormal price behavior but does not explain the causes of the observed price increases.

This study goes a step further by examining the impact of speculation and agricultural fundamentals on price spikes and volatility, where price spikes are the short-term ups and downs of prices following short-term shocks and volatility is the variability of price around its trend. The distinction between price spikes and volatility is more important from a welfare perspective than trends in overall price levels because price spikes and volatility are the primary indicators of food crises.[5] Furthermore, this distinction is also essential to differentiate among factors that generate risks for poor consumers to cope, and uncertainties for agricultural investors to plan. We argue that a food crisis is more closely related to extreme price spikes, while long-term volatility is more strongly connected to general price risks.

In particular, this study provides empirical evidence on the quantitative importance of widely discussed determinants of commodity prices. In our empirical analysis, we consider agricultural supply shocks, stock-to-use ratios, demand shocks (energy prices and gross domestic product [GDP]), and futures market shocks (speculative activity in commodity futures trading and financial crises). The empirical analysis is carried out using three models: (1) a price spike model where monthly food price returns (spikes) are estimated against oil prices, supply shocks, stock-to-use ratios, demand shocks, and volume of speculative futures trading; (2) a volatility model where annualized monthly variability of food prices is estimated against yearly observable variables such as supply shocks, stock-to-use ratios, economic growth, volume of speculative futures trading, oil price volatility, and a financial crises index; and (3) a trigger model that estimates extreme values of price spikes and volatility using quantile regressions. The adopted methodology will allow us to shed light on the formation of price spikes and price risks rather than simply so-called "high food prices." The food commodity prices under investigation are for wheat, maize, and soybeans.[6] The rest of the paper is organized as follows: Section 'Conceptual framework' presents the conceptual framework of the approach. Sections 'Estimation methods' and 'Data' describe the setup of the adopted models and the variables included in the empirical analysis. Section 'Results and discussion' discusses the econometric results. Section 'Conclusion' concludes.

Conceptual framework

The recent literature identifies the determinants of food price hikes as biofuel demand, speculation in commodity futures markets, and macroeconomic shocks. These determinants represent the demand and supply side of the world food equation. In an attempt to distinguish how different factors affect price changes, three groups of potential causes have been singled out: exogenous shocks, also called "root" causes; "conditional" causes; and "internal" drivers (Fig. 2). Root causes, such as extreme weather events, oil price shocks, production shocks, and demand shocks, are independent core factors affecting food price fluctuations. They are exogenous because the possibility of a causal relationship going from the agricultural sector to root causes is minimal. The exogenous shocks are expected to generate food price spikes and volatility, and the magnitude of their impacts depends partly on the political and economic environment of a given country. In other words, a second group of factors related to specific political and economic conditions – labeled here as conditional drivers—can dampen or exacerbate the exogenous shocks. Some of these factors (such as a high concentration of production or low transparency in commodity markets) are rather time-invariant and difficult to measure; they are therefore not considered in the empirical analysis of this article. The third group of causes consists of factors that are triggered by the same price dynamics, and these internal causes are endogenous shock-amplifiers and include discretionary

[5] Although there is no universally agreed-on definition of "food crisis," here it is understood as an abrupt and unanticipated change that affects people severely and negatively.

[6] We do not include rice because of its different international market patterns.

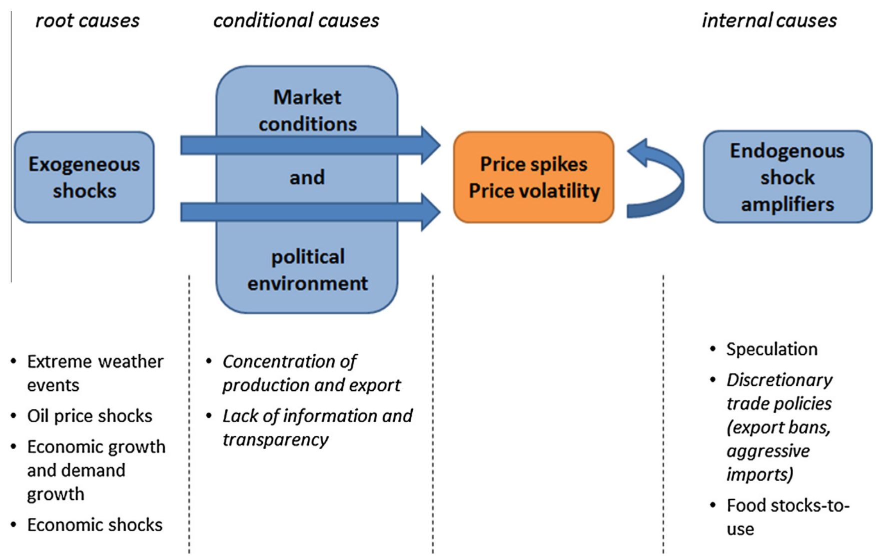

Fig. 2. Stylized framework of the causes of global food price volatility and spikes. *Note*: Exogenous shocks are the "root" causes of price volatility and price spikes. To what extent exogenous shocks translate to food price changes depends on the market conditions and political environment of a given country ("conditional" causes). Food price shocks can further be amplified by non-linear endogenous responses ("internal" causes) to food price shocks. The factors in italics are not considered in the econometric analysis as they are time-invariant or as there is no appropriate quantitative indicator available. *Source*: Authors' elaboration.

trade policies, speculative activities (driven by price expectations), and declines in world food stocks. The present study focuses primarily on exogenous shocks because they may be the major root factors that stimulate the emergence of the other factors. At the same time, special attention is given to the (partly) endogenous factors of speculation and food stocks.

There is a caveat to this categorization of drivers: the line distinguishing endogenous and exogenous causes is very subtle. There are multiple and complex interactions between factors, and drivers influence each other through various linkages and feedback loops. For example, restrictive trade policies induced by price increases have further contributed to price surges. Likewise, low US stock-to-use ratios have been considered an important factor in increased price volatility. Low stock levels are, however, caused by reduced government activities in public storage (exogenous) as well as current supply and price expectations (endogenous), as highlighted by Piesse and Thirtle (2009). Furthermore, the UNCTAD 2011 *Report on Trade and Development* (UNCTAD, 2011) indicated that there could be some correlations among different factors. For example, extreme weather may render financial investment in commodity futures more attractive. However, empirical evidence suggests that the correlation among these variables is not strong (Appendix A).

Fig. 2 shows that extreme weather events such as droughts and floods—exacerbated by global warming—are considered a root cause of global food price fluctuations because they cause crop failure and reduce global food supply with a consequent increase in prices. In this analysis, we used short-term global food supply fluctuation and its projection as an indicator of extreme weather changes.

A second root cause consists of oil price shocks, which affect grain commodity prices in a number of ways. On the supply side, a rise in oil prices exerts upward pressure on input costs such as fertilizer, irrigation, and transportation costs. The rise in costs in turn leads to a decline in profitability and production, with a consequent rise in commodity prices. On the demand side, higher crude oil prices induce a higher derived demand for maize and soybeans and other grains such as wheat destined for biofuel production and thus result in higher prices of these grains. The demand for biofuels has been further facilitated by indirect and direct subsidies and biofuel mandates. Both the United States and the European Union, for instance, have adopted mandatory blending policies that require a sharp increase in their use. Studies have shown that higher biofuel demand and energy mandates have a large impact on food prices (Mitchel, 2008; Chen et al., 2010; Chakravorty et al., 2011). A further linkage between oil and agricultural prices operates through index investments. Tang and Xiong (2012) found an increasing correlation between futures prices of agricultural commodities and oil after 2004 when significant index investments started to flow into commodity markets. The two authors highlighted that the stronger correlation with oil prices was significantly more pronounced for indexed commodities than for off-index commodities, because oil is an important index constituent (Basak and Pavlova, 2013).

A third root cause is the high demand mainly from emerging markets, primarily China and India. In Krugman's words (2010), rising commodity prices are a sign that "we are living in a finite world, in which the rapid growth of emerging economies is placing pressure on limited supplies of raw materials, pushing up their prices." In addition, economic development and income growth are changing not only the quantity of food demanded, but also the structure of demand for food commodities. As dietary patterns move away from starchy foods toward meat and dairy products, there is an intensifying demand for feed grains that drives their prices up (von Braun, 2011).

Other root causes of price increases are economic shocks, such as the depreciation of the US dollar, the currency of choice for most international commodity transactions. These shocks put upward pressure on demand from non-US dollar commodity consumers and producers.

While there is a certain consensus on the impact of some root causes, such as oil prices and extreme weather conditions, on food prices, the debate about some internal causes is still open. In particular, it is highly debatable whether speculation has exacerbated food price volatility. Two conflicting hypotheses prevail: the perfect market hypothesis and the speculative bubble hypothesis. The first, sometimes referred to as "traditional speculation" hypothesis, argues that speculation helps to stabilize prices by facilitating increased liquidity and improved price discovery in the market. The second hypothesis claims that speculation tends to generate spikes and instabilities because of a herd mentality in the commodity exchanges. The UNCTAD (2011) report elaborated in detail the different types of herd behavior and how they can drive prices far away from fundamentals: the basic mechanism is that traders base their decisions on past price trends rather than on new information on market fundamentals. This situation makes it difficult for other market participants to distinguish between fundamental causes for price increases and the herd behavior–driven causes and thereby impedes the price formation role of speculation. Even informed traders may not be willing or able to intervene to correct prices if they can benefit from a potential bubble or if their arbitrage possibilities are limited. Herd behavior can therefore reinforce price increases, which may also lead to excess correlation if bubbles spill over to related markets.

Despite some arguments against the importance of speculation for the 2007–2008 food price hikes (Irwin et al., 2009; Wright, 2011), empirical evidence shows the possibility of the speculative bubble hypothesis (Robles et al., 2009). An increase in speculative activities raises the volume of futures trading, with a consequent increase in futures prices and inventory accumulation. This will then translate into an increase in spot prices. However, skepticism remains about the link between volume of futures and futures price. According to some economists (such as Krugman, 2008), speculation is a random bet whereby traders' actions of buying and selling futures cancel out and hence do not have a significant impact on futures prices. This theoretical skepticism is supported by a lack of empirical evidence on the accumulation of inventory, especially in 2007–2008, when prices skyrocketed. If speculative actions were responsible for the rise in food prices, private inventories should have been accumulated. On the contrary, a substantial decline in global food stocks was registered. This fact has been a justification for the assumed insignificance of speculation in causing food price spikes (Krugman, 2008). However, wheat and maize reserves in the United States did not decline substantially during the 2007–2008 crisis (they declined substantially after the crisis). And even when stocks decline because of supply shortage and high prices, grain releases could have been higher without speculation. This can be answered only by conducting an econometric analysis and not simply by comparing stocks over time.

Another aspect of financialization refers to investors' increasing use of commodity futures contracts as part of a portfolio diversification strategy, particularly when other asset classes become less attractive. This has produced rapid growth in commodity index investments in recent years. According to the capital asset pricing model, an optimal portfolio should include assets with low or negative correlation to riskier high-return assets (such as equity). This strategy reduces overall portfolio risk. Hence, investors may choose commodity futures not because they expect increasing commodity prices but because of the potential of commodity futures to reduce their overall portfolio risk. In this view, commodities become attractive if alternative assets such as real estate, bonds, metals, or gold become too risky or expensive. This process can have significant economic consequences for food commodity markets. On the one hand, the presence of commodity index investors can facilitate the sharing of commodity price risk; on the other hand, their portfolio rebalancing can spill price volatility across commodity markets (Tang and Xiong, 2012).

Both the theoretical and empirical skepticism require further explanations and empirics. The current literature uses different approaches for identifying empirical evidence. For instance, storage modeling and price threshold analyses have been used to evaluate accumulation of stocks motivated by speculation (Tadesse and Guttormsen, 2011); Granger-causality analyses have been adopted to investigate the relations between futures prices and spot prices (Robles et al., 2009). In this study, we explore the price effects of an "excessive" volume of futures contracts based on the disaggregated position of futures traders plus a financial crisis index developed by Reinhart and Rogoff (2009). The two financial variables together with a set of other fundamental drivers may shed light on how different sets of exogenous and endogenous variables affect price spikes and volatility. Our study differs from existing ones by combining fundamentals-based drivers with financial market–based factors in price changes.

Other internal factors are (1) restrictive trade policies and (2) declining world food stocks. A host of authors (Yang et al., 2008; Headey, 2011; Martin and Anderson, 2012) have shown that the sequence of export restrictions and bans implemented by countries such as India, Thailand, China, and Russia helped to create panics in international markets and exacerbated price increases. Trade restrictions are designed to curtail the effects of higher global prices on domestic prices and to protect consumers. From the perspective of a single country, restrictive policies seem to have the desired effect: as world prices overshoot, domestic prices are shielded from the full impact. The effect on the world market, however, is negative. When many countries restrict exports, so much food disappears from global markets that prices rocket higher than they would have if governments had not intervened. Inventory stock levels have a crucial role in commodity pricing and at the same time are affected by commodity prices. When prices are low, rational firms tend to store some units of the commodity, and total demand equals demand for current use plus demand from inventory holders. Thus positive inventory implies that total demand is more elastic than demand for current use. When prices are high, storage is unprofitable, inventory goes to zero, and total demand equals current-use demand.

Estimation methods

We differentiate between price spikes, volatility, and trends. Since trends are somewhat anticipated long-term price changes that have little relevance for food crises, this study focuses only on price spikes and volatility.

A price spike is a large, quick, and temporary rise or fall in price following a short-term shock. Price spikes can cause crises for consumers, investors, and farmers. Food price spikes are usually measured using the logarithm of period-over-period prices. Formally:

$$d\ln P_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{1}$$

where $t = m \times y$, m denotes the month, and y denotes the year. To capture the contemporaneous correlation of shocks across commodities, a seemingly unrelated regression has been used to estimate spikes of maize, wheat, and soybean prices.[7] The model is specified as

$$d\ln P_t = \beta R_t + \varepsilon_t, \tag{2}$$

where $d\ln P_t$ is a $Ix1$ vector of price spikes (returns) with I number of commodities identified as $i = 1,2,3,\ldots I$; R_t is a vector of explanatory variables that include monthly supply shocks, oil price spikes, economic shocks, beginning stock-to-use ratios, and excessive volume of speculative futures; and $\varepsilon_t = I \times 1$ is the error term where $\text{cov}(\varepsilon_{it}, \varepsilon_{jt}) \neq 0$ for $i \neq j$. Some of the R_t are commodity specific, such as supply shocks and excessive volumes of speculative futures. Others are general.

Monthly supply shocks are measured as log ratios of the US Department of Agriculture forecasts on global production

[7] Using a standard ordinary least squares model, however, gives similar results: signs and significances, as well as the order of magnitude of the coefficients, remain the same.

Table 1
Seemingly unrelated regression results on food price spikes (coefficients and z-values).

	1986–2009	1986–1999	2000–2009
Maize price spike			
Production shock (%), led	−0.8607***	−0.8124***	−1.1293**
	(−3.84)	(−3.46)	(−2.23)
Speculation (1000 contracts)	0.000070***	0.000072***	0.000086***
	(8.00)	(7.34)	(4.73)
Beginning stock-to-use ratio	0.0004	0.0005	0.0016
	(0.84)	(0.96)	(1.11)
Oil price spike (%)	0.0146	−0.0623	0.0958*
	(0.44)	(−1.59)	(1.69)
GDP shocks (%)	1.2333*	−0.2324	1.8303*
	(1.73)	(−0.23)	(1.67)
Constant	−0.0204**	−0.0208**	−0.0439
	(−2.12)	(−2.04)	(−1.54)
Wheat price spike			
Production shock (%), led	−1.4537***	−0.2039	−2.7769***
	(−2.93)	(−0.39)	(−3.21)
Speculation (1000 contracts)	0.000206***	0.000295***	0.000387***
	(5.37)	(7.40)	(3.44)
Beginning stock-to-use ratio	−0.0006	0.0020	−0.0032**
	(−0.64)	(1.60)	(−2.17)
Oil price spike (%)	0.0375	−0.0631*	0.1277**
	(1.05)	(−1.70)	(2.13)
GDP shocks (%)	2.0971**	0.1329	2.5479**
	(2.42)	(0.12)	(2.02)
Constant	0.0034	−0.0674**	0.0799**
	(0.15)	(−2.48)	(2.27)
Soybean price spike			
Production shock (%), led	−0.3413**	−0.3218	−0.4052**
	(−2.45)	(−1.08)	(−2.45)
Speculation (1000 contracts)	0.000083***	0.000080***	0.000136***
	(5.98)	(4.99)	(3.66)
Beginning stock-to-use ratio	0.0003	−0.0002	0.0001
	(0.47)	(−0.16)	(0.13)
Oil price spike (%)	0.0614**	−0.0155	0.1514***
	(2.07)	(−0.44)	(2.98)
GDP shocks (%)	1.9804***	1.5647	1.6171*
	(2.92)	(1.45)	(1.68)
Constant	−0.0204*	−0.0157	−0.0145
	(−1.87)	(−0.98)	(−0.71)
R^2	0.24	0.32	0.21
N	304	167	137

Note: Dependent variable: maize, wheat, and soybean price spike. Values in parentheses are *t*-values. All variables refer to monthly data; spikes and shocks (in %) denote therefore the deviation of that variable from the level in the previous month. Production shocks are led by 1 month as significance and explanatory power increases. The coefficients for production shock, oil price shock, and GDP shocks can be interpreted as elasticities (percentage change of commodity price due to a percentage change of the respective explanatory variable). Speculation refers to the excessive speculation index given in Eq. (3).
*** Imply level of significance at 1% respectively.
** Imply level of significance at 5% respectively.
* Imply level of significance at 10% respectively.

$d\ln X_t = \ln\left(\frac{X_t}{X_{t-1}}\right)$, as the USDA forecasts are widely recognized and play an important role for the price formation process that is influenced by monthly information on the available grain supply for the current agricultural year. Economic shocks are calculated with the same equation by using monthly interpolated global GDP per capita (nominal). Stocks-to-use ratios are the fraction of the beginning stocks (of the current agricultural year) and consumption as forecast by the USDA. Oil price spikes are estimated using the same procedure as for food commodity spikes (Eq. (1)).

We have hypothesized that the effect of speculative activity on commodity price dynamics depends on the extent of deviations between noncommercial and commercial trading activities. However, many observers, including the US Commodity Futures Trading Commission (CFTC), have recognized that the distinction between commercial and noncommercial is elusive, and hence measuring speculation relative to hedging can be misleading. One problem is that small speculators, which together may be influential, are exempted from certain reporting obligations. Another shortcoming is that categorizing traders as noncommercial does not allow for differentiating between traders who speculate on information based on fundamentals and those who follow "irrational herding" (UNCTAD, 2011). Both issues can lead to an underestimation of the impact of speculation due to irrational herding. Nevertheless, the data on this broad classification of traders constitute the only publicly available source and therefore provide the only possibility for approximating excessive speculation.

Previous studies (Irwin et al., 2009) have used the Working index to measure the impact of speculation on food prices. The Working index tries to measure speculation intensity relative to hedging activity. It is, however, insensitive to the net positions of speculators—that is, whether they are net long or net short. Because the reasoning above suggests that excessive net long speculation leads to price increases (and excessive net short speculation leads to price decreases), we preferred to give equal weight to both commercial and noncommercial trading activities and to measure speculation based on the deviation between the two. In a perfectly competitive commodity market, there should be no deviation between commercial and noncommercial trading activities. To meet commercial traders' demand for hedging, at most an equal number of noncommercial traders' contracts is necessary.[8] However, we have observed a significant difference between commercial and noncommercial positions. This could be associated with the existence of significant unsettled noncommercial positions for extended periods of time motivated by speculative behaviors and the increasing use of food commodities as an asset class. Thus, capturing the speculative effect using the excessive open interest of speculative futures seems a more appropriate way than using the Working ratio. Technically, the extent of excessive speculative activities in month t is measured as:

$$ESV_t = \frac{\sum_{d=1}^{N_t}[(NCL_d - NCS_d) - (CL_d - CS_d)]}{N_t}, \tag{3}$$

with N_t denoting the number of days d per month t where CFTC position data are available. As the trading position data are published every Friday for the preceding Tuesday, there are only four to five observations per month. NCL is the open interest of noncommercial long positions in a trading day, NCS is the open interest of noncommercial short positions in a trading day, CL is the open interest of commercial long positions in a day, and CS is the open interest of commercial short positions in a day.

Price volatility is a long-term price movement indicating the risk associated with price changes. It is usually measured in terms of price dispersion from the mean. Realized total volatility is measured in terms of the coefficient of price variations (CV) that captures both monthly and yearly variability. The normal coefficient of variation captures only the monthly price variability in a year. However, the mean price is changing over years and thus unable to capture inter-year price variability. To capture both changes, we divided each year's standard deviation by the mean price of the entire sample. This allows us to measure variability relative to a common price level.

$$CV_y = \frac{\sum_{m=1}^{12}(P_m - \overline{P_y})^2}{\sum_{t=0}^{T} P_t} \frac{T}{12},$$

where y indicates year, m month, and t month by year.

[8] Fewer non-commercial traders are necessary if commercial traders can already match their different short and long hedges, i.e., when a producer makes a contract with a processor.

Table 2
Historic quantitative impact of speculation on price spikes.

	Maize (%)	Wheat (%)	Soybean (%)
Price spike due to one standard deviation increase in speculation	2.2	1.6	1.4
Average monthly price spike due to speculation during July-2007 and June-2008	3.2	0.2	1.8
Compound (12-months) price spike due to speculation during July-2007 and June-2008	37.9	2.5	22.1

Note: The first row was calculated by multiplying the standard deviation of speculation by the respective speculation coefficient in Table 1 for the full sample. The second row was calculated by multiplying the average monthly speculation volume between July 2007 and June 2008 with the respective speculation coefficient in Table 1; for the third row, the value of the second row was multiplied by the number of months (12).

This metric does not measure direction, but rather appraises price risks. This means that high variability does not necessarily reflect high price. Realized total volatility is the sum of high- and low-frequency volatility (Peterson and Tombek, 2005; Karali and Power, 2009; Roache, 2010). While high-frequency volatility is related to price spikes, low-frequency volatility is related to cyclical movement of agricultural prices. Since high-frequency volatility is already modeled in the price spikes equation, we do not disaggregate volatility into its high- and low-frequency components. Instead we attempt to explain the realized total volatility using the percentage of annual standard deviation from the long-term average price.

Volatility is estimated using a panel regression in which commodities are represented as panels and years as time variable. Two alternative specifications, using OLS and feasible generalized least squares (FGLS), have been adopted. The first, which assumes no heterogeneity across commodities, is formally expressed as

$$V_{iy} = \alpha + \beta' X_{iy} + \varepsilon_{iy}, \tag{4}$$

where i and y denote commodities and years respectively, and X consists of the aforementioned explanatory variables—that is, supply shocks, volatility of oil price, global nominal economic growth rates, beginning stock-to-use ratios, excessive speculative futures volume, and, alternatively to speculation, an annual financial crisis indicator. The supply shock variable is measured as the normalized deviation of total annual production from its long-term trend to account for the market size of each commodity. Formally, normalized supply shocks are given by $SS = \frac{|Q_t - HQ_t|}{HQ_t}$, where Q_t is the world production for each specific commodity and HQ_t is the Hodrick-Prescott smoothed production times series. Shocks derived from the production series using the Hodrick-Prescott filter have a similar distribution to those obtained with other time-series filters such as Baxter-King, Butterworth, and Christiane-Fitzgerald. However, the Hodrick-Prescott filter is preferred because it considers extreme values (Baum, 2006). All the variables in this equation are measured annually.

The FGLS specification with fixed effects controls instead for heterogeneity among commodities and is expressed as

$$V_{iy} = \alpha + \beta' X_{iy} + \gamma_i + \varepsilon_{iy}, \tag{5}$$

where γ_i denotes the fixed effect.

To complete the empirical assessment and to account for endogenous shock amplifiers, a price trigger model has been computed. The impact of a price trigger might be different at high and low prices. When prices are getting high, markets are expected be more sensitive to a given shock than when prices are low. This effect is sometimes referred to as tipping effect. The tipping effect is estimated using a quantile regression in order to capture the effect of explanatory variables at lower and upper tips of the response variable (Koenker and Hallock, 2001). Put differently, it measures how an explanatory variable affects the τth quantile of the response variable as opposed to the mean value of the response variable in OLS. It helps to compare the effect at the upper and lower tail of the price distribution. Eqs. (2) and (4) are estimated at τth quantile, where $\tau \in \{0.05, 0.15, 0.25 \ldots 0.95\}$. If a variable is significant and has a higher effect at the upper tail, the variable indeed triggers price changes. In the price spike equation, lower quantiles represent negative values and upper quantiles positive values. In the volatility equation, both lower and upper quantile are positive values with the upper quantile denoting higher values.

Data

The nominal prices of maize, wheat, soybeans, and crude oil were collected from the World Bank database (World Bank, 2011). We used current prices quoted as "US No. 2 yellow f.o.b" for maize, "US HRW" for wheat, "c.i.f. Rotterdam" for soybeans, and "average spot prices of Brent, Dubai, and West Texas" for crude oil. Nominal prices were chosen because of the lack of an accurate consumer price index for deflating world prices.[9] Although different sample periods are used for different analyses, most of the datasets are based on data from 1986 to 2009. Position data before 1986 are missing, and production data after 2009 are missing.

Data for annual supply shocks estimation were collected from FAO (FAO, 2011)—specifically, annual production data of the major producing countries. Data for monthly supply shocks were obtained from the world agricultural supply and demand estimates published monthly by the USDA.[10] Open interest of futures trading of the Chicago Board of Trade (CBOT) were obtained from the CFTC for maize, wheat, and soybeans.[11] The CFTC reports disaggregated open interest of futures trading positions as long, short, and spread by commercial and noncommercial participants. Since a spread represents the equal value of long and short positions, it is not included in our calculation of excessive speculative activities.

Results and discussion

Determinants of food price spikes

Results of the seemingly unrelated regression estimates for different time periods are presented in Table 1. Production is led by 1 month as it is presumed that markets anticipate supply shocks slightly before the publication of the USDA estimates as a result of private market research and information acquisition.[12] As expected, price spikes are negatively correlated with (anticipated) supply shocks and positively correlated with economic growth (demand) shocks. The results show a positive and significant effect of excessive speculative activities on food price spikes, although anticipation of supply and demand shocks is controlled for. The extent of excessive speculation is significant both before and after

[9] Many studies use the US consumer price index. However, this could be a biased deflator that fails to account for the higher budget share of food in developing countries. For comparison, real (based on US CPI) and nominal prices are presented in Appendix 2. The real and nominal prices have similar trends and movements over time.

[10] Data are available at http://www.usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1194 (accessed 18.02.13).

[11] Data are available at http://www.cftc.gov/MarketReports/CommitmentsofTraders/HistoricalCompressed/index.htm (accessed 18.02.13).

[12] The anticipation effect vanishes, however, for a lead of two or more months.

Table 3
OLS and FGLS regression results for food price volatility.

Explanatory variables	With speculation				With financial crisis index			
	OLS	OLS elasticities	FGLS	FGLS elasticities	OLS	OLS elasticities	FGLS	FGLS elasticities
Normalized production shock in millions of tons	0.3773**	0.2138***	0.3395	0.1608	0.3690***	0.1865***	0.3340	0.1438
	(2.31)	(2.35)	(1.10)	(1.10)	(2.40)	(2.47)	(1.56)	(1.56)
Oil price coefficient of variation	0.3595***	0.4202***	0.3506***	0.4939***	0.3801***	0.4306***	0.3771***	0.5031***
	(7.29)	(6.76)	(5.20)	(5.20)	(6.63)	(5.87)	(6.84)	(6.84)
Beginning stock-to-use	0.1020	0.3405	0.0385	0.1002	0.1067	0.3862	0.0894	0.2526
	(1.35)	(1.35)	(0.41)	(0.41)	(1.50)	(1.47)	(0.94)	(0.94)
GDP growth rate	0.0132**	0.5629***	0.0130***	0.4552***	0.0038	0.1793	0.0035	0.1322
	(2.24)	(2.34)	(7.14)	(7.14)	(0.48)	(0.48)	(0.44)	(0.44)
Speculation (1000 contracts)	0.00001	0.0714	0.0001	0.0839				
	(1.39)	(1.64)	(1.66)	(1.66)				
Financial crisis index					0.0007**	0.3915**	0.0007**	0.3417**
					(1.96)	(2.05)	(2.30)	(2.30)
*R*2	0.57		0.59		0.58		0.58	
Breusch-Pagan LM test			Prob = 0.823				Prob = 0.936	
Modified Wald test			Prob = 0.274				Prob = 0.939	
Wooldridge test			Prob = 0.549				Prob = 0.601	
Number of obs.	69	69	69	69	88	88	88	88

Note: Dependent variable: Food price volatility. *t*-values are in brackets. The models control for heteroskedasticity using the VCE robust estimator. Elasticities are calculated as marginal effects at mean values. Diagnostic checking rejects the presence of cross-sectional dependence, heteroskedasticity, and serial correlation. The Breusch-Pagan LM test (H_o: no cross-sectional dependence) reveals that there is independence, thus residuals are not contemporaneously correlated. The modified Wald test for groupwise heteroskedasticity (H_o: homoscedasticity) does not reject the null and concludes for homoscedasticity. The Wooldridge test for autocorrelation in panel data (H_o: no serial correlation) fails to reject the null and concludes that data do not have first-order autocorrelation.

** $p < 0.05$.

*** $p < 0.01$.

2000. However, the effect is stronger after 2000 than before. There exists a strong belief among financial practitioners that speculative activity became detrimental only after 2000, when commodity markets were deregulated and financialization intensified (UNCTAD, 2011). For example, Gheit (2008), Masters (2008), and Frenk (2010) among others, argued that since the 2000 Commodity Futures Modernization Act, "speculative money" has been flowing into commodity derivatives, which in turn drives commodity spot prices up and down far beyond their fundamental values. Our results, together with the research of Gilbert (2010) and Henderson et al. (2012) provide further evidence of this claim.

Although the coefficient of speculation variable is smallest for maize and largest for wheat, variation of speculation is much larger for maize than for wheat. Table 2 indicates the impact of one standard deviation change of speculation on spikes, showing that maize price spikes are more affected by speculation than wheat price spikes are. Regarding the role of speculation in the 2007–2008 crisis, excessive speculation predicts that *ceteribus paribus* an approximate 38% increase of the maize price within the 12 months following July 2007 but an increase of only less than 3% for wheat. These numbers must be treated with caution, however, because not only is speculation caused by exogenous (financial market) events, but it is also endogenous to price expectations. By considering anticipated information on market fundamentals, speculation could be endogenous to other factors that influence price expectations, such as export bans, that are difficult to control for. Financial market shocks, however, constitute a clear exogenous element in the speculation variable.[13]

[13] There are two standard approaches to dealing with endogeneity: lagging variables and instrument variables. In our case, both are problematic. A one-month lag of data on speculation is already too long; financial markets operate on a daily basis, and speculative activities a month previous should not have an impact on price spikes. Selection of appropriate instrument variables that explain speculation volume due to financial market shocks should be guided by a portfolio model, such as the Capital Asset Pricing Model (CAPM). This model, however, considers complex relationships between expected returns, variances, and co-variances among many different assets, which cannot be subsumed under a linear combination of a few financial market variables.

The results further suggest the role of anticipated production fluctuations as an important cause of short-term food price spikes. Supply shocks measured by USDA monthly forecasts were found to be statistically significant in most of the estimations. Production shocks were included to represent extreme weather or flood outbreaks that could lead to supply shortfalls in one part of the world and expectations in other parts of the world. For example, a flood in Australia may affect food supply from Australia and farmers' and traders' price expectations in Europe or the United States. These effects were supposed to cause temporary price spikes. The results confirm that expectations about production influence prices. Thus, short-term price spikes are partly created by information about supply related to weather events.

Oil price spikes have had increasing effects on food price spikes over time (Table 1). Before 2000, the effect was insignificant or negative (wheat). After 2000, however, it became positive and statistically significant for maize, wheat, and soybean prices. As mentioned above, oil prices are linked to food prices through demand (biofuels), supply channels (cost of production), and to increased index-fund activities. The significance of the impact of oil prices on food prices in recent years suggests that demand factors and financialization dynamics are more relevant than supply factors in explaining price increases. The United States accounts for about 40% of world maize production. In 2010, about 40% of the total US maize harvest was consumed by ethanol producers (USDA, 2013). Increasing demand for biofuel affects prices not only through a direct conversion of food crops to feedstock, but also through the reallocation of production resources, such as land and water, to the production of biofuel commodities. Reallocation of production resources affects non-biofuel food commodities as well. The link between oil and food prices is more important than the actual scarcity caused by biofuel demand for the incidence of short-term food price spikes. When energy prices are linked to food prices, political, environmental, and commercial shocks can easily translate to food crises. Stock-to-use ratios are insignificant, except for wheat since 2000, for which low stocks increased spikes.

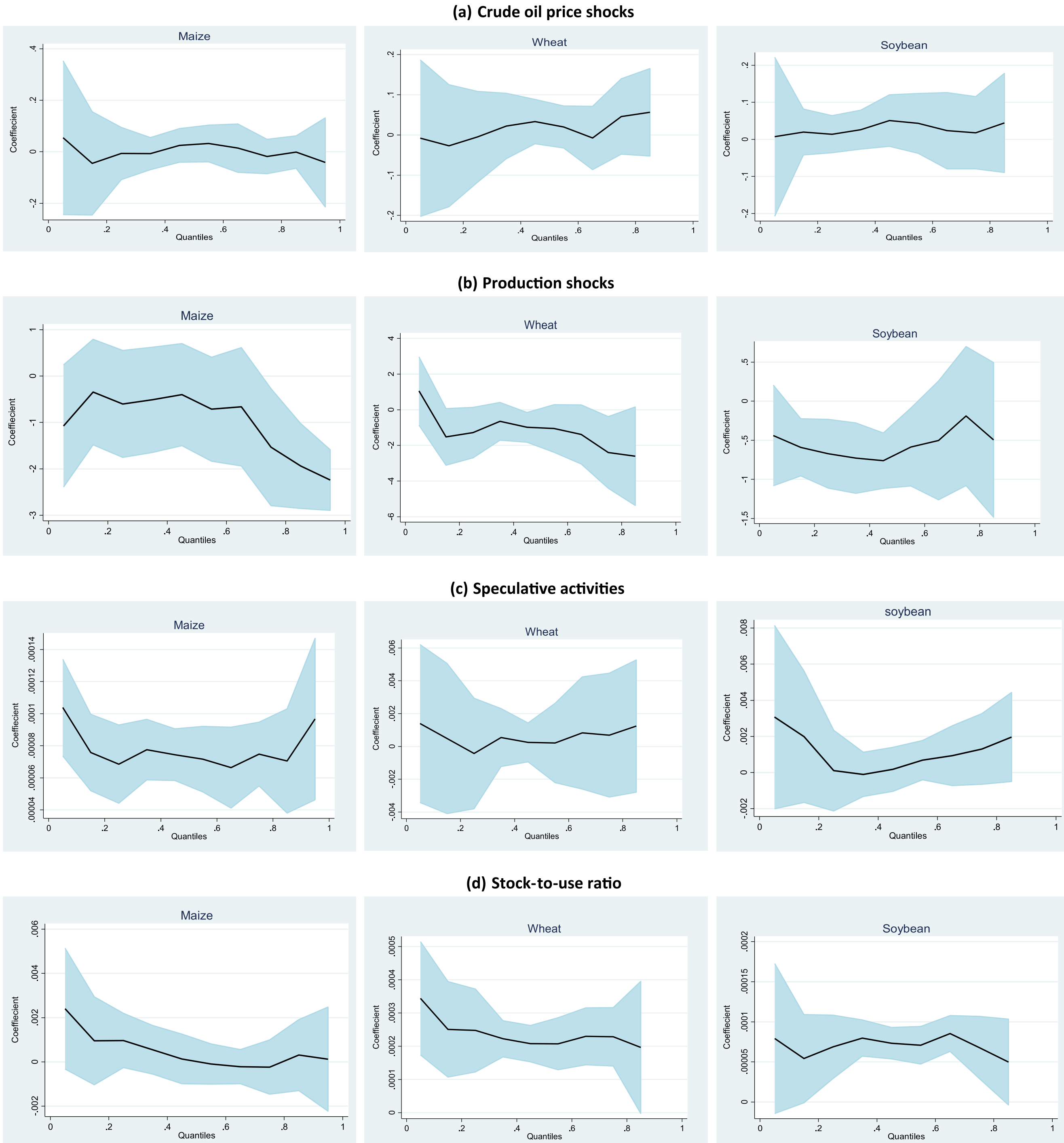

Fig. 3. Triggers of food price spikes. *Note*: The middle line shows the coefficient explaining price spikes according to (a) oil price shocks, (b) production shocks, (c) excessive speculation and (d) stock-to-use ratios. The quantile regression shows the coefficients for different quantiles of commodity price spikes. At a low quantile, the corresponding coefficient shows the impact on price spikes when price spikes are low; at a high quantile, the corresponding coefficient shows the impact on price spikes when price spikes are already high. Shaded regions are 95% confidence intervals, and the line in the middle is the coefficient. *Source*: Authors' estimation based on data explained in Sections 'Estimation methods' and 'Data'.

Food price volatility

A panel analysis is used to quantify the relative importance of supply, demand, and financial shocks on food price volatility. The explanatory variables included in this volatility equation are the same as above, except for two differences. First, the variables are measured on an annual basis; for example, the normalized supply shock, the GDP growth, and the beginning stock-to-use ratios are calculated using annual data, excessive speculation is calculated based on the number of marketing days in a year, and oil price volatility is measured based on annual coefficients of variation. Second, we also included the financial crisis index developed by Reinhart and Rogoff (2009). This index combines measures of banking crises, foreign debt defaults, domestic debt defaults, inflation crises, and exchange rate crises. The index serves as a proxy for financialization and speculation in the commodity futures

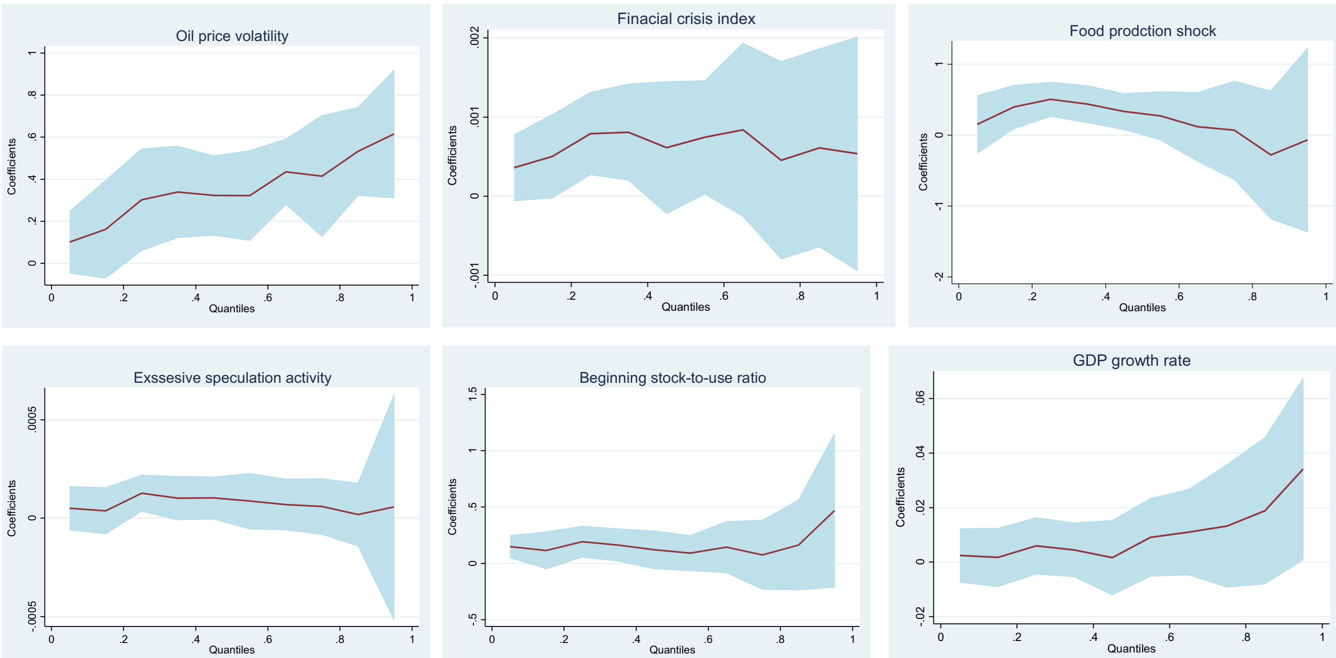

Fig. 4. Triggers of global food price volatility. *Note*: The middle line shows the coefficient explaining food price volatility according to different explanatory variables. The quantile regression shows the coefficients for different quantiles of food price volatility. At a low quantile, the corresponding coefficient shows the impact on price volatility when volatility is low; at a high quantile, the corresponding coefficient shows the impact on price volatility when volatility is high. Shaded regions are 95% confidence intervals, and the line in the middle is the coefficient. *Source*: Authors' estimation based on data explained in 'Estimation methods' and 'Data'.

market, and hence speculation and the financial crisis index are used alternatively.

The different estimates of the models are presented in Table 3. A comparison of the effect of an excessive volume of futures trading and the financial crisis index on volatility indicates the importance of commodity-specific and common economic factors in affecting food prices. The result clearly shows the insignificance of futures trading on volatility, which is in contrast with the results of the price spikes estimation. This underlines the importance of distinguishing between volatility and spikes in this type of analysis. Conversely, the effect of the financial crisis index is significant and robust across all specifications, implying that the financial crisis is more relevant than excessive futures trading in explaining food price volatility.[14] It is worth noting that in terms of elasticity, a 1% increase in the financial crisis index leads to a rise in price volatility of about 0.40% in the OLS estimation and 0.35% in FGLS estimation. The positive relationship between the financial crisis index and food price volatility implies the significance of food commodities as financial instruments. When banks, sovereign debt, and exchange rates experience a crisis, the food market enters a crisis too.

The normalized supply shock variable has a statistically significant effect on food price volatility when the restriction of homogeneity is imposed. The variable turns out not to be significant when the restriction is relaxed. This could be due to the fact that heterogeneous production shocks can offset each other because of geographical variation without affecting price volatility. In the presence of homogeneity, extreme weather events exert an effect on the food crisis and agricultural risks.

The results show that oil prices and GDP—which can be viewed mainly as demand-side shocks—have a stronger impact than market shocks (speculative volumes and financial crisis), and supply-side shocks in explaining food price volatility when they are sig-

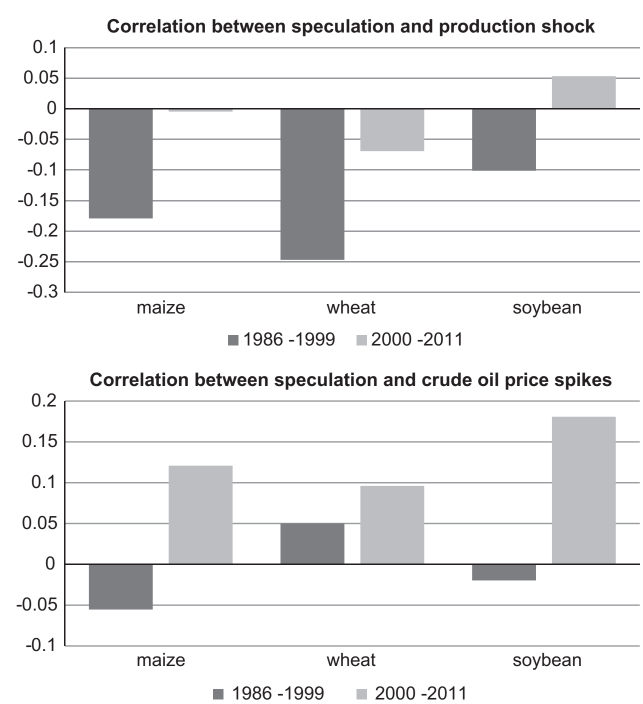

Fig. A.1. Correlations among factors affecting food prices. *Notes*: All the variables are measured annually. The figures show the correlation coefficients. The darker bars show correlation coefficients before 2000, and the light shaded bars show coefficients after 2000. *Source*: Authors' estimation based on the data explained in Sections 'Estimation methods' and 'Data'.

[14] We also estimated the models using the lagged values of the speculation and financial crisis variables. Although this is a nice way to technically correct for endogeneity, the economic sense behind this choice could be questioned because it would imply that one-year lagged financial variables can influence current price volatility. For this reason we preferred to consider only the current values of all the variables.

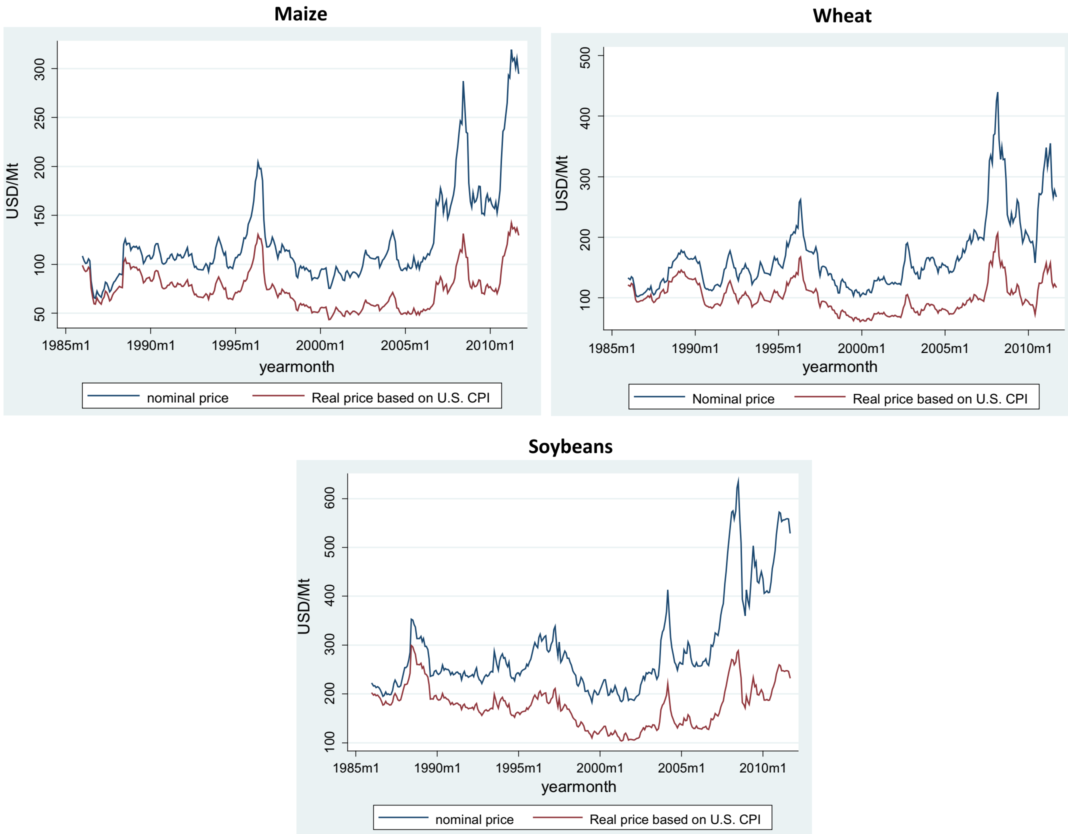

Fig. A.2. Trends and movements of nominal and real prices. *Note*: Both lines show monthly prices. The upper blue line shows nominal prices, and the lower red line shows real monthly prices. The real price is calculated as the ratio of nominal price to the US consumer price index. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.) *Source*: Authors' estimation based on World Bank (2011) nominal prices.

nificant (Table 3). This is because the marginal effect of oil price and GDP growth on food price volatility is higher than the effect of speculation and supply shocks. Specifically, a 1% increase in oil price volatility leads to a rise of 0.42–0.45% in food price volatility when the model controls for speculation. When the financial index is included, volatility rises by 0.43–0.50%. A 1% upsurge in global growth rates generates an increase of 0.56% and 0.45% when the model controls for speculation. The variable becomes insignificant when the financial crisis is considered. The importance of oil prices in explaining food price spikes and volatility suggests that food and energy markets have become more interwoven.

The variable stock-to-use ratio turns out to be insignificant in explaining food price volatility. As described in the theoretical section, the effect of exogenous shocks depends on the economic and political environment. If the stock-to-use ratio is low in times of financial and environmental shocks, exogenous shocks may well have a greater impact than they would if stocks were high. As we control for exogenous shocks in the models, the direct impact of stocks on volatility might vanish. This may suggest that the stock-to-use ratio is an amplifier or intermediate variable that reflects the effect of market supply and demand shocks on food price volatility.

In sum, determinants of price spikes and price volatility are somehow different at least in terms of level of significance and the magnitude of marginal effects. Market-related shocks (speculation) affect price spikes much more than demand- and supply-side shocks. In contrast, demand-side shocks (oil prices and GDP) lead to higher price volatility than market and supply-side shocks.

Food price triggers

Recent food price discussions indicate the possibility of tipping points where the "normal" response of markets changes and exaggeration and overreactions might occur. In order to identify triggers and test the tipping point hypothesis, we estimated a series of quantile regressions for both the price spike and volatility equations. The quantile regressions indicate at which price or volatility levels the dynamics of price spikes and price volatility changes (or, whether the dynamics estimated in Tables 1 and 3 are robust for all price and volatility levels). In the price spike equation, the effects of oil prices, speculative futures trading, and supply shocks are compared at high and lower prices. In the volatility equation, the effects of supply shocks, oil price volatility, and the financial crisis index are compared at lower and higher volatility. The tips in the price spike and price volatility equations are therefore different. In the price spike equation, the upper tip is the highest spike, but in the price volatility equation a high quantile refers to high volatility.

The results are presented in Figs. 3 and 4. The figures show the marginal effects of explanatory variables on response variables at different level of quantiles. The line graphs indicate point estimates, and the shaded regions show the 95% confidence intervals. A variable is said to be a trigger if the confidence intervals do not include zero values in the shaded region and the line graph is visibly increasing (if the relationship between food price and variable is positive) or decreasing (if the relationship between food price and the variable is positive) as the quantile increases. The results of triggering price spikes are mixed. Of all the variables included in price spike equation (Fig. 3), only the production shock for maize and wheat and speculation for maize show trigger effects. Other variables such as oil prices and stock-to-use ratio have no trigger effects, as depicted by flat and insignificant marginal values over quantiles.

The effect of production shocks on price spikes is getting bigger and bigger as the quantile increases except for soybeans. This result could imply that the USDA production forecasts have a larger impact on price movements when prices are high than when they are low. Thus, production shocks are a significant contributor to food price spikes.

The u-shape visible in the quantile regressions for speculation suggests that speculation is more important in times of extreme price dynamics. An increasing price trend, driven by changes in fundamentals (commodity demand and supply), gives rise to market nervousness that brings speculators to overheat the market. Speculation is also observed to have a strong impact on price spikes at lower quantiles of price spikes. This is an indication of the stabilization effect of speculation when markets are calm. When markets are drowning, since the lower spike quantiles are negative values, an increase in speculative activities restores market prices. In sum, speculative actions have the capacity to create price hikes and reduce price slumps.

Results from the volatility quantile regression suggest the importance of oil prices in triggering food price volatility (Fig. 4). The effects of supply shocks, stock-to-use ratio, and global GDP growth also increase over quantiles, but they all are statistically insignificant. The evidence also shows that financial crisis and speculation do not necessarily trigger volatility, in contrast to price spikes as shown in the quantile analysis above.

Oil prices have remained a prime factor in extreme volatility in food prices. Apart from the production and biofuel effects, oil prices affect food price volatility though a real income effect because of their dominant impact on the overall economy. The trigger effect may be associated with the interaction of these effects. All the effects are displayed at higher level of food prices.

Conclusions

This study has investigated the main drivers of food price spikes and volatility for wheat, maize, and soybeans, and shown how these factors trigger crisis at extreme price changes. The analysis has indicated that exogenous shocks as well as the linkages between food, energy, and financial markets play a significant role in explaining food price volatility and spikes.

In addition to demand and supply shocks, speculation is an important factor in explaining and triggering extreme price spikes. Excessive speculation is more strongly associated with price spikes at extreme positive price changes than with negative price changes, implying that the stabilizing effect of speculation through price discovery is smaller than its destabilizing effect through creating market bubbles.

The results also confirm that supply shocks are reflected in price spikes and that the effect of oil price shocks is greater for price risk than for food crisis. The effect of oil prices on food price spikes has emerged as significant only in recent years. Financial crisis exerts a strong impact on food price volatility, which confirms the increasing link between financial and commodity markets.

On the basis of the empirical results, it seems opportune for policy makers to prevent excessive speculative behaviors in the commodity market in order to reduce price spikes and prevent short-term food crises. In this context, caps on trading under extreme market situations, or taxation of food commodity futures trading along the lines of the Tobin tax, could be framed. Designing flexible biofuel policies that are responsive to the food supply situation can also help stabilize prices and reduce volatility spillovers from oil markets in times of food crisis. Recent changes in the US biofuel mandate, for example, include flexibility mechanisms that allow for relaxing the blending requirement in one year if compensated in another year.

Improving the market information base would further help all market actors to form expectations based on fundamentals and to detect shortages early. While the Agricultural Market Information System (AMIS) initiative of the G20 strives for higher transparency, sufficient contributions from some member states are still lacking.

Recent developments in many countries to increase national grain stocks to reduce volatility and import dependency lead to increased grain scarcity and thus higher prices in the short run. International levels of storage are, however, only one option to reduce volatility, which turned out to be mostly insignificant in our analyses. One reason might be lack of cooperation: governments building stocks only for their citizens tend to complement storage policies with trade restrictions, which effectively withdraw their stocks from the global grain market. Such collective action failure needs to be addressed in regional and global trade talks that should also consider the international consequences of national stock-holding policies.

Besides policies to reduce volatility and extreme price spikes, governments can increase resilience of producers and consumers to deal with price changes. This can be done by supporting contract farming and price insurance mechanisms on the production side and by enhancing safety nets and access to financial services on the consumer side.

Governments and their international associations such as the G20 should therefore carefully analyze all available options for preventing food price spikes and volatility—from interventions in financial markets to biofuel policies—and they should also facilitate market information.

Appendix

See Figs. A.1 and A.2.

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