
Drivers and Triggers of International Food Price Spikes and Volatility

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3.1 Introduction

The global food system recently showed exceptional developments in international commodity prices. 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. 3.1). Though the two events were different in terms of the commodities affected,¹ a strong correlation was found among most food prices. More importantly, prices of all food commodities soared above the long-term average, with an adverse impact on poor people in developing 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 affect the poor because they spend a large share of their income on staple foods. Volatility causes economic uncertainty and may result in lower investment, especially in small businesses which

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¹The sugar price index was lower than its historical average during the first food price crisis (2007–2008) but reached a historic high in 2010–2011. 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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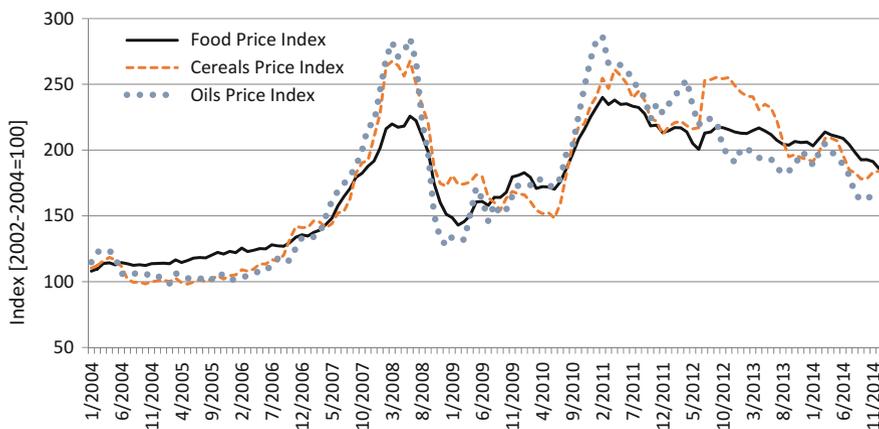


Fig. 3.1 FAO food price indices from January 2004 to November 2011. *Source:* FAO (2011)

lack access to credit. Although food grains are regarded mainly as commodities on the global market, they constitute the basic food of the poor and the “currency” of the poorest two billion people in the world.

Faced with rising food insecurity, social unrest, and accelerated inflation driven by food prices, developing and advanced countries as well as the international community began responding with a new sense of urgency. For instance, the G20 agenda of 2011 addressed food security. Nonetheless, although the price crises in 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 to stabilize 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 may be different. Traditional market fundamentals—that is, supply and demand factors—were found to be inadequate to explain the extreme price spikes in 2007–2008 and 2010–2011.

In the past few years, many studies have investigated 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 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 how weather, biofuel production, and export restrictions affect food commodity markets, the dispute surrounding speculation on the commodity food markets is far from settled. Most of the empirical studies focus primarily on using the Granger-causality test 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 the period 2007–2008 (Gilbert 2009; Phillips and Yu 2011; Shi and Arora 2012). The Granger-causality test, however, has been criticized for presuming a time-lag structure that might be too long to allow any reaction on the liquid financial market to be observed (Gilbert and Pfuderer 2012; Grosche 2012). Analyzing bubbles may be useful for identifying abnormal price behavior, but it does not explain the causes of the observed price increase.

This study goes a step further by examining the impact of speculation and agricultural fundamentals on price spikes and volatility. 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. From a welfare perspective, the distinction between price spikes and volatility is more important than trends in overall price levels. This is because price spikes and volatility are the primary indicators of food crises.² Furthermore, this distinction is also essential for differentiating between factors that cause risks to poor consumers and those that cause uncertainties to agricultural investors. 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 about 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 in which monthly food price returns (spikes) are estimated against oil prices, supply shocks, stock-to-use ratios, demand shocks, and the volume of speculative futures trading; (2) a volatility model in which annualized monthly variability of food prices is estimated against yearly observable variables, such as supply shocks, stock-to-use ratios, economic growth, the volume of speculative futures trading, oil price volatility, and a financial crisis index; and (3) a trigger model that estimates the extreme values of price spikes and volatility using quantile regression. The methodology will allow us to shed light on the formation of price spikes and price risks, rather than simply considering the so-called high food prices. The food commodities whose prices are investigated are wheat, maize, and soybeans.³ The rest of the paper is organized as follows: Sect. 3.2 presents the conceptual framework of the approach. Sections 3.3 and 3.4 describe the setup of the adopted models and the variables included in the empirical analysis. Section 3.5 discusses the econometric results. Section 3.6 presents the conclusion of this study.

²Although there is no universal definition of “food crisis,” here it is understood as an abrupt and unanticipated change that affects people severely and negatively.

³We do not include rice because of its different international market patterns.

3.2 Conceptual Framework

Recent literature has identified the determinants of food price hikes as biofuel demand, speculation in commodity futures markets, and macroeconomic shocks. These determinants represent both the demand and the 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. 3.2). 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 between the agricultural sector and root causes is minimal. 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 exogenous shocks. Some of these factors (such as a high concentration of production or low transparency in commodity markets) are time invariant and rather difficult to measure; they are

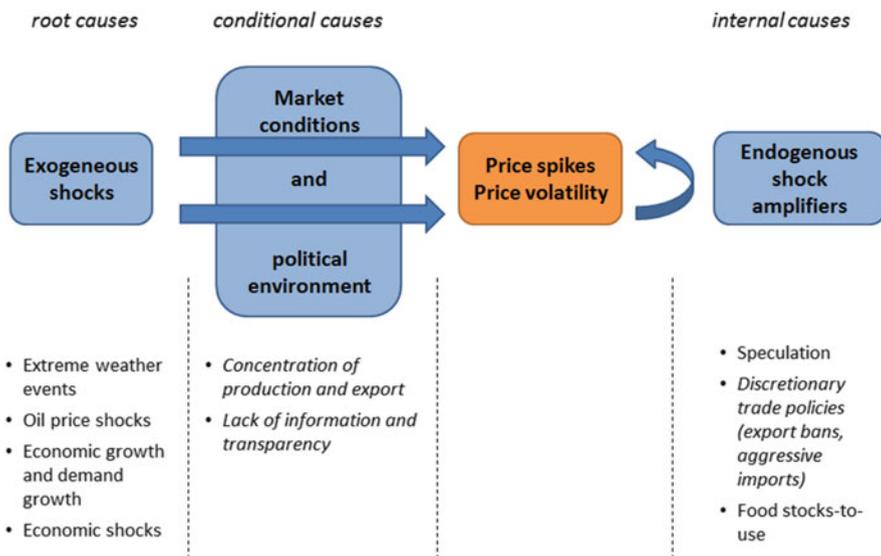


Fig. 3.2 Stylized framework of the causes of global food price volatility and spikes. *Source:* authors’ elaboration. *Note:* Exogenous shocks are the “root” causes of price volatility and price spikes. The extent to which exogenous shocks translate to food price changes depends on the market conditions and political environment of a given country (“conditional” causes). Food price shocks can further be amplified by nonlinear endogenous responses (“internal” causes) to food price shocks. The factors in *italics* are not considered in our econometric analysis as they are time invariant or as there is no appropriate quantitative indicator available

therefore not considered in the empirical analysis in this chapter. 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 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 cause that stimulates the emergence of the other factors. At the same time, special attention is given to speculation and food stocks, which are (partly) endogenous factors.

This categorization of drivers comes with a caveat: the line between endogenous and exogenous causes is very subtle. There are multiple and complex interactions between the factors, and the 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 increasing 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.

Figure 3.2 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, which consequently causes food prices to increase. In this analysis, we used short-term global food supply fluctuation and its projection as an indicator of extreme weather changes.

Another 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 grains destined for biofuel production—maize, soybeans, and other grains such as wheat—thus resulting 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 biofuel usage. 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 correlation with oil prices was significantly stronger for indexed commodities than

off-index commodities because oil is an important index constituent (Basak and Pavlova 2013).

The third root cause is the high demand for food crops coming mainly from emerging markets, primarily China and India. Krugman (2010) noted that 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).

One of the other root causes of price increases is 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 commodity consumers and producers not trading in US dollars.

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 the “traditional speculation” hypothesis, argues that speculation helps to stabilize prices by facilitating increased liquidity and improving price discovery in the market. The second hypothesis claims that speculation tends to generate spikes and instabilities because of a herd mentality in commodity exchanges. The UNCTAD (2011) report elaborated the different types of herd behavior in detail and explained how they can drive prices far away from their fundamentals. The basic mechanism is that traders base their decisions on past price trends rather than new information on market fundamentals. This situation makes it difficult for other market participants to distinguish between fundamental causes of price increases and the causes driven by herd behavior, thereby impeding the role of speculation in price formation. 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 in causing 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 trading and futures prices. According to some economists (such as Krugman 2008), speculation is a random bet, whereby traders’ buying and selling futures cancel each other 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 increased steeply. If speculative actions were responsible for the rise in food prices, private inventories should have accumulated. On the contrary, a substantial decline in global food stocks was registered. This fact has been used to justify the assumption that speculation plays an insignificant role 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 shortages 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 their 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 with riskier high-return assets (such as equity). This strategy reduces the overall portfolio risk. Hence, investors may choose commodity futures not because they expect increasing commodity prices, but because commodity futures have the potential to reduce their overall portfolio risk. In this view, commodities become attractive if alternative assets (such as real estate, bonds, metals, and 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 empirical analysis. The existing 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 (1) an "excessive" volume of futures contracts based on the disaggregated position of futures traders and (2) 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 other existing studies because it considers fundamental-based drivers *and* financial market-based factors of 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 a sequence of export restrictions and bans implemented by countries such as India, Thailand, China, and Russia caused 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 a country's perspective, restrictive policies seem to have the desired effect:

Domestic prices are shielded from the full impact of a steep price increase. However, restrictive policies affect the world market negatively. When many countries restrict exports, so much food disappears from the global market that prices rocket higher than without government intervention. 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 consumption 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.

3.3 Estimation Methods

We differentiate between price spikes, volatility, and trends. Since trends are somewhat anticipated long-term price changes that have little relevance to 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. Expressed as a formula:

$$d \ln P_t = \ln \left(\frac{P_t}{P_{t-1}} \right), \quad (3.1)$$

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.⁴ The model is specified as:

$$d \ln P_t = \beta R_t + \varepsilon_t, \quad (3.2)$$

where $d \ln P_t$ is a $I \times 1$ vector of price spikes (returns) with I number of commodities identified as $i = 1, 2, 3, \dots, I$; 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, whereas others are commodity nonspecific.

⁴Using 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.

Monthly supply shocks are measured as log ratios of the US Department of Agriculture forecasts on global production $d \ln X_t = \ln \left(\frac{X_t}{X_{t-1}} \right)$, as the USDA forecasts are widely recognized and play an important role in the price formation process, which is influenced by monthly information on the available grain supply in the current agricultural year. Economic shocks are calculated using the same equation with monthly interpolated global GDP per capita (nominal). The stocks-to-use ratio is the relationship between the beginning stocks (of the current agricultural year) and consumption as forecasted by the USDA. Oil price spikes are estimated using the same procedure as in the case of food commodity spikes (Eq. 3.1).

We have hypothesized that the effect of speculative activities on commodity price dynamics depends on the extent of deviation 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 it can be misleading to measure speculation relative to hedging. One problem is that small speculators, who may be influential as a whole, are exempted from certain reporting obligations. Another shortcoming is that categorizing traders as noncommercial does not allow for differentiating traders who speculate based on fundamentals from those who engage in “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, as mentioned above, excessive net long speculation leads to price increases (and excessive net short speculation leads to price decreases), we prefer to give equal weight to commercial and noncommercial trading activities and to measure speculation based on the deviation between the two types of trading activities. In a perfectly competitive commodity market, there should be no deviation between commercial and noncommercial trading activities. To meet commercial traders’ demand for hedging, an equal number of noncommercial traders’ contracts is necessary at most.⁵ However, we have observed a significant difference between commercial and noncommercial positions. This could be associated with the existence of a significant number of unsettled noncommercial positions for an extended period of time, motivated by speculation and the increasing use of food commodities as an asset class. Thus, using the excessive open interest of speculative futures seems to be a more appropriate way of capturing the speculative effect than using the

⁵Fewer noncommercial 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.

Working ratio. Technically, the extent of excessive speculative activities in month t is expressed as:

$$ESV_t = \frac{\sum_{d=1}^{N_t} [(NCL_d - NCS_d) - (CL_d - CS_d)]}{N_t}, \quad (3.3)$$

with N_t denoting the number of days d in month t in which CFTC position data are available. As the trading position data are published every Friday for the preceding Tuesday, only four to five observations are available 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), which captures both monthly and yearly variability. The normal coefficient of variation captures only the monthly price variability in a year. However, the mean price changes from year to year, and thus inter-year price variability cannot be captured. 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.

$$CV_y = \frac{\sum_{m=1}^{12} (P_m - \bar{P}_y)^2}{\sum_{t=0}^T P_t} \frac{T}{12}, \quad (3.4)$$

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

This metric does not measure the direction of price changes but rather evaluates price risks. This means that high variability does not necessarily reflect high prices. 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 the 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 have been adopted: ordinary least squares (OLS) and feasible generalized least squares (FGLS). The first, which assumes no heterogeneity across commodities, is expressed as:

$$V_{iy} = \alpha + \beta' X_{iy} + \varepsilon_{iy}, \quad (3.5)$$

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 an annual financial crisis indicator (an alternative to speculation). The supply shock variable is defined as the normalized deviation of total annual production from its long-term trend; this is to account for the market size of each commodity. 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 time series. The results derived from the production series using the Hodrick–Prescott filter have a similar distribution to those obtained using other time-series filters, such as Baxter–King, Butterworth, and Christiane–Fitzgerald. However, the Hodrick–Prescott filter is preferred to the others because it considers extreme values (Baum 2006). All the variables in this equation are measured annually.

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

$$V_{iy} = \alpha + \beta'X_{iy} + \gamma_i + \varepsilon_{iy}, \quad (3.6)$$

where γ_i denotes the fixed effect.

A price trigger model has been designed to complete the empirical assessment and to account for endogenous shock amplifiers. The impact of a price trigger at high prices might be different from that at low prices. When prices are getting high, markets are expected to be more sensitive to a shock than when prices are low. This effect is sometimes referred to as the 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 τ th quantile of the response variable as opposed to the mean value of the response variable in OLS. It gives a comparison of the effect at the upper and lower tail of the price distribution. Equations (3.2) and (3.4) are estimated at the τ th quantile, where $\tau \in \{0.05, 0.15, 0.25, \dots, 0.95\}$. 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, the lower quantiles represent negative values, and the upper quantiles positive values. In the volatility equation, both the lower and upper quantile are positive values, with the upper quantiles denoting higher values.

3.4 Data

The nominal prices of maize, wheat, soybeans, and crude oil were obtained 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. 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 unavailable.

Data for annual supply shock estimation were collected from the 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.⁶ Open interest of futures trading of the Chicago Board of Trade (CBOT) was obtained from the CFTC for maize, wheat, and soybeans.⁷ The CFTC reports disaggregated open interest of futures trading positions into long and 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.

3.5 Results and Discussion

3.5.1 Determinants of Food Price Spikes

Table 3.1 presents the results of the seemingly unrelated regression estimates for different time periods. Production is led by 1 month as markets are assumed to anticipate supply shocks shortly before the USDA publishes its estimates; this is a result of private market research and information acquisition.⁸ As expected, price spikes are negatively correlated with (anticipated) supply shocks and positively correlated with economic growth (demand) shocks. The results show the positive and significant effect of excessive speculative activities on food price spikes, although the anticipation of supply and demand shocks is already controlled for. The extent of excessive speculation is significant both before and after 2000; however, the effect is stronger after 2000. A strong belief exists 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 introduction of 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.

⁶Data are available at <http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1194> (accessed February 18, 2013).

⁷Data are available at <http://www.cftc.gov/MarketReports/CommitmentsofTraders/HistoricalCompressed/index.htm> (accessed February 18, 2013).

⁸The anticipation effect vanishes, however, for a lead of 2 or more months.

Table 3.1 Seemingly unrelated regression results on food price spikes (coefficients and *z*-values)

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

(continued)

Table 3.1 (continued)

	1986–2009	1986–1999	2000–2009
Constant	−0.0204* (−1.87)	−0.0157 (−0.98)	−0.0145 (−0.71)
R^2	0.24	0.32	0.21
N	304	167	137

Note: Dependent variable: maize, wheat, and soybean price spike. ***, **, * denote that the level of significance is at 1, 5, and 10 %, respectively. 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. (3.3)

Table 3.2 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-month) 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 3.1 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 3.1; for the third row, the value of the second row was multiplied by the number of months (12)

Although the coefficient of speculation variable is smallest for maize and largest for wheat, the variation of speculation is much larger for maize than for wheat. Table 3.2 shows the impact that one standard deviation change in speculation has on spikes, showing that maize price spikes are more affected by speculation than wheat price spikes. Regarding the role of speculation in the 2007–2008 crisis, excessive speculation predicts that, all other things being equal, maize price increased by approximately 38 % within the 12 months following July 2007, but wheat price increased by only less than 3 %. These numbers must, however, be treated with caution 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. These factors are

difficult to control for. Financial market shocks, however, clearly constitute a part of the exogenous elements in the speculation variable.⁹

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

Oil price spikes have increasing effects on food price spikes over time (Table 3.1). Before 2000, the effect was insignificant or negative (in the case of 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 increased index fund activities. The significant impact of oil prices on food prices in recent years suggests that demand factors and financialization dynamics are more relevant in explaining price increases than supply factors. The United States accounts for about 40 % of the world's 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 through not only a direct conversion of food crops to feedstock, but also 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 a more important factor in causing short-term food price spikes than the actual scarcity caused by biofuel demand. 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; low wheat stocks increased the magnitude of price spikes.

⁹There are two standard approaches to dealing with endogeneity: lagging variables and instrument variables. In our case, both are problematic. A 1-month lag is already too long for data on speculation; financial markets operate on a daily basis, and speculative activities in the preceding month should not have any impacts 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 covariances among many different assets, which cannot be subsumed under a linear combination of a few financial market variables.

3.5.2 Food Price Volatility

A panel analysis is used to quantify the relative importance of supply, demand, and financial shocks in affecting food price volatility. The explanatory variables included in this volatility equation are the same as for food price spikes, 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, the financial crisis index developed by Reinhart and Rogoff (2009) is also included in the equation. 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 market, and hence speculation and the financial crisis index are used as alternatives.

The different estimates of the models are presented in Table 3.3. 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 in explaining food price volatility than excessive futures trading.¹⁰ It is worth noting that in terms of elasticity, a 1 % increase in the financial crisis index caused price volatility to rise by about 0.40 % in the OLS estimation and 0.35 % in the 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 will enter 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 was determined not to be significant when the restriction is relaxed. This could be because 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 food crises and agricultural risks.

The results show that when significant, oil prices and GDP—which can be regarded mainly as demand-side shocks—are more meaningful in explaining food

¹⁰We also estimated the models using the lagged values of the speculation and financial crisis variables. Although this is a convenient way to technically correct for endogeneity, the economic sense behind this choice is questionable because it implies that 1-year lagged financial variables can influence current price volatility. For this reason, we prefer to consider only the current values of all the variables.

Table 3.3 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 ^{**} (2.31)	0.2138 ^{***} (2.35)	0.3395 (1.10)	0.1608 (1.10)	0.3690 ^{***} (2.40)	0.1865 ^{***} (2.47)	0.3340 (1.56)	0.1438 (1.56)
Oil price coefficient of variation	0.3595 ^{***} (7.29)	0.4202 ^{***} (6.76)	0.3506 ^{***} (5.20)	0.4939 ^{***} (5.20)	0.3801 ^{***} (6.63)	0.4306 ^{***} (5.87)	0.3771 ^{***} (6.84)	0.5031 ^{***} (6.84)
Beginning stock-to-use	0.1020 (1.35)	0.3405 (1.35)	0.0385 (0.41)	0.1002 (0.41)	0.1067 (1.50)	0.3862 (1.47)	0.0894 (0.94)	0.2526 (0.94)
GDP growth rate	0.0132 ^{**} (2.24)	0.5629 ^{***} (2.34)	0.0130 (7.14)	0.4552 ^{***} (7.14)	0.0038 (0.48)	0.1793 (0.48)	0.0035 (0.44)	0.1322 (0.44)
Speculation (1000 contracts)	0.00001 (1.39)	0.0714 (1.64)	0.0001 (1.66)	0.0839 (1.66)				
Financial crisis index					0.0007 ^{**} (1.96)	0.3915 ^{**} (2.05)	0.0007 ^{**} (2.30)	0.3417 ^{**} (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. ^{***} $p < 0.01$, ^{**} $p < 0.05$, and ^{*} $p < 0.10$. 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_0 : no cross-sectional dependence) reveals that there is independence, thus residuals are not contemporaneously correlated. The modified Wald test for groupwise heteroskedasticity (H_0 : homoskedasticity) does not reject the null and concludes for homoskedasticity. The Wooldridge test for autocorrelation in panel data (H_0 : no serial correlation) fails to reject the null and concludes that data do not have first-order autocorrelation.

price volatility than market shocks (speculative volumes and financial crisis) and supply-side shocks (Table 3.3). This is because the marginal effect of oil price and GDP growth on food price volatility is higher than that of speculation and supply shocks. Specifically, a 1 % increase in oil price volatility caused food price volatility to rise by 0.42–0.45 % when the model controls for speculation. When the financial index is included, volatility rose by 0.43–0.50 %. A 1 % upsurge in global growth rates generated an increase in food price volatility of 0.56 and 0.45 % when the model controls for speculation. The variable becomes insignificant when considering the financial crisis. 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 when stocks are 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 supply and demand shocks on food price volatility.

In sum, the determinants of price spikes and price volatility are somehow different, at least in terms of the degree 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.

3.5.3 Food Price Trigger

Recent discussions about food prices noted the possibility of a tipping point where the market may stop responding “normally” to market changes, opting instead to exaggerate and overreact. In order to identify triggers and test the tipping-point hypothesis, we estimated a series of quantile regressions for both the price spike and the volatility equations. The quantile regressions indicate the price or volatility levels at which the dynamics of price spikes and price volatility change (or whether the dynamics estimated in Tables 3.1 and 3.3 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 both higher and lower prices. In the volatility equation, the effects of supply shocks, oil price volatility, and the financial crisis index are compared at both lower and higher volatility. The tips in the price spike and price volatility equation are therefore different. In the price spike equation, the upper tip denotes the highest price, but in the price volatility equation, a high quantile signifies high volatility.

The results are presented in Figs. 3.3 and 3.4. The figures show the marginal effects of the explanatory variables on the response variables at different level of quantiles. The line graphs indicate point estimates, and the shaded regions

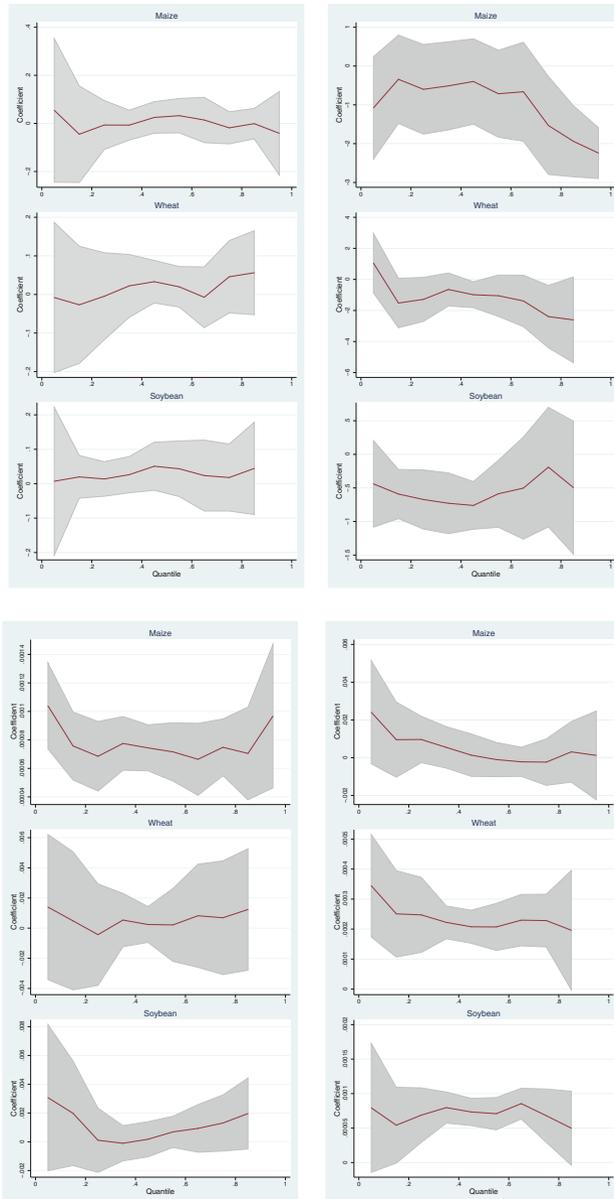


Fig. 3.3 Triggers of food price spikes. *Source:* Authors’ estimation based on data explained in Sects. 3.3 and 3.4. *Note:* The *middle line* shows the coefficient which explains price spikes using (a) oil price shocks, (b) production shocks, (c) excessive speculation, and (d) stock-to-use ratios. The quantile regression shows the coefficients for different quantiles of commodity price spikes. At low quantiles, the corresponding coefficient shows the impact on price spikes when price spikes are low; at high quantiles, the corresponding coefficient shows the impact on price spikes when price spikes are already high. Shaded regions are the 95 % confidence intervals, and the *line* in the *middle* is the coefficient

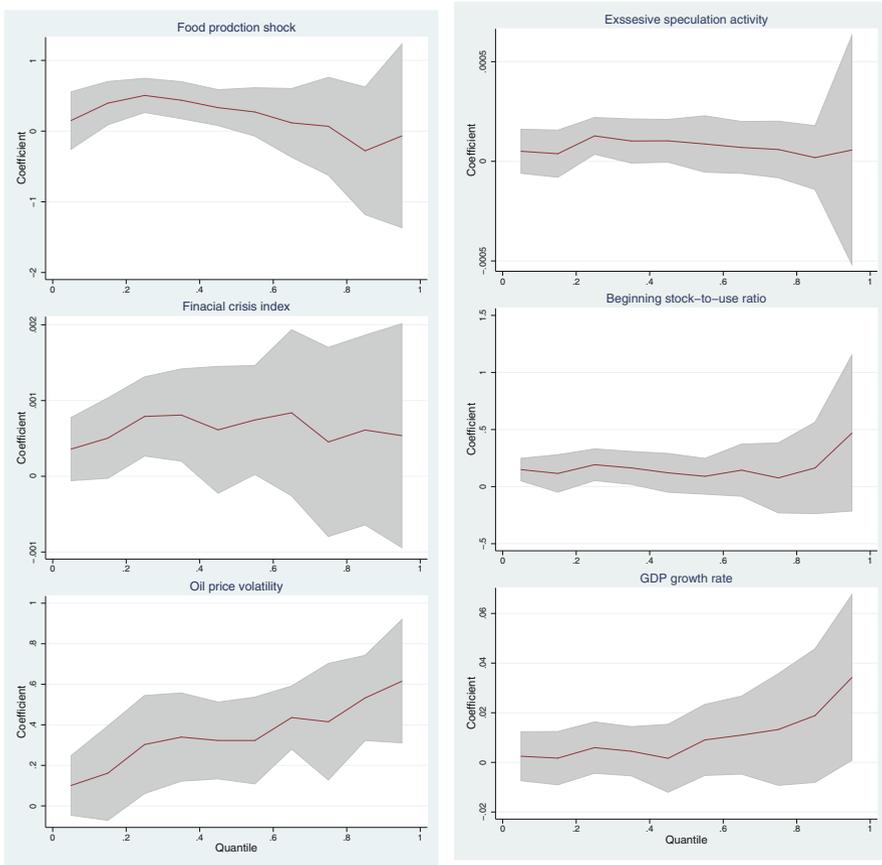


Fig. 3.4 Triggers of global food price volatility. *Source:* Authors’ estimation based on data explained in Sects. 3.3 and 3.4. *Note:* The *middle line* shows the coefficient which explains food price volatility using different explanatory variables. The quantile regression shows the coefficients for different quantiles of food price volatility. At low quantiles, the corresponding coefficient shows the impact on price volatility when volatility is low; at high quantiles, the corresponding coefficient shows the impact on price volatility when volatility is high. *Shaded regions* are the 95 % confidence intervals, and the *line in the middle* is the coefficient

show the 95 % confidence intervals. A variable is defined as a trigger if the confidence intervals do not include zero values in the shaded region and if the line graph is visibly increasing (a positive relationship between food price and variable) or decreasing (a negative relationship between food price and the variable) as the quantile increases. The results of triggering price spikes are mixed. Of all the variables included in the price spike equation (Fig. 3.3), the trigger effect is evident only when maize or wheat production experiences a shock, or when there is speculation on maize. 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 generally becomes stronger as the quantile increases, except in the case of soybeans. This result could imply that the USDA production forecasts have a larger impact on price movements when prices are high rather than low. Thus, production shocks are a significant contributor to food price spikes.

The u-shaped curve 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, causing 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 stabilizing effect of speculation when markets are calm. When markets are flooded, since the lower spike quantiles are negative values, an increase in speculative activities restores market prices. In sum, speculation has the capacity to create price hikes and reduce price slumps.

The results from the volatility quantile regression suggest the importance of oil prices in triggering food price volatility (Fig. 3.4). The effects of supply shocks, stock-to-use ratio, and global GDP growth also increase over quantiles, but they are all statistically insignificant. The evidence also shows that financial crises and speculation do not necessarily trigger volatility, in contrast to price spikes as shown in the quantile analysis above.

Oil prices have remained a primary factor in causing extreme volatility in food prices. Apart from being affected by production costs and biofuel-related demand, food price volatility is also affected by oil prices through a real income effect. This is because of oil prices' dominant impact on the overall economy. The trigger effect may be associated with the interaction between these effects. All the effects are evident at the higher level of food prices.

3.6 Conclusion

This study has investigated the main drivers of food price spikes and volatility for wheat, maize, and soybeans. It has also shown how these factors trigger a crisis when there are 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 price 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 rather than negative price changes. This implies that the stabilizing effect of speculation (generated through price discovery) is smaller than its destabilizing effect (generated through creating market bubbles).

The results also confirm that supply shocks are reflected in price spikes and that oil price shocks affect price risk more than they affect food crises. The effect of oil

prices on food price spikes has become significant only in recent years. Financial crisis exerts a strong impact on food price volatility, which confirms that the link between financial and commodity markets is becoming stronger.

On the basis of the empirical results, it seems opportune for policymakers to prevent excessive speculative behaviors in the commodity market in order to reduce price spikes and prevent short-term food crises. In this context, policymakers could put caps on trading in extreme market situations or impose a tax on food commodity futures trading, along the lines of the Tobin tax. 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 a food crisis. Recent changes in the US biofuel mandate, for example, include flexibility mechanisms that allow for relaxing the blending requirement in a certain year if compensated for in another year.

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

Recently, many countries are increasing their national grain stocks to reduce domestic volatility and import dependency, leading to an increased grain scarcity and in turn higher grain prices in the short term. International levels of storage, however, are only one of the options to reduce volatility, and they turned out to be mostly insignificant in our analyses. One reason might be the lack of cooperation between countries: The governments which build stocks only for their citizens tend to complement storage policies with trade restrictions, effectively withdrawing their stocks from the global grain market. Such failure to act collectively needs to be addressed in regional and global trade talks. The international consequences of national stock-holding policies should also be discussed during these talks.

Besides policies to reduce volatility and prevent extreme price spikes, governments can improve the resilience of producers and consumers to price changes. This can be achieved 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.

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References

- Abbott PC, Hurt C, Tyner WE (2009) What's driving food prices? Farm Foundation
- Abbott PC, Hurt C, Tyner WE (2011) What's driving food prices in 2011? Farm Foundation
- Basak S, Pavlova A (2013) A model of financialization of commodities. Available at <http://dx.doi.org/10.2139/ssrn.2201600>
- Baum CF (2006) Time-series filtering techniques in STATA. Department of Economics, Boston College, July 2006. Available at http://www.stata.com/meeting/5nasug/TSTFiltering_beamer.pdf. Accessed 10 July 2013
- Chakravorty U, Hubert M, Moreaux M, Nøstbakken L (2011) Do biofuel mandates raise food prices? Working paper no. 2011-01, Department of Economics, University of Alberta
- Chen ST, Kuo HI, Chen CC (2010) Modeling the relationship between the oil price and global food prices. *Appl Energy* 87(8):2517–2525
- Conforti P (2004) Price transmission in selected agricultural markets. FAO working paper no. 7
- Dawe D (2008) Have recent increases in international cereal prices been transmitted to domestic economies? The Experience in Seven Large Asian Countries. Working paper no. 08-03. ESA-FAO
- Díaz-Bonilla E, Ron JF (2010) Food security, price volatility and trade: some reflections for developing countries. Issue paper 8. International Centre for Trade and Sustainable Development (ICTSD), Geneva
- Dorosh PA, Dradri S, Haggblade S (2009) Regional trade, government policy and food security: recent evidence from Zambia. *Food Policy* 34:350–366
- FAO (2011) FAOSTAT. Food and Agriculture Organization of the United Nations
- Frenk D (2010) Speculation and financial fund activity and the impact of index and swap funds on commodity futures markets. Available at http://blog.newconstructs.com/wp-content/uploads/2010/10/FrenkPaperReutingOECDStudy_IrwinAndSanders.pdf.
- Gheit F (2008) Testimony before the subcommittee on oversight and investigations of the committee on energy and commerce, U.S. House of Representatives
- Gilbert CL (2009) Speculative influences on commodity futures prices 2006–2008. United Nations Conference on Trade and Development
- Gilbert CL (2010) How to understand high food prices. *J Agric Econ* 61:398–425
- Gilbert CL, Pfuderer S (2012) Index funds do impact agricultural prices. Money, macro and finance study group workshop on commodity markets, London
- Grosche S (2012) Limitations of Granger causality analysis to assess the price effects from the financialization of agricultural commodity markets under bounded rationality. Institute for Food and Resource Economics Discussion Paper 1
- Headey DD (2011) Rethinking the global food crisis: the role of trade shocks. *Food Policy* 36:136–146
- Henderson B, Pearson N, Wang L (2012) New evidence on the financialization of commodity markets. George Washington University, Available at <http://dx.doi.org/10.2139/ssrn.1990828>
- Hernandez A, Robles M, Torero M (2011) Beyond the numbers: how urban households in central America responded to the recent global crises. IFPRI Issue Brief 67. International Food Policy Research Institute, Washington, DC
- Irwin SH, Sanders DR, Merrin RP (2009) Devil or angel? The role of speculation in the recent commodity boom (and bust). *J Agric Appl Econ* 41:393–402

- Karali B, Power GJ (2009) What explains high commodity price volatility? Estimating a unified model of common and commodity-specific high and low frequency factors. In: Agricultural and applied economics association conference 2009, Milwaukee, Wisconsin
- Koenker R, Hallock KF (2001) Quantile regression. *J Econ Perspect* 15(4):143–156
- Krugman P (2008) Speculative nonsense, once again. *Conscience of a liberal*. NY Times, 23 June 2008
- Krugman P (2010) The finite world. NY Times, 26 Dec 2010
- Martin W, Anderson K (2012) Export restrictions and price insulation during commodity price booms. *Am J Agric Econ* 94:422–427
- Masters MW (2008) Testimony before the committee on homeland security and government affairs. U.S. Senate, 20 May 2008
- Mitchel D (2008) A note on rising food prices. Policy research working paper 4682. World Bank Development Prospect Group, Washington, DC
- Peterson HH, Tombek WG (2005) How much of commodity price behaviour can a rational expectations storage model explain? *Agric Econ* 33:289–303
- Phillips PCB, Yu J (2011) Dating the timeline of financial bubbles during the subprime crisis. *Quant Econ* 2:455–491
- Piesse J, Thirtle C (2009) Three bubbles and a panic: an explanatory review of the food commodity price spikes of 2008. *Food Policy* 34(2):119–129
- Reinhart CM, Rogoff K (2009) This time is different: eight centuries of financial folly. Princeton University Press, Princeton
- Roache SK (2010) What explains the rise in food price volatility? IMF working paper /10/129. International Monetary Fund, Washington, DC
- Robles M, Torero M, Braun JV (2009) When speculation matters, IFPRI Issue Brief 57. International Food Policy Research Institute, Washington, DC
- Shi S, Arora V (2012) An application of models of speculative behaviour to oil prices. *Econ Lett* 115:469–472
- Tadasse G, Guttormsen AG (2011) The behavior of commodity prices in Ethiopia. *Agric Econ* 42:87–97
- Tang K, Xiong W (2012) Index investment and the financialization of commodities. *Financ Anal J* 68:54–74
- UNCTAD (2011) Trade and development report 2011: post-crisis policy challenges in the world economy. In: United Nations conference on trade and development
- USDA (2013) Feedgrains database
- von Braun J (2011) Increasing and more volatile food prices and the consumer. In: Lusk J, Roosen J, Shogren J (eds) *The Oxford handbook of the economics of food consumption and policy*. Oxford University Press, Oxford, pp 612–628
- World Bank (2011) Global economic monitor (GEM) commodities World Bank data
- Wright B (2011) The economics of grain price volatility. *Appl Econ Perspect Policy* 33:32–58
- Yang J, Qiu H, Huang J, Rozelle S (2008) Fighting global food price rises in the developing world: the response of China and its effect on domestic and world markets. *Agric Econ* 39:453–464