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Causes of the 2000s Food Price Surge: Insights from Structural VAR

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Abstract

In 2001 began a rise in the prices of food commodities not seen since the 1970s. The prices of grains—the major staple foods—increased fivefold between 2003 and 2008, leading to the additional malnutrition of millions around the world. Many observers attribute the strong increase in part to speculation in derivatives markets. We examine this hypothesis by comparing the impact of speculation to that of fundamental supply and demand forces. We estimate the share of the price increase attributable to the respective market forces using a sign identified structural vector autoregressive model. Speculation is identified using storage data, though a residual price shock is allowed to ensure the robustness of the findings.

1 Introduction

Grain Prices gradually decreased between 1974 and 2001 in real terms. The growth in world population was outweighed by breeding and adopting higher-yielding crop varieties (see Wright 2011). After the turn of the millennium, however, a sustained increase of prices and price volatility began. Between 2005 and 2008 alone, the food price index of the Food and Agriculture Organization of the United Nations (FAO) increased by 71 percent. The index of real prices rose 46 percent (see figure 1). After a short but steep break prices continued climbing up. The price increase was particularly high for grains. As staple foods, these are of great importance. The three grains rice, corn and wheat alone cover around half of the worldwide human calorie consumption. Real prices for these three grains doubled between 2005 and 2008.

While the price increases that happened for other commodities may had important consequences for the world economy, the surge in staple food prices entailed more immediate and imminent threats. According to Rosen et al. (2008) the number of undernourished people has risen by 30 million following the 2008 price pike. FAO (2008) even puts the number at 75 million. Since people in developing countries have to spend up to 70 percent of their income on food, a price increase also has a significant impact on the living standards of those who can still afford an adequate

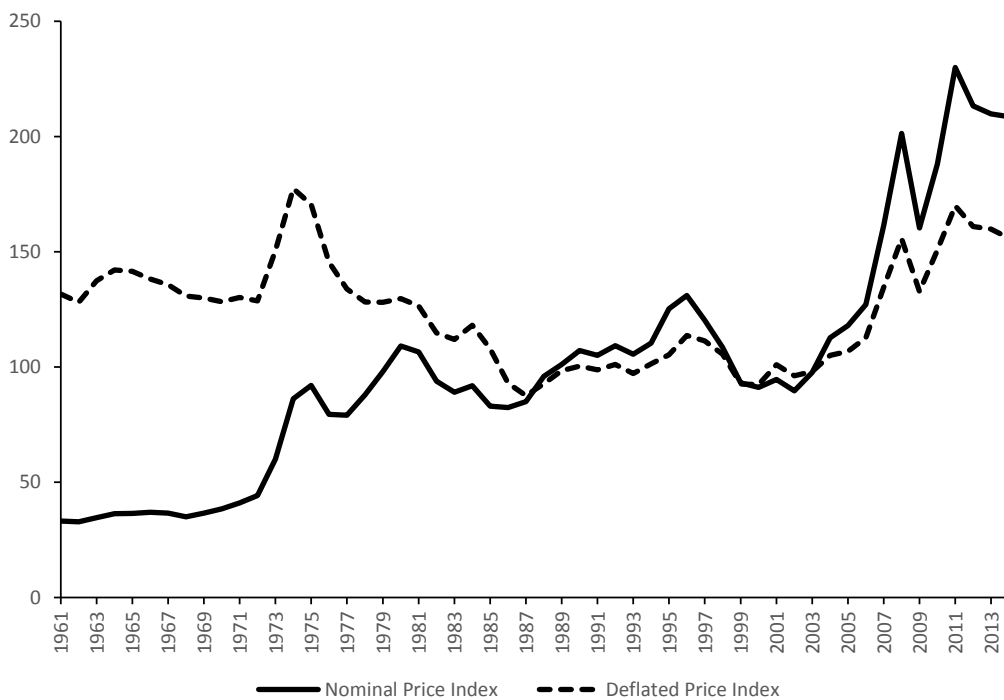


Figure 1: FAO Food Price Index in nominal and real terms.

diet. According to estimates by the World Bank (2008), over 100 million people might have fallen into poverty due to the price spikes in 2007/08. The renewed spike in 2010 might have driven 44 million people into extreme poverty (Ivanic et al. 2011). Headey and Fan (2008) pointed out that those figures ignore that many poor farmers benefited from rising prices and thereby escaped poverty. In any case it is clear that for many, especially for the urban poor, the price increases caused serious harm. Rising food prices are regarded as having triggered political unrest in over 40 countries, including the uprisings in the Middle East known as Arab Spring (Breisinger et al. 2011; von Braun and Tadesse 2012).

The price boom also affected other foods beside grains as well as other commodities like oil and metals. Here, we focus on grains to represent food prices. In addition to the importance in feeding mankind, there are other reason to focus on grains instead of a broader group of foods. Grains were among the most affected foods and also it seems plausible that the price increase of foods like meat and diary products is in part attributable to the transmission of grain price increases. Grains are a major driver of the production costs through their role as animal feed (von Braun and Tadesse 2012).

A multitude of possible drivers for the rising commodity prices of the past thirteen years has been discussed. For a summary of the possible causes see, for example, Wright (2008) or Headey and Fan (2008). A particularly controversial explanation assumes that a sharp rise in the trading volume in commodity derivatives was a major cause. As a result of financial market liberalizations and the development of exchange traded funds, large sums have been invested into commodity futures. This allegedly has caused increases in the futures prices or at least in the price volatility. The price pressure could then have been transmitted to the spot market. Market participants and experts have since demanded tightened regulation of com-

modity markets (see, e.g. Masters 2008) and non-governmental organizations have demanded financial institutions active in this market to refrain from commodities trading.

Since 2008, numerous studies have emerged that evaluate the impact of derivatives trading on commodity prices. The results regarding the impact of derivatives trading are, however, quite mixed. For more details the reader is referred to one of the many reviews, for example von Braun and Tadesse (2012), Baffes and Haniotis (2010), Bass (2011), Branson et al. (2010), and Irwin and Sanders (2010, 2011). Existing empirical studies often use single equation models to examine the explanatory power of futures prices, or another set of variables, for commodity prices. Granger causality tests are frequently employed. In most cases though, they do not allow for a clear causal interpretation and merely provide information about correlation. An alternative to the prevailing approach in the literature is offered by Kilian and Murphy (2012, 2013). They propose a structural vector autoregression (VAR) model to investigate the impact of speculation on oil prices, allowing the decomposition of the price of oil into the effects of speculation, consumption-demand and production. To this end, they use a structural model identified by sign restrictions. The identification of the causal structure using sign restrictions is less restrictive with regard to simultaneous changes in the variables. It thus allows a better—i.e. more agnostic—identification in spite of strong interdependences. A major issue using sign restrictions stems from the large number of identified models (Fry and Pagan 2011). This model identification problem can be reduced with the approach proposed by Kilian and Murphy (2012, 2013). The resemblance in the price determination for different commodities makes the approach of Kilian and Murphy appealing for grain markets (see for example Williams and Wright 1991, p. 8-9). We follow Kilian and Murphy (2013) in using inventory data to control for expectations and thus speculation.

Such an application has—to the best of our knowledge—not been undertaken in the literature thus far. In an unpublished paper, Carter et al. (2013) estimate a sign-identified structural VAR to investigate the influence of biofuel production on food prices. Their approach is also partially building on Kilian and Murphy (2013) but differs distinctly from ours due to the different underlying question. Hausman et al. (2012) also examine the effects of biofuel production on the price of grain by means of a structural VAR but use a different identification strategy. Both studies do not evaluate the impact of speculation. The present work thus complements the existing literature by using a framework especially suited to study the causal effect of speculation and applying it to grain markets. For this purpose, a structural vector autoregression is estimated for the most important food markets—the prices of the three grains corn, rice, and wheat.

The remainder is structured as follows: Section 2 briefly introduces a theoretical framework of commodity and derivatives markets. Section 3 explains the methodological framework used in estimating the structural VAR. The data and the model specification are presented in 3.1. In Section 4 the estimation and identification procedure is presented and section 5 provides and discusses the results. Section 6 provides a summary and conclusions.

2 Basic Relations of Grain Markets

The history of derivatives trading is closely linked to grain markets. The first futures trading at organized exchanges took place in the beginning of the 18th century in Osaka, Japan; the underlying commodity was rice (Schaede 1989). About one century later in Europe and the United States, organized futures trading also evolved around grain markets. With the emergence of speculative markets soon professional speculators also became to play an important role. It didn't take long for heated debates about their economic and moral legitimation to erupt (see Jacks 2007). Given this controversial background, it is important to find some common ground regarding the functioning of grain markets to build our model on. The challenge is to deduce causal relationships from the data without imposing strong economic assumptions. For the identification of our model, we need theoretical assumptions about the signs of the effects of shocks. These should not depend on the exact theoretical notion of the researcher. In the following we will therefore present a very general and basic framework to build our econometric model on.

The agricultural price determination was first addressed theoretically for example by Working (1953), Vaile (1948), and Kaldor (1939). A comprehensive account can be found in Williams and Wright (1991). Building on this work, we will briefly sketch a basic supply and demand model with storage.

We assume three groups that constitute the market for grains. These are producers, consumers, and speculators. The producers decide at the end of a year about the planned production (seed) for next year, S_t . The realised production, the harvest H_t , then depends on the planned production and a stochastic component ν_t that might be interpret as a weather shock. Thus, we have

$$H_t = S_t * \nu_t. \quad (1)$$

If we assume rational expectations we do not need to assume the weather component ν_t to be independently distributed with mean zero.¹ Instead, we assume the forecast error for the weather made by the producers is *iid* with mean zero. From profit maximization in a competitive market it follows that planned production is a function of the expected price, i.e.

$$S_t = S(E_{t-1}[P_t]), \quad (2)$$

with first order condition

$$\frac{\partial S_t}{\partial E_{t-1}[P_t]} > 0.$$

Further, we assume demand to be a function of prices P_t and income Y_t , this is

$$D_t = D(P_t, Y_t), \quad (3)$$

with

¹The assumption of rational expectations also ensures internal consistency of the model (Williams and Wright, 1991, p. 33). Internal consistency means, producers take into account that other producers will react to a change in the expected price by adjusting their production—which in turn changes next periods expected price.

$$\frac{\partial D_t}{\partial P_t} < 0 \quad \text{and} \quad \frac{\partial D_t}{\partial Y_t} > 0 .$$

Because households are able to save and to some extent to borrow money, past values of P and Y as well as expectation of future income and prices should be incorporated in equation (3). Past values will be covered by lags in our VAR specification. Insofar expectations are a linear function of past values, they also are covered by the model. In addition, we control for expectations by including storage, which should reflect expectations about future supply and demand if speculators conduct consumption smoothing. The quantity harvested—resulting from equation (1) and (2)—can be consumed or stored. In addition to this years harvest, there may thus also be inventory from the last year. For the available quantity in each year we therefore have

$$\begin{aligned} H_t + I_{t-1} &\equiv D_t + I_t \\ \text{i.e.} \quad H_t &\equiv D_t + \Delta I_t , \end{aligned} \tag{4}$$

where I_t represents the inventory at the end of year t .² The inventories are subject to a non-negativity constrained, i.e. $I_t > 0$ at all times t . In our empirical investigation we do not incorporate this nonlinearity into the model.

The storage decision is made by profit-maximizing speculators. By trying to buy low and sell high their profit depends on the current and future grain (spot) prices. In addition, they bear the costs for storing the commodity from one period to the next, the so-called Cost-of-Carry (CoC). Oftentimes it is furthermore assumed that physical ownership of a commodity also provides advantages—for example enabling the owner to profit from short-time price spikes or to cover supply shortfalls in a production process. These advantages are termed convenience yield (cf. Kaldor 1939). We simplify the convenience yield to a dividend from storage and as a part of the Cost-of-Carry. Clearly, storage is more attractive if next periods expected price is high and the current price and the CoC are low. Thus, the profit maximization of speculators leads to the inventory demand function

$$I_t = I(P_t, E_t[P_{t+1}], CoC_t) , \tag{5}$$

with

$$\frac{\partial I_t}{\partial E_t[P_{t+1}]} > 0 , \quad \frac{\partial I_t}{\partial P_t} < 0 \quad \text{and} \quad \frac{\partial I_t}{\partial CoC_t} < 0 .$$

Speculators will store if and only if the expected profit from buying, storing and selling the commodity exceeds the Cost-of-Carry. If we assume furthermore that all speculators have identical expectations we have the intertemporal equilibrium

$$P_t = E_t[P_{t+1}]/(1 + r_t) - CoC_t, \quad \text{assuming } I_t > 0 . \tag{6}$$

We now allow trading contracts that guarantee delivery of an agreed quantity at a future date. Assuming risk neutral speculators, the equilibrium futures price for delivery in the next year should equal the expected price, i.e.

$$F_t = E_t[P_{t+1}] \tag{7}$$

² We confine our presentation to between-harvest changes. Within each harvest year, the amount stored will experience obvious declines starting after the harvest season and lasting until the next harvest. These regular patterns are of no particular relevance to our investigation.

By substituting (7) into equation (6) we get

$$P_t = F_t/(1 + r_t) - CoC_t, \quad \text{assuming } I_t > 0. \quad (8)$$

Equation (6) establishes a connection between expected prices and current prices via speculation and (8) establishes the same connection through arbitrage. Put differently, the basic predictions of the model are independent of the existence or functioning of derivatives markets if we maintain the assumption of risk neutral speculators (cf. Williams and Wright, 1991).

This has important implications. The link between derivatives and spot markets is established through cash-and-carry arbitrage. If this link was not functioning, derivatives trading would be irrelevant and the discussion about the distorting influence of derivatives trading ungrounded. If the link exists and thus futures prices can guide spot markets, the influence of derivatives can be captured by controlling for storage. Our model thus includes all major market forces including derivatives without explicitly including futures prices. Our model offers theoretically sound predictions of the sign of effects of one variable onto another without requiring strong assumptions.

Now consider the predictions of the model regarding the question of interest, i.e. the effects of speculation and derivatives trading on spot prices. After all, the model has to allow both views about these effects to be true. This is, we do not want to "get out what has been stuck in, albeit more polished and with numbers attached" (Uhlig 2005).

Building up stocks will raise the price. The usual presumption is that this will happen in times of low prices and the opposite happens in times of high prices. This means dampened price fluctuations. However, we do not restrict storage (and thus speculation) to only occur when prices are low. This is, we do not make any assumptions about when or why speculation takes place. We only identify speculation by its effects: It increases inventories and lowers the available supply, thus raising the price. In the empirical model, we even account for the possibility that speculation is not captured by the inventory data and thus only affects prices.³ Hence, our assumptions remain very agnostic with regard to the role speculation and derivatives markets play.⁴

3 Structural VAR Methodology

We estimate a vector autoregressive model for the three grain markets wheat, corn, and rice, respectively and identify the structural form following the line of Kilian and Murphy (2013). The identification builds on the conclusions from chapter 2. We use the model to evaluate different explanations of the 2007/08 price spike.

³This comes, of course, at the price of a broader set of possible (identified) structural models. But, this also reduces the risk of incorrectly excluding the true model from the set of identified models.

⁴ Still, the model described is drawing on a number of assumption for which it is not clear whether or not they are fulfilled. For example, Newbold et al. (1999) find mixed evidence for the rational expectations hypothesis for commodity futures markets.

We try to estimate the effects of supply, demand, and speculation on the price of the aforementioned grains. If the inventory data can sufficiently approximate the privately and publicly held stocks we will be able to capture the effects of physical speculation on the price of grains. If futures and spot markets are linked by arbitrage relationships, as implied in equations (8) and (7), we will also capture the effects of derivatives trading. If this arbitrage channel does not exist, it is difficult for futures prices to influence spot price. It is argued that this may still happen, though, via an information channel. Since we want to allow for this possibility, we can only determine a wider range for the magnitude of the price effect of speculation. This approach is less precise than other estimates in the literature but also much more careful in the interpretation and very much in line with the original idea of Faust (1998). Faust intended the sign identification approach to be used in an agnostic way, only ruling out hypotheses that clearly do not match the data at hand.

3.1 Data

We examine the three major grain markets—the markets for corn, rice, and wheat—using data covering the period 1961 to 2013. 1961 is the first year for which global production and inventory data is available.

The four (endogenous) variables used in our vectorautoregressive model are – for each of the three grains respectively – the yearly grain production (calendar year), the harvest-year ending stocks, the average price of the calendar-year, and world real GDP at year end. The choice of variables thus by and large follows Kilian and Murphy (2013). The only exogenous variables included is a constant term.

The price data are obtained from the World Bank and are measured in US-Dollar. We deflate the price series using the US-CPI, also obtained from the World Bank. We use only spot prices because, as argued above, futures prices are redundant if storage is well captured by the inventory data (cf. Alquist and Kilian; Kilian and Murphy 2013). This is particularly convenient since futures data is not available for all grains from the beginning of the sample period.

We use GDP data to control for demand effects. We do not use per-capita GDP in an attempt to capture total demand, i.e. the combined effect of income per head and the world population count. For the same reason, we do not use the Kilian (2009) index of real economic activity as used by Kilian and Murphy (2013) for the case of oil prices and also by Carter et al. (2013) for agricultural prices. Furthermore, this index starts only in 1967 and more importantly is not as applicable to food markets as it is to oil markets, because business cycles are not as important for the former as they are for the latter. These considerations make world real GDP the variable of choice. The data is obtained from the World Bank.

The production data is obtained from FAO. The data is somewhat unreliable as it is based on official announcements from governments around the world. The USDA also publishes production data that is mostly similar but also includes unofficial information from market analysts in some cases. Despite this, we do not use the USDA data because it is aggregated over harvest years rather than calendar years. These differ between individual countries/regions and are thus inconsistent after

being aggregated over all countries.

Inventory data is obtained from United States Department of Agriculture’s Foreign Agricultural Service (USDA FAS) and represents the stocks at the end of the respective harvesting cycle. The data for grain inventories is somewhat unreliable as it is mainly based on information provided by government officials from all countries. The extend to which it reflects the true storage, including inventories held by private companies or individual farmers, is hence dubious. We do not include cost of carry, assuming that they are either constant in real terms or do not play an important role.

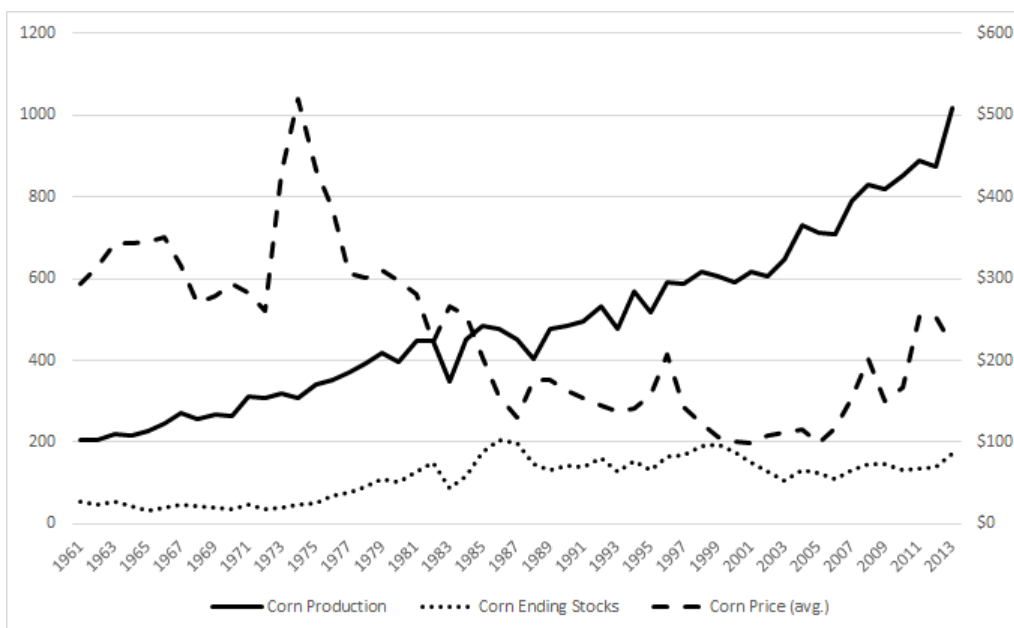


Figure 2: Corn market data on production, inventories and prices, 1961 to 2013. Production in million metric tons (left axis), prices in 2006 USD (right axis).

We test all variables for Unit Roots. Augmented Dickey Fuller tests and KPSS-tests clearly confirm all variables are integrated of order one (see Appendix A). We therefore also test for cointegration. Theory suggests there might be a stable long-term relationship, especially between production and inventories. We conduct Johansen system cointegration tests for a variety of specifications. The results were, however, also inconclusive. Notably, referring to the Maximum Eigenvalue test and the Trace test leads to opposing results (see Appendix B for a selection of results). Given the inconclusive theoretical and empirical guiding, we hesitate to assume cointegration. Hence, we decided to specify one model using natural logarithms of all variables and an alternative model with log-differences for all variables. Information criteria suggest lag lengths between one and six lags (see Appendix ??). Due to the small sample size we refrain from including six lags. Tests for autocorrelation and normality of the residuals suggest, on the other hand, that one and two lags are insufficient. We therefore incorporate three lags for all grains—irrespective of whether we specify the model in logs or in log differences.

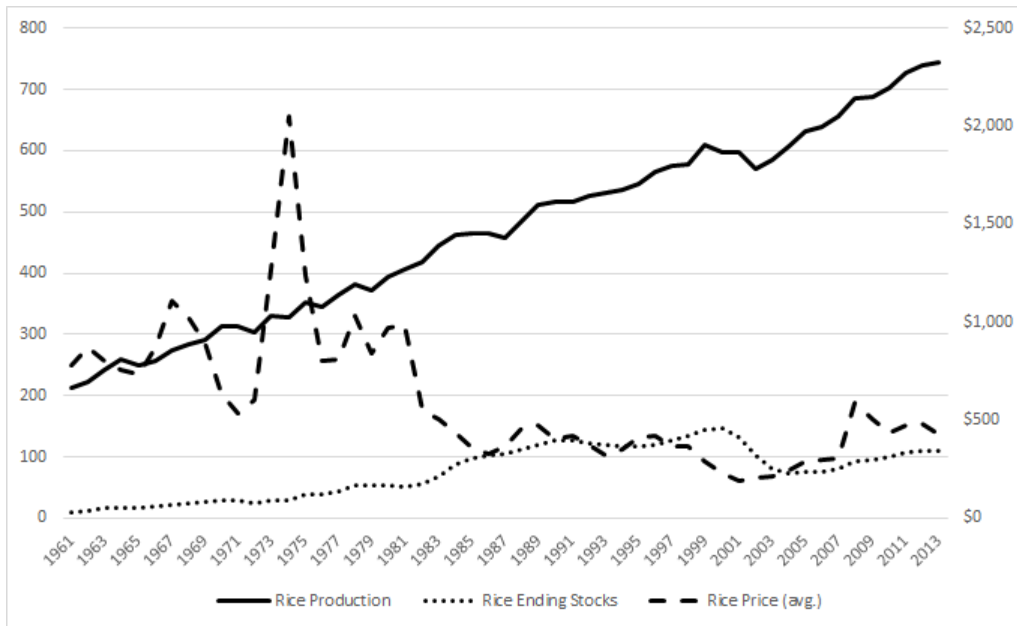


Figure 3: Rice market data on production, inventories and prices, 1961 to 2013. Production in million metric tons (left axis), prices in 2006 USD (right axis).

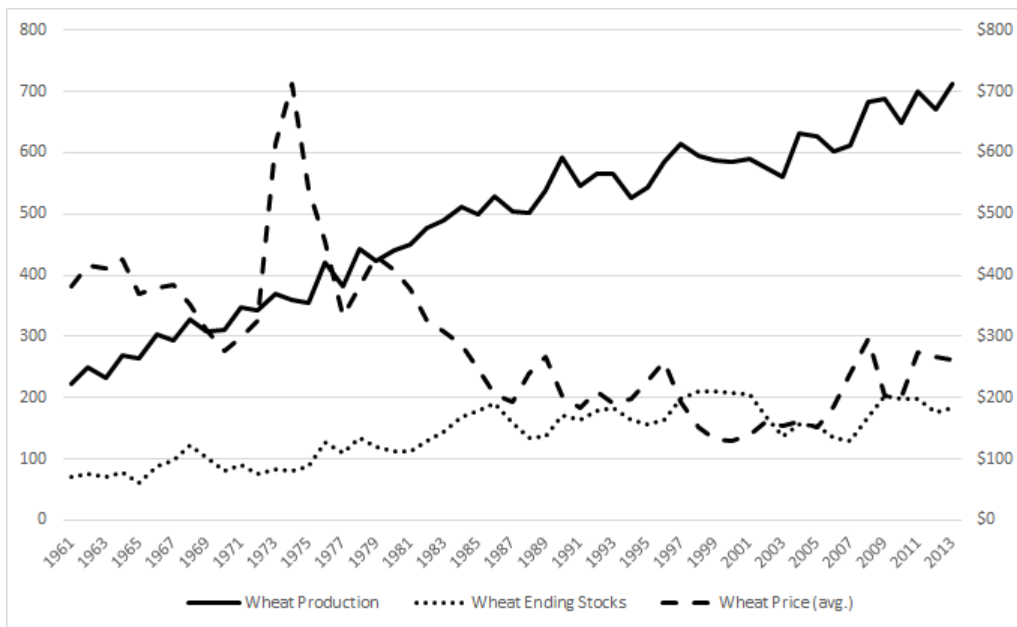


Figure 4: Wheat market data on production, inventories and prices, 1961 to 2013. Production in million metric tons (left axis), prices in 2006 USD (right axis).

3.2 Structural VAR methodology

We estimate the reduced form VAR-model as

$$\mathbf{y}_t = \boldsymbol{\alpha} + \mathbf{B}_1 \mathbf{y}_{t-1} + \mathbf{B}_2 \mathbf{y}_{t-2} + \mathbf{B}_3 \mathbf{y}_{t-3} + \boldsymbol{\varepsilon}_t \quad , \quad (9)$$

$$\text{with } \mathbf{y}_t = \begin{pmatrix} \text{production}_t \\ \text{gdp}_t \\ \text{price}_t \\ \text{stocks}_t \end{pmatrix} \text{ for } t = 1964, \dots, 2013 \text{ .}$$

Thus, \mathbf{y}_t is the $(k \times 1)$ vector of endogenous variables, $\boldsymbol{\alpha}$ represents a constant, $\mathbf{B}_1, \dots, \mathbf{B}_p$ are the $(k \times k)$ coefficient matrices for the lags of the endogenous variables and $\boldsymbol{\varepsilon}_t$ represents the $(k \times 1)$ vector of the reduced form error terms. These are distributed as $iid(\mathbf{0}, \boldsymbol{\Sigma}_\varepsilon)$. As explained above, the variables are in one case specified in logarithms and in one case as first differences of their logarithm, i.e. as growth rates. We estimate equation (9) using Least Squares. In case of serially uncorrelated, homoscedastic and normally distributed error terms, the least squares estimate is equivalent to the Maximum Likelihood estimator and results in asymptotically normally distributed, consistent estimates (cf. Amisano and Giannini 1997). The ML estimate we use for $\boldsymbol{\Sigma}_\varepsilon$ is given by

$$\hat{\boldsymbol{\Sigma}}_\varepsilon = T^{-1} \sum_{t=1}^T \hat{\boldsymbol{\varepsilon}}_t \hat{\boldsymbol{\varepsilon}}_t' \quad (10)$$

To interpret the results of the VAR model we present Impulse Response Functions (IRF). These can be computed using the Wold Moving-Average representation of the process \mathbf{y}_t , i.e.

$$\mathbf{y}_t = \boldsymbol{\varepsilon}_t + \Phi_1 \boldsymbol{\varepsilon}_{t-1} + \Phi_2 \boldsymbol{\varepsilon}_{t-2} + \dots \quad (11)$$

with

$$\Phi_s = \sum_{j=1}^s \Phi_{s-j} \mathbf{B}_j \text{ for } s = 1, 2, \dots \text{ and } \Phi_0 = \mathbf{I}_k \quad (12)$$

For a shock to be interpreted under a ceteris paribus assumption it is required, however, that the shocks are uncorrelated between the individual equations in (9). This is not the case in our model. The existing correlation between the individual error terms indicates a causal relationship between the variables that is not captured in the regression coefficients (Uhlig 2005). We hence need identifying assumptions to orthogonalize the reduced form error terms and thus receive structural form error terms. The assumptions we will use are grounded on the considerations of section 2.

3.3 Identification of the structural shocks

We need the theoretical basis of section 2 in order to shrink the free parameter space to a degree where the structure is either uniquely defined or at least narrowed down to the extent that some hypotheses can be ruled out and other kept as plausible. This means, we try to narrow the number of explanations for the phenomenon of interest

down to those that are in accordance with the data *and* the a priori assumption. The hereby identified structural form then allows a quantitative estimate of the influence of different drivers on the development of the grain prices in the sample period in general and the time around the spikes of 2007/08 in particular.

The especially agnostic approach of using sign restrictions for identification was originated by Faust (1998). In order to evaluate a hypothesis, Faust suggested to estimate a model using only weak and uncontroversial assumptions and to then test whether the hypothesis falls within the set of identified structural models. Uhlig (2005) advanced the method to yield a more narrow set of structural models. This, however, still leads to a large number of identified, possible models that are consistent with the data and theory. This identification problem stems from the reduced form error terms, $\boldsymbol{\varepsilon}_t$, in (9). We want to identify the still unexplained causal relationship between the variables in \mathbf{y}_t , i.e. create uncorrelated innovations. This can be achieved by multiplying with a matrix, say \mathbf{D} , to create a contemporaneously uncorrelated structural error term $\mathbf{u}_t = \mathbf{D}\boldsymbol{\varepsilon}_t$. Our task at hand is now to find a matrix \mathbf{D} that satisfies this requirement. Consider the structural form VAR model from the reduced form model (9) by substitution $\mathbf{B}_0\mathbf{u}_t$ for $\boldsymbol{\varepsilon}_t$, where $\mathbf{B}_0 = \mathbf{D}^{-1}$. This gives

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{B}_1^*\mathbf{y}_{t-1} + \mathbf{B}_2^*\mathbf{y}_{t-2} + \mathbf{B}_3^*\mathbf{y}_{t-3} + \mathbf{u}_t \quad , \quad (13)$$

where $\mathbf{B}_i^* = \mathbf{B}_0\mathbf{B}_i$ for $i = 1, \dots, 3$ and

$$\mathbf{u}_t := \mathbf{D}\boldsymbol{\varepsilon}_t \sim (\mathbf{0}, \boldsymbol{\Sigma}_u = \mathbf{B}_0\boldsymbol{\Sigma}_\varepsilon\mathbf{B}_0') \quad . \quad (14)$$

Assuming \mathbf{B}_0 to be invertible, we can obtain a MA representation of the structural form analogous to (11) as

$$\mathbf{y}_t = \Theta_0\mathbf{u}_t + \Theta_1\mathbf{u}_{t-1} + \Theta_2\mathbf{u}_{t-2} + \dots \quad (15)$$

with

$$\Theta_j = \Phi_j\mathbf{B}_0^{-1} \text{ for } j = 0, 1, 2, \dots \quad .$$

We already have ML estimates of the reduced form coefficients \mathbf{B}_i and the covariance matrix $\boldsymbol{\Sigma}_\varepsilon$. The off-diagonal elements of the structural form covariance matrix $\boldsymbol{\Sigma}_u$ are zero by assumption of orthogonal shocks. The diagonal elements can be normalized to one. Both settings do not pose limits on $\boldsymbol{\Sigma}_\varepsilon$ since there will always exist a matrix \mathbf{B}_0 such that $\boldsymbol{\Sigma}_u = \mathbf{B}_0\boldsymbol{\Sigma}_\varepsilon\mathbf{B}_0'$. The structural parameters \mathbf{B}_0 are unknown, though, and cannot be computed from $\boldsymbol{\Sigma}_u = \mathbf{B}_0\boldsymbol{\Sigma}_\varepsilon\mathbf{B}_0'$ even after the restrictions on $\boldsymbol{\Sigma}_u$. They can only be identified using model-external information.

Out of the existing possibilities we choose the sign restriction approach due to its sparse use of prior information. But, we additionally employ a Cholesky decomposition as a robustness check. The latter represents a triangular factorization which requires a causal ordering between the impacts of the shocks. The sign restrictions only imposes restrictions on the signs of the coefficients of the shocks for the immediate impact and possibly on their long-term impact (Uhlig 2005).

The procedure can be carried out as follows (Kilian and Murphy 2013): We start from the structural form VAR (13), i.e.

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{B}_1^*\mathbf{y}_{t-1} + \mathbf{B}_2^*\mathbf{y}_{t-2} + \dots + \mathbf{B}_p^*\mathbf{y}_{t-p} + \mathbf{u}_t \quad .$$

As above, we have $\mathbf{u}_t := \mathbf{D}\boldsymbol{\varepsilon}_t$, or equivalently $\boldsymbol{\varepsilon}_t := \mathbf{B}_0^{-1}\mathbf{u}_t$. We simplify the notation to $\tilde{\mathbf{B}} \equiv \mathbf{B}_0^{-1}$ and thus

$$\boldsymbol{\varepsilon}_t := \tilde{\mathbf{B}}\mathbf{u}_t . \quad (16)$$

The fundamental shocks \mathbf{u}_t are assumed to be mutually uncorrelated with their variance normalized to one. We now have to find the matrix $\tilde{\mathbf{B}}$ that satisfies (16). We can decompose the covariance as

$$\boldsymbol{\Sigma}_u = \mathbf{P}\boldsymbol{\Lambda}\mathbf{P}' , \quad (17)$$

with $\mathbf{B} = \mathbf{P}\boldsymbol{\Lambda}^{1/2}$ such that

$$\boldsymbol{\Sigma}_\varepsilon = \mathbf{B}\mathbf{B}' . \quad (18)$$

Then, for each orthogonal ($k \times k$) matrix \mathbf{D}

$$\boldsymbol{\Sigma}_\varepsilon = \mathbf{B}\mathbf{D}(\mathbf{B}\mathbf{D})' = \mathbf{B}\mathbf{D}\mathbf{D}'\mathbf{B}' = \mathbf{B}\mathbf{B}' . \quad (19)$$

We can simply compute \mathbf{B} as the square root of $\hat{\boldsymbol{\Sigma}}_\varepsilon$. Because \mathbf{B} is not uniquely defined, we set the matrix of the structural form parameters we are looking for to

$$\tilde{\mathbf{B}} = \mathbf{B}\mathbf{D} . \quad (20)$$

We can thus compute the coefficient matrix if we know \mathbf{D} because

$$\boldsymbol{\Sigma}_\varepsilon = \tilde{\mathbf{B}}\tilde{\mathbf{B}}' . \quad (21)$$

Using (14), i.e. $\boldsymbol{\Sigma}_u = \mathbf{B}_0\boldsymbol{\Sigma}_\varepsilon\mathbf{B}_0'$ we thus have the structural covariance matrix as

$$\boldsymbol{\Sigma}_u = \mathbf{B}_0\mathbf{B}_0^{-1}\mathbf{B}_0^{-1'}\mathbf{B}_0' = \mathbf{I}_k \quad (22)$$

as desired.

4 Identification of the Structural Model

4.1 Identification Algorithm

Because (19) holds for any orthogonal matrix \mathbf{D} we can draw indefinitely many candidate matrices for the structural parameters \mathbf{B}_0 . For that, we can draw at random from the set of orthogonal ($k \times k$) matrices and compute $\mathbf{B}_0 = \tilde{\mathbf{B}}^{-1}$. The obtained structural parameters suffice $\boldsymbol{\Sigma}_u = \mathbf{B}_0\boldsymbol{\Sigma}_\varepsilon\mathbf{B}_0'$ but satisfy no further restrictions. We can then, for every candidate, compute the orthogonalized IRFs and check for each whether or not the sign restrictions are satisfied. We only retain those matrices that suffice as potentially true and dismiss the others.

We follow the algorithm of Rubio-Ramirez et al. (2010, p. 688) to efficiently generate the candidate matrices. This means we generate the ($k \times k$) orthogonal matrix \mathbf{D} from a Matrix \mathbf{W} with independently standard normally distributed elements. \mathbf{W} is decomposed by the QR-factorization into an orthogonal Matrix \mathbf{Q} (i.e. $\mathbf{Q}\mathbf{Q}' = \mathbf{I}_k$) and a lower triangular matrix \mathbf{R} .⁵ By setting $\mathbf{Q} = \mathbf{D}'$ we are able to compute

⁵The QR-decomposition is based on a Householder transformation. Rubio-Ramirez et al. propose using the Givens transformtaion instead. Both yield equivalent results, the Givens method however is computationally more expensive (Fry and Pagan 2007, 2011).

the IRFs based on (20), $\tilde{\mathbf{B}} = \mathbf{B}\mathbf{D}$. This step is conducted many times, in our case 1 million times. Each time, the results are examined with regard to the sign restrictions and those that satisfy the restrictions are stored (following the algorithm of Kilian and Murphy, 2013). The result is a set of candidate structural coefficient matrices.

It follows, that in our sign identified structural VAR we have a great many observationally equivalent structural form parameters.⁶ Hence, Fry and Pagan (2011) describe sign identified SVARs as set identified but not model identified. Different approaches for interpreting the set of admissible models are discussed in the literature. A common way is to look at the median IRF. This median cannot, however be interpreted as a mid point of the distribution in the classical sense (Fry and Pagan, 2011). Another problem regarding the interpretation is related to the often used quantiles of the IRF distribution. These represent point-specific intervals and it is therefore not guaranteed—or even unlikely—that the different points all stem from the same impulse function (Fry and Pagan, 2011). Since confidence bands for small samples cannot reliably be computed from a frequentist point of view, Bayesian confidence bands are often used instead (Sims and Zha 1999, p. 1114). For these reasons, we also adopt Bayesian bands.

4.2 Identifying Restrictions

We identify four structural shocks. The identifying restrictions are varied between three different scenarios in order to account for different possibilities of the true model and to stay true to our intention of being agnostic.

Scenario I

Scenario I is a minor adjustment of the oil market specification of Kilian and Murphy (2013). They identify a flow supply shock, a flow demand shock, a speculative demand shock and a residual shock. Why do we adopt the oil market specification for grain markets? There are enough similarities to make an adoption feasible. For example, both are storable commodities produced and consumed worldwide. Also, this serves as a good starting point and a way of making our approach and results transparent and comparable with those of Kilian and Murphy. We are, however more hesitant in imposing restrictions and do not clearly separate all shocks from each other within this scenario.

A speculative demand shock in this scenario is defined as causing an increase in inventories for any future purpose. Thus, there exists no discrimination between "excessive" and "normal" speculation or between storage by "hedgers" and "financial speculators" as in other studies related to speculation in agricultural markets.

The sign restrictions are shown in table 1. Here and later, all shocks are normalized to imply a price increase. A '+' denotes a positive instantaneous effect of the shock

⁶The problem is that two parameters, say $(\mathbf{B}_0, \mathbf{B}_+)$ and $(\mathbf{C}_0, \mathbf{C}_+)$, are observationally equivalent if and only if they imply the same reduced form parameters (Rubio-Ramirez et al., 2010, p. 669). This is the case if an orthogonal matrix \mathbf{P} exists such that $\mathbf{B}_0 = (\mathbf{C}_0\mathbf{P}$ and $\mathbf{B}_+ = (\mathbf{C}_+\mathbf{P}$. A global identification of $(\mathbf{B}_0, \mathbf{B}_+)$ only exists if no observationally equivalent parameter exists (Rubio-Ramirez et al., 2010, p. 669).

on the respective variable and a '-' denotes a negative effect. A blank cell indicates that no restriction was imposed. An example for interpreting table 1: A flow supply shock, normalized to be some kind of crop failure or bad harvest, will cause grain production and the world GDP to drop, while the price is assumed to increase. The effect on inventories is not restricted as a bad harvest might draw on inventories while it may also incite speculators to store more in anticipation of further crop failures.

	Flow Supply Shock	Flow Demand Shock	Speculative Demand Shock	Residual Shock
Production	-			
GDP	-	+	-	
Price	+	+	+	
Inventories			+	

Table 1: Sign Restrictions for scenario I, following Kilian and Murphy (2013).

Most restriction are supposedly trivial and need little further justification beyond that given in section 2. The negative effect of a supply disruption is a necessary restriction because agricultural production is a part of GDP.

In addition to the impact sign restrictions, we impose restrictions on the relative size of an impact. We restrict a flow supply shock to have a smaller percentage effect on GDP than on production. This is, we restrict the quotient $\tilde{\mathbf{B}}_{2,1}/\tilde{\mathbf{B}}_{1,1}$ to $-1 < \tilde{\mathbf{B}}_{2,1}/\tilde{\mathbf{B}}_{1,1} < 1$, where the subscripts denote the element of the matrix $\tilde{\mathbf{B}}$. Equivalently, a demand shock should mainly affect GDP and not production, i.e. $-1 < \tilde{\mathbf{B}}_{2,3}/\tilde{\mathbf{B}}_{2,4} < 1$. Also a speculative shock cannot have an instantaneous impact on production or GDP. Therefore, we limit the impact of speculative shocks to less than one percent of production and less than one percent of GDP. This is, we impose $-0.01 < \tilde{\mathbf{B}}_{1,3} < 0.01$ and $-0.01 < \tilde{\mathbf{B}}_{2,3} < 0.01$. These assumption should not lead to the exclusion of any realistically conceivable structural form.

Scenario II.A

In our second scenario, we impose more demanding restrictions. First, we allow the storage data to reflect primarily public storage. Thus, changes in inventories are only in part represented by the data. We have to allow for another shock on prices from private speculation. These can, for example, be arbitrage buys triggered by rising futures prices or information conveyed from futures markets through other channels. We abandon the unrestricted residual shock in favor of such a residual price shock already advertised in section 2. This shock will capture all effects on the price that go beyond those explained by supply and demand shocks, including non speculative shocks. It can thus only be seen as a sort of 'worst case' scenario in terms of the possible role that speculation may have played. The impact sign restrictions are as presented in table 2.

Again, we also restrict supply and demand shocks to mainly impact production and GDP, respectively. We also restrict speculative shocks to not having a strong immediate impact on production and GDP. Since we now have two speculative shocks, we have the additional restriction $-0.01 < \tilde{\mathbf{B}}_{1,4} < 0.01$ and $-0.01 < \tilde{\mathbf{B}}_{2,4} < 0.01$ for the residual price shock.

	Supply Shock	Demand Shock	Speculative Inventory Shock	Residual Price Shock
Production	-			
GDP	-	+		
Price	+	+	+	+
Inventories			+	

Table 2: Sign Restrictions for scenario II, using a residual price shock.

Scenario II.B

We expect a demand shock to not affect production within the same year. As just outlined, we also do not expect speculative shocks to impact production and GDP and do not necessarily expect the speculative price shock to impact storage. Looking at table 2 and taking into account that we ideally expect the effect of most shocks to be close to zero, we may assume that we should be able to use a Cholesky decomposition in order to identify the structural shocks by assuming a causal ordering between the variables. This is done as a robustness check and to evaluate how plausible our sign restrictions are. We can compare the signs obtained (without restrictions) from the Cholesky factorization with the assumptions made in table 2. If our presumptions are right, we should see the same signs for the instantaneous impacts. The causal ordering we assume is, following the aforementioned line of reasoning: A supply shock can immediately impact all four variables, demand is restricted to not immediately influencing production, an inventory shock only has an impact on prices within the same year and the residual price shock has not immediate impact on the other three variables.

Scenario III

In scenario three we are more specific in the identification of the shocks. We now require inventories to react to supply and demand shocks in order to counteract price swings and smooth consumption over time. The inventories also react in accordance to speculative shocks. This is, we assume storage represents mainly public storage and is aimed on reducing price fluctuations. If private speculators drive up prices, through storage not captured by the data or by other means, governments will sell of stocks to dampen the price swings. This assumption is crucial as we would otherwise reverse causality in our interpretation: If stocks are sold in times of rising prices and this were indeed captured by the inventory data, the residual price shock would be incorrectly identifying a reversed causal chain. Our sign restriction are shown in table 3. As in scenario II, we again impose signs on the relative impact of supply and demand shocks and restrict the impact of the two speculative shocks on production and GDP.

	Supply Shock	Demand Shock	Speculative Inventory Shock	Residual Price Shock
Production	-			
GDP	-	+		
Price	+	+	+	+
Inventories	-	-	+	-

Table 3: Sign Restrictions for scenario III, again using a residual price shock.

5 Results

Due to the many different scenarios considered we will confine our presentation to the results from scenario III for the log-level specification. The conclusions do not change qualitatively if we used the other specifications instead. To document this point, consider as an example the following two figures of IRFs for all admissible models resulting from the log-level specification (figure 5) compared to the IRFs obtained from all admissible models using log-differences (figure 6) for the corn market. The IRFs for differences are displayed as cumulative responses to allow a direct comparison. The two figures are very similar. Furthermore, the signs obtained from the Cholesky factorization mostly coincide with the restrictions imposed under scenario II.A as well as those of scenario III.⁷ In moving forward, we are thus confident that the results presented below are robust to different specifications.

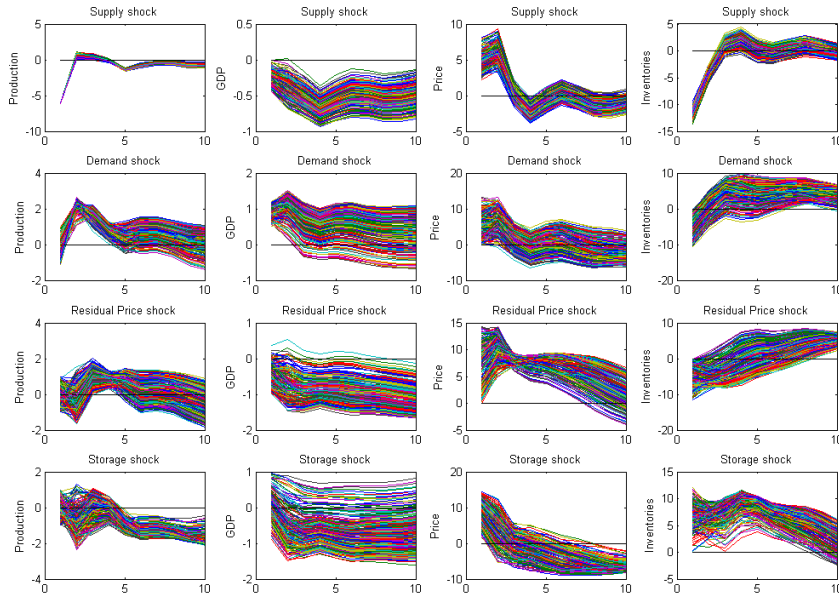


Figure 5: Impulse response functions for the corn market of all admissible models using the restrictions of scenario III and variables in log-levels.

⁷Results are available upon request.

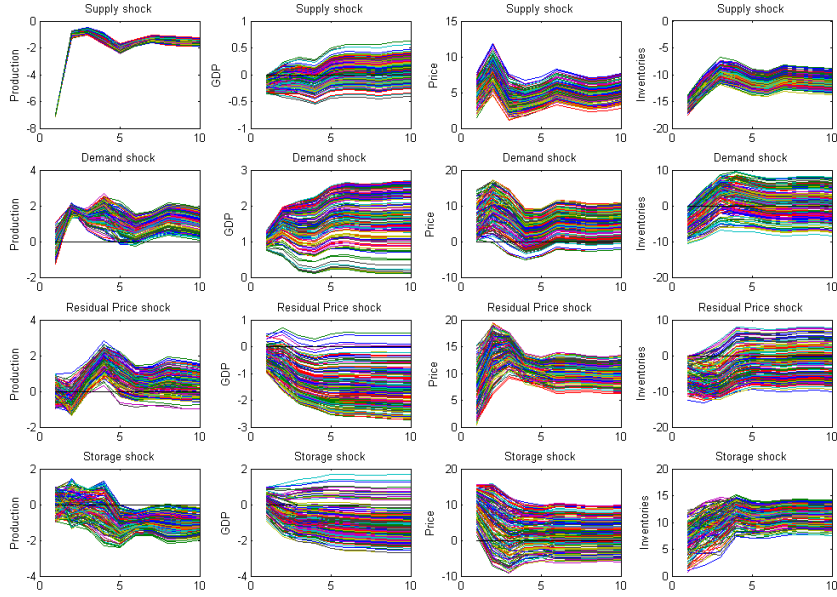


Figure 6: Impulse response functions for the corn market of all admissible models using the restrictions of scenario III and variables in log-differences.

We now discuss selected IRFs computed under the impact sign restrictions of scenario III for the three grains considered (see figures 7, 8, and 9). Presented is, firstly, the median of all admissible models out of the one million draws (solid red lines). The median is computed by first sorting all admissible IRFs according to the impact of a speculative price shock on the grain price. Second, we present an upper (light blue dashed line) and a lower (dark blue dashed line) response function. These are computed as the 10% and 90% percentiles of the posterior distribution. This is, we multiply the estimated covariance matrix of the VAR model by a Wishart-distributed random matrix to account for the parameter uncertainty. We draw 200 different random matrices and for each, we again draw 200,000 candidate structural coefficient matrices following the same algorithm as described in section 4.1. These are then also sorted according to the size of speculative price shock impact on prices.

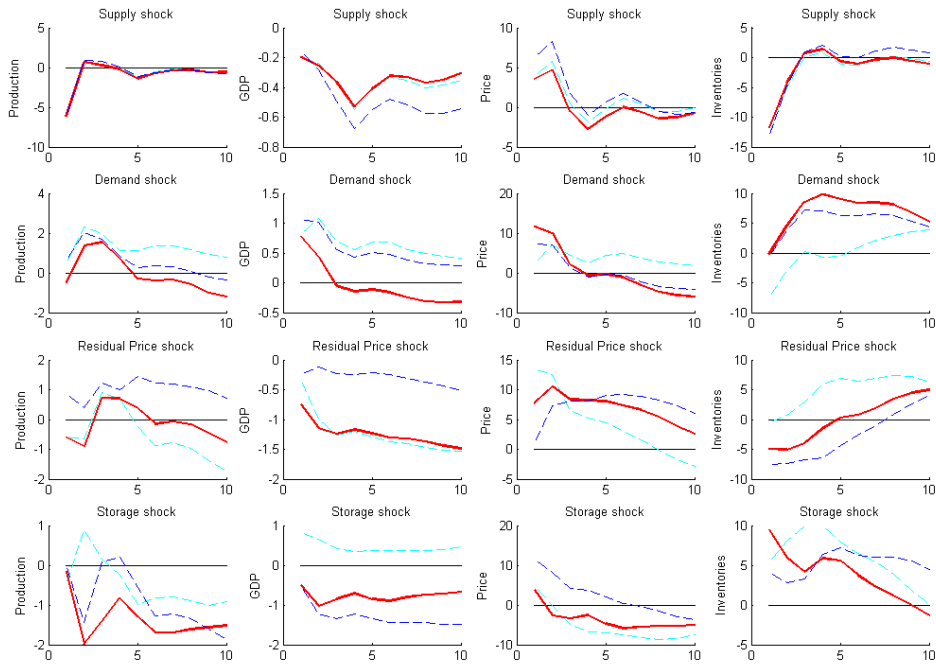


Figure 7: Impulse response functions for the Corn market using the restrictions of scenario III and variables in log-levels.

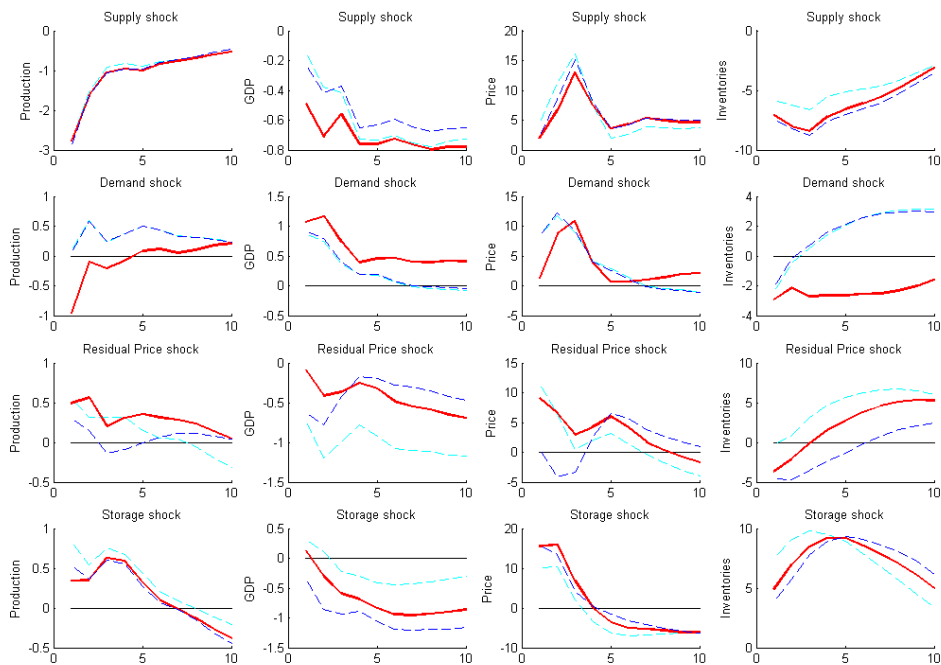


Figure 8: Impulse response functions for the Rice market using the restrictions of scenario III and variables in log-levels.

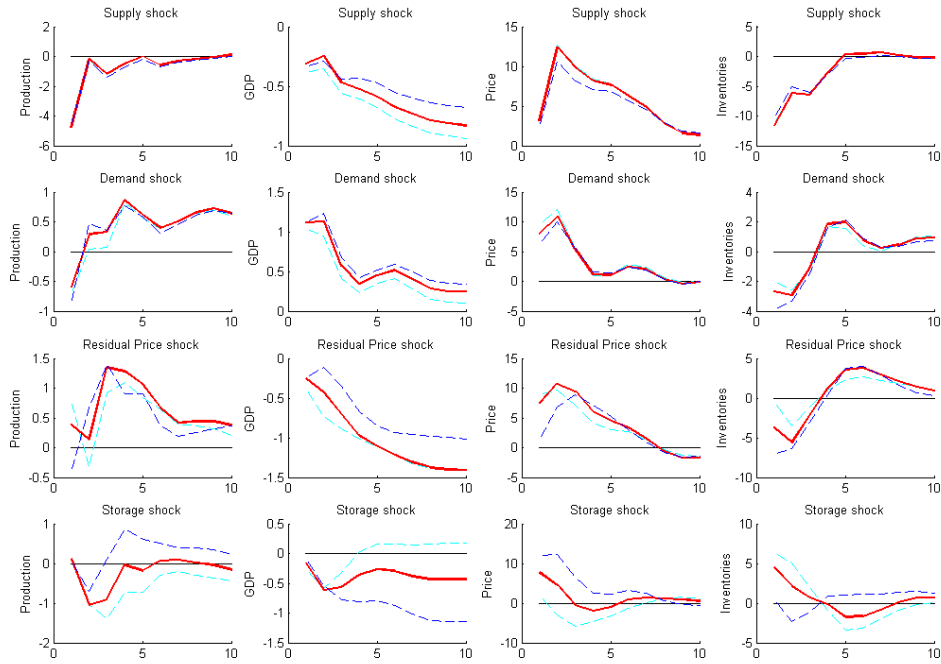


Figure 9: Impulse response functions for the Wheat market using the restrictions of scenario III and variables in log-levels.

5.1 Historical decomposition of prices for 2001-2013

After having gauged the resulting impulse response functions as plausible we turn to the assessment of the 2007/08 price spikes. To provide an answer as to whether speculation caused the rise in grain prices we compute a historical variance decomposition for the three grain markets using the structural models underlying the IRFs presented in the previous section (i.e. models corresponding to the median and the 10th and 90th percentile IRFs). To examine what drove the grain prices surge we compute the contribution to the price for each of the four shocks. To be precise, we compute by how much the actual price deviates from a counterfactual scenario in which the respective shocks had not occurred. We compute the counterfactual by setting the respective structural shocks to zero for the years from 2001 to 2013 and then compare the resulting hypothetical price to the actual price (both in real terms).

Displayed in figures 10, 11, and 12 are the price differences caused by the respective shock based on the structural form identified under scenario III. Since results differ between the grain markets, we discuss each figure at a time. First, consider the decomposition for the corn price (see figure 10 below).

It is worth noting that bad harvests seem not to be responsible for the price increase. It comes somewhat as a surprise that this major price spike went along with positive supply shocks. However, the time frame evaluated here was a time of increasing facilitation of biofuel production, which could have led to increased corn production. Since we consider the total production instead of the production net of biofuel

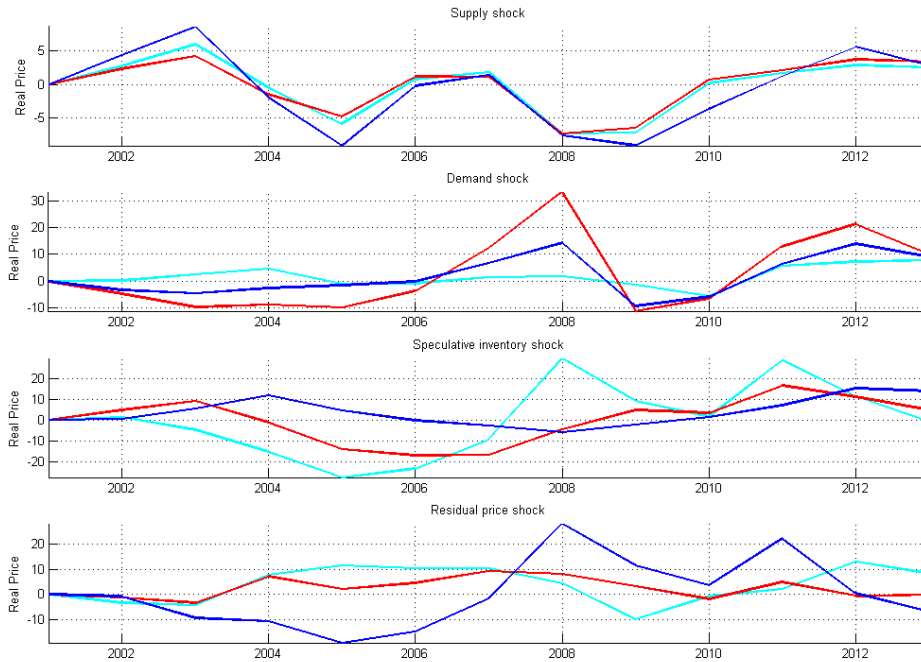


Figure 10: Historical decomposition of the real price of corn using the restrictions of scenario III and variables in log-levels.

disposition, the supply effects after taking biofuel usage into account might well look distinctly different.

Given the data and model we have, what did then cause corn prices to rise? The results suggest a major impact of strong economic development—up to 30% of the price increase is attributed to the effects of demand shocks by the median structural model. Storage seems to play no role but for the case of the 10th percentile model, which attributes about 30% to this shock while at the same time attributing almost nothing to the demand shocks. The residual price shock is estimated to have had an effect of about plus 10% on the price during 2007 and 2008. Only the 90th percentile model attributes 30% to this shock. Trying to draw conclusions from this heterogeneous results is not clear-cut. As a simple first conclusion, we can most likely rule out bad harvest as drivers of the corn price spike. A possible impact of biofuel policies remains an open question, though. Second, the median model suggests strong demand as the single most important driver of corn prices in the time of the global food crisis. Other admissible models however just assign the same impact to inventory shocks and to residual price shocks. It thus becomes clear, that our restrictions are not tight enough to discriminate between the price contribution of these three shocks. The reasons for this become clear when inspecting table 3 again. The last three shocks remain ambiguous. It is not possible to clearly distinguish between a demand and a residual price shock on the basis of these restrictions. The speculative inventory shock, in addition, can be replicated as a linear combination of the other two. It thus remains an open question for future research to more clearly distinguish these shocks while at the same time not restricting the model in a way that predetermines much of its outcome. However, it is nevertheless possible to learn something about the impact of speculation: As demonstrated by

the median model, it is possible to attribute the majority of the price increase to a well defined demand shock—with only a 10% increase captured by the residual price shock. Thus, we have proven that the seemingly extreme price spikes can in fact be largely explained by markets fundamentals—a conjuncture highly controversial and disputed by many experts. Even under this structural model it remains possible, however, that speculators did in fact worsen the food crisis by driving up prices for a couple of years by around 10% in the extreme event.

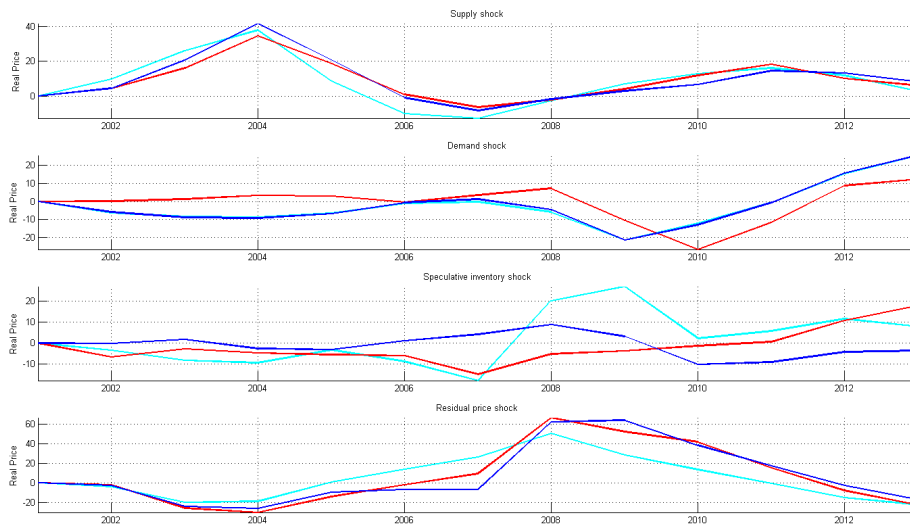


Figure 11: Historical decomposition of the real price of rice using the restrictions of scenario III and variables in log-levels.

Moving on to the rice market, it is striking that we neither find a major impact of supply nor of demand for the price increase around the time of 2008 (figure 11). The price spike for rice, which was largest amongst the three grains, is exclusively explained by speculative shocks, in particular the residual price shock (plus 60%). This comes as a surprise because rice is not as actively traded at futures markets as corn or wheat (Wright 2011). We therefore suspect that our model does not capture the dynamics of rice markets sufficiently well.⁸ If this strong impact of the residual price shock were caused by derivatives trading, we would expect the impact to be at least equally visible in the price of corn and wheat. It is, on the other hand, also conceivable that the financialization of grain futures markets had an especially strong impact on rice due the lower liquidity in the market.

Last, we turn our attention to the wheat market (see figure 12). In sharp contrast to before, we now see a strong impact of supply disruptions along with demand shocks of comparable magnitude as to the case of corn. Here, the interpretation is more straight forward as all three models yield very similar decompositions. Also, these results shed some light on the results obtained for corn markets: If supply disruption were responsible in the grain market and not in the corn market while both experienced similar price patterns, it becomes more likely that we indeed would

⁸For example, Wright (2008, 2011) stresses the importance of export restriction enacted after the prices started climbing up.

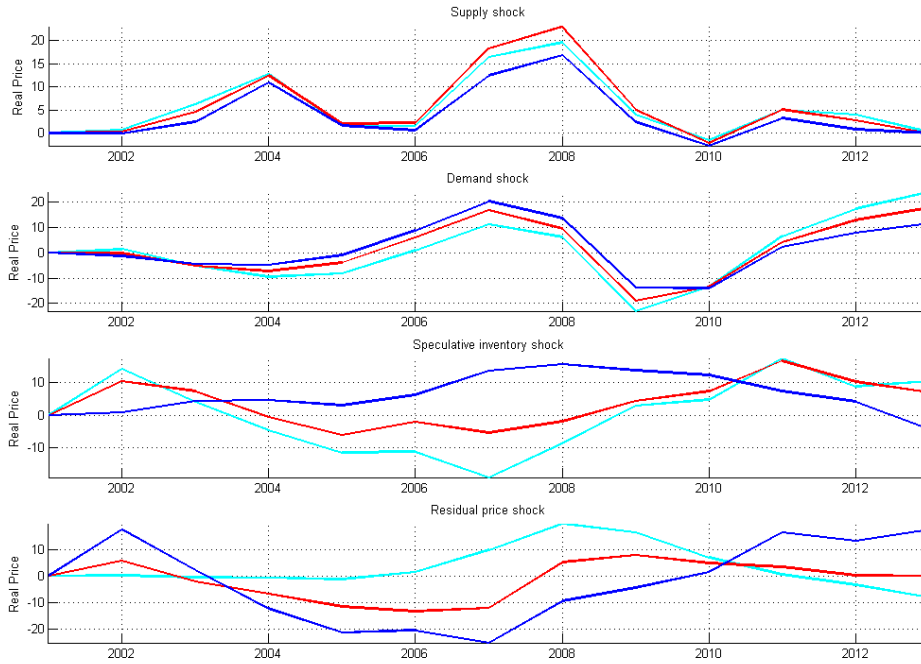


Figure 12: Historical decomposition of the real price of wheat using the restrictions of scenario III and variables in log-levels.

need to control biofuel production in modelling the corn market. Shifts in inventories and the residual price shift both account for increases of nearly 20%. As in the case of corn, it is again possible however to attribute the price variance almost exclusively to the fundamental shocks in supply and demand (see the red-lined median model). This again constitutes a valuable insight, contributing to the ongoing debate about what drove food prices.

6 Conclusions

We employed an agnostic approach of identifying structural relationships for the grain markets for wheat, rice, and corn. We considered a structural VAR using four endogenous variables. Supply was captured using global production data, demand was controlled for by using global GDP. We attempted to catch expectations using storage but also allowed in more lenient scenarios for the storage data to only reflect government inventories. To stay true to our agnostic approach we considered three different sets of sign restrictions in identifying the structural models. The restrictions were based on a basic theoretical model outlined in section 2. To check whether the derived presumptions would adequately describe the data, we also identified a possible structural form using a causal ordering between the variables. As a further safeguard for robustness, we considered both a specification using the log-levels of the variables and the log-differences as we cannot safely reach a conclusion about possible long-term (cointegrating) relationships. All these different specifications lead to fairly similar results. We were thus confident to present to the reader only the results for our most restrictive—while still very general—scenario of sign restrictions.

We were able to show for the markets of corn and wheat, that it is possible to attribute the majority of the price increase to fundamental drivers, i.e. supply and demand. In both cases, only about 10% were attributed to our residual price shock, which constitutes the most extreme impact derivatives trader could have. Our results were less useful for the price of rice. This grain is only thinly traded at derivatives markets but our model suggests a major impact of the residual price shock.

Taking together, we contribute to the ongoing debate on the drivers of food prices by deriving a plausible structural model for the markets of corn and wheat. These models allow us to appraise the possible contributions to the price increase during the time of the price spikes around 2008. We are able to identify models that assign the major part to fundamental market variables. Thus we refute the claims of some observers, that the extreme price movements of the last years cannot be explained by fundamental variables and thus have to be attributed to speculators. We are, however, not able to rule out a major price increasing impact of speculators, especially in the case of rice.

Some issues remain open for further research. First, we need to think of a better model for rice markets. It might be beneficial for all three market models to incorporate futures data to more precisely catch the impact of speculation in derivatives markets. Also, one might wish to distinguish between demand driven by income and demand driven by population growth.

We could also have investigated possible cointegrating relationships more carefully, for example even estimating a model with some cointegrated $I(1)$ variables and some $I(0)$ variables using vector error correction models. Since it is, both from a theoretical and an empirical point of view, not clear which variables should be cointegrated, our approach of using two different models seems more informative and less likely to erroneously exclude the true structural relationships. This last point is also emphasized by our results, that are relative comparable across models and grain markets. Our investigation hence delivered useful insights into the drivers of grain prices. These were shown to be robust to different model specifications as well as different notions about the functioning of grain and derivatives markets and also to different notions about the transmission channel of speculative pressure to the spot price of grains.

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A Unit Root Tests

	Level		First Differences	
	ADF (p-Value)	KPSS (critical value)	ADF (p-Value)	KPSS (critical value)
GDP	1	0.977543	0.0001	0.793504
Corn Production	0.9999	0.9666	0	0.474168
Corn Stocks	0.5212	0.704421	0	0.113172
Corn Price	0.4625	0.69279	0	0.144596
Rice Production	0.9594	0.993712	0	0.105876
Rice Stocks	0.3963	0.741487	0.0244	0.138429
Rice Price	0.3705	0.680963	0	0.340989
Wheat Production	0.6587	0.974093	0	0.5
Wheat Stocks	0.3638	0.839897	0	0.150059
Wheat Price	0.0955	0.672445	0	0.168542

Table 4: Unit Root tests for all variables

B Cointegration Tests

	Trace		Max-eig	
	No. CE	p-value when rejected	No. CE	p-value when rejected
Corn	1	0.0901	0	0.2889
Rice	4	na	0	0.1313
Wheat	3	0.0825	1	0.2031

Table 5: Johannsen Cointegration Tests of the log-levels of the variables using three lags. Specified with a constant but no trend term in both equations.