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Daniel Grabowski

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

Coordination: Bernd Hayo • Philipps-University Marburg
School of Business and Economics • Universitätsstraße 24, D-35032 Marburg
Tel: +49-6421-2823091, Fax: +49-6421-2823088, e-mail: hayo@wiwi.uni-marburg.de

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

Daniel Grabowski*

University of Giessen, Department of Economics

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Abstract

In 2001 began a rise in the prices of food commodities not seen since the 1970s. Some observers attribute the increase in part to food commodity speculation. This hypothesis is examined by disentangling the impact of speculation on grain prices from that of fundamental supply and demand forces. Even though results point to a generally stabilising influence of speculation on prices, speculation is shown to have pushed prices further up during crisis years. The analysis is based on a structural vector autoregressive model identified by sign and zero restrictions. The model is estimated for global corn, wheat and rice markets.

Keywords: food price crisis, grain prices, structural VAR, sign restrictions

1 Introduction

Global grain prices gradually decreased between 1974 and 2001 in real terms. While the world population was growing, this growth was outweighed by breeding and adopting higher-yielding crop varieties (Wright, 2011). After the turn of the millennium however, a sustained increase of prices and price volatility began. Between 2005 and 2008, the food price index of the Food and Agriculture Organization of the United Nations (FAO) increased by 71%. The index of real prices rose by 46%. After a short but steep break, prices continued to climb up in 2011. The price increases were particularly high for grains: Real prices of rice, corn, and wheat doubled between 2005 and 2008. These three grains cover around half of the worldwide human calorie consumption. As a result of the price increases, the number of undernourished people is estimated to have risen by 30 to 75 million (Rosen et al., 2008, FAO 2008). 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).

* *Email address:* `daniel.grabowski@wirtschaft.uni-giessen.de`

A multitude of possible drivers for the rising food prices has been discussed. For a summary and discussion of possible causes see for example Wright (2008) and Headey and Fan (2008). The focus of this article is on one particularly controversial explanation which assumes that a sharp rise in the trading volume in commodity derivatives was a major cause. As a result of financial market liberalisations and the development of exchange traded funds, large sums have been invested into commodity futures. This allegedly has caused increases in the futures prices. The price pressure could then have been transmitted to the spot market. Market participants and experts have since demanded tightened regulations of commodity markets (e.g. Masters, 2008). Many non-governmental organizations have demanded that financial institutions active in this market refrain from commodities trading. Some have complied with these demands.

Since 2008, numerous studies have evaluated the impact of speculation and in particular of derivatives trading on a variety of commodity prices such as oil and grains. The results were mixed (see e.g. Baffes and Haniotis, 2010; Bass, 2011; Branson et al., 2010; Irwin and Sanders, 2010, 2011; Kilian and Murphy, 2014). Extensive literature reviews have already been written, most notably Haase et al. (2016). Their conclusion is that the empirical evidence predominantly finds no effect of speculation or, more specific, of derivatives trading on commodity prices. Some studies do find significant effects, but out of these some find that speculation actually *lowered* prices. Looking only at agricultural markets, the conclusions are similar. For comprehensive accounts of studies for agricultural prices see, e.g., Shutes and Meijerink (2012), von Braun and Tadesse (2012), Brümmer et al. (2013) and Will et al. (2016).

The existing empirical studies often use single equation models or Granger causality tests to examine the explanatory or predictive power of one variable for another, e.g., of index trader positions for prices of agricultural commodities. Instead, I propose a structural model that enables us to quantify the causal effect of speculation on agricultural prices for selected time periods. This allows to distinguish between the contributions of speculation and fundamental factors to price movements. For this, a vector autoregressive model is estimated for the three major grain markets. The structural model is identified using agnostic sign restrictions combined with zero restrictions. This article is thus most closely related to Kilian and Murphy (2014) who use structural vector autoregression to investigate the influence of speculation on oil prices and also to Hausman et al. (2012) as well as Carter et al. (2016) who use a similar method to identify the influence of biofuel production on agricultural prices. I consider global data for grain prices and production. Inventory data is used to identify speculation but a residual price shock is allowed in order to ensure robustness of the results. A separate model is estimated for each of the three markets corn, rice, and wheat. The combined evidence from all three markets lends additional weight to the results. Based on impulse response functions, I confirm a price stabilising effect of speculation. However, in contrast to the most common view in the literature, I show that speculation did increase prices further during the price spikes in 2008 and 2011. This is done using a counterfactual analysis, decomposing price changes into effects from supply, demand, and speculative factors.

The following section 2 introduces the model and data. section 3 discusses the identification of the structural model and section 4 presents the results. After discussing robustness in section 5, section 6 provides conclusions.

2 Data and Model

The object of investigation of this article are the major grain markets corn, wheat, and rice. I use yearly global data covering the period 1961 to 2015. The year 1961 is the first for which global production and inventory data is available. The four endogenous variables used for each of the three grain markets are: yearly grain production, year-ending stocks, average price over the year, and world real GDP. The time series of prices, production, and storage for each market are displayed in Figures 1, 2, and 3.

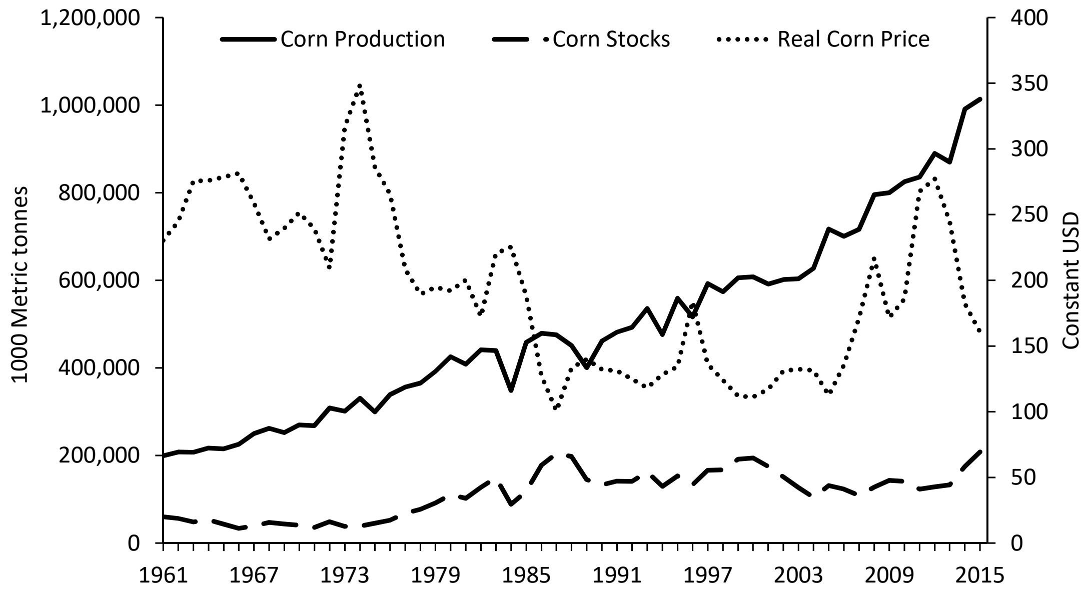

Figure 1: Corn production, inventories and prices. Production and stocks in million metric tons (left axis), prices in 2010 USD (right axis).

Price data are obtained from the World Bank and are measured in US-Dollar (USD). The price series is deflated using the US-CPI (2010=100). The inventories are obtained from the United States Department of Agriculture's Foreign Agricultural Service (USDA FAS). These are aggregated official estimates of stocks from most countries in the world. The data for global production are also obtained from USDA FAS. I use world GDP to represent demand effects. This is preferred over per-capita income or the Kilian (2009) index of real economic activity (as used for example in Kilian and Murphy (2014) or Carter et al. (2016)) for the following reason. Grain prices may be affected by two demand factors: income per capita and population size.[1] Total GDP is regarded as best suited to include both components. World GDP data is obtained from the World Bank and also deflated using US-CPI.

[1]Income does not only affect the ability to purchase food but also the type of food. Higher-income households might increase the demand for meat and diary products. Because grains are a major driver of the production costs through their role as animal feed (von Braun and Tadesse, 2012), this also affects grain prices.

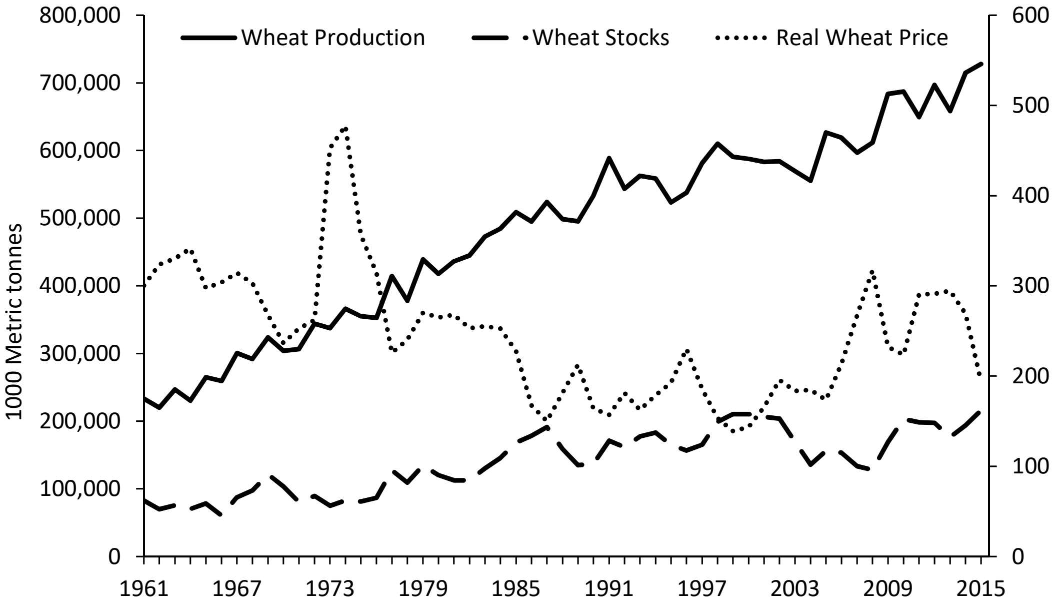

Figure 2: Wheat production, inventories and prices. Production and stocks in million metric tons (left axis), prices in 2010 USD (right axis).

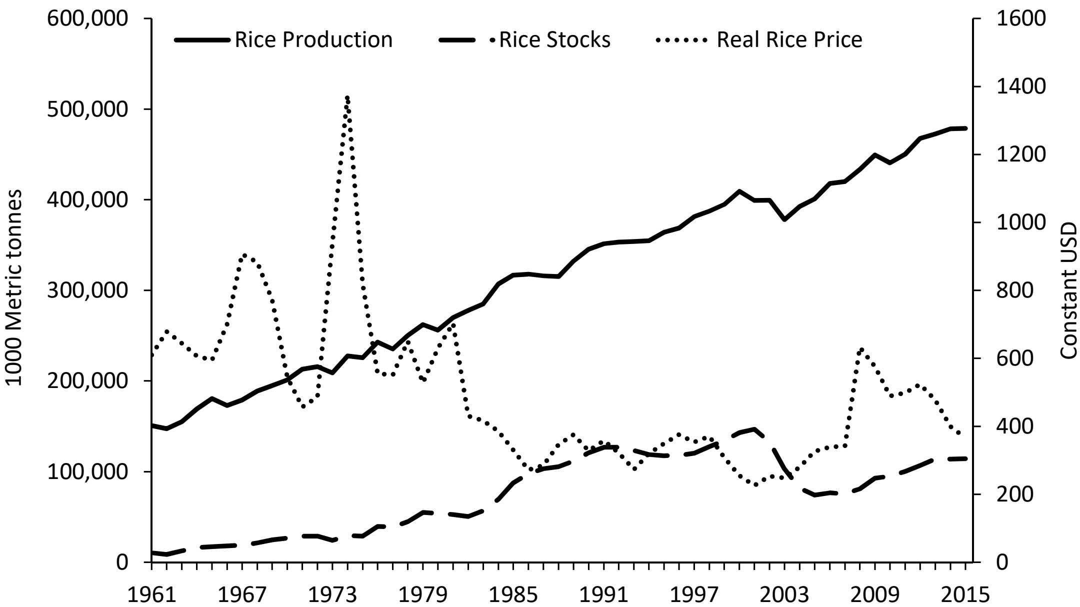

Figure 3: Rice production, inventories and prices. Production and stocks in million metric tons (left axis), prices in 2010 USD (right axis).

As can be seen, only spot prices but not futures prices are used. One reason is that the latter are not available for the entire time period. Furthermore, futures prices are redundant if storage is captured by the inventory data, see Alquist and Kilian (2010) and Kilian and Murphy (2014) for a discussion of this point. If futures markets are connected via arbitrage to spot markets, the inventory data should reflect expectations and futures prices. In case such arbitrage relations do not exist, derivatives cannot affect spot markets anyway. Thus, the existence of arbitrage linkages is not required for the analysis to be valid. This argument breaks down if an information channel exists through which information is transmitted from futures to spot markets, as for example argued by Masters (2008). Another potential problem arises if inventory data do not sufficiently represent storage. This could be the case for grain inventory data because the data is based on USDA estimates and official government announcements. Thus, private storage in particular might not be sufficiently represented in the data and the effects of derivatives trading therefore underestimated. Both caveats—the information channel and data quality—will be addressed by the identifying assumptions discussed in section 3.

2.1 Vector Autoregressive Model

Vector autoregressive (VAR) models offer an easy and systematic approach for analysing the dynamics between multiple variables. Each variable is explained by past values of itself and every other variable. Contemporaneous dependencies between variables are captured in the covariance between the residuals, as further discussed in section 2.2. I estimate a VAR model for each of the three grain markets wheat, corn, and rice separately. The reduced form VAR model with lag order $p = 2$ is

$$\boldsymbol{y}_t = \boldsymbol{\alpha} + \boldsymbol{B}_1 \boldsymbol{y}_{t-1} + \boldsymbol{B}_2 \boldsymbol{y}_{t-2} + \boldsymbol{\varepsilon}_t \quad , \tag{1}$$

$$\text{with } \boldsymbol{y}_t = \begin{pmatrix} production_t \\ gdp_t \\ stocks_t \\ price_t \end{pmatrix} \quad \text{for } t = 1963, ..., 2015 \ ,$$

where $\boldsymbol{y}_t$ is the vector of endogenous variables, $\boldsymbol{\alpha}$ are constants, $\boldsymbol{B}_1, \boldsymbol{B}_2$ are the (4×4) parameter matrices for the lags of the endogenous variables and $\boldsymbol{\varepsilon}_t$ represents the (4×1) vector of the reduced form error terms. The error term is assumed to be *iid* distributed as $\mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}})$. Thus, errors are uncorrelated over time but may be contemporaneously correlated (captured by $\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}$). The four endogenous variables are used in logarithms. I estimate equation (1) using Least Squares. For the covariance matrix of the error term I use the Maximum Likelihood (ML) estimate, given by

$$\hat{\boldsymbol{\Sigma}}_{\boldsymbol{\varepsilon}} = T^{-1} \sum_{t=1}^{T} \widehat{\boldsymbol{\varepsilon}}_t \widehat{\boldsymbol{\varepsilon}}_t'. \tag{2}$$

In case of serially uncorrelated, homoscedastic and normally distributed error terms, the Least Squares estimator is equivalent to the ML estimator and results in asymptotically normally distributed, consistent estimates (Amisano and Giannini, 1997).

All variables are tested for stationarity. On the 5% significance level, Augmented Dickey Fuller tests show all variables are integrated of order one. From a theoretical point, a stable long-run relationship between the variables seems plausible. Therefore, I test for cointegration using the Johansen (1991) test. The test results, based on the Trace statistic, confirm cointegration for each of the three markets (again, on the 5% level). Hence the variables are used in log levels. Because focus is not on a long run equilibrium but on the short term dynamics, I do not use a Vector Error Correction Model. A level VAR also has the advantage that a specific cointegration structure does not have to be assumed.

The lag length p of model (1) is determined by sequential likelihood ratio testing. The lag lengths obtained are two lags for the corn as well as the wheat market model and one lag for the rice market. Because the residuals of the rice market model with only one lag still show indications of autocorrelation on the 10% significance level, I specify all three models with a lag order of two. Optimal lag lengths according to the Akaike Information Criterion (AIC, see Akaike (1974)) for corn, wheat and rice are three, two and one, respectively. These specifications are used as a robustness check, but the results remain similar, see section 5.

To interpret the results of the VAR model (1), Impulse Response Functions (IRF) are used. These can be computed using the Wold Moving-Average representation of the process $\boldsymbol{y}_t$, i.e.

$$\boldsymbol{y}_t = \boldsymbol{\varepsilon}_t + \Phi_1 \boldsymbol{\varepsilon}_{t-1} + \Phi_2 \boldsymbol{\varepsilon}_{t-2} + \dots \tag{3}$$

with

$$\Phi_s = \sum_{j=1}^{s} \Phi_{s-j} \boldsymbol{B}_j \text{ for } s = 1, 2, \dots, \; \Phi_0 = \boldsymbol{I}_k \text{ and } \boldsymbol{B}_j = 0 \text{ for } s > p\,.$$

For a shock to be interpreted under a ceteris paribus assumption, it is required that the shocks are uncorrelated between the individual equations in (1). This is, as usual, not the case here. The existing correlation between the individual error terms indicates a causal relationship between the variables that is not captured in the regression coefficients but in the estimated covariance matrix $\hat{\boldsymbol{\Sigma}}_{\boldsymbol{\varepsilon}}$. Hence, identifying assumptions are needed to orthogonalize the reduced form error terms and receive uncorrelated, structural form error terms.

2.2 Identification Procedure

The reduced form model presented in equation (1) does not meet the requirements for causal interpretation. Therefore, we consider the corresponding structural form model

$$\boldsymbol{B}_0 \boldsymbol{y}_t = \boldsymbol{B}_1^* \boldsymbol{y}_{t-1} + \boldsymbol{B}_2^* \boldsymbol{y}_{t-2} + \boldsymbol{u}_t \quad , \tag{4}$$

where the structural parameters $\boldsymbol{B}_i^*$ are related to the reduced form parameters by

$$\boldsymbol{B}_i^* = \boldsymbol{B}_0 \boldsymbol{B}_i \;\text{ for }\; i = 1, \dots, 2\,. \tag{5}$$

The structural error terms $\boldsymbol{u}_t$ and their covariance matrix are related to the reduced form via

$$\boldsymbol{u}_t = \boldsymbol{B}_0 \boldsymbol{\varepsilon}_t \tag{6}$$

and

$$\boldsymbol{\Sigma}_{\boldsymbol{u}} = \boldsymbol{B}_0 \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}} \boldsymbol{B}_0'\,. \tag{7}$$

In this structural model given by (4), the error terms are contemporaneously uncorrelated, but the endogenous variables can instantaneously affect each other through the parameters in $\boldsymbol{B}_0$. We want to identify this still unexplained causal structure between the variables in $\boldsymbol{y}_t$, i.e. identify $\boldsymbol{B}_0$. From the estimation of the reduced form model (1) we already have estimates for $\boldsymbol{B_1}$, $\boldsymbol{B_2}$ and $\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}$. Thus, to identify $\boldsymbol{B_0}$ we have to find a matrix $\boldsymbol{D}$ such that

$$\boldsymbol{D} \hat{\boldsymbol{\Sigma}}_{\boldsymbol{\varepsilon}} \boldsymbol{D}' = \boldsymbol{\Sigma}_{\boldsymbol{u}}\,. \tag{8}$$

There exist infinitely many matrices $\boldsymbol{D}$ for which this holds. In order to uniquely identify a structural model, we need model-external assumptions. Sims (1980) originally proposed using a recursive ordering of variables to identify $\boldsymbol{D}$. This comes down to zero restriction on the impact of a shock in one variable on another variable. It is also possible to assume non-recursive zero restrictions or to derive assumptions about the long run impact of a shock from economic theory, see Blanchard and Quah (1989). Faust (1998) suggested that, in order to evaluate a hypothesis, a model should be identified using only weak, uncontroversial assumptions. Then, it can be tested whether a hypothesis falls within the set of identified structural models. The reason that his approach only identifies a set of models, i.e. that there are many potential models identified, is due to the use of weaker, more agnostic assumptions: Instead of zero restrictions he uses only inequality restrictions for the impact of shocks. Uhlig (2005) advanced this method to yield a more narrow set of structural models. However, this still leads to a large number of identified, possible models that are consistent with the data as well as the theory. This approach seems appropriate for analysing the controversial issue of the impact of speculation on grain markets. Since model (1) contains variables that can adjust quickly (prices, inventories) and others that cannot (grain production, GDP), I combine the sign restrictions with zero restrictions. These identifying assumptions are introduced in the next section. A robustness check that uses only inequality constraints and no zero restrictions is discussed in section 5.

In order to derive numerical values for $\boldsymbol{D}$ and thus for the structural model, the following algorithm is used. A random matrix $\boldsymbol{D}$ that satisfies the zero restrictions and satisfies (8) is generated. This is based on the algorithm of Rubio-Ramirez et al. (2010) to efficiently generate the candidate matrices. Their algorithm is adjusted to draw orthogonal matrices satisfying the zero restrictions based on Arias et al. (2014), algorithm 3 and theorems 3 and 4. For this candidate it is checked whether it meets the inequality assumptions. If so, the matrix $\boldsymbol{D}$ is stored, otherwise it is discarded and a new matrix is drawn. This procedure is repeated, with a new random matrix $\boldsymbol{D}$ each time, until the desired number of admissible models (those that satisfy the restrictions) is obtained. Thus, we obtain a range of structural models. Subsequently, it can be verified if the hypothesis of interest falls within this range. If, for example, none of the identified models attributes the price increase in grain markets to speculation, we can safely rule this hypothesis out. If, however, all of the models do show such a result, we can conclude that speculation did affect food prices. Of course, the identified set could easily encompass both hypotheses and thus not permit a clear conclusion.

2.3 Representing the Identified Models

To visualize and interpret the results for the structural model, impulse response functions and historical decompositions are used. These are based on a median model and 10% and 90% quantiles. The median model and the quantiles are derived from a set of possible structural models. This set captures the model uncertainty and estimation uncertainty. The model uncertainty is the result of not having uniquely identified a structural model, i.e., using weak assumptions.[2] Estimation uncertainty of course is due to the unknown model parameters, which have to be estimated. Because both sources of uncertainty are combined, the interval between the 10% and 90% quantiles is not a confidence interval in the classical sense, neither from a frequentist nor from a Bayesian point of view. For a discussion of the problems in dealing with the model uncertainty and estimation uncertainty see Sims and Zha (1999) and Fry and Pagan (2011). For ease of expression, I will nonetheless refer to them as confidence intervals and describe a function as significant if its quantiles do not contain zero.

The median model and the intervals are computed separately for each of the three grain types in the following way. The VAR parameters are estimated. Based on the coefficients and the residuals I construct 1,000 bootstrap time series. For the bootstrap, the residuals are re-sampled by drawing vectors $\hat{\varepsilon}_t$ from their empirical distribution with replacement. Thus, the contemporaneous correlation structure is preserved but not potential serial dependencies. For each bootstrap series I apply the identification procedure from section 2.2 until one admissible structural model is identified. Based on this set of 1,000 structural models, I determine the model whose IRFs are closest to the median of the 1,000 IRFs over all periods, shocks and variables jointly. This corresponds to the median target method in Fry and Pagan (2011). For this median model I display the IRFs and the historical decomposition. Then, for the IRFs and the historical decompositions, at each period the 10% and 90% quantile are displayed to obtain the confidence intervals. Thus, the median impulse responses for one grain type are all based on the same structural model, which is important for a meaningful interpretation. The points of the confidence intervals, however, are not necessarily based on the same structural model. The 80% interval is chosen as a compromise between displaying the uncertainty and still providing informative, narrow intervals.

3 Assumptions of the Structural Model

The VAR model distinguishes four structural shocks, which I identify as a supply shock, a demand shock, a speculation shock and a residual price shock. The assumptions regarding the instantaneous effects of the shocks are displayed in Table 1. They are normalised to imply a price increase.

The supply shock is assumed to cause grain production to fall and the price to increase. The effect on inventories and on GDP is not restricted. Even though one might expect GDP to fall because agricultural production is part of GDP, a disruption of agricultural production could, for example, cause farm workers to search for work in other sectors and thus increase GDP. Also, while I expect a bad harvest to draw on inventories to smooth consumption, it could also incite speculators to store more in anticipation of even higher prices in the future. Since the aim is to confine the assumptions to the necessary minimum, I do not impose these restrictions.

[2]Exactly identified structural models also suffer from model uncertainty because alternative identifying restrictions, which correspond to the same reduced form VAR model, always exist.

A demand shock is assumed to increase GDP and increase prices. The effect on grain production can go in both ways or could be zero. The reaction of inventories is not restricted, as was the case for the supply shock. This means that supply and demand shocks are not clearly distinguished based on the assumptions and can potentially be confounded. This does not pose a problem for the analysis because we are primarily interested in distinguishing between these two fundamental shocks on the one hand and the speculative shock on the other.

A speculative shock is assumed to lead to a build-up in inventories and thereby cause prices to increase. This can be due to physical speculation with grain or because of speculation in derivatives markets. Derivatives trading creates cash-and-carry arbitrage possibilities and thus causes arbitrageurs to store the grain. Increases in inventories equal a reduced supply of grains for other purposes. This causes prices to rise—or, at least, does not cause them to fall.

A price shock, on the other hand, is assumed to increase prices and thus cause inventories to be sold, or at least not to increase. This shock represents an increase in prices for reasons not connected to supply, demand or storage speculation. If speculators react to the increased prices, I assume they use the increased prices to sell stored goods. The effect on inventories is therefore assumed to be less or equal to zero. The residual shock captures effects on prices from various sources and allows for potential effects of speculation not captured by the speculative shock. As was discussed in section 2, the inventory data might fail to represent speculation due to the presence of an information channel or due to the insufficient quality of the data. The residual shock could capture such effects of speculation. An insignificant effect of the "speculation shock" would therefore not necessarily demonstrate the absence of speculation, as long as we find a significant effect of the residual price shock.

The speculative shock and the price shock are assumed to have no instantaneous effect on GDP. The assumption thus is that increased speculative activity in agricultural commodities or increasing grain prices do not influence global GDP within the same year. The robustness analysis in section 5 shows that this assumption is not crucial for the results obtained. One could also impose zero restrictions on the effect on production, if one is willing to argue that grain production cannot adjust

	Supply Shock	Demand Shock	Speculative Inventory Shock	Residual Price Shock
Production	-		+	+
GDP		+	0	0
Inventories			+	-
Price	+	+	+	+

Table 1: Sign and zero Restrictions. The restrictions are imposed on the instantaneous impact of a shock on the respective variable. A '+' denotes a restriction of the instantaneous impact of that shock to the respective variable to be greater or equal zero. Such a restriction thus rules out a negative impact in the same year as the shock takes place. A '-' denotes a less or equal to zero restriction. A '0' indicates a zero restriction, that is, the assumption that such a shock does not instantaneously affect the respective variable. A blank cell indicates that no assumption about the impact is made, i.e. no restriction is imposed.

within the same year to increased prices. For the sake of being agnostic, I do not impose this restriction. If production reacts, however, it should increase with higher prices. Thus, the effect of a speculative and a price shock on grain production are assumed to be greater or equal to zero.

Since a speculative shock is only defined as causing an increase in inventories, this analysis cannot differentiate between 'excessive' and 'normal' speculation or between storage by 'hedgers' and 'financial speculators'.

4 Results

This section first presents a description of the dynamics of grain markets using impulse response functions (IRF) based on the structural VAR model. This also provides insights into the role of storage and speculation in the price determination. Second, a counterfactual analysis of grain prices is used to show the price effect of speculation during times of price spikes.

4.1 Impulse Response Analysis

The impulse response functions in this section show the dynamics of grain markets and serve in particular to highlight the role of inventories in the price determination. They also serve to verify that the identified structural model is plausible before we turn to the historical decomposition of the price series. The IRFs for the corn market are shown in Table 4, for wheat in Table 5, and for the rice market in Table 6. Displayed are the impulse responses that belong to the median models as well as 80% confidence intervals. Because the median IRFs for one market are jointly determined over all sub-plots, they are quite likely to lie outside of the confidence intervals in some periods. Note that, because the variables are expressed in log-levels, the interpretation of the IRFs corresponds to percentage changes of a variable in response to the respective shock. Because the results consist of quite many response functions, I discuss the essential results which are common across the models of all three markets at once.

Starting with the supply shock, we can see that it leads to a significant reduction of about 4% of global production—judging by the median IRF. In the following years, production returns to its former levels. GDP is unaffected from a drop in corn production but might be slightly lowered for a few years in response to reduced wheat and rice production. Inventories are reduced by around 10% in reaction to a supply disruption, as was expected. Prices are estimated to increase around 6 or 7%. Inventories and prices return to normal levels within the following years.

The demand shock is characterised by a significant and persistent increase in GDP of about 1%. The short-term impact on production is not clearly identified but is close to zero. There is evidence that in the long run production is increased between 0.5 and 1% in response to higher demand. The reaction of inventories is estimated at minus 3% in case of corn but not significantly different from zero for wheat and

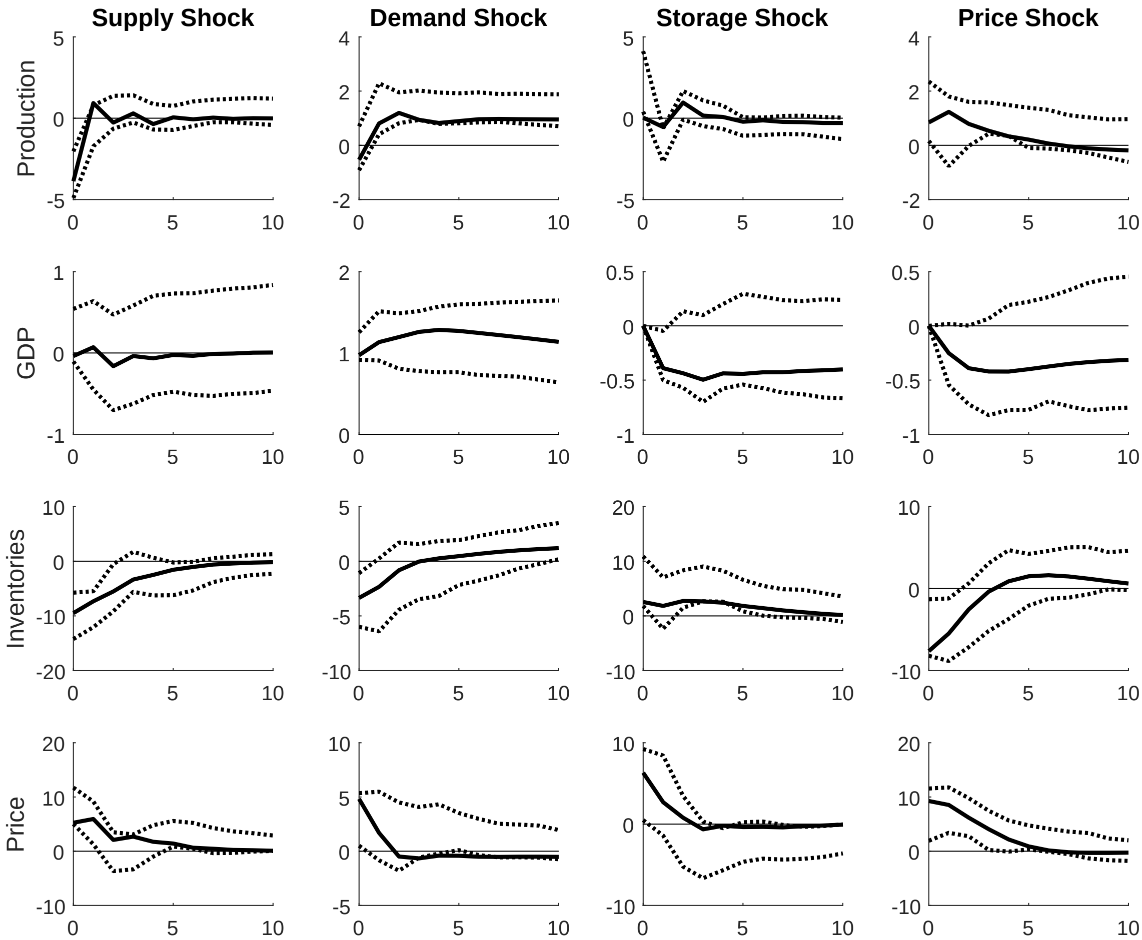

Figure 4: Impulse response functions for the corn market corresponding to the median structural model (solid line) and 80% confidence intervals (dotted lines).

rice. Prices for wheat and corn increase in response to the demand shock, while the reaction of rice is not clear. The prices of all three grains quickly return to previous levels. A potentially different reaction of rice prices in response to higher GDP is in line with the observation that citizens of developing countries partly use additional income to purchase meat products instead of grain products. This can drive up prices of corn and wheat and lower the price of rice because the former are more commonly used as feed grains than the latter.

Turning to the storage shock, we see that it is characterised by an increase in inventories of 3 to 4%. This increased demand for grains from building up inventories leads to an increase in prices about 7 to 10%. Production does not react or increases slightly. There is some indication that production falls one year after a speculative shock (in case of corn and wheat markets), or falls in the long run (in the case of the rice market). This effect on future grain production could be explained by the anticipation of a supply disruption which triggers speculative storage of the grain. Thus, the kind of speculation identified by the storage shock might in principle be a desirable one. The reaction GDP is restricted to zero for the first period. In the years following a speculative shock in the corn and rice market, GDP falls.

The residual price shock is associated with an increase in prices of 5 to 10%. This leads to sales of inventories. Storage returns back to base levels within a few years.

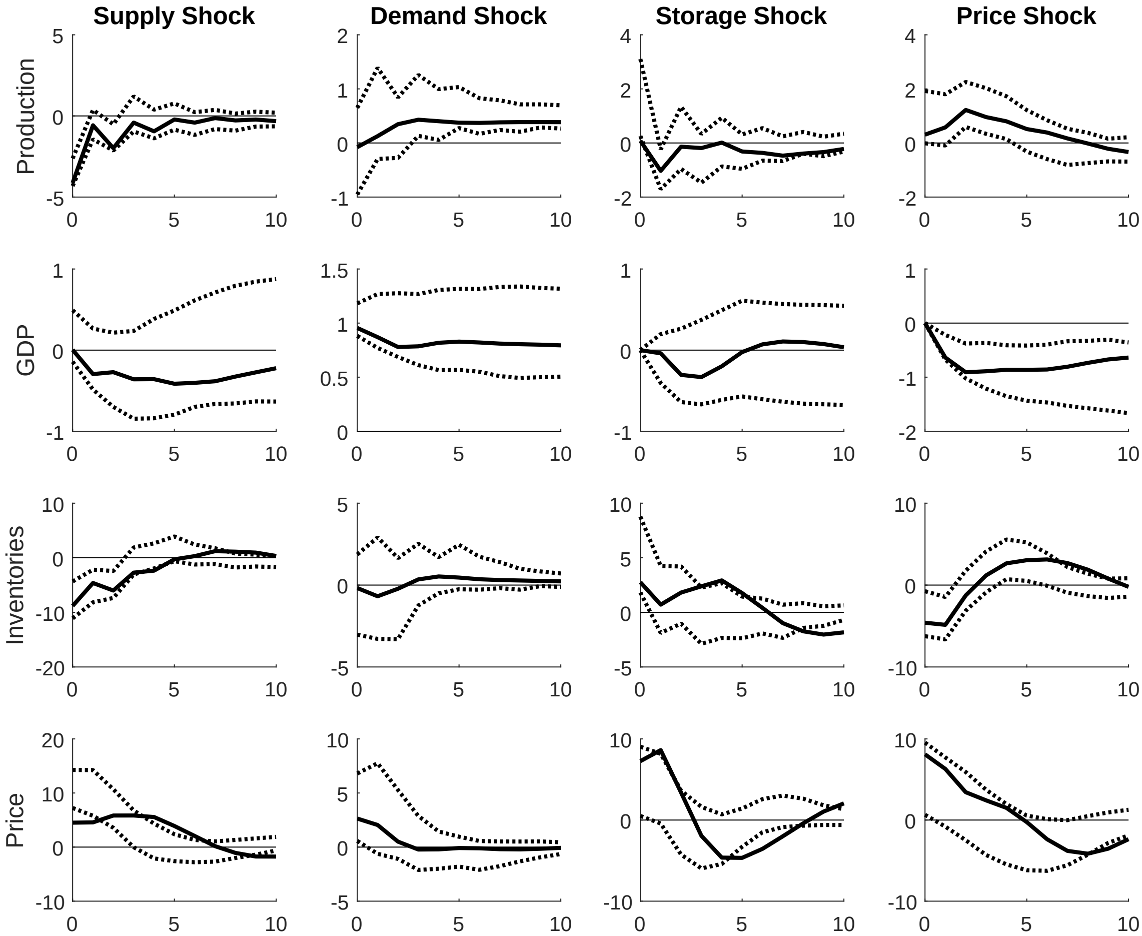

Figure 5: Impulse response functions for the wheat market corresponding to the median structural model (solid line) and 80% confidence intervals (dotted lines).

GDP is again restricted to 0 in the year of the shock and decreases in the following years. Production might initially increase slightly but then returns to base levels.

From the inspection of a supply disrupting shock and of the storage and the price shock, a tendency of GDP to react negatively to those shocks over the long run seems to emerge. A negative response to increased agricultural prices might be explained by the various channels trough which the prices can have an impact on economic conditions. As one such possibility, it was already mentioned that increased food prices can cause social and political unrest and uncertainty, which in turn can be considered harmful to economic growth. Further, by causing malnutrition there might be direct effects on productivity.

Overall, the impulse responses provide economically plausible and meaningful descriptions of the dynamics of grain markets. Supply and demand forces move prices and inventories in theoretically expected ways. Inventories generally move in opposite direction to prices. This provides evidence for a predominantly price-stabilising role of speculation.

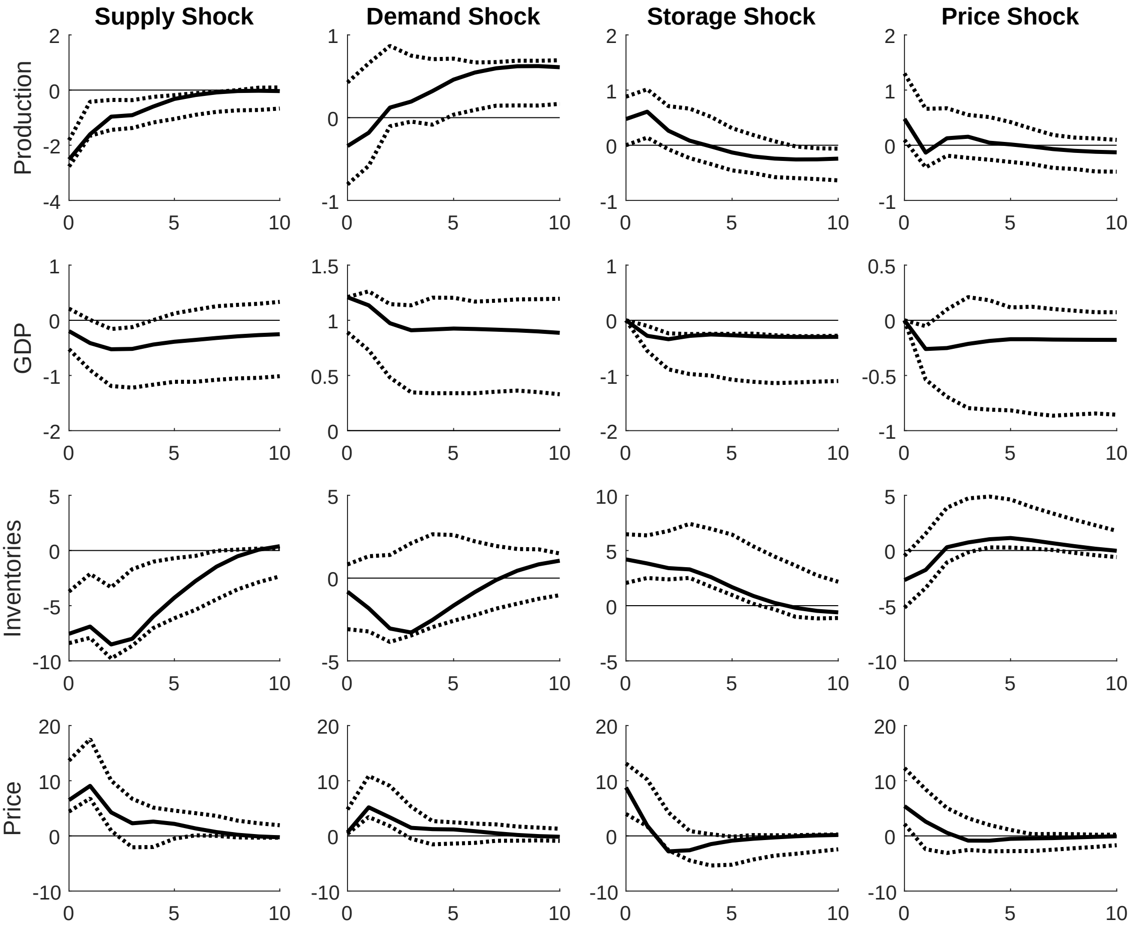

Figure 6: Impulse response functions for the rice market corresponding to the median structural model (solid line) and 80% confidence intervals (dotted lines).

4.2 Historical decomposition of prices

To answer the question whether or not speculation contributed to the rise in grain prices, a historical decomposition of the price for the three grain markets is computed. This analysis shows by how much the actual price deviates from a counterfactual scenario in which the respective shocks have not occurred. For this, the respective structural shock is set to zero for the years 1990 to 2015 and a counterfactual price series is constructed. The percentage deviation of the actual price from the resulting hypothetical price is computed. Figures 7, 8 and 9 show the relative effects of a shock on prices as percentage deviations. The counterfactual represents a scenario in which the respective shock has not occurred during the time frame under consideration, i.e. 1990 to 2015. Given the nonstationarity of the data, previous shocks still resonate within the system since it has infinite memory.

During the time period under consideration there have been three major episodes of price spikes. These occurred in 1996, 2008 and 2011. The first instance, that in 1996, was most prominent for corn and least so for rice, as could be seen in Figures 1, 2 and 3. From Figure 7 we see that the price of corn in 1996 was increased by supply shocks while demand forces lower the price slightly. However, the speculative shock

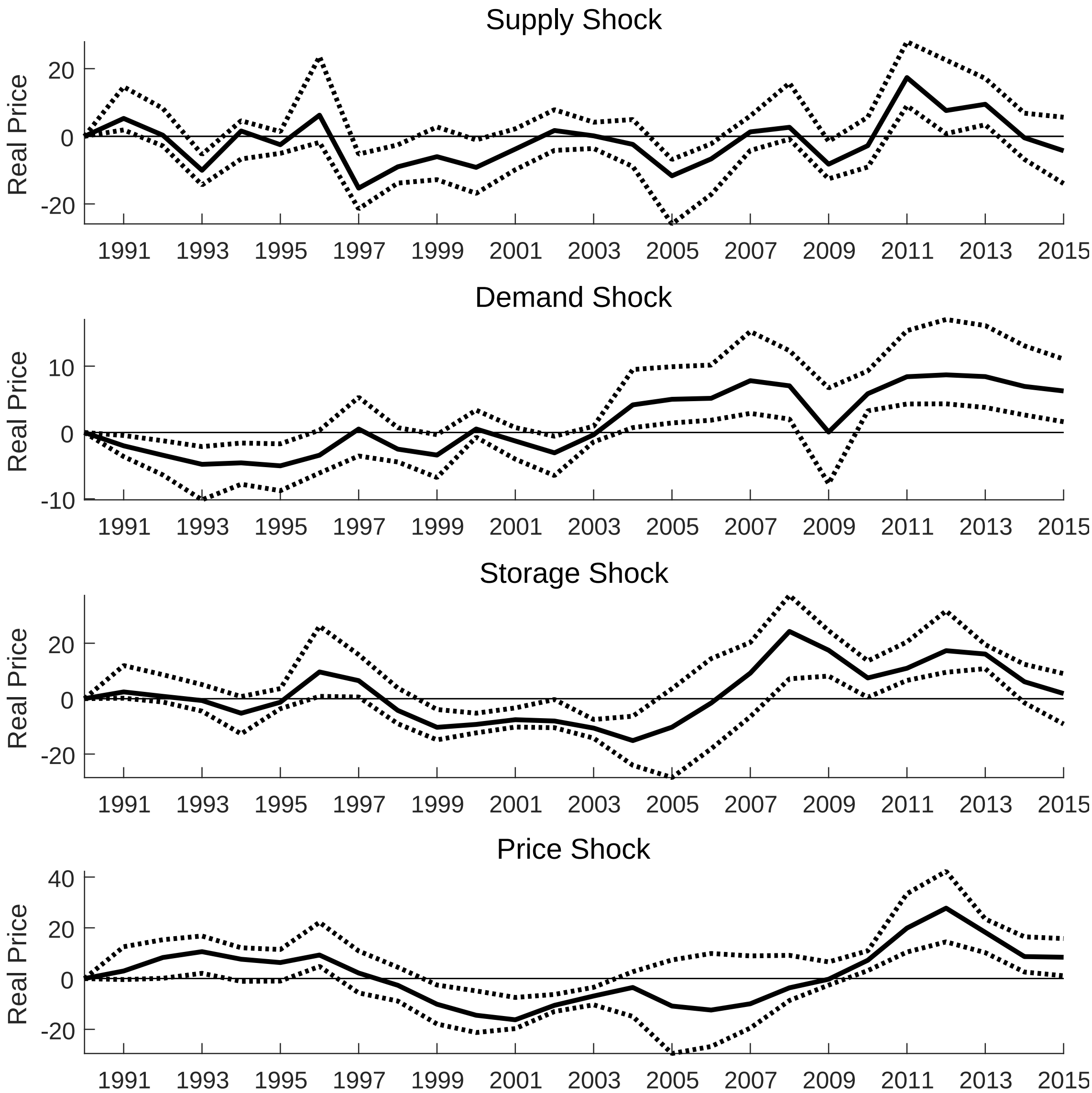

Figure 7: Historical decomposition of the real price of corn. The solid line shows the percentage deviation of the actual price from the counterfactual price without the respective shock according to the median structural model defined in section 2.3. Dashed lines represent 80% confidence intervals.

and the residual shock had strong effects of more than 10% each, judging by the median structural model. Wheat prices (Figure 8) were affected by a severe supply shock that raised prices about 20%. All the other shocks played an immaterial role. For the case of rice, displayed in Figure 9, the 1996 price is estimated to have been raised due to supply shocks as well as residual price shocks by 10% each. The speculative shock is insignificant. Thus, the 1996 price spikes overall exhibit no signs of a strong influence of speculators. There is a small contribution of the speculative shock in case of corn. The rise in wheat prices, on the other hand, is attributed to supply shocks. Rice is neither affected by strong speculative nor strong supply shocks but also did not experience a particularly sharp price increase. For both corn and rice, the residual price shock contributed to increased prices. While this leaves room for effects of speculation, it can also be due to substitution effects among the different grains. This way, a strong supply shock in wheat production can raise

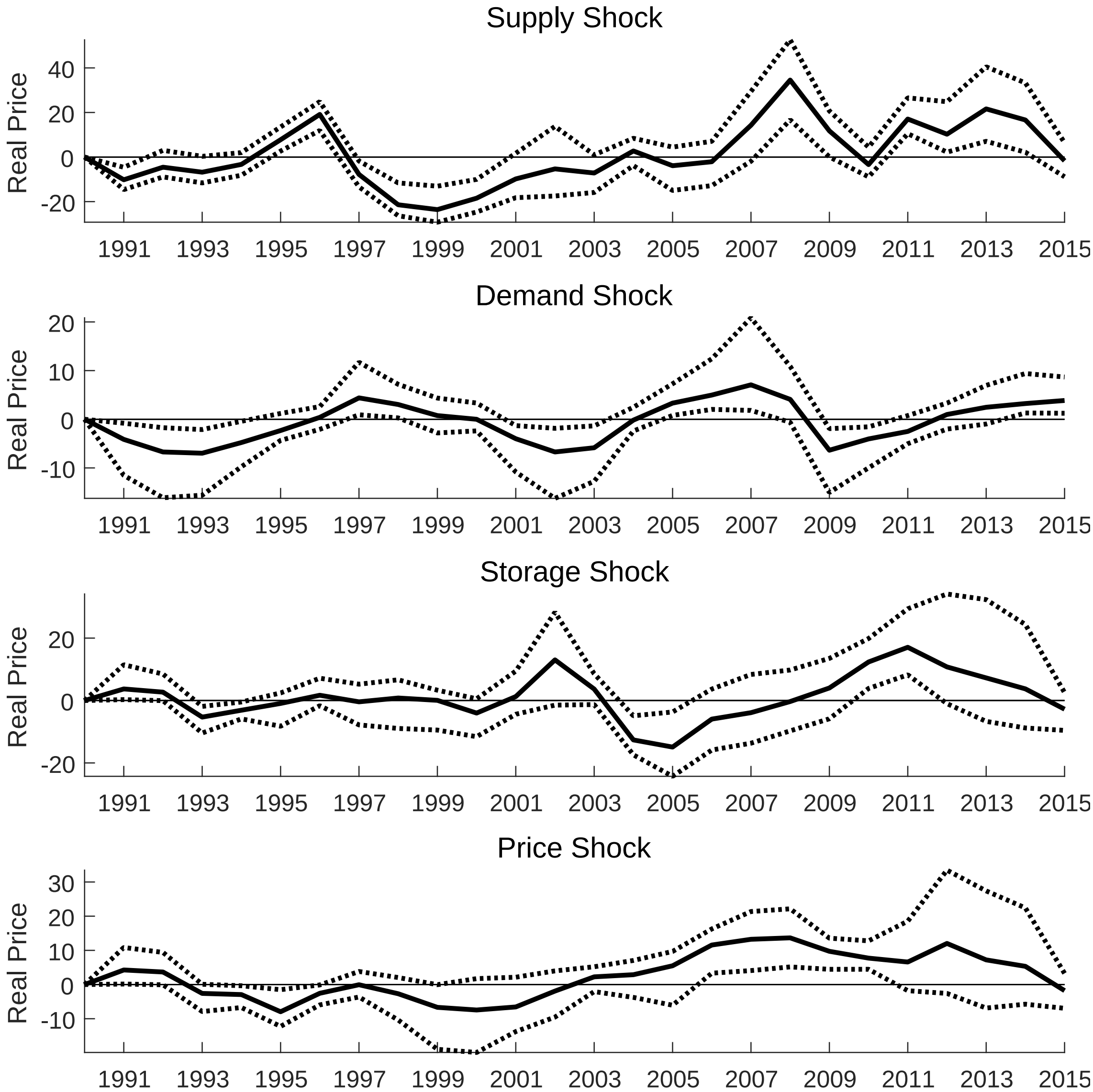

Figure 8: Historical decomposition of the real price of wheat. The solid line shows the percentage deviation of the actual price from the counterfactual price without the respective shock according to the median structural model defined in section 2.3. Dashed lines represent 80% confidence intervals.

prices for corn and rice. Therefore, this price spike seems in line with fundamental supply and demand forces.

The price spikes in 2008 are characterised by demand driving up prices until the outbreak of the financial crisis in 2008. Demand pressure faded in 2008/2009 but was still raising prices of corn and rice in 2008 by 5 to 10%. In 2008, the price of wheat was subject to a major supply shock, pushing prices up by over 30%. The shock of interest, speculation, had a strong influence on corn prices, estimated around 20%, and on the price of rice, estimated around 40%. For wheat, there is no such effect. Instead, an impact of about 15% is attributed to the residual shock. In conclusion, the 2008 spike was preceded by a build-up of prices that was largely fuelled by high demand. When demand started dwindling, supply of wheat is hit by a major shock. This was accompanied by rising levels of corn and rice inventories despite soaring prices for these grains. Such a contradictory market behaviour leads to the models

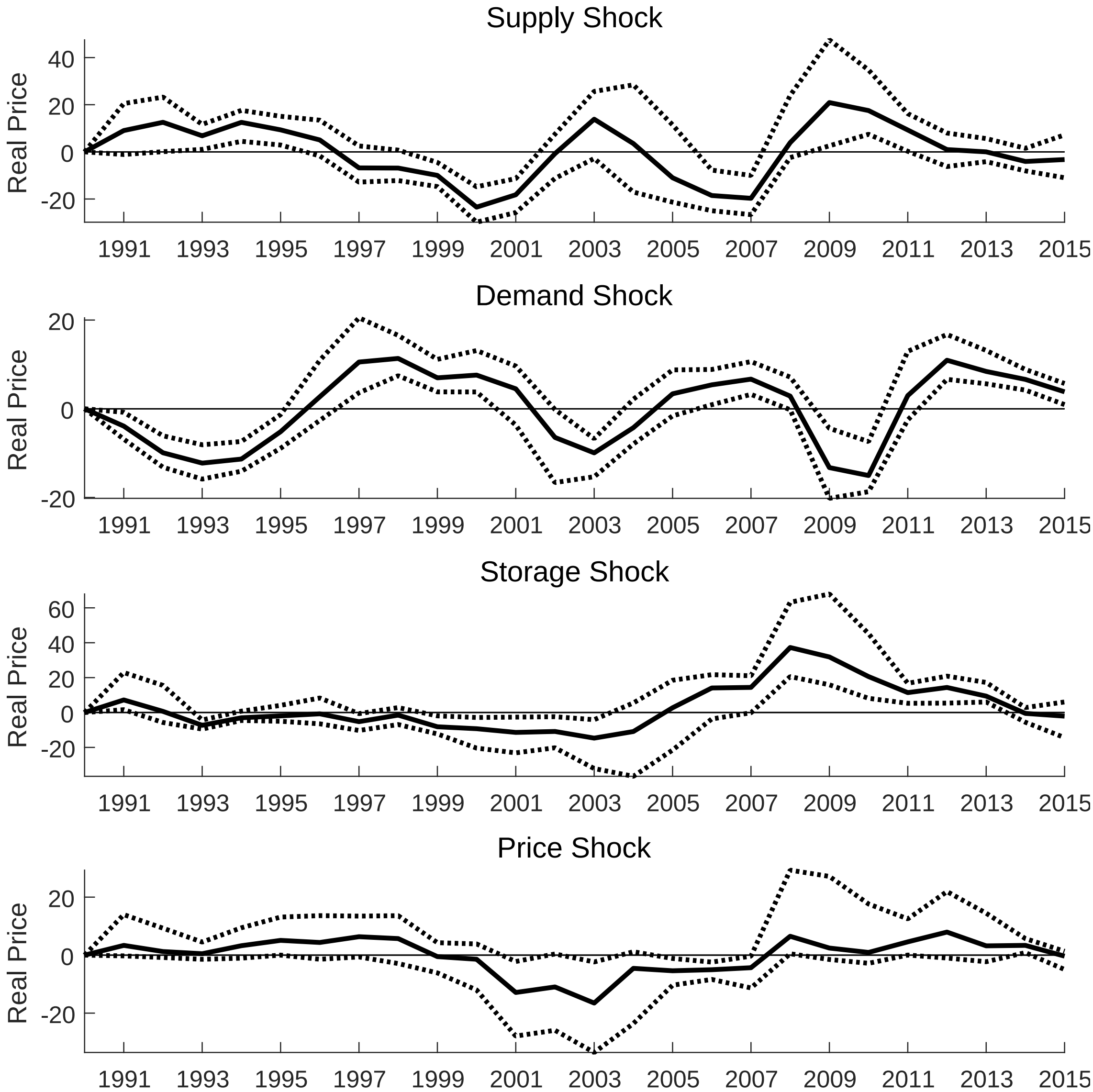

Figure 9: Historical decomposition of the real price of rice. The solid line shows the percentage deviation of the actual price from the counterfactual price without the respective shock according to the median structural model defined in section 2.3. Dashed lines represent 80% confidence intervals.

conclusion that speculative forces drove this development. Thereby, we are left to explain why speculative pressures would affect corn and rice markets but not wheat. One possible explanation could be that speculators in corn and rice markets were driven by expectations of higher prices based on the observation of such prices on wheat markets. Another could be that the thinned out wheat market left little room for excessive storage, while conditions in the other markets did. Thus, speculation would either not have affected wheat prices (which were quite high already) or this effect simply does not show up in the inventory data—which could explain the price effect assigned to the residual shock in the case of wheat. Overall, the 2008 price spikes appear to be substantially driven by speculative forces—supply and demand factors do not explain the extreme price movements.

The last period of interest, the price spikes around the year 2011, saw strong supply disruptions in corn and wheat markets—two grains that saw particularly sever price spikes. These led to price increases of close to 20%. Demand also rebounded and contributed to rising price levels, raising them by around 10%. Interestingly, all three grain prices are found to be driven up by speculative shocks by nearly 20%. Thus, the majority of the price increase is attributed to the speculative shock. The residual shock played a major role especially for prices of corn. Possible explanations of the price shock again span a wide range, and include in particular the usage of corn for biofuel production. Overall, the 2011 price spikes seem to be driven by low supply colliding with strong demand. However, the distressed market conditions with spiking prices did not result in the expected reaction of inventories, again raising reasonable suspicion that speculation worsened conditions that were already challenging.

5 Robustness Checks

This section briefly discusses the robustness of the findings with regard to two presuppositions that could potentially distort the results. First, the effect of different lag lengths is examined. As noted previously, results shown so far were based on lag lengths uniformly set to $p = 2$. The AIC however recommended different lag orders for the cases of corn and rice. Thus, the reduced form VAR model is re-estimated with one lag for the rice market and with three lags for the corn market. The resulting historical decompositions are given in appendix A.1. These changes leave the conclusions from the historical decompositions qualitatively unchanged. The impulse response functions change in terms of their smoothness and short term dynamics, as might be expected.

Second, I investigate the effect of different identifying restrictions. To this end, the zero restrictions from section 3 for the speculative and the residual shock are dropped. This allows global GDP to instantaneously react to a price change. Impulse responses and the historical decomposition remain mostly similar, but confidence intervals become wider. The resulting historical decomposition is shown in appendix A.2. Thus the main results are considered stable over different model specifications and different identifying assumptions.

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

Table 2: Alternative sign and zero Restrictions. Only inequality assumptions imposed on the instantaneous impact of shocks on the respective variables are used. A '+' denotes a restriction of the instantaneous impact of that shock to the respective variable to be greater or equal zero. A '-' denotes a less or equal to zero restriction. A blank cell indicates that no assumption about the impact is made, i.e. no restriction is imposed.

6 Conclusions

The analysis of impulse response functions has shown that storage plays a stabilising role in smoothing prices in reaction to unexpected changes in supply and demand. In particular, inventory movements balance supply in reaction to a distortion of grain production. Inventories are generally build up in times of high supply and low prices—and are reduced in the opposite cases. Regarding the problematic food price surges around the years 1996, 2008, and 2011 however, our analysis suggests that speculative shocks played a detrimental role by further increasing prices in an already distressed market. For the later episodes, 2008 and 2011, speculation played a major role in pushing up the prices of the three major grains, corn, wheat, and rice. The influence of speculation was strongest where the price spikes where most pronounced. For the earlier food price spike in 1996 we find only weak evidence for the influence of speculation. This lends some credibility to the financialisation hypothesis, which is said to have started after the turn of the millennium. The time period until 2008 is characterised by strong demand for all three grains and a sharp unexpected supply shortage for wheat. Speculation was found to have increased prices of corn and rice by around 20% and 40%. Wheat was not significantly influenced by speculation but subject to strong supply and residual shocks. In 2011, speculative forces accounted for price increases for corn, wheat and rice of close to 20%. In these later years, the residual price shock also contributed to higher prices. This shock was included to capture effects not directly measured by the variables in the model. These effects can range from the influence of Bioethanol production to derivatives trading. No attempt to further identify this shock is made.

In summary, it was shown that speculative storage generally serves an important purpose by stabilising prices. However, there are times when speculation becomes detrimental to price stability. In periods of distressed markets and severe price spikes, inventory movements appear to drive up prices even further. Whether this constitutes market failure, or is due to government intervention or the result of the financialisation of commodities markets cannot be definitively answered with the methodological framework employed in this article. A need for improved measures of ensuring a functioning smoothing of supply disruptions and price peaks is, however, been clearly documented.

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A Appendix

A.1 Historical decomposition for different lag lengths

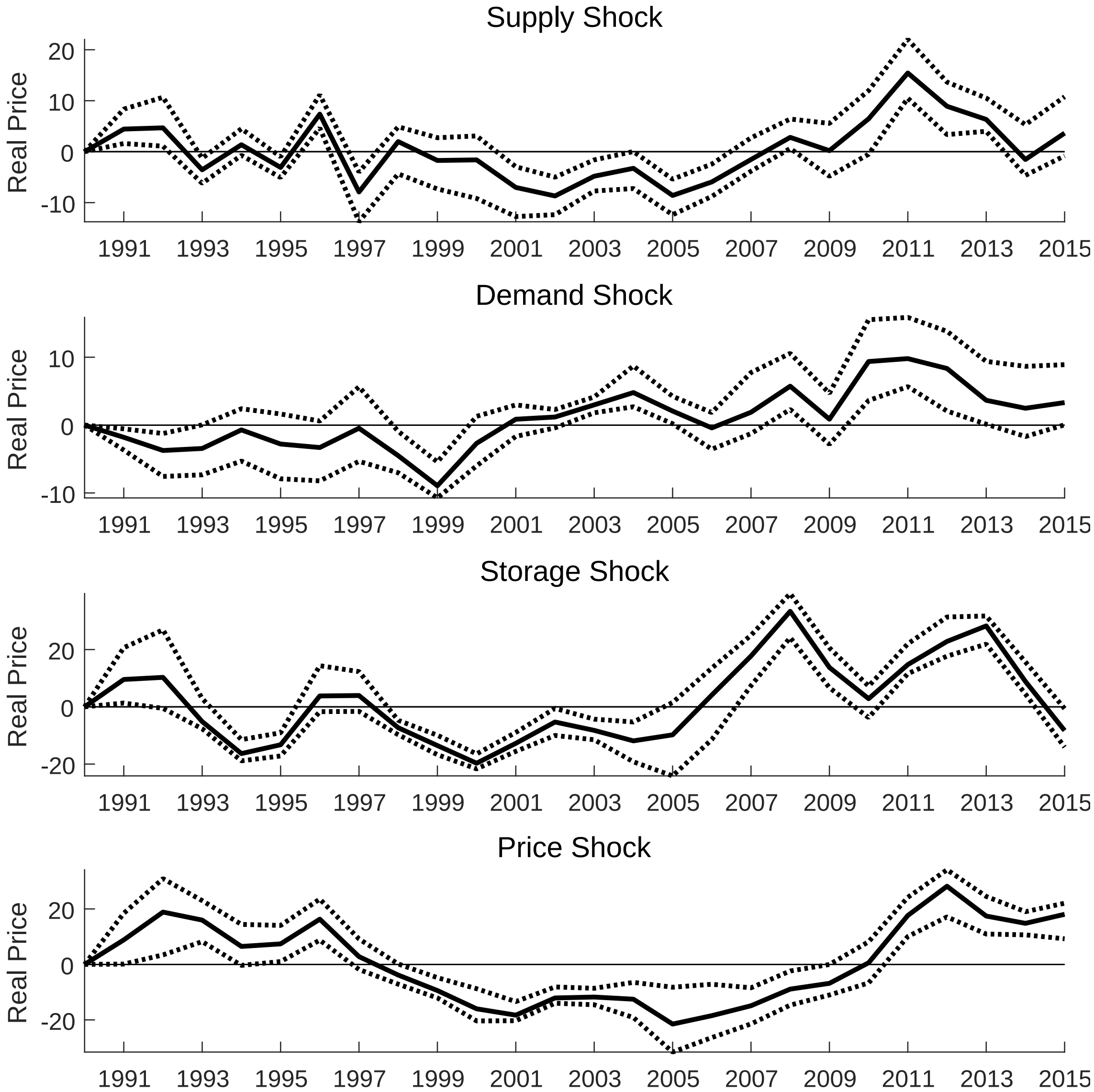

Figure 10: Historical decomposition of the real price of corn. Estimation of a VAR model with 3 lags. The solid line shows the percentage deviation of the actual price from the counterfactual price without the respective shock according to the median structural model defined in section 2.3. Dashed lines represent 80% confidence intervals.

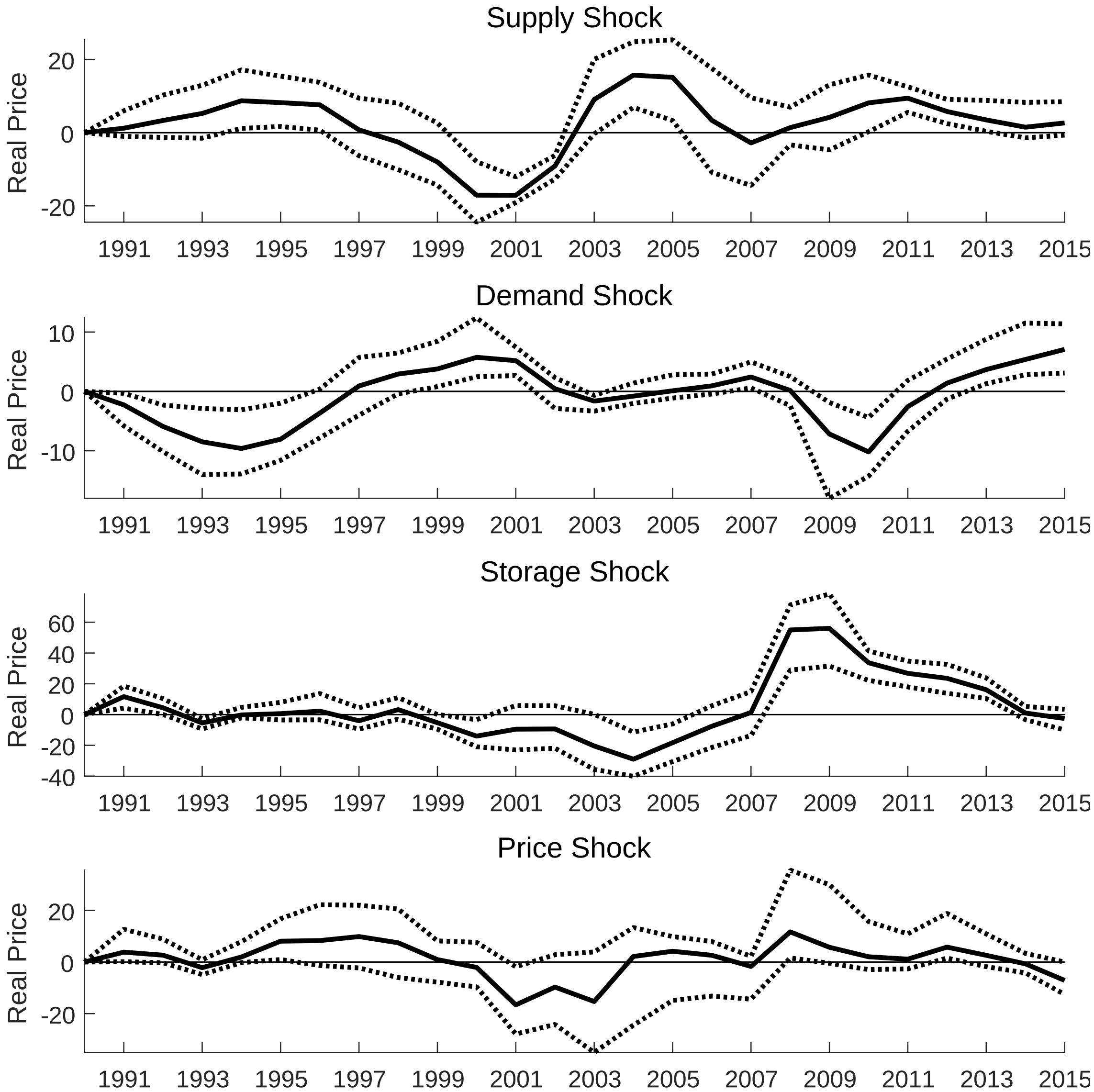

Figure 11: Historical decomposition of the real price of rice. Estimation of a VAR model with 1 lag. The solid line shows the percentage deviation of the actual price from the counterfactual price without the respective shock according to the median structural model defined in section 2.3. Dashed lines represent 80% confidence intervals.

A.2 Historical decomposition without zero-restrictions

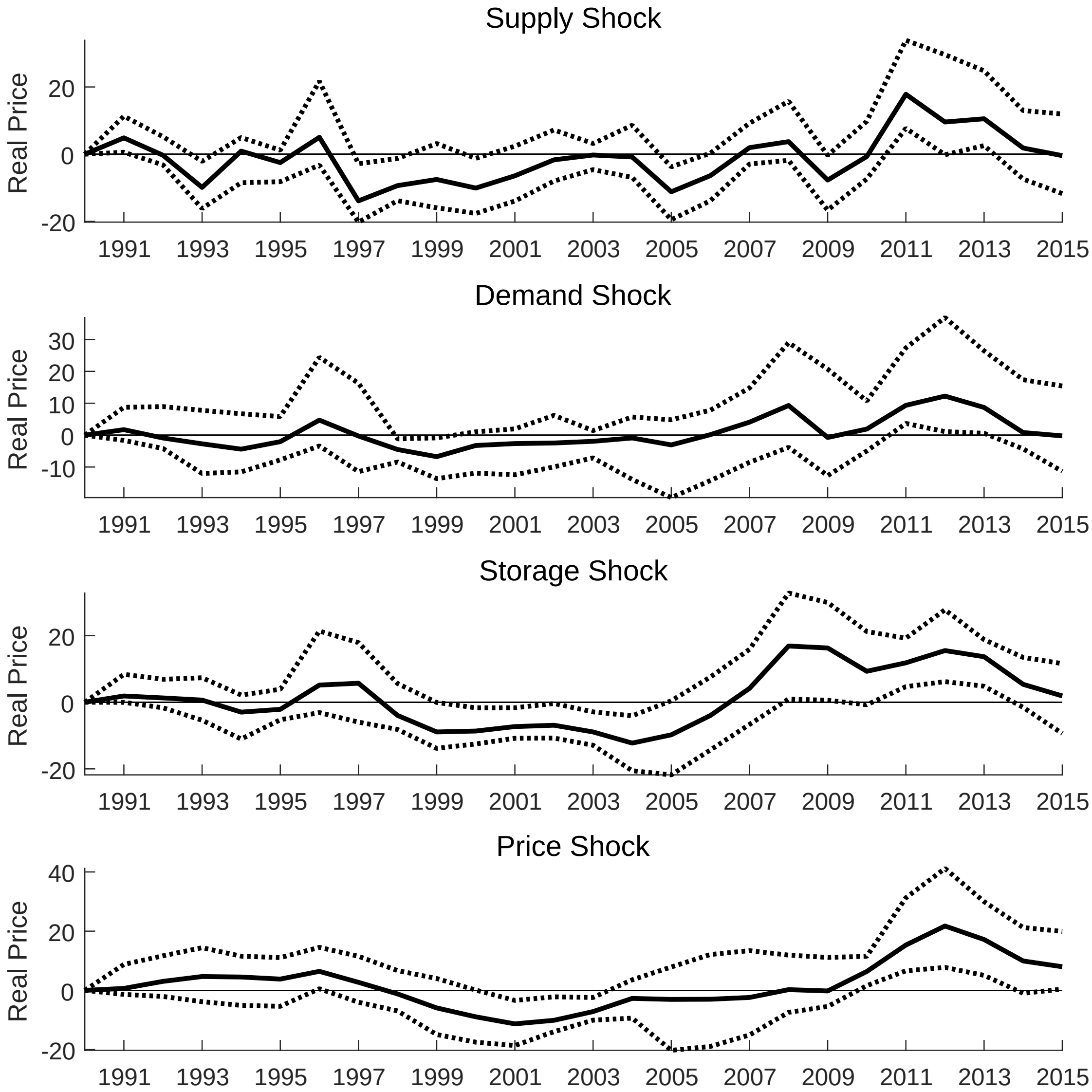

Figure 12: Historical decomposition of the real price of corn based on structural models identified with sign restrictions only. The solid line shows the percentage deviation of the actual price from the counterfactual price without the respective shock according to the median structural model defined in section 2.3. Dashed lines represent 80% confidence intervals.

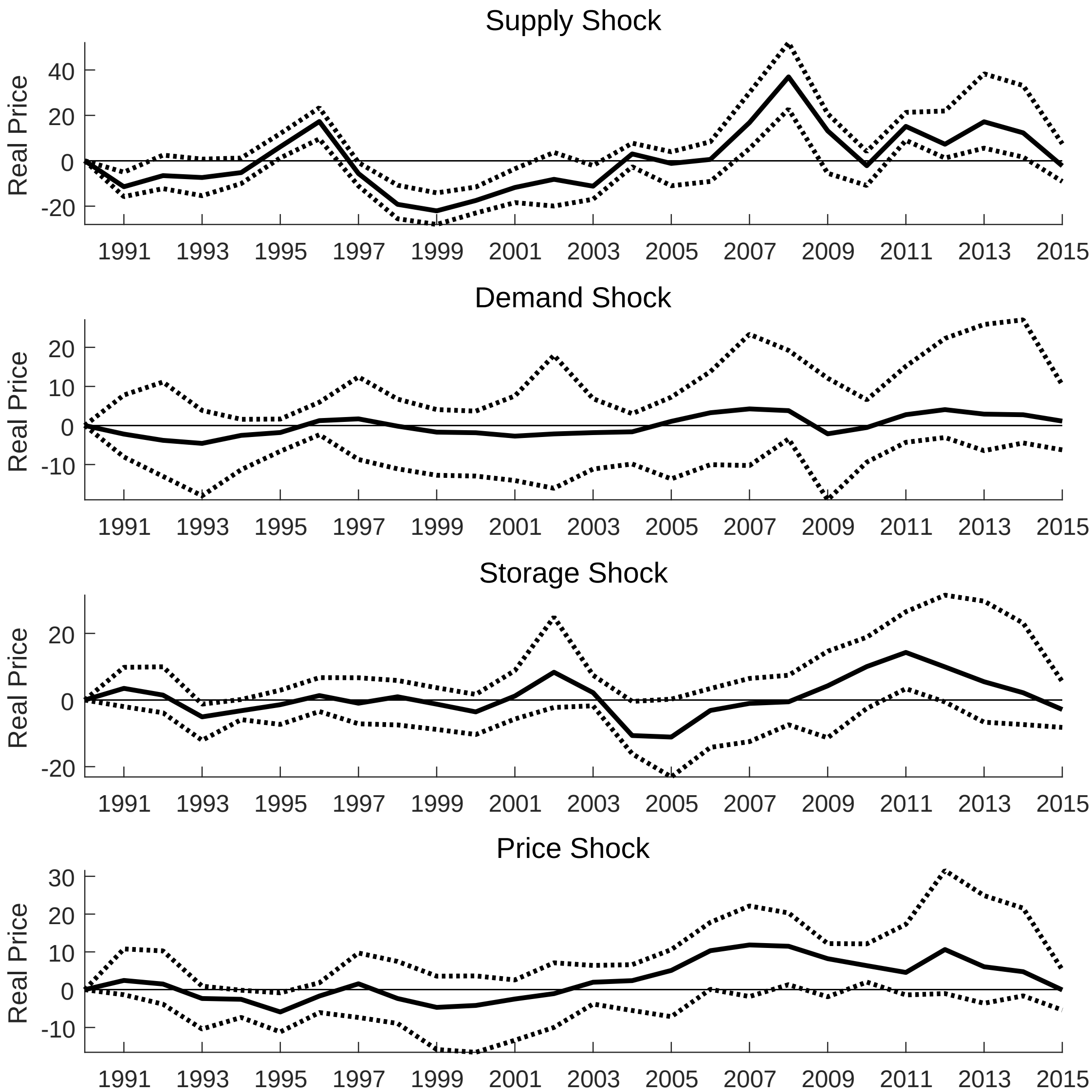

Figure 13: Historical decomposition of the real price of wheat based on structural models identified with sign restrictions only. The solid line shows the percentage deviation of the actual price from the counterfactual price without the respective shock according to the median structural model defined in section 2.3. Dashed lines represent 80% confidence intervals.

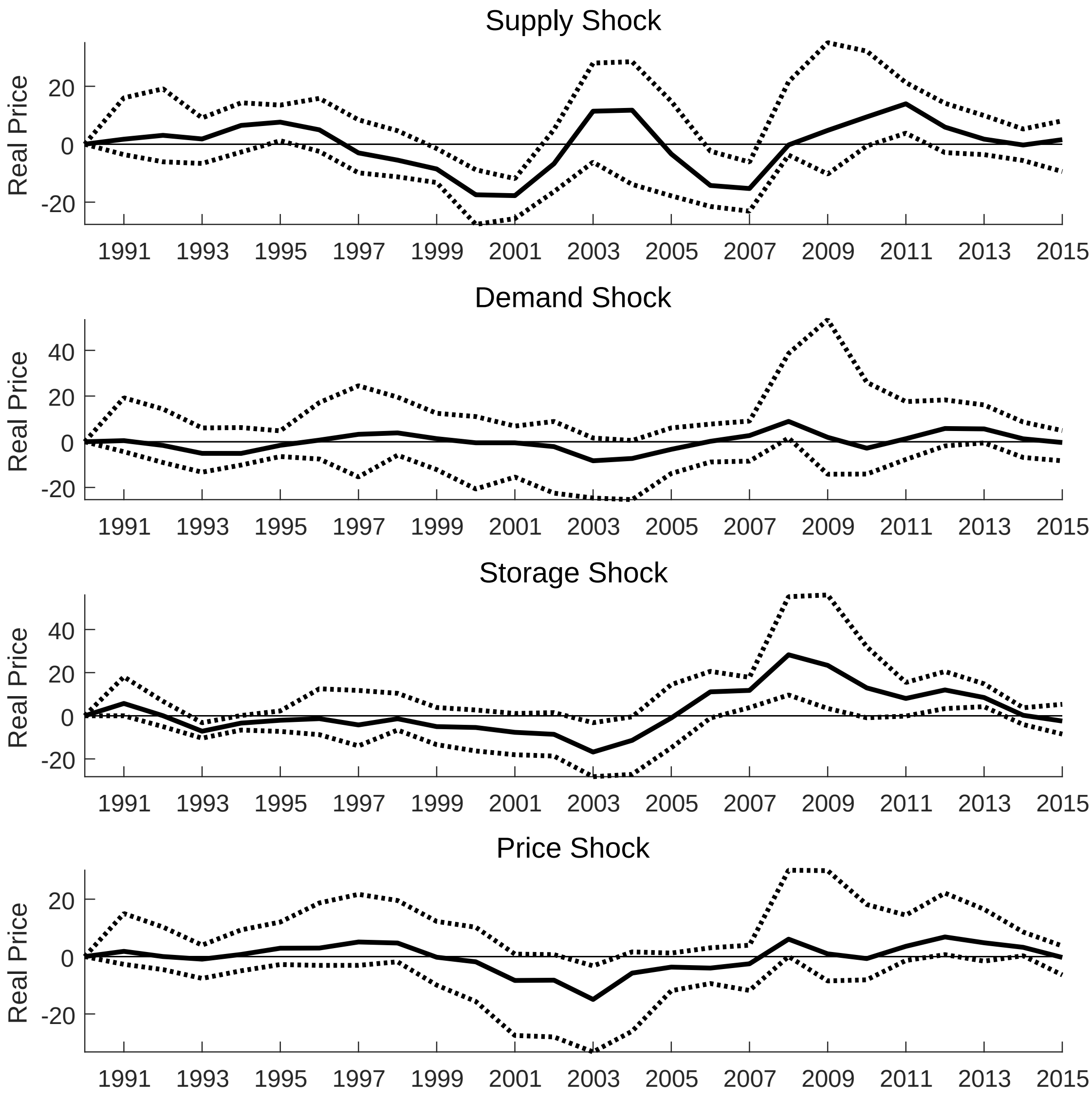

Figure 14: Historical decomposition of the real price of rice based on structural models identified with sign restrictions only. The solid line shows the percentage deviation of the actual price from the counterfactual price without the respective shock according to the median structural model defined in section 2.3. Dashed lines represent 80% confidence intervals.