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Summary

We present a Bayesian structural Vector Autoregressive model of the global wheat market to examine the relative importance of supply and demand shocks, which are interpreted as the fundamental driving forces of wheat price. To our knowledge, this is the first SVAR analysis that jointly considers (i) a Bayesian non-recursive specification, (ii) production and inventories as endogenous variables (iii) and an inventory-based detection strategy. Our main results indicate that: (i) the posterior median estimates for the price elasticity of supply and demand are mostly similar in their order of magnitude but opposite in signs (0.19 for supply and -0.20 for demand); (ii) the price and the inventories respond to global wheat market shocks differently, depending on the type of structural shock. We also show that the results obtained from Cholesy-type identified annual SVAR models for wheat market are potentially misleading and difficult to reconcile with the economic theory of competitive storage. Finally, we illustrate how unpredictable shifts in supply and demand contributed to the dynamic of wheat price between 2000 and 2022.

Keywords: Bayesian structural VAR model, Price analysis, Global wheat market

JEL Classification: C11, C32, Q11, Q13

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Understanding the role of supply and demand factors in the global wheat market: a Structural Vector Autoregressive approach

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October 26, 2023

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1 Introduction

In this paper we develop a Bayesian structural Vector Autoregressive (BSVAR) model to analyse the response of the real price of wheat to supply and demand shocks.

Developing countries are particularly vulnerable to food price shocks with implications for undernutrition and health, which in turn, could lead to social unrest and food riots (see e.g. Berazneva and Lee (2013), Bellemare (2015) and Kosec and Song (2021). The extent to which the low-income countries are affected by food insecurity and problem of hunger depends on the magnitude and on the type of the price-shock under scrutiny. Moreover, the grain price shocks are predicted to rise costs of food production chain, to reduce labor productivity, consumer spending and economic growth even for advanced countries. On this respect, a recent study by Peersman (2022) shows that a 1% increase in the international food price shock raises the inflation volatility in the euro area by 30% and reduce the real GDP by 4% over one year. Our paper provides a specific investigation of the global wheat market and it focuses on two main research questions: (i) what is the response of grain price to unexpected changes in its supply and demand; and (ii) are price shocks all alike. Identifying the economic factors which exert the greatest influence on the price of wheat has important implications for any policymakers and researchers who are intended to enhance optimal food management strategies and to address global food security.[1]

Our work can be cast in the literature dealing with the the effects of supply and demand factors on agricultural commodity prices (see e.g. Goodwin and Schroeder (1991), Pietola et al. (2010),Baffes and Haniotis (2016), De Winne and Peersman (2016), Bastianin et al. (2018), Ghoshray (2002) and Ghanem and Smith (2022). For instance, the study of Janzen et al. (2014) performs an SVAR analysis for US wheat spot prices from January 1991 to December 2011. Gutierrez et al. (2015) use a Global Vector Autoregressive (GVAR) wheat market model to investigate the wheat export price dynamics and to account for the spillovers effects across countries. The relationship among market-specific factors and a broad set of

[1]In our analysis, wheat supply shocks are primarily linked to both *availability* and *accessibility* dimensions of food security. Moreover, wheat consumption demand shocks and economic activity shocks are related to *stability* of food security. Finally, *utilization* represents an individual dimension of food security, hence it is difficult to reconcile with shocks that have macroeconomic interpretation.

macroeconomic variables is also investigated by Algieri (2014), who use a Vector Error Correction (VEC) model in her study. More recently Carter et al. (2017) estimate a SVAR model of corn-inventory dynamics to estimate the effect of biofuel policies on corn prices. Finally a study by Peersman (2022) investigates the effect of international food prices on the inflation in the euro-area, using a SVAR model in which food commodity price shocks are identified with an external instrument.
Our study is also related with the theory of competitive storage (see e.g. Deaton and Laroque (1996), Mitra and Boussard (2012), Vercammen and Doroudian (2014), Knittel and Pindyck (2016) and Schewe et al. (2017)) and the role of speculation on agricultural price formation (see e.g. Irwin (2013), Hamilton and Wu (2015), Cheng and Xiong (2014) and Janzen et al. (2018)). The intensity of financial speculation in grain, livestock and equity markets is also investigated by Bruno et al. (2017) in the context of a recursively identified SVAR model with high-frequency data. The authors find that economic activity shocks are more important than speculative shocks in explaining the commodity-equity and cross-commodity return co-movements during the global financial crises.

Relative to the existent literature, our paper offers three main contributions. First, ours is the first analysis of the effects of supply and demand shocks on wheat price that jointly considers: (i) *a Bayesian non-recursive SVAR model*, (ii) *production and change in inventories as endogenous variables*, (iii) *an inventory-based detection strategy* which is grounded on the theory of competitive storage. The empirical approach applied to our analysis relies on the identification algortihm for BSVAR models developed by Baumeister and Hamilton (2015). Compared to traditional methods based on sign-restricted SVAR models, the Baumeister and Hamilton (henceforth, BH) approach allows to correctly compute supply and demand elasticities directly from the structural equations of interest (see Baumeister and Hamilton (2019) and Baumeister and Hamilton (2021)).[2] Moreover, the use of production and invento-

[2]In sign-restricted SVAR models, the price elasticity of demand (or supply) can be calculated as ratio of change in consumption (production) to change in price that results from a supply (or demand) shock. As discussed in Baumeister and Hamilton (2021), this approach has two main drawbacks. First, the interpretation of these elasticities are often misleading because they are directly derived from the impact multiplier matrix, which represents a non linear combination of multiple elasticities. Second, the inequality constraints – which characterize the sign restrictions – imply a large drop-off in the probability distribution at any fixed values, resulting in an unrealistic assumption.

ries as endogenous variables facilitates the identification of the structural shocks, which can be interpreted as the fundamental driving forces of the global wheat market. Specifically, data on production help to identify the wheat supply shocks, which are mostly linked to planting decisions and weather conditions (see Haile et al. (2014) and De Winne and Peersman (2016)). At the same time, data on inventories are useful to achieve the market-clearing condition and to identify the speculative component of wheat price in a way consistent with the absence of arbitrage opportunities (see e.g. Wright (2011), Carter et al. (2017) and Bruno et al. (2017)).[3]
We provide empirical evidence that the posterior median estimates for the price elasticity of supply and demand are mostly similar in their order of magnitude but opposite in signs (0.19 for supply and -0.20 for demand), suggesting that both supply and demand curves are price inelastic. For the income elasticity of demand, the posterior median estimate is less than one and amounts to 0.42. Moreover, our results indicate that price and inventory responds to global market shocks differently, depending on the economic motivation behind each shock. Specifically, we find a negative relationship between the impact responses of the price of wheat and the inventory changes to global wheat market-driven shocks, which are not related to speculative factors. This result is grounded on the theory of competitive storage and it is consistent with the view that inventories' management plays an important role in consumption and/or production smoothing during periods of market stress.

Second, we show that the endogenous relationship between the price of wheat and the change in inventories requires to depart from SVAR models with annual data and recursive identification schemes. We provide empirical evidence that the posterior distribution for the price demand elasticity in case of Cholesky-type identified SVAR model is concentrated between -3.5 and 2.6, using 68% of credible region. These results imply that economic restrictions on the wheat supply elasticity are associated with implausible values of the price

[3] Is worth recalling that Bruno et al. (2017) investigate the impact of financial speculation on commodity equity linkages that considers physical market fundamentals. Their specification includes the crop-production index as an exogenous variable and the futures-spot price spread as a measure of the tightness of wheat inventory. Moreover, Ghanem and Smith (2022) use a triangul SVAR to assess the importance of global supply and demand shocks. This study uses the variable production which is expressed as the sum of the caloric value of specific crops. In contrast, our study includes *global wheat production as endogenous variable* and exploits an *inventory-based detection strategy* to identify the structural shocks in a *non-recursive SVAR model*.

elasticity of wheat demand, analogous to the case of global crude oil market (see Caldara et al. (2019) and Baumeister and Hamilton (2019)).

Finally, our study offers a clear picture of the historical evolution of price, production and change in inventories of the global wheat market since the early 2000s. This allows us to assess the quantitative importance of consumption demand shocks as opposed to supply and other demand shocks at each point in time. To illustrate this point, we focus on three exogenous events in global wheat markets, notably in (i) the commodity prices surge and their subsequent collapse (2005-2009), (ii) droughts and weather shocks in some producer countries (2010 and 2012) and (iii) the COVID-19 outbreak and the Russia-Ukraine war (2020-2022).

The rest of the paper is organized as follows. Section 2 describes data and variables. Section 3 illustrates the methodology. The empirical results are presented in Section 4, while Section 5 concludes.

2 Data and variables

To describe the international wheat market we consider the joint dynamics of $n = 4$ endogenous variables, that is, the global wheat production (Q), the world industrial production index – wip – (Y), the real price of wheat (P) and the wheat inventory changes (ΔI). Our study is based on annual data during the period 1960-2022, as reported in Table (1).

Table 1: Data description and sources

	name	definition	source, raw data
Global wheat production	Q	Aggregate sum of country-level data on wheat production, (1000mt)	Wheat production
Real price of wheat	P	Wheat (U.S.), no. 2 hard red winter Gulf export price; June 2020 backwards, no. 1, hard red winter, ($/mt)	HRW real price
Global wheat inventories	ΔI	Algebraic sum of country-specific wheat inventory changes, which are obtained by the difference between ending and beginning annual stocks, (1000mt)	Wheat inventories
World industrial production	Y	Annual average of the World Industrial Production (wip) index, 100-basis	World industrial production index

Notes: All data have been collected in March 2023.

Data on global wheat production (Q) are obtained from the aggregate sum of 145 countries-level data, available from the United States Department of Agriculture - Foreign

Agricultural Service, (USDA-FSA) database. The global measure of real economic activity is the annual average of monthly OECD+6 World Industrial Production index – wip – (Y), as proposed by Baumeister and Hamilton (2019). This measure of real output includes data for OECD and non-OECD countries – namely China, India, Brazil, Russia, South-Africa and Indonesia – and it allows to exploit our prior beliefs on the income elasticity of wheat demand, given the methodology applied to recover the structural shocks. Moreover, we download the US Hard Red Winter (US-HRW) price of wheat (P), which is converted in real terms, from the World Bank commodity database. Finally, we compute data on global wheat inventory changes (ΔI) as the algebraic sum of the difference between ending and beginning annual stocks for each of the 145 countries available from USDA-FSA dataset. Therefore the vector of endogenous variable is $\mathbf{y}_t = [q_t\, y_t\, p_t\, \Delta i_t]'$ where $q_t = 100 \times \ln\left(\frac{Q_t}{Q_{t-1}}\right)$, $y_t = 100 \times \ln\left(\frac{Y_t}{Y_{t-1}}\right)$, $p_t = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right)$ and $\Delta i_t = 100 \times \left(\frac{\Delta I_t}{Q_{t-1}}\right)$.

3 Methodology

The structural form of the VAR model of the global wheat market is:

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{v}_t \tag{1}$$

where $\mathbf{y}_t = (y_{1t}, y_{2t}, \cdots, y_{nt})'$ is a $n \times 1$ vector of endogenous variables, $\mathbf{A}$ is a $n \times n$ matrix of instantaneous structural parameters, $\mathbf{x}_{t-1}$ is a $mn + 1$ vector containing m lags of the endogenous variables and a constant, namely $\mathbf{x}'_{t-1} \equiv \left[\mathbf{y}'_{t-1},\ \mathbf{y}'_{t-2}, 1\right]'$ and $\mathbf{B} = [\mathbf{B}_1, \mathbf{B}_2, \mathbf{b}_0]$ is a $[n \times (nm + 1)]$ matrix of structural coefficients. Specifically, $\mathbf{b}_0$ is a $n \times 1$ vector of intercepts and $\mathbf{B}_1$ and $\mathbf{B}_2$ are $n \times n$ matrices governing the past structural dynamics of the variables. We set the number of lags $m = 2$. This choice takes into account both agriculture business cycle duration and autocorrelated residual (see Erten and Ocampo (2013)). The vector of structural shocks $\mathbf{v}_t \equiv [v_{1t}, v_{2t}, \cdots, v_{nt}]'$ is assumed to be normally distributed with zero mean and diagonal variance-covariance matrix $\boldsymbol{D}$.

The reduced form representation of model (1) is:

$$\mathbf{y}_t = \mathbf{\Pi}\mathbf{x}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{2}$$

where $\mathbf{\Pi} = \mathbf{A}^{-1}\mathbf{B}$ is a $(n \times nm + 1)$ matrix of reduced-form coefficients and $\boldsymbol{\varepsilon}_t$ is a $(n \times 1)$ vector of the reduced-form shocks that is assumed to be normally distributed with zero mean and variance-covariance matrix $\mathbf{\Omega} = \mathbf{A}^{-1}\mathbf{D}(\mathbf{A}^{-1})'$.

The Maximum Likelihood estimates of the reduced form parameters are given by:

$$\hat{\mathbf{\Pi}} = \left(\sum_{t=1}^{T} \mathbf{y}_t\mathbf{x}'_{t-1}\right)\left(\sum_{t=1}^{T} \mathbf{x}_t\mathbf{x}'_{t-1}\right)^{-1}; \tag{3}$$

$$\widehat{\mathbf{\Omega}} = T^{-1}\sum_{t=1}^{T} \widehat{\boldsymbol{\varepsilon}}_t\widehat{\boldsymbol{\varepsilon}}'_t. \tag{4}$$

where $\widehat{\boldsymbol{\varepsilon}_t} = \mathbf{y}_t - \hat{\mathbf{\Pi}}\mathbf{x}_{t-1}$ is a $(n \times 1)$ vector of reduced-form residuals.

We estimate the structural coefficients of model (1) using the Bayesian identification algorithm developed by Baumeister and Hamilton (2015). The BH approach delivers set-identified SVAR models and estimates the structural model directly without having to go through the reduced form specification. Specifically, the estimation of model 1 is mainly based on two steps. The first step consists of a specification of informative prior beliefs about the structural parameters **A**, **B** and **D**. We use priors for **A** grounded on the theory of storage and empirical results obtained from earlier studies, while for **B** and **D** we use natural conjugate priors. The second stage relies on sampling draws from the posterior distribution of the structural coefficients using a random walk Metropolis-Hastings algorithm.[4]

[4]Further description about the BH identification algorithm is provided in the Appendix.

3.1 A SVAR model of the global wheat market

To better illustrate the economic structure of the international market for wheat, we re-write model (1) as a system of four equations:

$$\begin{cases} q_t = a^s_{qp} p_t + \mathbf{b}'_1 \mathbf{x}_{t-1} + v_{1t} & \text{(5a)} \\ y_t = a_{yp} p_t + \mathbf{b}'_2 \mathbf{x}_{t-1} + v_{2t} & \text{(5b)} \\ q_t = a^d_{qy} y_t + a^d_{qp} p_t + \Delta i_t + \mathbf{b}'_3 \mathbf{x}_{t-1} + v_{3t} & \text{(5c)} \\ \Delta i_t = a_{iq} q_t + a_{ip} p_t + \mathbf{b}'_4 \mathbf{x}_{t-1} + v_{4t} & \text{(5d)} \end{cases}$$

where $\mathbf{b}'_i$ contains all structural parameters on the lagged variables of the i^{th} equation and corresponds to the i^{th} row of $\mathbf{B}$. Thus the structural system implies that all variables are affected by their past values through vector $\mathbf{x}_{t-1}$.

Given the structural system of model 1, the contemporaneous structural matrix is:

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & -a^s_{qp} & 0 \\ 0 & 1 & -a_{yp} & 0 \\ 1 & -a^d_{qy} & -a^d_{qp} & -1 \\ -a_{iq} & 0 & -a_{ip} & 1 \end{bmatrix}. \qquad (6)$$

In the above system, equation (5a) models the global wheat supply curve, with a^s_{qp} representing the price supply elasticity. Equation (5a) involves two zero-restrictions, that is, $a^s_{qy} = a^s_{qi} = 0$. These exclusion restrictions are consistent with the view that, within one year, wheat supply is not *directly* explained by change in inventories and real economic activity.[5] In equation (5b), the world industrial production is contemporaneously affected only by the real price of wheat, via a_{yp}. Therefore, the global economic activity equation presents two exclusion restrictions, namely $a_{yq} = a_{yi} = 0$. Following Baumeister and Hamilton (2019), Equation (5c) represents the global wheat consumption demand approximated by

[5] It is worth noting that the zero restrictions on a^s_{qy} and a^s_{qi} are not controversial. Equation (5a) implies that production depends on inventories only through the effect of inventories on price. Analogously, we assume that production depends on real output only through the effects of world industrial production on price. In other words, the contemporaneously effects of economic activity and inventories is indirectly captured through the equilibrium impacts of the structural shocks, as reported in equation 3.3.

the difference between the quantity supplied q_t and the change in inventories Δi_t. Thus, the parameters a^d_{qy} and a^d_{qp} represent the income and the price elasticity of wheat demand, respectively. Lastly, equation (5d) represents the wheat inventory demand curve and it states that any changes in production and real price of wheat contribute directly to demand for storage, through $a_{\Delta iq}$ and $a_{\Delta ip}$ but we use an exclusion restriction on the structural parameter $a_{\Delta iy}$. Therefore, the SVAR model presented in this article allows inventories to respond endogenously to shocks arising from both the supply side and the demand side of the world wheat market (see e.g. Pindyck (1994) Knittel and Pindyck (2016)).

3.2 Priors information for the contemporaneous structural coefficients

The main idea is to use priors for **A** that draw on the estimates of the elasticity parameters obtained by different studies in the literature on grain markets. Therefore, for the identification of the structural shocks, we use a mixture of dogmatic (e.g. zero restrictions) and non-dogmatic priors (in terms of Student t density function) on the elements of **A**, as illustrated in equation 6 and Table 2.

Table 2: Specification of prior distributions for structural parameters **A**

		Student t			
parameter	economic interpretation	mode (c)	scale (σ)	dof (ν)	sign
a^s_{qp}	Price elasticity of wheat supply	0.1	0.2	3	+
a_{yp}	Effect of p_t on global economic activity	-0.05	0.1	3	-
a^d_{qy}	Income elasticity of wheat demand	0.3	0.2	3	+
a^d_{qp}	Price elasticity of wheat demand	-0.1	0.2	3	-
a_{iq}	Effect of q_t on wheat inventories	0	0.5	3	()
a_{ip}	Effect of p_t on wheat inventories	0	0.5	3	()

Notes: the location parameter is the mode of the t distribution, the scale parameter is its standard deviation, while "dof" denotes its degrees of freedom. "Sign" indicates whether a sign restriction has been enforced.

Priors for coefficients of the wheat supply equation. Most of the empirical studies find evidence of small positive price elasticity of wheat supply. Lin and Dismukes (2007) report the country-specific acreage responses to domestic producer prices in the range $0.08 - 0.41$.[6]

[6] Lin and Dismukes (2007) find that the average supply elasticity in the case of wheat is equal to 0.18. For

Moreover, Roberts and Schlenker (2013) show that the response of agricultural producers to unexpected increase in the prices of corn, rice, soybeans and wheat ranges approximately from 0.09 to 0.12. Similarly, Haile et al. (2016), using a cross-country panel dataset, show that the price supply elasticity of wheat is 0.11. Consistently with these studies, we set for a^s_{qp} a Student t prior distribution with mode $c_{a^s_{qp}} = 0.1$ and support restricted on a positive domain.

Priors for coefficients of the economic activity equation. The structural parameter a_{yp} measures the impact of a change in the real price of wheat on the world industrial production index. For the parameter a_{yp} we use a Student t distribution whose support is constrained to be negative. Since agricultural expenditure represents a small share of the global GDP, a rise in the price of wheat causes a small decline in the proxy for real economic activity, we set $c_{a_{yp}} = -0.05$.[7]

Priors for coefficients of wheat consumption demand equation. The first structural parameter of equation 5c is $a^d_{q,y}$, which represents the income elasticity of wheat demand. Kumar et al. (2011) show that the income elasticity of wheat in India is remarkably stable across different households wealth-groups and consistent over time at around 0.075. Moreover, Femenia et al. (2019) show that the estimate income elasticity of cereals demand ranges from 0.21 to 0.43. Other empirical studies investigate the calorie-income elasticities in Asia (e.g. China, India, Indonesia, Philippines, Vietnam), South America (e.g. Brazil, Mexico) and in a limited number of African regions (e.g. Kenya, Nigeria, Rwanda, Tanzania, Uganda), with an average income elasticity of 0.30, as shown by Ogundari and Abdulai (2013) and Zhou and Yu (2015). In this literature it is widely accepted that the income elasticity of food commodities is positive and smaller than one. This is consistent with the fact that spending on food increases less than proportionally with total expenditures (i.e. Engel's law). Specifically, for low income countries, food makes up an important share of household

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each country, the numerical estimates of the wheat price supply elasticity are reported in parenthesis. Egypt (0.25), South Africa (0.09), China (0.09), India (0.29), Pakistan (0.23), Argentina (0.41), Brazil (0.43), Turkey (0.20), Iran (0.08), EU (0.12), Russia (0.19), Canada (0.39), United States (0.25) and Australia (0.33).

[7] FAO shows that agricultural contribution to real GDP fell from 5% to 3.9% over the period 1970-2017, see `http://www.fao.org/3/cb2279en/cb2279en.pdf`.

spending, whereas for middle and high income countries the share of total wealth devoted to food consumption declines. Therefore, we form our prior beliefs about a^d_{qy} based on previous studies and we assign Student t prior distribution with mode at $c_{a^d_{qy}} = 0.3$ and support constrained to be non-negative. For the price elasticity of wheat demand, a^d_{qp}, we use a Student t prior distribution, centered at $c_{a^d_{qp}} = -0.1$, whose support is constrained to be negative. The location parameter and the sign restrictions are consistent with a large body of empirical studies, such as Chabot and Dorosh (2007), Imai et al. (2011), Roberts and Schlenker (2013) and Gouel et al. (2016).

Priors for coefficients of wheat inventory demand equation. For the parameters describing the effects of production and price on change in inventories, namely $a_{\Delta i,q}$ and $a_{\Delta i,p}$, we opt for relatively uninformative Student t prior distribution, with location parameters set at 0 and with support over the entire real line. Our choice of these priors is consistent with the view that changes in wheat inventories can be driven by both production or consumption smoothing and precautionary decisions.

3.3 The equilibrium feedback effects and the structural shocks

This subsection provides the economic interpretations of the structural shocks, describing their effects on the endogenous variables. Thus, the equilibrium impacts of the structural shocks on $\mathbf{y}_t$ are given by $\mathbf{H} \equiv \mathbf{A}^{-1} = \frac{1}{\det(\mathbf{A})}\mathbf{H}^*$,
where the determinant of the contemporaneous structural matrix is:

$$\det(\mathbf{A}) = a^s_{qp} - a^d_{qp} - a_{ip} - a_{iq}a^s_{qp} - a^d_{qy}a_{yp}$$

and $\mathbf{H}^*$ is defined as follows:

$$\mathbf{H}^* \equiv \begin{bmatrix} -a_{ip} - a_{yp}a^d_{qy} - a^d_{qp} & a^s_{qp}a^d_{qy} & a^s_{qp} & a^s_{qp} \\ a_{yp}(a_{iq} - 1) & a^s_{qp} - a^d_{qp} - a_{ip} - a^s_{qp}a_{iq} & a_{yp} & a_{yp} \\ a_{iq} - 1 & a^d_{qy} & 1 & 1 \\ -a_{ip} - a_{iq}a^d_{qp} - a_{iq}a^d_{qy}a_{yp} & a^d_{qy}(a^s_{qp}a_{iq} + a_{ip}) & a^s_{qp}a_{iq} + a_{ip} & a^s_{qp} - a^d_{qp} - a_{yp}a^d_{qy} \end{bmatrix}$$

It is worth noting that, we do not use any priors on the elements of $\mathbf{H}$ for the identification of the structural shocks, as opposed to traditional sign-restricted SVAR models. Thus, the sign of the impact multiplier matrix is:

$$\text{sign}(\mathbf{H}) = \begin{pmatrix} \underbrace{-}_{(89\%)} & \underbrace{+}_{(89\%)} & \underbrace{+}_{(89\%)} & \underbrace{+}_{(89\%)} \\ \underbrace{-}_{(86\%)} & \underbrace{+}_{(98\%)} & \underbrace{-}_{(89\%)} & \underbrace{-}_{(89\%)} \\ \underbrace{+}_{(86\%)} & \underbrace{+}_{(89\%)} & \underbrace{+}_{(89\%)} & \underbrace{+}_{(89\%)} \\ \underbrace{-}_{(67\%)} & \underbrace{-}_{(68\%)} & \underbrace{-}_{(68\%)} & \underbrace{+}_{(89\%)} \end{pmatrix} \tag{7}$$

and the values in parenthesis represent the prior probabilities implied by model (1) that the impact responses of the endogenous variables to each structural shock are coherent with the sign-structure grounded on the theory of competitive storage.[8]

A wheat supply shock (v_{1t}). A negative wheat supply shock corresponds to a shift to the left of the contemporaneous wheat supply curve along the wheat demand curve. This shock represents wheat production shortfalls which are mainly driven by adverse weather conditions (e.g. extreme rainfall, temperature anomalies and threats from fungus and emerging diseases), scarcity of natural resources (e.g. land deterioration for urbanization, water-related risks, declining soil fertility, droughts and flooding), use of petroleum-based inputs (e.g. pesticides, fertilizers and costs of transports) and biofuel programs (e.g. land deterioration of area dedicated to planting wheat in favour of more efficient energy crops). According to equation (7), a negative wheat supply shock causes a simultaneous reduction in the global wheat production and world industrial production, both with probabilities of 89% and 86%. Moreover, this shocks induces a contemporaneous reduction in inventories with the probability of 67% and it is associated with an instantaneous increase in the real price of wheat with probability of 86%.

[8]The single column of $\mathbf{H}$ indicates the response of each endogenous variable to a given structural shock. For example, the impact response of the real price of wheat (III variable) to an economic activity shock (II structural shock) is given by the element $\mathbf{H}[3, 2]$.

An economic activity shock (v_{2t}). A positive economic activity shock represents a shift to the right of the contemporaneous wheat demand curve along the wheat supply curve, mainly driven by economic growth. This reflects a rise in the aggregate demand for wheat and possibly for others world's most predominant staple food commodities, such as corn, rice, and soybeans driven by fluctuations in the global business cycle (e.g. increase in the consumption patterns of emerging Asian and other developing countries). Thus, a positive economic activity shock is contemporaneously associated with a rise in the world industrial and wheat production, with probabilities of 98% and 89%, respectively. Moreover, this shock induces an increase in the real price of wheat with probability of 89% and a reduction in the inventory changes with probability of 68%, on impact.

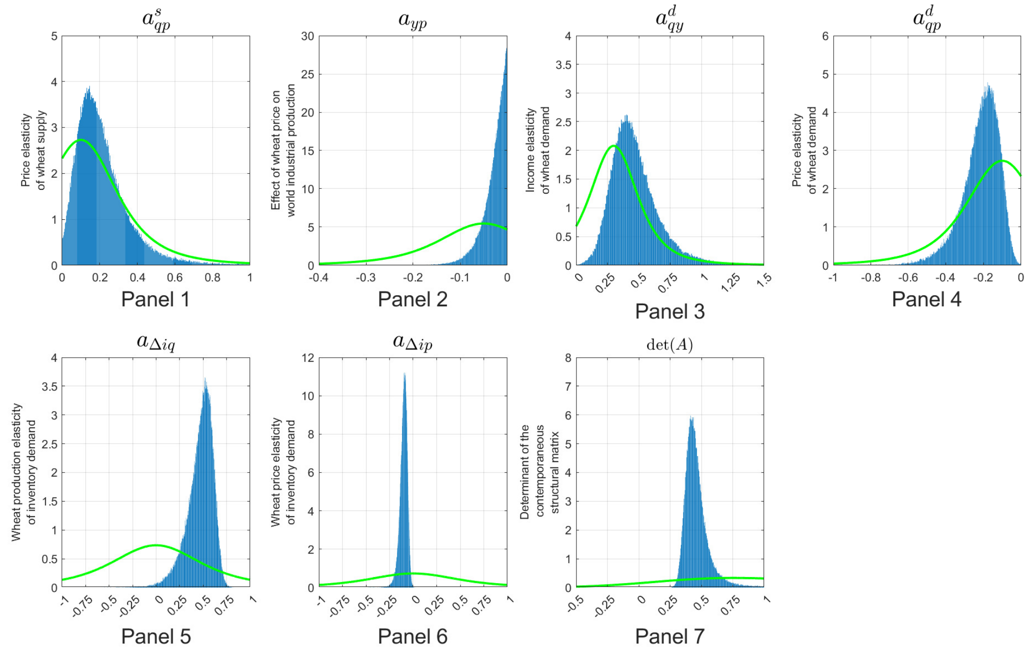
A wheat consumption demand shock (v_{3t}). A positive consumption demand shock represents a shift to the right of the contemporaneous wheat demand curve along the wheat supply curve, not already captured by shocks to the real economic activity (e.g. increase in the demand for domestic food, for livestock feed and for non-food and industrial applications). Thus, a positive wheat consumption demand shock causes a contemporaneous increase in the real price of wheat and in the wheat production with probabilities of 89%. As opposed, world industrial production and wheat inventories are negatively affected by positive shifts in the consumption demand curve, with probability of 89% and 68%, respectively.[9]

A wheat inventory demand shock (v_{4t}). An inventory demand shock induces a shift in the demand for storage in the global wheat market. This shock it is designed to capture changes in the expectations-driven components of the real price of wheat related to future supply and demand conditions (e.g. holding inventories for strategic decisions, trade policy interventions such as export restrictions). A positive inventory demand shock assigns a 89% probability to cause a contemporaneous increase in wheat stocks, production and price and a reduction in the industrial production index. The standard arbitrage assumptions imply a speculative pass-through from the futures market to the spot market, via inventory shifts.[10]

[9]It is worth noting that the effect of a positive consumption demand shock on wheat inventories corresponds to $\mathbf{H}^*[4,1]/\det(\mathbf{A})$ and its uncertainty arise from the sign restrictions imposed on the determinant of $\mathbf{A}$ and the parameters a^s_{qp}, a_{iq} and a_{ip}.

[10]It is worth noting that, in presence of asymmetric information, financial speculation can drive up the

Figure 1: Priors and posteriors for structural coefficients in model (1).



Note: blue bars denote the posterior distributions for the contemporaneous structural coefficients, while green line plots the corresponding priors.

4 Empirical results

4.1 Priors and posteriors for the contemporaneous structural coefficients

Posteriors for the wheat supply equation. The posterior median distribution of the price elasticity of wheat supply, a^s_{qp}, is 0.19 and its distribution is skewed to the right, as reported in Panel 1 of Figure 1. This result implies that, holding everything else constant, a 10% increase in wheat price tends to rise global wheat production by 1.9%. The posterior median for a^s_{qp} is slightly higher than its prior-mode and the empirical estimates available in the literature (e.g. see Haile et al. (2016) and Iqbal and Babcock (2018)).[11]

Posteriors for the economic activity equation. The posterior distribution of a_{yp} has median of -0.01 and has smaller variance than the corresponding prior. This result suggests that

spot price of a storable commodity without necessarily reducing the aggregate consumption and raising inventories, as discussed in Sockin and Xiong (2015). However, we expect that in case of annual data the arbitrage impediments do not represent an issue for our structural analysis.

[11]In the Appendix, we assess the robustness of our empirical results along two main dimensions. First, we increase the uncertainty of the priors assigned to a^s_{qp} and a^d_{qp}. Second, we estimate model 1 by replacing the WIP index with a different measure of economic activity, that is the global real GDP.

an increase in the real price of wheat is associated with a very small reduction in the world industrial production index, within the year.

Posteriors for the wheat consumption demand equation. Our estimates of the posterior median of the own-price elasticity of wheat demand, a^d_{qp}, is -0.20 and its distribution is skewed to the left, as shown in Panel 4 of Figure 1. The posterior median estimate for a^d_{qp} is smaller than the prior-mode but it is in line with the literature (see e.g. Roberts and Schlenker (2013)).[12] Panel 3 of Figure 1 plots the posterior distribution for the income elasticity of wheat demand, with a median of 0.4. Based on our estimate we conclude that a 10% increase in the world industrial production raises the consumption of wheat by 4%. This suggests that the wheat demand for current consumption is positively influenced by an economic growth.

Posteriors for the wheat inventory demand equation. The posterior distribution of a_{iq} reported in Panel 5 of Figure 1 has median equal to 0.3 and mass concentrated on the positive support. This is reasonable, since the abundance of wheat production causes a stock build-up in the storage market. The posterior median of the wheat price elasticity of inventory demand a_{ip} – reported in Panel 6 of Figure 1 – amounts to -0.1 and its distribution is narrower than the prior, suggesting that the data are very informative about the negative relationship between price and inventories. This result implies that farmers are willing to release inventories in an effort to smooth consumption and/or production, especially during periods of wheat market stress (see e.g. Pindyck (1994) and Schewe et al. (2017)).

Posteriors for the determinant of $\mathbf{A}$ *and for the sign of* $\mathbf{H}$. Panel 7 of Figure 1 shows that the prior distribution is almost flat when viewed on the scale adjusted for the posterior distribution of $\det(\mathbf{A})$. Since the mass of $\det(\mathbf{A}|\mathbf{Y_t})$ is concentrated on a positive domain we are able to recognize the signs of the structural shocks. Thus, we show that the sign-structure on the impact multiplier matrix, denoted by $\text{sign}(\mathbf{H}|\mathbf{Y}_T)$, is consistent with the

[12] We refer to the estimate of the maize log-price demand elasticity reported in panel B of Table 7 in the study of Roberts and Schlenker (2013).

theory of competitive storage, that is:

$$\text{sign}(\mathbf{H}|\mathbf{Y}_T) = \begin{pmatrix} \underbrace{-}_{(100\%)} & \underbrace{+}_{(100\%)} & \underbrace{+}_{(100\%)} & \underbrace{+}_{(100\%)} \\ \underbrace{-}_{(100\%)} & \underbrace{+}_{(100\%)} & \underbrace{-}_{(100\%)} & \underbrace{-}_{(100\%)} \\ \underbrace{+}_{(100\%)} & \underbrace{+}_{(100\%)} & \underbrace{+}_{(100\%)} & \underbrace{+}_{(100\%)} \\ \underbrace{-}_{(100\%)} & \underbrace{-}_{(61\%)} & \underbrace{-}_{(61\%)} & \underbrace{+}_{(100\%)} \end{pmatrix} \tag{8}$$

Two main points emerge from the results reported in Section 4.1. First, most of the coefficients are well identified – when priors are combined with the sample data – due to the fact that their posterior distributions move away – with small variance – from the corresponding prior distributions, as shown in Figure 1. Second, the comparison between equations 7 and 8 shows a drastic drop in the uncertainty around most of the signs of the equilibrium impacts of the structural shocks.

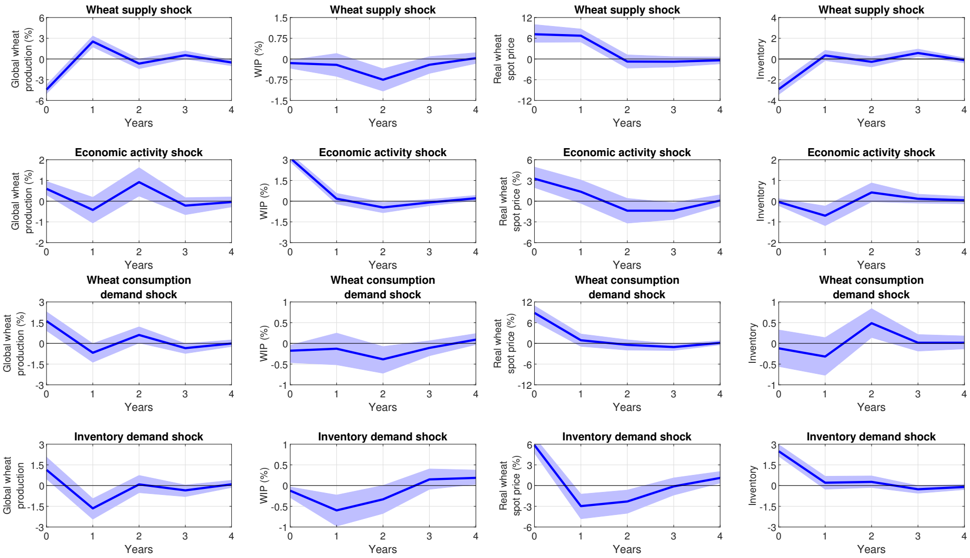
4.2 Impulse response functions

Figure 2 relies on a panel of graphs, each of one plotting the median impulse responses of the endogenous variables to each (one-standard deviation) structural shock, together with the highest posterior credible region set at 68% level.

The first row of the panel shows that a wheat supply disruption immediately declines wheat production by 4.4%, raises its price by 7.2% and reduces inventories and economic activity by 2.9% and 0.15%, respectively. This shock generates a large transitory increase in global production during the first year after the shock, which is highly credible if 68% density region is considered. Finally, our result indicates that wheat supply shocks have persistent price effects over two years.

The second row of the panel illustrates that a positive economic activity shock raises the world industrial production and the real price of wheat by 3.1% and 3.3%, on impact. The dynamic effect of an economic activity shock on production is uncertain, when 68% posterior credible sets are considered and inventories reduce by 0.7% in the next year after the shock.

Figure 2: Impulse response functions of model 1



Note: blue lines indicate the posterior median impulse responses to a one-standard deviation structural shock, for model 1. Blue shaded bands indicate the posterior credibility regions at 68%. The wheat supply shock has been normalized to imply an increase in the real price of wheat.

This results are consistent with the fact that producers takes time to respond fully to such a change in demand and in the meantime, inventories are drawn down to compensate for the slow adjustment in production.

The third row of the panel shows that a standard deviation shock to consumption demand raises the real price of wheat and production up to 8.8% and 1.6%, on impact. This shock induces a small reduction in both inventories and real output after one year, however the 68% posterior credibility sets are wide and include the zero value.

Finally, the fourth row of the panel presents the response of the variables to a positive inventory demand shock. This causes an immediate jump in the inventory levels and in the real price of wheat by about 2.5% and 5.9%, respectively. Its positive effect on price and inventories declines gradually during the horizon of reference. This shock induces an increase in wheat production up to 1.1%, on impact. However, this effect seems to be short-lived, indeed the response of production gradually declines and its largest reduction is around 1.7%, in the next year after the shock. Finally, our results indicate that a positive inventory demand shock is accompanied by a persistent drop in the growth rate of world industrial production.

Figure 2 shows some important features. First, the impact responses of the endogenous variables to each structural shock are grounded on the theory of competitive storage. Second, we find that supply shocks have persistent price effect and the dynamics of the response of change in inventories to a positive consumption demand shock is rather different from the response to a wheat supply disruption. Our results indicate that inventory-holding countries are aware of the adverse effects of supply shock and tend to release large amount of stocks in an effort to smooth consumption. Third, our analysis is based on the presumption that these shocks are mutually uncorrelated but they could simultaneously hit the market, at each point in time. Therefore, understanding how different price-shocks influence storage can be useful for midstream and downstream wheat-specific industry, for several reasons. First, it allows to reduce marketing costs and to avoid stock-outs. Second, it optimizes the exposure to futures markets and it helps to implement accurate stocks management strategies which combine expected price returns with optimal levels of inventories net of the storage and opportunity costs. Finally, our results are consistent with the view that inventory demand shocks cause a substantial reduction in the level of stocks available for production and/or consumption smoothing. Therefore it is also important to encourage measures for price-stabilization, which are based on trade integration and complementary to inventory-management strategies (e.g. see Glauber and Miranda (2016), Martin and Ivanic (2016) and Bouët and Laborde Debucquet (2016)).

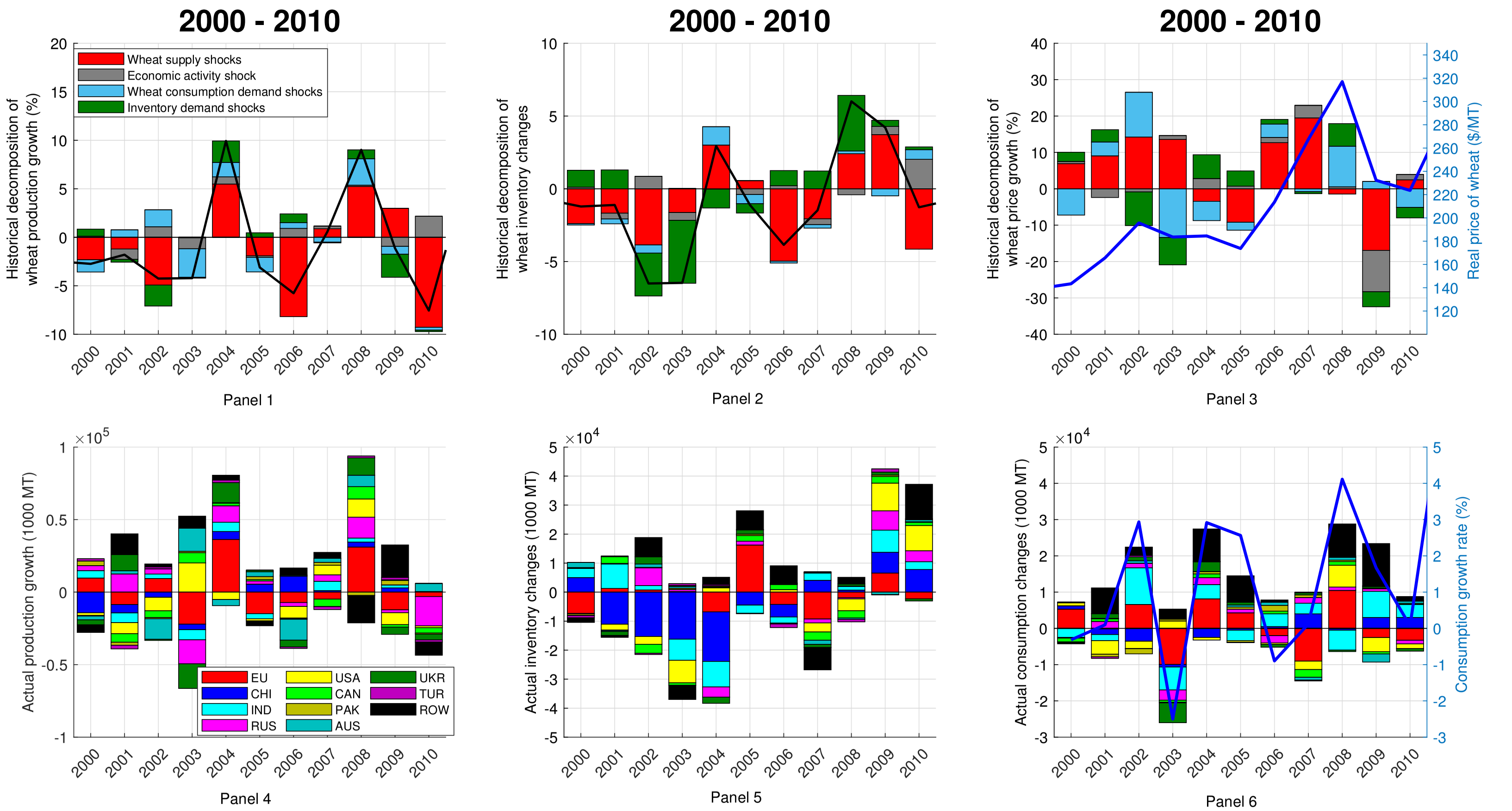
4.3 Historical decomposition

In this section, we present results of historical decomposition for production, price and inventories during three important exogenous events in the global wheat market.[13]

The commodity prices surge and their subsequent collapse (2006-2009). The real price of wheat rose by 214 to 317 dollars per metric tons, that represented a 60% increase between 2006 and 2008. Over the time period under analysis, the wheat price spike was mainly

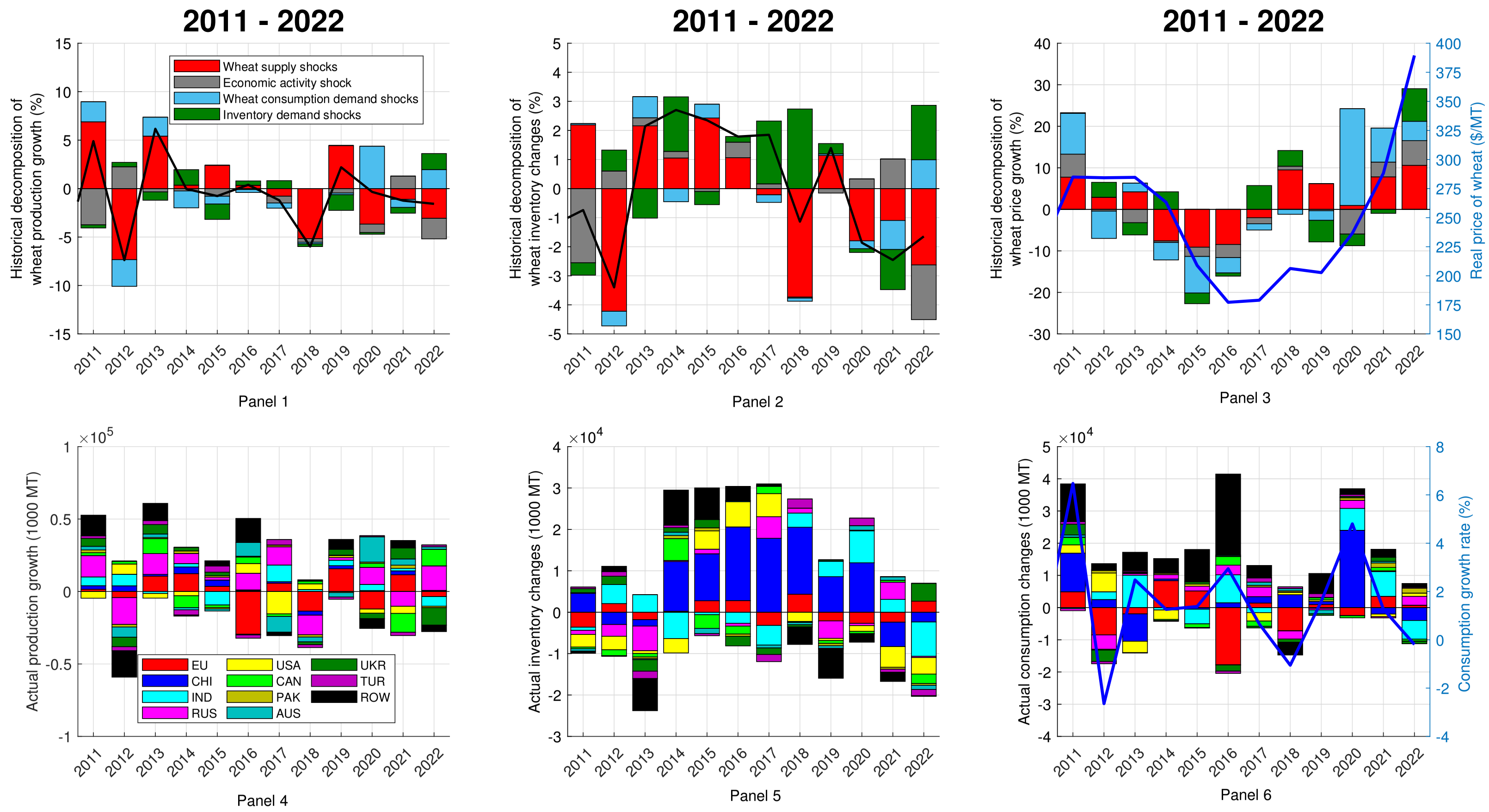
[13]The results of the historical decomposition for the inventory changes and the annual growth rates of production and price of wheat are illustrated in the upper panels of Figures 3 and 4. The actual series of changes in global wheat production, inventory and consumption of the most relevant wheat producing countries are shown in the bottom panels of Figures 3 and 4. Finally, the historical decomposition of the variables under scrutiny is normalized to obtain the value of the actual data.

Figure 3: Historical decomposition of production, price and inventory during the period 2000-2010



Note: The first row of the panel shows the (posterior median) historical decomposition derived from model (1). The bars illustrate the contribution of each structural shock to the growth rate of production, price and inventory changes during the period 2000-2010. The second row of the panel illustrates the breakup of changes in production, inventory and consumption.

Figure 4: Historical decomposition of production, price and inventory during the period 2011-2022



Note: The first row of the panel shows the (posterior median) historical decomposition derived from model (1). The bars illustrate the contribution of each structural shock to the growth rate of production, price and inventory changes during the period 2011-2022. The second row of the panel illustrates the breakup of changes in production, inventory and consumption.

explained by supply and consumption demand shocks, as illustrated in Panel 3 of Figure 3. Specifically, negative shocks to supply – likely explained by an increase in the energy price costs (e.g. see Baffes and Haniotis (2016)) – raised the real price of wheat by 13% in 2006 and 19% in 2007, while positive shocks to consumption demand – likely driven by the use of agricultural commodities in biofuel production (e.g. see Carter et al. (2017)) – increased by 11% the real price of wheat in 2008. Our analysis shows that the combined effects of supply and consumption demand shocks accounts for 45% of the total log-price change during the period 2006-2008.

The importance of inventory demand shocks turn out to be high and non-negligible during the 2008 food crisis. Panel 2 of Figure 3 shows that the estimated increase in the global wheat stocks in 2008 is about 6%, out of which 2% due to supply shocks and 4% due to inventory demand shocks. Moreover, we find that inventory demand shocks affect wheat price by 6% in 2008, as illustrated in Panel 3 of Figure 3. These results are consistent with the view that, national-policy based on trade restrictions – in terms of export bans and reduction of import barriers – exacerbated panics in the global wheat market and increased the demand for storage.[14] Moreover, panel 5 of Figure 3 shows that, in 2008, the change of inventory increased by 41558 metric tons, out of which is 32% due to Russia and European Union, 23% due to United States, 18% is due to India and 17% is due to China, as shown in . By late 2009, the real price of wheat fell by 31%. We find that 17% of the price reduction can be explained by supply shocks, 11% by economic activity shocks and 2% by the net-effects of consumption and inventory demand shocks, as show in panel 3 of Figure 3.

Droughts and weather shocks in some producer countries (2010 and 2012). In 2010, annual global wheat production decreased by 37520 metric tons, a 6% reduction from the previous year, as shown in Panel 4 of Figure 3. This sharp contraction was primarily driven by poor harvests due to droughts and adverse weather conditions in Russia and Ukraine, which both accounted for 54% and 11% of wheat disruption at the world level. Panels 1 and 3 of Figure 3 point out that negative supply shocks lowered production by 9% and increased wheat prices by 2%. The positive response of wheat prices to supply disruption was more than offset

[14]For instance, on January 29, 2008, Russia levied a 40 percent export tax on wheat traveling to all countries other than those in their customs union.

by negative shocks to consumption and inventory demand. The combined effect of these shocks caused a drop in the real price of wheat by about 8%. In 2012, droughts in Russia, Ukraine together with below-average rainfall in Australia and adverse weather conditions in the rest of the world caused a contraction of wheat production by 6% relative to the previous year. Panel 3 of Figure 4 shows that, in 2012, negative supply shocks raised price by 3%. Moreover, shocks to inventory demand – as a form of insurance against food insecurity – affected price by 4%. Conversely, negative consumption demand shocks induced a reduction in the real price of wheat by 7%. As a result, the net effect of all shocks on the annual growth rate of the real price of wheat was nil.

The COVID-19 outbreak and the Russia-Ukraine war (2020-2022). Between 2020 and 2022, the rise in the real price of wheat was followed by a number of exogenous events, such as, the COVID-19 pandemic, the Russia's invasion of Ukraine and the episodes of heatwaves in some crop-producing countries. Panel 3 of Figure 4 shows that a negative economic activity shock – likely driven by the downturn in world industrial production due to the COVID-19 outbreak – reduced the real price of wheat by 6% in 2020. At the same time, a negative shock to demand for storage lowered wheat price by 3%, while a positive shock to wheat consumption increased the real price of wheat up to 23%. It is worth noting that, within the pandemic period, China was the most important contributor to consumption of wheat at the world level, as show in panel 6 of Figure 4). During the 2022 crisis, the Russia-Ukraine war caused a phenomena of trade disruption, which represented a serious impediment to transport grain from Ukraine to rest of the world. This resulted in a significant accumulation of wheat inventory from Ukraine, as illustrated in panel 5 of Figure 4. This episode is linked to positive inventory demand shock, that caused an increase in the real price of wheat by 8% as reported in panel 3 of Figure 4). Moreover, economic activity shock and consumption demand shocks contributed to increase price by 6% and 5%, respectively. Finally, negative supply shocks – likely driven by climate conditions and crop disruptions triggered by the Russia-Ukraine war – rose the real price of wheat by 11%. Overall, in 2022, all structural shocks contributed to raise the real price of wheat by 29%.

4.4 The recursive SVAR model

The aim of this section is to propose a Bayesian interpretation of the Cholesky identification scheme considered in model 1, with the endogenous variables ordered as $(q_t, y_t, \Delta i_t, p_t)$.

The Cholesky-type identified SVAR model is:

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ -a_{yq}^{\text{Chol}} & 1 & 0 & 0 \\ -a_{iq}^{\text{Chol}} & -a_{iy}^{\text{Chol}} & 1 & 0 \\ -a_{pq}^{d\text{Chol}} & -a_{py}^{d\text{Chol}} & -a_{pi}^{d\text{Chol}} & 1 \end{bmatrix}}_{\mathbf{A}^{\text{Chol}}} \underbrace{\begin{bmatrix} q_t \\ y_t \\ \Delta i_t \\ p_t \end{bmatrix}}_{\mathbf{y}_t^{\text{Chol}}} = \mathbf{B}^{\text{Chol}} \mathbf{x}_{t-1}^{\text{Chol}} + \underbrace{\begin{bmatrix} v_{1t}^{\text{Chol}} \\ v_{2t}^{\text{Chol}} \\ v_{3t}^{\text{Chol}} \\ v_{4t}^{\text{Chol}} \end{bmatrix}}_{\mathbf{v}_t^{\text{Chol}}} \tag{9}$$

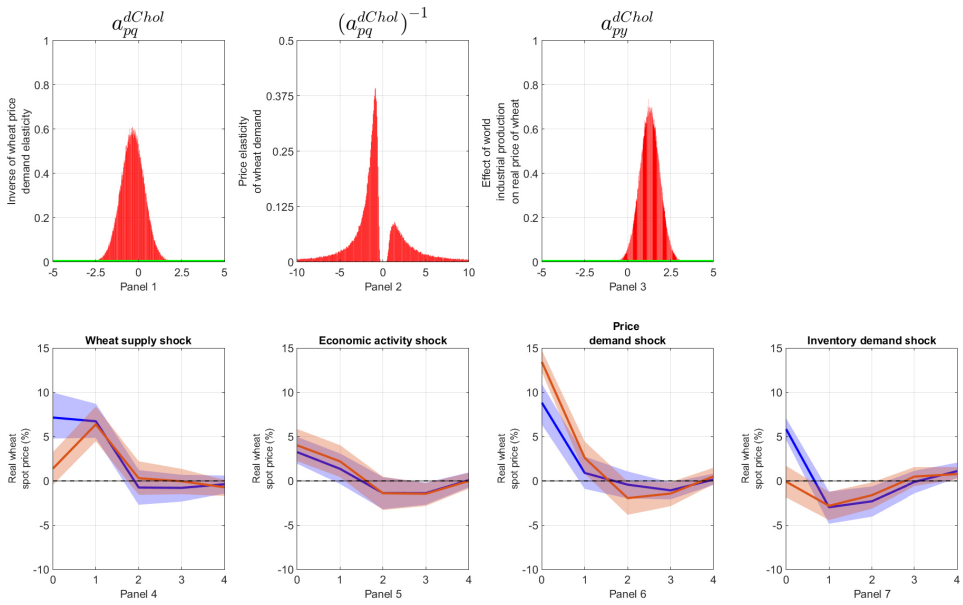
and the implied triangular structure can be motivated by the sequence of economic decisions in the global grain market, as discussed in Ghanem and Smith (2022).[15] Given the recursive scheme of model 9, the first structural shock v_{1t}^{Chol} is related to the global production of wheat (wheat supply shock). The second shock is v_{2t}^{Chol} and it captures innovations triggered by unpredictable fluctuations in the global business cycle (economic activity shock). The third shock is v_{3t}^{Chol} and it refers to unexpected shifts in the demand for wheat inventories (inventory demand shock). Finally, the residual structural shock is v_{4t}^{Chol} and it is designed to capture the wheat-specific demand shock (price demand shock).

The recursively identified model implies that we know with certainty that wheat producers do not react to changes in any variables of the system. In other words, model 9 is fully consistent with the assumption of a vertical supply curve, that is $a_{qp}^s = a_{qy}^s = a_{qi}^s = 0$. Moreover, the world industrial production is not contemporaneously affected by the change in inventories and price, that is $a_{yi} = a_{yp} = 0$. Finally, the change in inventories is predetermined with respect to the real price of wheat, namely $a_{ip} = 0$. After using six exclusion restrictions, we act as *nothing at all is known* about the remaining structural coefficients. Thus, for the free-parameters, that is, $a_{yq}, a_{yp}, a_{iq}, a_{pq}^d, a_{py}^d$ and a_{pi}^d we assign completely uninformative

[15]It is worth noting that the inclusion of the inventory – among the set of the endogenous variables – renders the Cholesky identification difficult to reconcile with the economic theory. This is motivated by the fact that it is not trivial to establish an ordering between inventories and price without relying on any strong assumptions. Therefore, we propose an alternative recursive SVAR, whose identification and results are discussed in the Appendix.

Student t prior distributions, with mode 0, standard deviation 100 and 3 degrees of freedom.

Figure 5: Cholesky-type identification SVAR model.



Note: Prior (green lines) and posterior (red histograms) distributions considered in model ?? using Cholesky identification. Solid red lines indicate the median impulse response estimates based on model 9. Solid blue lines refer to the median posterior estimated of model 1. Shaded regions indicate the corresponding 68% credible set.

Panel 1-3 of Figure 5 plots the prior and posteriors distributions for model 9. Panels 4-7 report the median impulse responses of the growth rate of the real price of wheat to each structural shock, implied by the structural models 9 and 1, respectively. The validity of model 9 relies on the economic motivations behind each zero restriction. On this respect, three important issues emerge. First, the assumption of a vertical supply curve in case of annual and global analysis might be less realistic and difficult to justify from the economic point of view. Second, the exclusion restriction on a_{ip} is not consistent with the theory of competitive storage that highlights the important role for the change in inventories to buffer the adverse effects of price-shocks during the year. Finally, the idea of having full knowledge about the value of some parameters and being completely agnostic on other coefficients leads to unrealistic estimates of the price demand elasticity. Our non-recursive model presented in Section 3, assigns a 82% probability to the price consumption demand elasticity falls in the interval [-0.3,0], a 5% probability to a_{qp}^{d} less than -0.4 and no mass of probability exists for values of the elasticity smaller than -0.8. Following Baumeister and Hamilton (2019), Instead, for model 9 we find that the posterior distribution for $a_{pq}^{d\text{Chol}}$ has most of its mass between -1.5 and 0.5. Moreover, the posterior distribution for the price demand elasticity $(a_{pq}^{d\text{Chol}})^{-1}$ falls within $(-\infty, -0.5] \cup [0.5, +\infty)$ and has median estimate of -1.08. These outcomes indicate extremely large values for $(a_{pq}^{d\text{Chol}})^{-1}$ and they are consistent with the view that the demand curve is flat and possibly upward sloping. This outcome can be explained by a low correlation between the reduced-form residuals for production and price, as discussed in Baumeister and Hamilton (2019) and Caldara et al. (2019). Consistent with the estimates of these elasticities, the triangular SVAR attributes a somewhat larger explanatory power to price demand shocks and less explanatory power to wheat supply shocks, as shown in panels 4 and 6 of Figure 5.

Overall, the empirical results based on annual data and obtained from the recursive configuration of the global wheat market are potentially misleading and difficult to reconcile with the economic theory of competitive storage.

5 Conclusions

International food price spikes might exacerbate poverty and food insecurity and undermine the power of political leaders for low-income countries. Price shock might be triggered by shifts in demand for consumption, demand for storage and demand related to economic activity or by a contraction in supply. Therefore, for policymakers it is crucial to understand which factors are relevant in explaining the wheat-price dynamics. To this end, we use a revised version of the Bayesian SVAR model, originally developed by Baumeister and Hamilton (2019) – for crude oil market – to identify the underlying structural shocks, which are interpreted as the fundamental driving forces of the international market for wheat.

To our knowledge, this paper offers the first SVAR analysis of the global wheat market that considers observations regarding production jointly with change in inventories and exploits an inventory-detection strategy to identify the structural shocks of interest. We provide empirical evidence that: (i) the posterior median estimates for the price elasticity of supply and demand amount to 0.19 and -0.20, respectively; (ii) the response of price to a negative supply shock is positive and persistent after more than one year; while consumption demand shocks cause a rise in price but the effect is less persistent if compared to supply shocks; (iii) economic activity and inventory demand shocks are rapidly absorbed and (iv) the results obtained by recursively identified SVAR model of the global wheat market with annual data are potentially misleading and difficult to reconcile with the economic theory of competitive storage. We believe these findings are relevant in order to understand the possible propagation of global wheat market shocks and to design specific policy to encourage food security.

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Appendix

Contents

A The identification algorithm

This section provides a brief description of the Baumeister and Hamilton (henceforth, BH) identification approach.[1] The SVAR model of the global wheat market can be written as:

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{v}_t \tag{1}$$

where:

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & -a_{qp}^{s} & 0 \\ 0 & 1 & -a_{yp} & 0 \\ 1 & -a_{qy}^{d} & -a_{qp}^{d} & -1 \\ -a_{iq} & 0 & -a_{ip} & 1 \end{bmatrix}.$$

$$\mathbf{y}_t \equiv [\Delta q_t, y_t, p_t, \Delta i_t]'\,;$$

$$\mathbf{B} = \begin{bmatrix} \mathbf{b}_1' \\ \mathbf{b}_2' \\ \mathbf{b}_3' \\ \mathbf{b}_4' \end{bmatrix};$$

$$\mathbf{b}_1' = [b_{1,qq}^{(s)},\ b_{1,qy}^{(s)},\ b_{1,qp}^{(s)},\ b_{1,qi}^{(s)},\ b_{2,qq}^{(s)},\ b_{2,qy}^{(s)},\ b_{2,qp}^{(s)},\ b_{2,qi}^{(s)},\ 1];$$

$$\mathbf{b}_2' = [b_{1,yq},\ b_{1,yy},\ b_{1,yp},\ b_{1,yi},\ b_{2,yq},\ b_{2,yy},\ b_{2,yp},\ b_{2,yi},\ 1];$$

$$\mathbf{b}_3' = [b_{1,qq}^{(d)},\ b_{1,qy}^{(d)},\ b_{1,qp}^{(d)},\ b_{1,qi}^{(d)},\ b_{2,qq}^{(d)},\ b_{2,qy}^{(d)},\ b_{2,qp}^{(d)},\ b_{2,qi}^{(d)},\ 1];$$

[1] It is worth noting that for the sake of transparency our notation is very similar to that reported in the BH algorithm and for further technical details the reader is referred to Baumeister and Hamilton (2015), Baumeister and Hamilton (2018) and Baumeister and Hamilton (2021).

$$\mathbf{b}_4' = [b_{1,iq},\ b_{1,iy},\ b_{1,ip},\ b_{1,ii},\ b_{2,iq},\ b_{2,iy},\ b_{2,ip},\ b_{2,ii},\ 1];$$

$$\mathbf{x}_{t-1}' \equiv \left[\mathbf{y}_{t-1}', \mathbf{y}_{t-2}',\ 1\right]';$$

$$\mathbf{v}_t = [v_{1t}, v_{2t}, v_{3t}, v_{4t}]';$$

$$\mathbf{D} = E[\mathbf{v}_t\mathbf{v}_t'] = \begin{bmatrix} d_{11} & 0 & 0 & 0 \\ 0 & d_{22} & 0 & 0 \\ 0 & 0 & d_{33} & 0 \\ 0 & 0 & 0 & d_{44} \end{bmatrix}.$$

Two main steps characterize the BH algorithm. In the first step, we specify priors on the structural parameters for the (i) contemporaneous relationship of the endogenous variables ($\mathbf{A}$), (ii) the variance-covariance matrix of the structural shocks ($\mathbf{D}$) and (iii) the past relationship between the variables ($\mathbf{B}$). In the second step we draw samples from the posterior distribution of the structural parameters using a random walk Metropolis-Hastings algorithm.

A.1 Setting priors for the structural coefficients.

Priors for $\mathbf{A}$. For the contemporaenous structural parameters we specify prior beliefs in terms of Student t density function, with mode, scale parameters and degrees of freedom as illustrated in Table 1 of our manuscript.

As a result, assuming independence across the elements of $\mathbf{A}$, the joint prior distribution of the contemporaneous structural coefficients, denoted by $p(\mathbf{A})$, is:

$$p(\mathbf{A}) = p(a_{qp}^s)p(a_{yp})p(a_{qy}^d)p(a_{qp}^d)p(a_{iq})p(a_{ip})p(h_1) \tag{2}$$

where h_1 denotes the determinant of $\mathbf{A}$.[2]

Priors for $\mathbf{D}|\mathbf{A}$. The prior for the variance-covariance matrix of the structural shocks is:

$$p(\mathbf{D}|\mathbf{A}) = \prod_{i=1}^{n} p(d_{ii}|\mathbf{A}) \tag{3}$$

where

$$d_{ii}^{-1}|\mathbf{A} \sim \Gamma(\kappa, \tau_i).$$

Thus, we assume that the prior for d_{ii} conditional on $\mathbf{A}$ is given by an inverse Gamma distribution where κ/τ_i and κ/τ_i^2 represent the first and second moments, respectively.[3]

Priors for $\mathbf{B} \mid \mathbf{D}, \mathbf{A}$. The prior for the structural matrix governing the past relationship of the variables is:

$$p(\mathbf{B}|\mathbf{D}, \mathbf{A}) = \prod_{i=1}^{n} p(\mathbf{b}_i|\mathbf{A}, \mathbf{D}) \tag{4}$$

where

$$\mathbf{b}_i|\mathbf{A}, \mathbf{D} \sim \mathcal{N}(\mathbf{m}_i,\ d_{ii}\mathbf{M}_i)$$

Thus, we assume that $\mathbf{b}_i$ conditional on $\mathbf{A}$ and $\mathbf{D}$ follows a multivariate Normal distribution where $\mathbf{m}_i$ is the first moment, that is our best guess about $\mathbf{b}_i$ before looking at the data and $\mathbf{M}_i$ is the second moment about the prior. For most parameters $\mathbf{m}_i = \mathbf{0}$ for $i = 1, 2, 3, 4$. The only exceptions are for the lagged coefficients of the supply and the consumption demand equations. Indeed, we set the third elements of $\mathbf{m}_1$ and $\mathbf{m}_3$ to 0.1 and -0.1, respectively. These priors are imposed to better distinguish and identify the effects of supply and consumption demand shocks. A standard Minnesota prior that assigns large confidence that coefficients related to higher lags are zero (see Doan et al. (1984)) is assigned to the prior variance $\mathbf{M}_i$ and the hyper-parameters of the prior for $\mathbf{B}$ are chosen accordingly to Baumeister and Hamilton (2015).

[2] Following Baumeister and Hamilton (2018), we impose a prior asymmetric t distribution to assign probability of observing $h_1 > 0$.

[3] We follow Baumeister and Hamilton (2019) in setting the prior mean for d_{ii}^{-1} equals to the reciprocal of the diagonal element of matrix $\mathbf{ASA}'$, where $\mathbf{S}$ represents the sample variance-covariance matrix of the residuals from the univariate autoregressive models (of order 2) estimated on each endogenous variable. Finally, we set $\kappa = 2$.

The joint prior for $\mathbf{A}, \mathbf{D}, \mathbf{B}$. The joint probability distribution of the prior information about model (1) is given by:

$$p(\mathbf{A}, \mathbf{D}, \mathbf{B}) = p(\mathbf{A})p(\mathbf{D}|\mathbf{A})p(\mathbf{B}|\mathbf{A}, \mathbf{D}) \tag{5}$$

A.2 The posterior distribution of the structural parameters.

The BH algorithm that takes advantage of natural-conjugate prior, therefore the posterior distribution of $\mathbf{A}$, $\mathbf{D}$ and $\mathbf{B}$ turn out to be of the same density of the corresponding priors. The overall joint posterior distribution of model (1) is given by:

$$p(\mathbf{A}, \mathbf{D}, \mathbf{B}|\mathbf{Y_T}) = p(\mathbf{A}|\mathbf{Y_T})p(\mathbf{D}|\mathbf{A}, \mathbf{Y_T})p(\mathbf{B}|\mathbf{A}, \mathbf{D}, \mathbf{Y_T})) \tag{6}$$

where $\mathbf{Y}_T$ represents the data sample and whose components are discussed below.

Posterior for $\mathbf{A}$. Baumeister and Hamilton (2015) derives a closed-form analytical expression for the marginal posterior distribution of the contemporaneous structural matrix ($\mathbf{A}$), which is given by:

$$p(\mathbf{A}|\mathbf{Y}_T) = \frac{\kappa_T p\left(\mathbf{A}\right)\left[\det\left(\mathbf{A}\boldsymbol{\Omega}_T\mathbf{A}'\right)\right]^{T/2}}{\prod_{i=1}^{n}\left[\left(2/T\right)\tau_i^*\right]^{\kappa_i^*}} \prod_{i=1}^{n} \tau_i^{k_i}, \tag{7}$$

where $\kappa_{ij}^* = \kappa_i + (T/2)$, $\tau_i^* = \tau_i + (\xi_i^*/2)$ and κ_T being a constant term for which (7) integrates to unity. Moreover, the value ξ_i^* can be calculated as follows:

$$\xi_i^* = s_i^{\mathbf{yy}} - s_i^{\mathbf{yx}}(s_i^{\mathbf{xx}})^{-1}(s_i^{\mathbf{yx}})'$$

where

$$s_i^{\mathbf{yy}} = \mathbf{a}_i' \sum_{t=1}^{T} \mathbf{y}_t\mathbf{y}_t'\mathbf{a}_i + \mathbf{m}_i'\mathbf{M}_i^{-1}\mathbf{m}_i$$

$$s_i^{\mathbf{yx}} = \mathbf{a}_i' \sum_{t=1}^{T} \mathbf{y}_t\mathbf{x}_{t-1}' + \mathbf{m}_i'\mathbf{M}_i^{-1}$$

$$s_i^{\mathbf{xx}} = \sum_{t=1}^{T} \mathbf{x}_{t-1}\mathbf{x}_{t-1}' + \mathbf{M}_i'$$

A random-walk Metropolis Hastings algorithm is performed to generate different draws of the unknown elements of the contemporaneous structural matrix $\mathbf{A}$.

Posterior for $\mathbf{D}|\mathbf{A}, \mathbf{Y}_T$. Conditional on $\mathbf{A}$ and $\mathbf{Y}_T$, the posterior distribution of the elements of the variance-covariance matrix of the structural shocks $\mathbf{D}$ follows an inverse-gamma with parameters k_i^* and τ_i^*.

Posterior for $\mathbf{B}|\mathbf{A}, \mathbf{D}, \mathbf{Y}_T$. The posterior distribution of the $i-th$ row vector of $\mathbf{B}$ conditional on $\mathbf{A}$, $\mathbf{D}$ and $\mathbf{Y}_T$ is multivariate Normal distribution with first and second moments equal to $\mathbf{m}_i^*$ and $d_{ii}^l\mathbf{M}_i^*$, respectively.

B Robustness checks

In this section we assess the robustness of our empirical results along three main dimensions. First, we perform a sensitivity analysis on both the price elasticity of wheat supply and demand. Second, we use a different measure of real economic activity as a proxy for the global business cycle. On this respect, we replace the world industrial production index with the global domestic product (GDP) at constant prices. Finally, we compare model 1 with a recursive specifications – different from that reported in the article – which relies on the Cholesky identification.

B.1 Sensitivity analysis

The first robustness check relies on a sensitivity analysis of the structural coefficients a^s_{qp} and a^d_{qp}. The main reason behind this exercise is that the data cause modest revisions in our priors about these parameters. Thus, we analyse the impacts of considering more uncertain priors. This can be done by raising the variance of the prior distribution. Therefore, we rely on a Student t density with location parameter and degrees of freedom identical as those reported in Table 2 of our manuscript but we raise the scale parameter. In particular, we increase the prior variance by a factor of 2, 4, and 8 to investigate the effects of using less informative priors on the coefficient under scrutiny.

B.1.1 The price elasticity of wheat supply

The baseline prior for a^s_{qp} is a Student t distribution, with mode set at 0.1, scale parameter set at 0.2, degrees of freedom set at 3 and support restricted to be positive. This implies a 71% probability that the annual price elasticity of wheat supply falls in the interval [0, 0.3], as illustrated in panel A of Table (B1). Thus, the baseline prior for a^s_{qp} is coherent with the main characteristics of the global grain market and it is in line with the empirical estimate of Haile et al. (2016). In contrast, the alternative priors for a^s_{qp} – with scale parameters $\sigma^s_{qp} = 0.2 \times 4 = 0.8$ and $\sigma^s_{qp} = 0.2 \times 8 = 1.6$ – are highly uninformative. Panels 2 and 3 of Figure A1 show that these priors are almost flat when compared to the baseline prior used in model 1. Moreover, these priors assign a 50% and a 67% probability to a price supply

Table B1: Implied probabilities for price supply and price demand elasticities

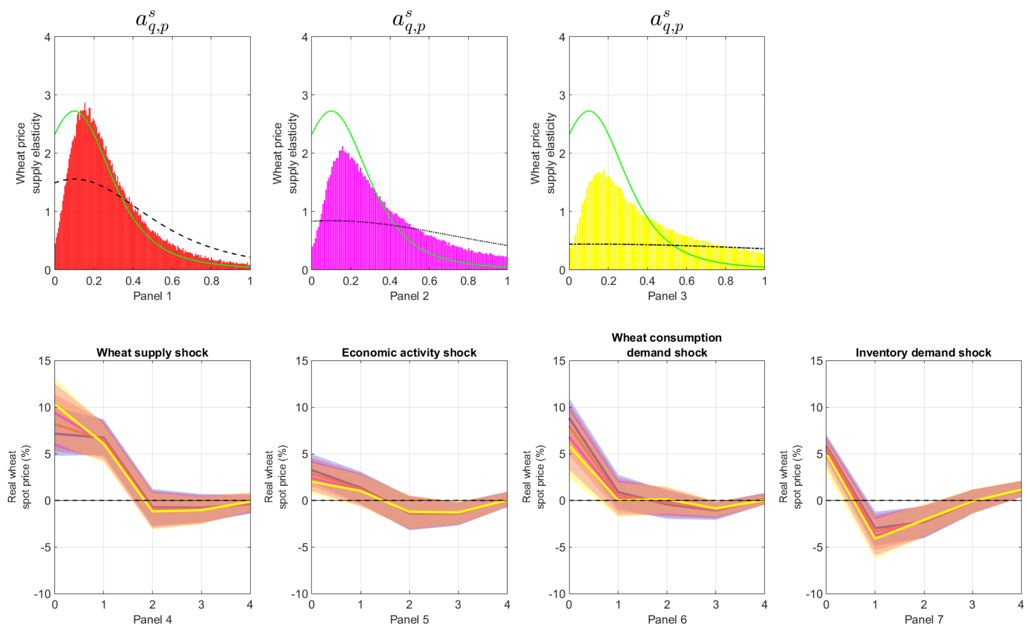
	Prior distributions for a^s_{qp}		
Panel A	Prob($0 \leq a^s_{qp} \leq 0.3$)	Prob($a^s_{qp} \geq 0.4$)	Prob($a^s_{qp} \geq 0.8$)
$\sigma_{a^s_{qp}} = 0.2$	71%	17%	3%
$\sigma_{a^s_{qp}} = 0.4$	45%	43%	15%
$\sigma_{a^s_{qp}} = 0.8$	40%	50%	26%
$\sigma_{a^s_{qp}} = 1.6$	25%	67%	41%
	Posterior distributions for a^s_{qp}		
Panel B	Prob($0 \leq a^s_{qp} \leq 0.3$)	Prob($a^s_{qp} \geq 0.4$)	Prob($a^s_{qp} \geq 0.8$)
$\sigma_{a^s_{qp}} = 0.2$	79%	10%	1%
$\sigma_{a^s_{qp}} = 0.4$	62%	25%	5%
$\sigma_{a^s_{qp}} = 0.8$	47%	41%	16%
$\sigma_{a^s_{qp}} = 1.6$	40%	50%	26%
	Prior distributions for a^d_{qp}		
Panel C	Prob($-0.3 \leq a^d_{qp} \leq 0$)	Prob($a^d_{qp} \leq -0.4$)	Prob($a^d_{qp} \leq -0.8$)
$\sigma_{a^d_{qp}} = 0.2$	71%	17%	3%
$\sigma_{a^d_{qp}} = 0.4$	45%	43%	15
$\sigma_{a^d_{qp}} = 0.8$	25%	67%	41%
$\sigma_{a^d_{qp}} = 1.6$	14%	82%	65%
	Posterior distributions for a^d_{qp}		
Panel D	Prob($-0.3 \leq a^d_{qp} \leq 0$)	Prob($a^d_{qp} \leq -0.4$)	Prob($a^d_{qp} \leq -0.8$)
$\sigma_{a^d_{qp}} = 0.2$	82%	5%	0%
$\sigma_{a^d_{qp}} = 0.4$	71%	13%	1%
$\sigma_{a^d_{qp}} = 0.8$	67%	16%	1%
$\sigma_{a^d_{qp}} = 1.6$	59%	24%	7%

Notes: $\sigma_{a^s_{qp}}$ and $\sigma_{a^d_{qp}}$ represent the scale parameters – the standard deviation – for both priors and posteriors of the price demand and price supply elasticities.

elasticity grater than 0.4, as reported in panel A of Table (B1). Moreover, the posterior medians of a^s_{qp} are 0.24 (for scale parameter equals 0.4), 0.32 (for scale parameter equals 0.8) and 0.41 (for scale parameter equals 1.6). These estimates are larger than 0.19 – the posterior median estimate of the price elasticity of wheat supply in the baseline model – and are difficult to reconcile with the price elasticity of wheat supply in the global market. Panels 4-7 of Figure A1 plot the response of the wheat price growth to each structural shock.

If we had limited prior information about the supply elasticity, the response of price to a wheat supply disruption would tend to be larger than that reported by the baseline

Figure A1: Priors and posteriors for alternative a^s_{qp} and price response to each structural shock.



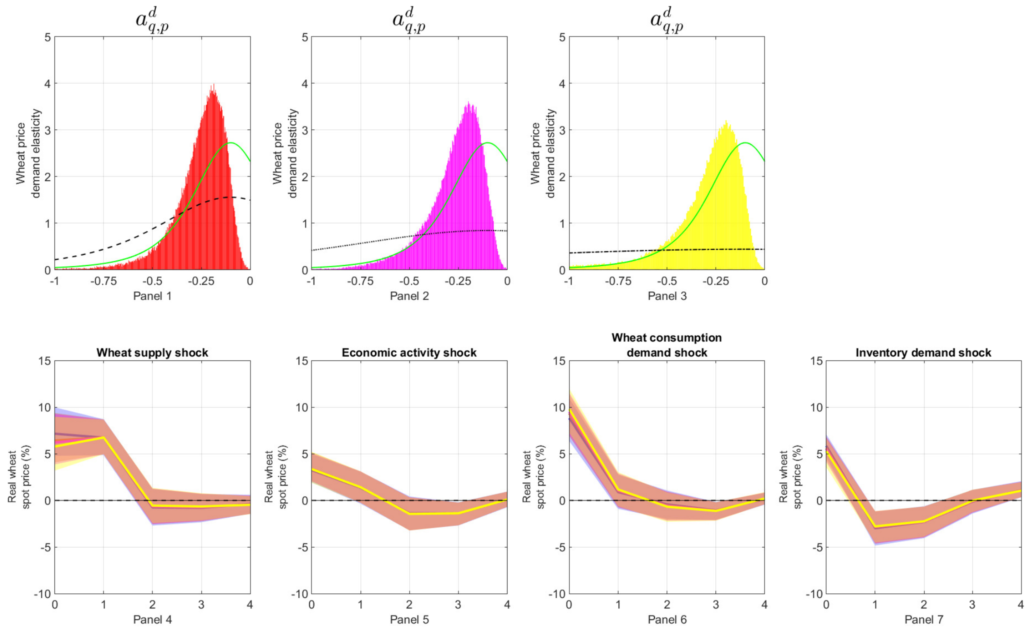
Note: Green solid lines and blue bars denote prior and posterior distributions used in model 1. The dashed, dotted and dash-dotted lines represent less informative priors with increasing scale parameters equal to 0.2 x 2 = 0.4, 0.2 x 4 = 0.8 and 0.2 x 8 = 1.6, respectively. Red, pink, yellow bars denote the cosponsoring posterior distributions of the contemporaneous structural coefficients. Solid red, yellow and pink lines indicate the posterior median estimate of the impulse response function under scrutiny. Shade bands correspond to 68% credible regions.

prior and the consumption demand shocks would tend to be less important in explaining the contemporaneous increase in the real price of wheat. These results suggest that, if we increase the value of scale parameter of the prior distribution for a^s_{qp}, the slope of the wheat supply curve becomes more elastic and any shifts of the consumption demand curve along the supply curve have less impact on the price of wheat, as shown in panel 6 of Figure A1. Overall, the dynamic response estimates of the real price of wheat to each structural shocks are quite robust to an increase in the uncertainty around the prior for a^s_{qp}.

B.1.2 The price elasticity of wheat demand

The baseline prior for a^d_{qp} is a Student t distribution, constrained on the non-negative support, with mode set at -0.1, scale parameter set at 0.2, degrees of freedom set at 3. Our prior for a^d_{qp} implies a 71% probability that price elasticity of wheat demand falls in the interval [-0.3, 0), as reported in panel C of Table (B1). If we had fully uninformative prior information about the price demand elasticity, the model would produce a very modest revision of the posterior distribution of a^d_{qp}, as illustrated in panels 1-3 of Figure A2.

Figure A2: Priors and posteriors for alternative a^d_{qp} and price response to each structural shock.



Note: see Figure A1

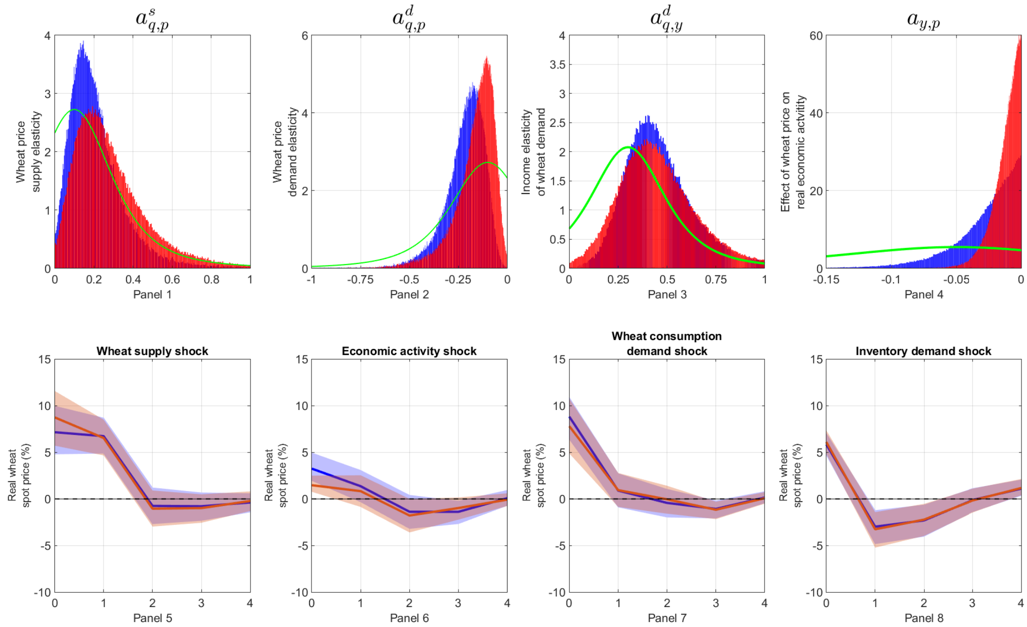
Finally, panels 4-7 of Figure A2 show that the response estimates of wheat price growth to economic activity, consumption demand and inventory shocks are substantially robust to changes in the prior of the price demand elasticity.

B.2 Alternative measure of global real economic activity

The second robustness check is based on a different measure of the global real economic activity. In this respect, we estimate model (1) by replacing the world industrial production index (wip) with the global real GDP growth rate. For the contemporaneous structural parameters of the economic activity equation we use the Student t prior distributions, as illustrated in Table 2 of our paper.

Panels 1-4 of Figure A3 plot the prior and posterior distributions for the price supply elasticity (a^s_{qp}), the price demand elasticity a^d_{qp}, the income elasticity a^d_{qy}, and the parameter governing the effect of wheat price on the real economic activity a_{yp}, when using the WIP index (blue bars) and the GDP (red bars). As shown in panel 4 of Figure A3, the real GDP growth rate is likely to be less affected by changes in the real price of wheat than the WIP index. Moreover, economic activity shocks – identified with the inclusion of GDP indicator

Figure A3: Global GDP vs WIP index.



Note: Prior (green lines) and posterior distributions considered in model 1 using global real GDP (red histograms) and world industrial production (blue histograms). Solid red and blue lines indicate the median impulse response estimates based on model 1 using real GDP and WIP, respectively. Shaded regions indicate the corresponding 68% credible set.

– play a less role in explaining the increase in the real price of wheat, as shown in panel 6 Figure A3. These results consistent with the idea that GDP is a coincident indicator of the real economic activity while the WIP index can be considered a forward-looking measure of the real economy, which is designed to capture unexpected changes in the global business cycle (e.g. Baumeister et al. (2020) and Hamilton (2021)). The model including real GDP provides only marginal revisions for the posterior distribution of the coefficients related to the consumption demand equation (see panels 1,2 and 3 of Figure A3). The dynamic effects of shocks to supply, consumption and inventory demand on the real price of wheat remain substantially robust to changes in the proxy for the global business cycle.

B.3 Alternative recursive SVARs

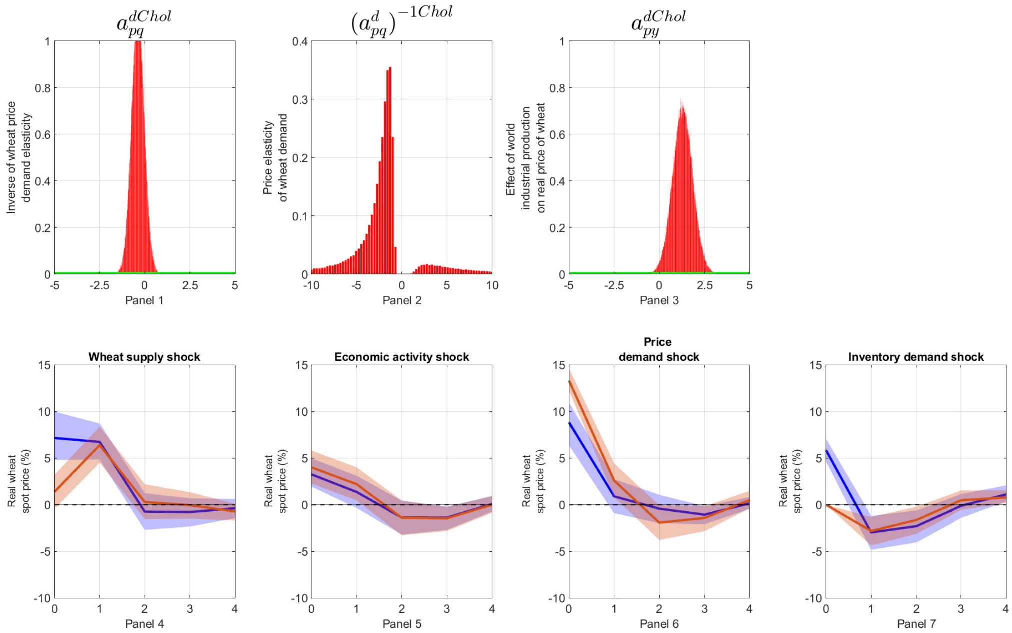
Last robustness exercise illustrates important differences between triangular SVARs and the SVAR model presented in our paper. On this respect, it is important to note that the inclusion of the inventory – among the set of the endogenous variables – renders the Cholesky identification difficult to reconcile with the theory of competitive storage. This is motivated by the fact that it is not trivial to establish the causal relationship between inventories and price. Therefore, we estimate an alternative recursively-type identified SVAR model to that presented in Sections 4.4 of our paper, whose identification and results are discussed below.

The second specification of Cholesky-type identified VAR model is:

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ -a_{yq}^{\text{Chol}} & 1 & 0 & 0 \\ -a_{pq}^{d\text{Chol}} & -a_{py}^{d\text{Chol}} & 1 & 0 \\ -a_{iq}^{\text{Chol}} & -a_{iy}^{\text{Chol}} & -a_{ip}^{\text{Chol}} & 1 \end{bmatrix}}_{\mathbf{A}^{\text{Chol}}} \underbrace{\begin{bmatrix} q_t \\ y_t \\ p_t \\ \Delta i_t \end{bmatrix}}_{\mathbf{y}_t^{\text{Chol}}} = \mathbf{B}^{\text{Chol}} \mathbf{x}_{t-1}^{\text{Chol}} + \underbrace{\begin{bmatrix} v_{1t}^{\text{Chol}} \\ v_{2t}^{\text{Chol}} \\ v_{3t}^{\text{Chol}} \\ v_{4t}^{\text{Chol}} \end{bmatrix}}_{\mathbf{v}_t^{\text{Chol}}} \tag{8}$$

Given the Cholesky identification considered in model (8), the first-two shocks have the same economic interpretation of model (9) – discussed in Section 4.4 of the manuscript – while the last-two shocks do not.

Figure A4: The Cholesky-type identification structural model.



Note: Prior (green lines) and posterior (red histograms) distributions considered in model 8 using Cholesky identification. Solid red lines indicate the median impulse response estimates based on model 8. Solid blue lines refer to the median posterior estimated of model 1. Shaded regions indicate the corresponding 68% credible set.

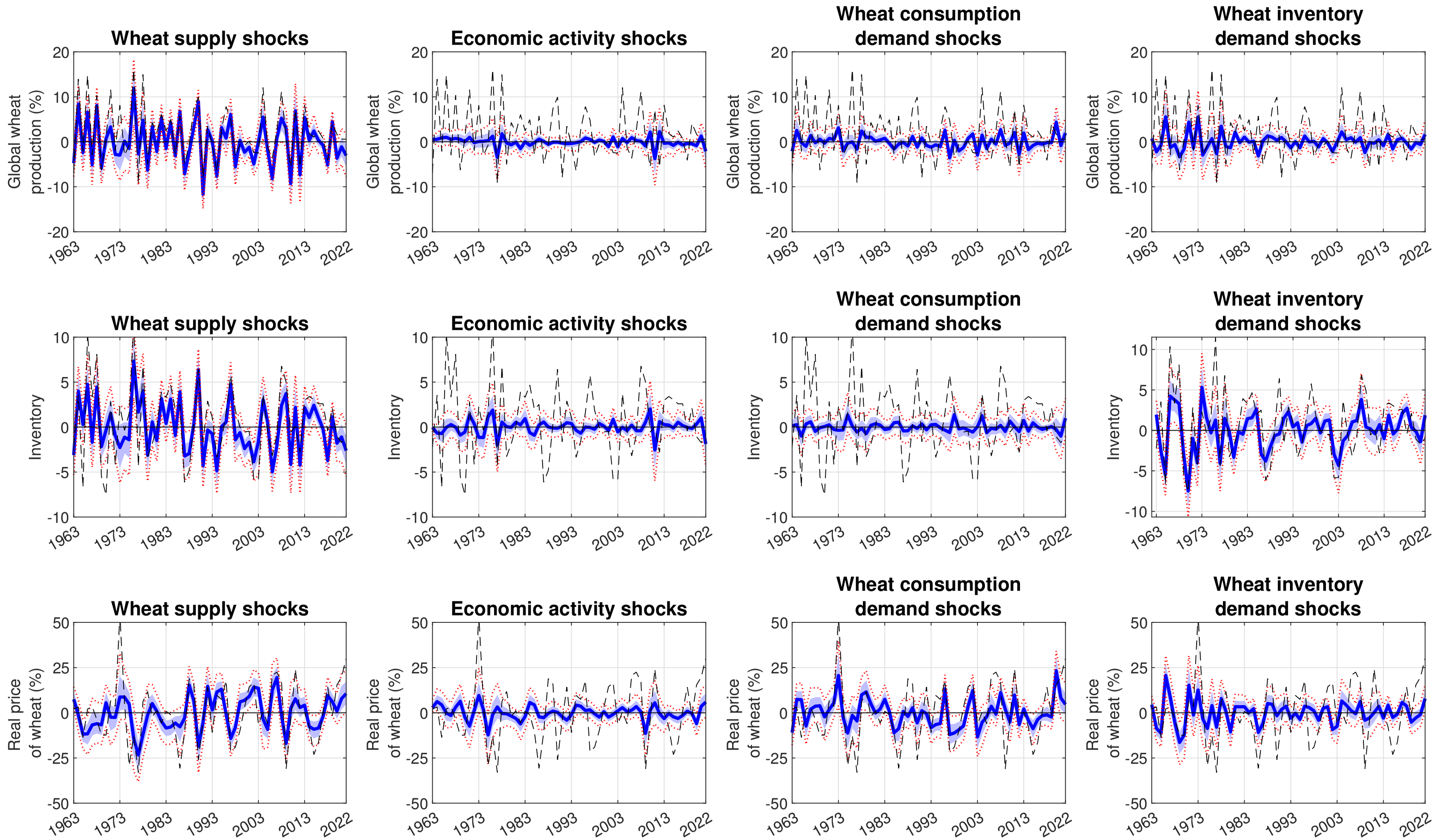
Specifically, the third shock is v_{3t} and it refers to a price demand shock, while the residual shock is v_{4t} and it is designed to capture the inventory demand shocks. As a result, in this model the price of wheat is predetermined with respect to the inventory, that is $a_{pi}^{d} = 0$. The latter helps to solve the identification problem of model (8) but it casts doubts on the economic interpretation of the inventory demand shock, since model (8) implies that any unexpected shifts in the inventory demand – driven by speculative reasons, for instance – do not affect the real price of wheat within the year. Analogous to the triangular SVAR model discussed above, for the remaining coefficients we assign completely uninformative Student t prior distributions, with location parameter centred at 0, scale parameter equals 100 and degrees of freedom set at 3.

Overall, the empirical results based on the recursive configuration of the global wheat market in 8 are difficult to reconcile with the economic theory of competitive storage and are remarkably different from the non-recursive model presented in our paper.

C Historical decomposition

Figure plots the historical decompositions of (i) the growth rate of global wheat production, (ii) the growth rate of US Hard Red Winter (US-HRW) price of wheat and the (iii) global changes in wheat inventory.

Figure A5: Historical decomposition



Note: cumulative effects of each structural shock on production, price and inventory level of model 1. Dotted black lines plot the actual data. Blue solid lines plot the median estimate of the historical decomposition. Blue shaded regions and red dotted lines indicate the 68% and 95% posterior credible sets.

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