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Understanding the role of supply and demand factors in the global wheat market

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Abstract

We develop a novel Bayesian SVAR model to analyse the impact of supply and demand shocks on the real price of wheat. This is the first SVAR model of the global wheat market to comprehensively account for the endogenous interactions between producers, inventory holders and consumers. Our results show that the real price of wheat responds differently to global wheat market shocks, depending on the economic motivations underlying each shock. Specifically, consumption demand shocks explain nearly 70 per cent of price fluctuations, while supply shocks account for 20 per cent and the remaining 10 per cent is attributed to shocks in economic activity, inventory demand and fertilizer prices.

Keywords: Bayesian Structural VAR model; price analysis; global wheat market.

JEL classification: C11, C32, Q11, Q13

1. Introduction

Wheat is a cornerstone of the global agricultural and food system, serving as a key ingredient in flour and many food products, such as bread, cookies, cakes and pasta, as well as a significant source of animal feed. A larger area of land is devoted to wheat cultivation than to any other crop worldwide and wheat represents the most traded agricultural commodity, with 30 per cent of global production sold internationally. Wheat production is highly sensitive to climate-related factors, such as rising temperatures and droughts. As a rain-fed crop, wheat is particularly vulnerable to the effects of global warming,

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serving as a key indicator of climate change's impact on agricultural systems. Furthermore, the wheat market is significantly shaped by government policies in both developing and developed countries (e.g. export restrictions and subsidies). The price spikes of 2007–2008, disruptions during the COVID-19 pandemic, and the ongoing effects of the Ukraine–Russia conflict highlight the profound impact of policy and geopolitical factors on wheat prices (see Martin and Minot, 2023). Thus, understanding the economic drivers of wheat price dynamics is also important to investigate the broader nature of food price spikes and their wider economic impacts.

In this paper, we analyse the relevance of supply and demand factors in driving wheat price dynamics, adopting a global perspective that accounts for production, consumption and inventory decisions. We focus on the response of the real price of wheat and other market-specific variables to unexpected shifts in supply and demand, commonly referred to as demand and supply shocks.

Our work offers deeper insights into the mechanisms driving unexpected changes in wheat prices, which can have severe implications for food accessibility, particularly in developing countries where a significant share of household income is allocated to food. The unexpected changes in the real price of wheat, often referred to as wheat price shocks, can worsen undernutrition and lead to serious health outcomes. In extreme cases, shocks to wheat and other cereal prices can trigger social unrest and even lead to food riots (see e.g. Berazneva and Lee, 2013; Bellemare, 2015; Winne and Peersman, 2021; Kosec and Song, 2021). The severity of food insecurity and hunger in low-income countries often depends on both the magnitude and the nature of the price shock. Even in advanced economies, significant food price spikes can lead to adverse macroeconomic effects, including rising production costs, slower economic growth and heightened inflation (see Peersman, 2022).

The impact of economic fundamentals on the real price of wheat is largely explained by the intrinsic characteristics of its global market, which are, in turn, driven by the price elasticity of both demand and supply. Most research in this field has focused on the supply side, particularly on analysing the short- and long-run responses of agricultural output proxies—such as production, acreage, yield and caloric production—to changes in expected prices (see e.g. Roberts and Schlenker, 2013; Haile *et al.*, 2016). A recent study by Letta *et al.* (2022) highlights the significant role of the expectations channel in driving preharvest price fluctuations in India's local crop markets, revealing that this mechanism accounts for over 80 per cent of the total price impact under the assumption of a completely inelastic consumption demand curve.

Most of these studies primarily rely on univariate econometric techniques using instrumental variable (IV) estimation, where weather serves as a valid instrument to disentangle supply effects from demand effects on agricultural commodity prices. However, a correct understanding of the effects of economic fundamentals on wheat price dynamics requires a structural model that not only separates supply shocks from demand shocks but also identifies wheat market-specific demand shocks that are unrelated to broader economic activity and energy conditions. To this end, we develop a Bayesian Structural Vector Autoregressive (BSVAR) model to analyse the price dynamics of the global wheat market. This class of models has also become increasingly popular to study agricultural commodity price dynamics. For example, Janzen *et al.* (2014) apply a recursively identified SVAR model to analyse the relative importance of demand and supply shocks specific to the US wheat market. Similarly, Bastianin *et al.* (2018) use a recursive SVAR model to examine the effects of the El Niño Southern Oscillation on Colombian coffee production, exports and prices. De Lipsis and Agnolucci (2024) adopt a proxy-SVAR model to study the impact of temperature and precipitation shocks on US wheat prices, inventories acreage and yield. Carter *et al.*, (2017) employ a sign-restricted SVAR model to assess the effects of biofuel policies on maize, wheat and soybean markets, with a particular focus on the role of inventories in stabilizing prices and identifying the effects of speculative demand shocks. Bruno *et al.* (2017) use a recursively identified SVAR model with high-frequency data to explore the intensity of financial speculation in grain, livestock and equity markets. Finally, Ghanem and Smith (2022) offer a comparison of the identification strategies in a recursive SVAR model of agricultural commodity markets versus a classical IV model, building on the work of Roberts and Schlenker (2013).

In this paper, we depart from the existing literature by developing a novel SVAR model of the international wheat market, characterized by three key features. First, to our knowledge, this study presents a novel SVAR model of the global wheat market that thoroughly considers the interaction between producers and inventory-holders, while placing appropriate emphasis on the role of consumers. We highlight the importance of the consumption demand equation, which has been relatively underinvestigated in this field. This gap likely stems from the prevailing belief that unexpected demand shifts along the supply curve account for only a small fraction of the variation in agricultural prices over time. Our work differs from studies that rely on dogmatic assumptions about the relationship between production and price, neglect the role of inventories or use structural model reparameterizations based on the impacts of structural shocks (see for instance, Hendricks *et al.*, 2015; Baumeister and Hamilton, 2024). Instead, our approach exploits the economic relationship between production and inventory changes to estimate the consumption price elasticity of demand and identify consumption demand shocks. These shocks are often linked to unpredictable changes in domestic food consumption, dietary behaviour and livestock feed use. Second, to the best of our knowledge, we are the first to rigorously combine production and inventory changes into the market-clearing condition to accurately estimate the consumption demand equation, addressing the most recent advancements in the literature on structural identification models (see Kilian 2022a, b). Third, our study employs a revised version of the BSVAR model originally developed by Baumeister and Hamilton (2019). The identification approach proposed by Baumeister and Hamilton (henceforth, the BH approach) offers a more flexible way to identify the underlying structural shocks that drive the global wheat market. This method estimates the structural coefficients directly by combining prior parameter distributions with the data's likelihood function, thus bypassing the need to estimate the corresponding reduced-form VAR model.

The novelty of our Bayesian SVAR model is to examine the wheat price dynamics, accounting for the contemporaneous relationships among the key representative traders in the global wheat market. Our main findings suggest that wheat consumption demand shocks account for nearly 70 per cent of price fluctuations, with supply shocks being the second most significant source, contributing approximately 20 per cent of the total price impact. The remaining 10 per cent is attributed to other factors, including economic activity-driven demand, speculative behaviour and energy-related shocks. We also show that the annual price elasticity of supply is highly inelastic, as producers increase production by only 0.3 per cent in response to a 10 per cent rise in the real price of wheat. Furthermore, given the persistent nature of dietary behavior changes, our analysis reveals low median estimates of demand elasticity with respect to price and income, at −0.41 and 0.63, respectively. Finally, we show that the real price of wheat from 1962 to 2022 has been shaped by a variety of shocks, reflecting the complex interaction between supply and demand factors, including climatic events, geopolitical developments and economic dynamics. These results offer valuable insights into the structural drivers of wheat price fluctuations, which are relevant for policy formulation and risk management in the global food system.

The rest of the paper is organized as follows. Section 2 describes the dataset. Section 3 outlines the structural equations used to model the global wheat market. Section 4 presents and discusses the empirical results. Section 5 proposes the policy implications and concludes. This paper includes an Online appendix that presents robustness checks and additional results.

2. Data

We use a database on the international wheat market provided by the USDA, including annual data from 1960 to 2022, on price (P), production (Q), planted acreage (A), yield (Y) and inventories (I) by aggregating national statistics based on each country's local marketing year. We acknowledge that annual aggregated data may hide spatial heterogeneity across countries and wheat varieties. However, this aggregation ensures consistency among key wheat market variables and facilitates the identification of representative global shocks to supply, consumption and speculative demand, under the assumption that aggregated data sufficiently capture overall market dynamics.

Our measure for the global price of wheat is the US No. 1 Hard Red Winter (HRW) price, widely recognized as a key international benchmark for several reasons. First, the USA is one of the largest wheat producers and exporters, with HRW wheat being the most widely exported variety, accounting for approximately 40 per cent of annual wheat exports over the past two decades. By comparison, Hard Red Spring and Soft Red Winter (SRW) account for roughly 25 per cent and 15 per cent of exports, respectively. Prices for these and other wheat varieties are often closely aligned with HRW prices, with premiums or discounts reflecting specific quality attributes. For instance, SRW typically trades at a slight discount due to its lower protein content and weaker gluten strength. Second, HRW wheat, with a protein content of 10 per cent to 13 per cent, is highly versatile due to its strong gluten and excellent milling and baking qualities. It is used in a wide range of products, including breads, rolls, croissants, flatbreads, Asian noodles, general-purpose flour and for blending purposes. Third, the US HRW wheat price serves as the underlying asset for futures contracts traded on the Kansas City Board of Trade. These futures, particularly those with short maturities, are actively traded, making them a natural choice to analyse price trends. Despite the steady decline in the US share of global wheat exports since the early 1980s, the US HRW wheat market continues to play a dominant role in price discovery, as documented by Janzen and Adjemian (2017).

The real price of wheat is obtained by multiplying the nominal price of wheat by 100 and then dividing it by the US Consumer Price Index (CPI). The reference price is then constructed as the annual average of monthly real prices over the international marketing year.[1] The choice of the 'time unit' for annual data plays a relevant role in explaining price dynamics. Unlike previous studies that adopt a national production-oriented approach—using planting-year cash prices (the price from the year before harvest) as the expected price and focusing on planting and harvesting seasons specific to each hemisphere—our work takes a broader perspective. We consider planting and harvesting in the global wheat market to occur throughout the entire year, as illustrated in Haile *et al.* (2014). This is consistent with the view that global planting decisions can respond instantaneously to current harvests and prices, which subsequently influence the global supply situation in future periods, as wheat is cultivated year-round in both the Northern and Southern Hemispheres. Additionally, fluctuations in consumption demand significantly influence changes in wheat prices. Therefore, it is reasonable to consider that global wheat consumption adjusts to price changes throughout the year. For these reasons, we argue that the annual average of monthly prices over the international marketing year effectively captures information from both the supply and demand sides of the international wheat market.[2]

Data on production and inventories are reported in metric tons and it is worth noting that, production can also be derived by multiplying harvested area (in hectares) by yield (in tons per hectare). This is consistent with the view that the annual production is explained by farmers' planting decisions

1 HRW wheat prices are available starting from the marketing year (MY) 1970/71. To extend the analysis back to MY 1960/61, we backcast missing values using the US 'All Wheat' price series as a proxy. The Pearson correlation coefficient between the two series during the overlapping period (MY 1970/71-MY 2022/23) is 0.99, demonstrating a strong alignment and validating the use of 'All Wheat' prices as an anchor for HRW wheat prices in earlier years.

2 It is worth noting that, since more than half of global wheat production, consumption and inventory adjustments occur within the international marketing year (July of the current year to June of the following year), all annual variables in this study are averaged over this period.

(e.g., how much wheat to plant) and by weather conditions (e.g. droughts or excessive rainfall) that ultimately impact yield.

The global measure of real economic activity is represented by the average of the monthly OECD+6 World Industrial Production Index (W), as proposed by Baumeister and Hamilton (2019). This measure of real output includes data from OECD and non-OECD countries—namely, China, India, Brazil, Russia, South Africa and Indonesia—and allows us to incorporate prior beliefs about the income elasticity of wheat demand, given the methodology applied to identify the structural shocks. Finally, to capture energy-related production costs (E), we calculate the real annual average of monthly values from the fertilizer price index, compiled by the World Bank and deflated using the US CPI, sourced from FRED.[3]

3. A model of the global wheat market

The international wheat market includes numerous participants, broadly classified as producers, consumers and inventory holders. To model the behaviour of buyers and sellers within this market, we propose a structural form of the VAR model expressed as:

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

where $\mathbf{y}_t = (q_t, w_t, e_t, \Delta i_t, p_t)'$ denotes the $(n \times 1)$ vector of the endogenous variables; $\mathbf{A}$ and $\mathbf{B}$ are $(n \times n)$ and $(n \times mn + 1)$ matrices of instantaneous and lagged structural parameters. Specifically, q_t represents the global wheat production, w_t world industrial production index, e_t the fertilizer price index, Δi_t the change in wheat inventories expressed as a fraction of current wheat production and p_t the real price of wheat. All variables, except Δi_t, are expressed in natural logarithms. The dynamics of model (1) are captured by $\mathbf{x}_{t-1} = (\mathbf{y}_{t-1}, 1)'$, a $(mn + 1)$ vector of m lags of the endogenous variables with constant. The number of lags m is set to 1 to account for the typical duration of the business cycle and residual autocorrelation. The $(n \times 1)$ vector of structural shocks, $\mathbf{v}_t$, is assumed to follow a Normal distribution with zero mean and diagonal variance–covariance matrix $\boldsymbol{D}$.

We estimate the structural coefficients of model (1) using the BH algorithm developed by Baumeister and Hamilton (2015). The BH approach estimates the structural model directly, bypassing the reduced-form specification. Specifically, the estimation involves two main steps. The first step specifies informative prior beliefs about the structural parameters $\mathbf{A}$, $\mathbf{B}$ and $\mathbf{D}$. Table 1 reports the priors for $\mathbf{A}$, which are grounded on the economic theory and aligned with empirical results from earlier studies, while for $\mathbf{B}$ and $\mathbf{D}$ we use natural conjugate priors. The second step involves sampling from the posterior

3 The fertilizer price index is a weighted average of essential agricultural inputs. The weights used by the World Bank are 17 per cent for Natural Phosphate Rock, 22 per cent for Phosphate, 20 per cent for Potassium and 41 per cent for nitrogenous fertilizers.

Table 1. Specification of prior distributions for structural parameters **A**.

Parameter	Economic interpretation	Student t			
		Mode (c)	Scale (σ)	Dof (ν)	Sign
a^s_{qe}	Effect of e on wheat supply	−0.1	0.3	3	–
a^s_{qp}	Price elasticity of wheat supply	0.1	0.3	3	+
a_{we}	Effect of e_t on world industrial production	0	0.4	3	()
a_{ep}	Effect of p_t on the fertilizer price index	0	0.4	3	()
a_{iq}	Effect of q_t on wheat inventories	0	0.5	3	()
a_{iw}	Effect of w_t on wheat inventories	0	0.5	3	()
a_{ie}	Effect of e_t on wheat inventories	0	0.5	3	()
a_{ip}	Effect of p_t on wheat inventories	0	0.5	3	()
a^d_{qw}	Income elasticity of wheat demand	0.3	0.4	3	+
a^d_{qp}	Price elasticity of wheat demand	−0.2	0.4	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.

distribution of the structural coefficients using a random walk Metropolis–Hastings algorithm.[4] Finally, to better illustrate our identification assumptions, we present the structural equations implied by model (1). These equations, explained in detail below, describe the key determinants of the global wheat market along with external factors, such as world real economic activity and energy price conditions.

3.1 The wheat supply equation

On a global scale, wheat planting and harvesting occur year-round, allowing producers—primarily farmers and agricultural cooperatives—to determine the amount of land to cultivate based on information available in the current marketing year. Thus, global production decisions respond immediately to changes in wheat and energy prices, as captured by the following dynamic supply equation:

$$q_t = a^s_{qe} e_t + a^s_{qp} p_t + \mathbf{b}'_s \mathbf{x}_{t-1} + v^s_t, \tag{2}$$

where $q_t = \ln(Q_t)$ is the quantity of wheat produced in a given year; $p_t = \ln(P_t)$ is the real price of wheat with a^s_{qp} and a^s_{qe} measuring the price elasticity of wheat supply and the responsiveness of wheat producers to changes in the fertilizer price index, respectively. Equation (2) models the global wheat supply curve using two exclusion restrictions, $a^s_{qw} = a^s_{qi} = 0$, consistent with the

4 The Bayesian approach offers a statistical framework that integrates subjective estimates (priors) with observed data, which are treated as fixed quantities. In contrast, the structural parameters of the model are treated as random variables. Bayesian inference updates prior beliefs using observed data to produce a posterior distribution of the structural coefficients. This methodology accommodates uncertainty arising from two key sources: (i) the sample size and (ii) the identification structure of the SVAR model. For a detailed discussion of the priors for **A**, **B** and **D** as well as a comprehensive description of the estimation algorithm, see the Online appendix.

view that wheat production is not directly influenced by changes in inventories and real economic activity within the same year (see, Ghanem and Smith, 2022; De Lipsis and Agnolucci, 2024). It is worth noting that the zero restrictions in Equation (2) imply that production is affected by inventories only indirectly, through their impact on wheat and fertilizer prices. Similarly, production is assumed to depend on real output solely via the influence of global industrial production on fertilizer prices. In other words, the contemporaneous effects of economic activity and inventories on global wheat production are taken into account through the equilibrium impacts of structural shocks. The dynamics of the production equation are captured by $\mathbf{x}_{t-1}$, while v_t^s denotes a wheat supply shock.

A negative wheat supply shock corresponds to a leftward shift of the contemporaneous wheat supply curve along the demand curve. Such shocks typically reflect wheat production shortfalls driven by planting decisions, adverse weather conditions (e.g. extreme rainfall, temperature anomalies, droughts and floods), and natural resource constraints (e.g. land degradation due to urbanization, water-related risks and declining soil fertility).

3.2 The global economic activity and the energy cost-related equations

The world industrial production index is contemporaneously affected by the fertilizer price index and past dynamics, leading to the following global economic activity equation:

$$w_t = a_{we}e_t + \mathbf{b}_w'\mathbf{x}_{t-1} + v_t^w, \tag{3}$$

where $w_t = \ln(W_t)$ with a_{we} capturing the sensitivity of real income to changes in the fertilizer price index and v_t^w representing an economic activity shock. For the identification of v_t^w, we impose three zero-restrictions on the structural coefficients a_{wq}, a_{wi} and a_{wp}.

A positive economic activity shock corresponds to a rightward shift of the contemporaneous wheat demand curve along the wheat supply curve, primarily driven by economic growth. This shock reflects an increase in aggregate demand for wheat and potentially other major staple food commodities, such as corn, rice and soybeans, influenced by fluctuations in the global business cycle.

The fertilizer price index is a proxy for production costs and is modelled by a dynamic equation of the form:

$$e_t = a_{ep}p_t + \mathbf{b}_e'\mathbf{x}_{t-1} + v_t^e, \tag{4}$$

where $e_t = \ln(E_t)$ and a_{ep} capturing the sensitivity of the fertilizer price to wheat price fluctuations and v_t^e being a fertilizer price shock.[5] A positive shock

5 The specification of an energy cost-related equation is justified by several considerations. First, fertilizer prices directly influence wheat production by affecting input costs, a relationship well-

to the fertilizer price index represents an unanticipated increase in fertilizer costs, while also capturing the broader impact of rising prices for petroleum-based inputs (e.g. pesticides, transportation costs and oil) and biofuel programs. These programs often contribute to land-use changes, such as the deterioration of areas traditionally allocated for wheat cultivation in favour of more energy-efficient crops.

3.3 The consumption demand equation

On the demand side, actors such as processors, wholesalers and large retailers purchase and transform raw wheat into consumer products, including flour and baked goods. These traders play a crucial role in linking primary production with the distribution of wheat-based products. Thus, the dynamic demand equation for consumption is given by:

$$c_t \equiv q_t - \Delta i_t = a^d_{qw} w_t + a^d_{qp} p_t + \mathbf{b}'_c \mathbf{x}_{t-1} + v^c_t, \tag{5}$$

where $\Delta i_t = \frac{\Delta I_t}{Q_t}$ is the change in wheat inventories expressed as a fraction of the current wheat production. Given that changes in inventories account for only a small fraction of global wheat production, c_t represents an accurate proxy for the logarithm form of C_t, which represents the amount of wheat consumed in the current year. Specifically, using the Taylor's theorem, we expand $\ln(Q_t - \Delta I_t)$ around Q_t. This expansion gives us:

$$\ln(Q_t - \Delta I_t) = \ln(Q_t) + \ln\left(1 - \frac{\Delta I_t}{Q_t}\right)$$

We approximate $\ln(1 - \Delta i_t)$ using the Taylor expansion of the logarithm, yielding $\ln(1 - \Delta i_t) \approx -\Delta i_t$. Thus, we obtain the approximation for the logarithm of consumption as:

$$\ln(C_t) \approx c_t = q_t - \Delta i_t$$

It is worth noting that this approximation holds under the condition that $\Delta I_t \ll Q_t$, with Δi_t is sufficiently small to motivate the linear approximation $\ln(1 - \Delta i_t) \approx -\Delta i_t$.[6]

Figure 1 examines how accurately c_t and Δc_t approximate c_t^{USDA} and $\Delta c_t^{\mathrm{USDA}}$, respectively. The term c_t^{USDA} denotes the logarithm of the USDA's international benchmark for global wheat consumption. Panel 3 shows a histogram of the measurement error for c_t, calculated as the difference $c_t^{\mathrm{USDA}} - c_t$. Panel 4 includes two histograms: one for the measurement error $\Delta c_t^{\mathrm{USDA}} -$

documented in the literature (e.g. Baffes, 2007; Dalheimer *et al.*, 2021; De Winne and Peersman, 2021). Second, incorporating the fertilizer price index allows for the isolation of production changes driven by pure supply shocks—such as those related to planting and harvesting—from those caused by energy price fluctuations and macroeconomic activity shocks. Finally, the fertilizer price index exhibits a strong correlation with Brent crude oil prices, with a linear correlation coefficient of 0.95 for annual data from 1960 to 2022, highlighting the close alignment between fertilizer price and crude oil price dynamics.

6 This approximation avoids the issue of taking logarithm of negative values of ΔI_t, ensuring the correct interpretation of the consumption demand equation.

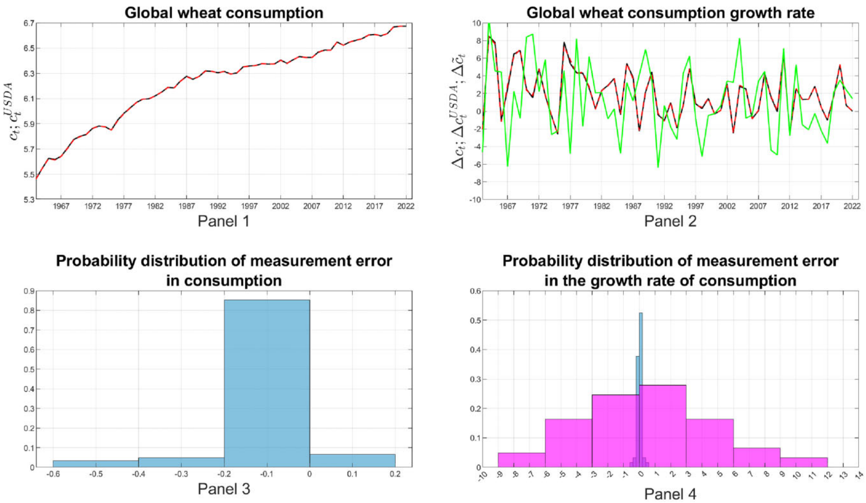

Fig. 1. Data on global consumption demand. Note: Panel 1: the solid black line represents the log-level of global wheat consumption (measured in MMT) as implied by model (B1), while the dotted red line shows the log-level of the USDA's benchmark for global domestic consumption (measured in MMT). Panel 2: the solid black and dotted red lines represent the growth rates of consumption, denoted as Δc_t and Δct^{usda}, respectively. The green line illustrates $\Delta\tilde{c}_t$. Panel 3: a histogram displays the measurement error $c_t^{usda} - c_t$. Panel 4: two histograms are presented: one in blue for $\Delta ct^{usda} - \Delta c_t$ and another in pink for $\Delta c_t^{usda} - \Delta\tilde{c}_t$.

Δc_t and another for $\Delta c_t^{\mathrm{USDA}} - \Delta\tilde{c}_t$. Here, $\Delta\tilde{c}_t$ is defined as the difference between the growth rate of production (Δq_t) and inventory changes ($\Delta\tilde{i}_t$), with the latter expressed as the ratio of current inventory changes to past production.[7]

The studies by Kilian (2022a, b) raise concerns about the validity of the consumption demand Equation (5) when $\Delta\tilde{c}_t$ is used as an approximation of $\Delta c_t^{\mathrm{USDA}}$. Panels 2 and 4 of Fig. 1 show that $\Delta\tilde{c}_t$ is a poor proxy for the USDA's international benchmark for world consumption. This is also reflected by the low linear correlation coefficient of 0.39 between $\Delta\tilde{c}_t$ and $\Delta c_t^{\mathrm{USDA}}$, with a mean absolute error of 3.26 percentage points (pp). Moreover, panel 4 shows that $\Delta\tilde{c}_t$ overstates wheat consumption growth by up to 12 pp and understates it by as much as 9 pp. These findings indicate that the SVAR model (1) would face similar issues if the production variable were specified in growth rate terms.

To address this concern, our approach adopts a log-level specification for both production and consumption equations. In this respect, panel 1 of Fig. 1 shows that $\tilde{c}_t$ provides an excellent approximation for c_t^{USDA}. The linear cor-

7 Baumeister and Hamilton (2019) suggest that $\Delta\tilde{c}_t = \Delta q_t - \Delta\tilde{i}_t$ offers a good approximation of the average consumption growth rate, as changes in oil stocks are relatively small compared to oil production. However both studies of Kilian (2022a, b) argue that BH approach ignores that, in modelling commodity prices, researchers are typically concerned with period-to-period consumption growth rates rather than average consumption growth.

relation coefficient between c_t (or Δc_t) and c_t^{USDA} (or $\Delta c_t^{\mathrm{USDA}}$) is 0.99, with mean absolute errors of just 0.08 per cent for c_t and 0.09 pp for Δc_t.

These findings suggest that the BH approach remains a reliable method to estimate the consumption demand equation, where the parameters a_{qw}^d and a_{qp}^d represent the income elasticity and the price elasticity of wheat demand and v_t^c denotes a wheat consumption demand shock. A positive consumption demand shock reflects a rightward shift in the contemporaneous wheat demand curve along the supply curve, driven by factors not captured by shocks to real economic activity—such as increases in demand for domestic food, livestock feed or nonfood and industrial applications.

3.4 The inventory demand equation

The inventory holders—including government reserves, commodity stockholders and trading firms—play a strategic role in stabilizing the wheat market. By holding substantial inventories, these traders can mitigate supply fluctuations and manage price volatility. This is consistent with the economic theory of storable commodities and it supports the view that inventories play an important role in smoothing consumption (or production). For example, storage responds to weather-driven harvest shocks by transferring production across periods to buffer consumption (see e.g. Deaton and Laroque, 1996; Letta *et al.*, 2022). Moreover, inventory demand shocks capture the speculative behaviour of economic agents. These traders may respond to harvest disruptions, heightened uncertainty and shocks specific to the wheat market by increasing storage demand, which in turn affects the price of wheat. Therefore, wheat purchased not for current consumption is added to storage, implying the following inventory demand equation:

$$\Delta i_t = a_{iq} q_t + a_{iw} w_t + a_{ie} e_t + a_{ip} p_t + \mathbf{b}_i' \mathbf{x}_{t-1} + v_t^i, \tag{6}$$

where changes in wheat inventories depend on all current and past variables in the model and v_t^i represents an inventory demand shock. This shock induces a shift in the demand for storage within the global wheat market. Under standard arbitrage assumptions, it implies a speculative pass-through from the futures market to the spot market via inventory adjustments. Additionally, inventories serve as a valuable source of information, helping to mitigate issues related to informational deficiencies, commonly referred to as nonfundamentalness (or noninvertibility) problems.[8] The inventory demand shock is designed to capture expectation-driven components of the real price of wheat, stemming from anticipated supply and demand conditions.

8 Informational deficiencies occur when the VAR model is not informationally sufficient to recover the 'true' structural shocks, as the econometrician's information set is typically smaller than that of economic agents. For example, anticipated disturbances—such as news, noise, omitted variables or latent variables—can lead to noninvertibility problems (see Canova and Ferroni, 2022). Moreover, informational deficiencies are independent of the identification strategy used to recover structural shocks. When such deficiencies are present, the innovations are not truly structural, rendering VAR (or SVAR) models misspecified (see for instance, Giannone and Reichlin, 2006; Forni and Gambetti, 2014).

4. Empirical results

4.1 Responses to shocks in the global wheat market

Figure 2 relies on a panel of graphs, each plotting the median impulse responses of the endogenous variables to one-standard deviation structural shock, along with the highest posterior credible regions at the 68 per cent and 95 per cent levels.[9]

The first row of the panels in Fig. 2 shows that a wheat supply disruption immediately decreases wheat production by 5.3 per cent, increases the price of wheat by 5.9 per cent, the price of fertilizer by 4.6 per cent, and reduces inventories and economic activity by 2.9 per cent and 0.02 per cent, respectively. After 1 year, the negative supply shock remains persistent in its effects on production, before gradually returning to equilibrium over longer horizons. The supply disruption induces a hump-shaped response in the real price of wheat, peaking at 8.7 per cent after 1 year, with 95 per cent credible intervals ranging from 2.9 per cent to 10 per cent. The persistence of this shock on fertilizer prices is even more pronounced than that on wheat prices, with fertilizer prices reaching a peak of 10.6 per cent 2 years after the shock.[10] Moreover, the response of world industrial production to a wheat supply disruption is negative and persistent, though highly uncertain when considering the 95 per cent credible intervals. In contrast, inventories drop temporarily as part of an effort to smooth consumption but return to their initial levels within 1 year after the shock.

The second row of the panel shows that a positive economic activity shock leads to a 2.8 per cent increase in world industrial production and a 3.9 per cent rise in the real price of wheat on impact. This shock also results in a small contemporaneous increase in global wheat production by 0.02 per cent, accompanied by a 3 per cent rise in the fertilizer price index. However, the response of inventories to this shock remains highly uncertain. Given the long-lasting nature of the shock, producers tend to accommodate the increased demand for wheat driven by economic activity by gradually raising production levels over longer horizons. This adjustment is accompanied by a gradual decline in the real price of wheat, which becomes indistinguishable from zero when considering the 95 per cent credible intervals, approximately 2 years after the shock. In contrast, fertilizer prices exhibit a hump-shaped response, peaking at 5.6 per cent after 1 year, further indicating that petroleum-based inputs are

9 It is important to note that our model is linear, implicitly assuming symmetric price responses to positive and negative structural shocks. While incorporating nonlinearities, such as thresholds in the inventory demand curve, could provide additional insights, this extension is beyond the scope of this paper. Moreover, the BH algorithm proposed is not designed to address nonlinearities (see Korobilis, 2022).

10 The positive response of e_t to a wheat supply disruption may be attributed to the positive correlation between e_t and p_t—as indicated by the positive posterior distribution of a_{ep} (see the Online appendix)—which is not controlled by any variable representing the production of fertilizer products. Nevertheless, it is worth noting that this paper concentrates on the determinants of the real price of wheat and not on those of the fertilizer price index.

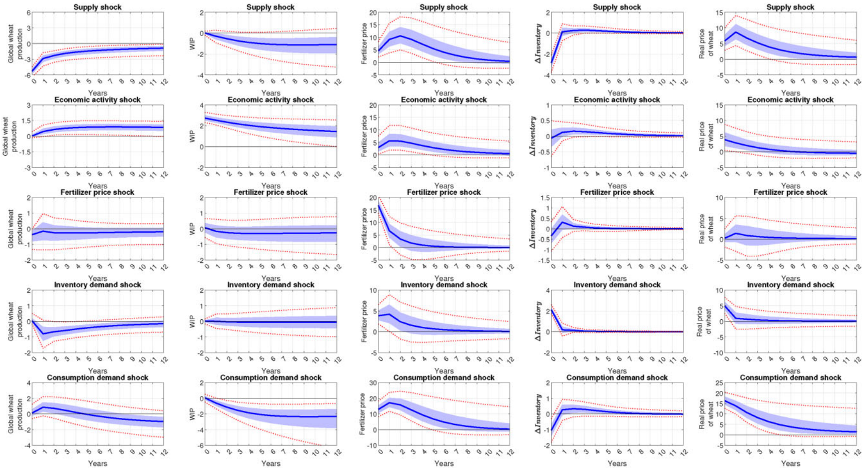

Fig. 2. Impulse response functions of model 1. Note: Blue lines indicate the posterior median impulse responses to a one-standard deviation structural shock, for model 1. The blue shaded bands and red dotted lines represent the posterior credibility intervals at 68 per cent and 95 per cent , respectively. The wheat supply shock is normalized to correspond to an increase in the real price of wheat.

endogenous to the economic system, as widely discussed in the global crude oil market literature.

The third row of the panel depicts the responses of all endogenous variables to a positive fertilizer price shock. This shock causes the fertilizer price to increase by 16.8 per cent on impact, followed by a rapid decline of 6.7 per cent in the second year, after which it becomes highly uncertain over subsequent periods. The effects of this shock on all variables are uncertain when considering the 95 per cent credible intervals. Despite the uncertainty in quantifying the impact of a fertilizer price shock, we provide empirical evidence that an unanticipated increase in fertilizer prices leads to a persistent decline in the posterior median estimates of wheat production and world industrial production. This is followed by a hump-shaped increase in the price of wheat and a reduction in inventories.

The fourth row of Fig. 2 illustrates the effects of an inventory demand shock. A positive shock to storage demand leads to a simultaneous increase in inventories by 2.1 per cent, the real price of wheat by 4.9 per cent and the fertilizer price index by 3.9 per cent. The contemporaneous response of wheat production to this shock is 0.04 per cent, but it is not statistically credible at the 68 per cent or 95 per cent levels. The impact of the shock is short-lived, as prices and inventories return to equilibrium within 1 year, indicating that speculative demand shocks have no-permanent effects on the variables of interest. Additionally, this shock has not significant impact on the world industrial production.

The effects of a consumption demand shock on global wheat market variables are illustrated in the last row of Fig. 2. A positive shock to consumption demand leads to a simultaneous increase in the real price of wheat by 16.3 per cent and the fertilizer price by 13 per cent, along with a 1 per cent decline in inventories, with all estimates falling within the 95 per cent credible regions. However, when focusing on the 68 per cent credible intervals, this shock induces a persistent increase in production, peaking at 0.85 per cent 1 year after the shock before gradually returning to zero. A positive consumption demand shock has a lasting impact on prices, which remain elevated at 10.7 per cent 2 years after the shock.

4.2 Wheat price responses to global shocks across varieties

The choice of price is an important aspect of our analysis, as it reflects a specific variety of wheat.[11] Although each wheat variety is shaped by local economic dynamics, their prices remain interdependent due to shared exposure to global undifferentiated wheat demand and supply factors. International prices serve as benchmarks for other wheat varieties, enabling a standardized approach to price discovery across local and global markets. Furthermore, while some shocks may primarily affect specific wheat types, the availability and the demand for one variety can influence the entire sector due to the partial substitution of wheat varieties in several industrial applications. To explore potential heterogeneous responses of different wheat price varieties to global shocks, we estimate model (1) using two alternative benchmarks in place of the US HRW wheat price. The first is the US Dark Northern Spring (DNS) price, representing a wheat variety primarily cultivated in the northern USA and closely competing with the second benchmark, the Canadian Western Red Spring (CWRS) price.

It can be shown that consumption demand and supply shocks are the primary drivers of price variability for all wheat prices of interest, both in the short and long term. Within the first year, supply shocks account for 10 per cent of HRW price variation, 7 per cent for CWRS and 5 per cent for DNS. In contrast, consumption demand shocks dominate, explaining 78 per cent of HRW price fluctuations, 85 per cent for CWRS and 89 per cent for DNS. Inventory demand shocks contribute modestly, accounting for 7 per cent of HRW price variation, 5 per cent for CWRS and 4 per cent for DNS. Finally, fertilizer price shocks have a negligible impact on wheat prices across all three varieties.

On average, unexpected changes in consumption demand explain 72 per cent of US HRW, 78 per cent of US DNS and 77 per cent of CWRS price variability. Supply shocks represent the second most significant source of price variation, playing a larger role in the long term. Global supply shocks account for 20 per cent of US HRW, 15 per cent of US DNS and 16 per cent of CWRS

11 Wheat is classified based on several key criteria, with three main factors being particularly important: protein content, kernel hardness and growing season. Protein content affects market demand and pricing, with high-protein wheat often trading at a premium compared to other qualities. The distinction between hard and soft wheat also influences prices, as hard wheat generally has a higher market value. Finally, the growing season plays a crucial role in the perceived quality and pricing structure of the global wheat market.

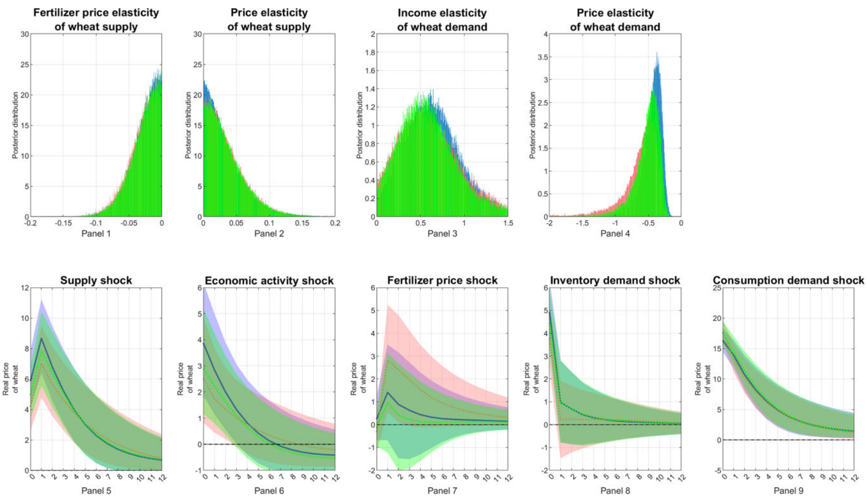

Fig. 3. Posterior distributions of a^s_{qe}, a^s_{qp}, a^d_{qw}, a^d_{qp} and impulse responses of the real price of wheat to structural shocks. Note: For the top panel, blue bars refer to the posterior distribution of the parameters using US HRW price. Light-red and green bars denote the posterior distributions of the coefficients using US DNS and Canadian WRS prices, respectively. For the bottom panel, blue lines indicate the posterior median impulse responses to a one-standard deviation structural shock, for model 1. Dotted light-red and green lines indicate the posterior median responses of US DNS and Canadian WRS prices. Blue, light-red and green shaded bands indicate the posterior credibility regions at 68 per cent. The wheat supply shock has been normalized to imply an increase in the real price of wheat.

price changes. In contrast, inventory demand shocks, fertilizer price shocks and economic activity shocks are less relevant in explaining the real wheat price variability during the period of analysis.

The fact that consumption demand shocks account for most of the variation in wheat prices is primarily explained by differences in short-run price elasticities. Fig. 3 shows that the posterior median of the price elasticity of supply is, in absolute value, lower than that of demand across all wheat classes. This implies a highly inelastic supply curve relative to a less inelastic demand curve. As a result, unexpected shifts in demand tend to generate large price movements and only modest quantity adjustments. By contrast, supply shocks—given the relatively higher elasticity of demand—translate into smaller price effects.

Our results confirm that global shocks similarly affect different wheat prices, regardless of the heterogeneity in regional growing conditions and quality standards.

These results are also consistent with the view that international prices serve as benchmarks, facilitating a standardized approach to price discovery across local and global markets.

Moreover, panels 1–4 of Fig. 3 display the posterior distributions of the price elasticities of wheat supply and demand across different international benchmarks. Using the same priors for the parameters of interest, as specified in Table 1, the posterior distributions of the elasticities across different price specifications appear very similar. Specifically, the posterior median of a^S_{qe} for HRW wheat is -0.023, while for DNS and CWRS wheats is -0.025 and -0.024, respectively. The posterior median of the price elasticity of wheat supply (a^S_{qp}) for HRW wheat is 0.026, whereas for DNS and CWRS wheats, it is slightly higher at 0.029. The probability of a wheat supply elasticity exceeding 0.1 is low: 3.9 per cent for HRW, 3.7 per cent for DNS and 4 per cent for CWRS. Conversely, the probability of a^S_{qp} falling between 0 and 0.05 is 77 per cent for HRW and 74 per cent for both DNS and CWRS. These results underscore the highly inelastic nature of global wheat supply, reflecting the rigidity of the supply structure in the global wheat market. We consider three main factors that help explain the low responsiveness of wheat production to changes in wheat prices. First, land availability represents a fundamental constraint. In most major wheat-producing regions, arable land is already intensively used and opportunities for expanding wheat cultivation are limited due to land competition with other crops, environmental regulations or physical constraints, such as soil suitability and climate. As a result, increases in wheat prices do not easily translate into area expansion in the short run. Second, technological constraints may also limit supply adjustments. While yield-enhancing technologies—such as improved seed varieties, fertilizers and irrigation—exist, their adoption is often costly, especially in the short term. Third, the annual frequency of the data used in estimation may contribute to the low estimated elasticity through an aggregation bias.[12]

Panels 3 and 4 of Fig. 3 show that most of the posterior mass of the estimated price elasticity of wheat consumption lies below 1, regardless of the wheat variety. This result supports the idea that wheat is a staple food in many countries—particularly in the form of bread, pasta and other essential products—which makes its demand relatively insensitive to price changes. Substitution possibilities are also limited. Other cereals such as rice or maize differ in taste, nutritional content and are therefore not perfect substitutes for wheat in most food systems. In addition, dietary habits tend to be rigid in the short run, especially in countries where wheat-based products are deeply embedded in everyday consumption. Finally, in high-income countries, wheat represents a small share of household food expenditure, so even large price changes have limited effects on total consumption. In low-income countries, where wheat accounts for a larger share of the food budget, substitution remains limited due to its role as a basic necessity.

Panels 5–9 of Fig. 3 reveal three main features regarding the dynamic responses of each price to global wheat market shocks. First, the responses of DNS and CWRS prices to supply, economic activity and inventory demand shocks are slightly smaller on impact compared to HRW, suggesting that DNS and CWRS are less exposed to these shocks. Second, a consumption demand

12 Short-run supply responses to price changes are not accurately captured in annual data, potentially biasing elasticity estimates downward. This issue is discussed in Section C.1 of the Online appendix.

shock induces a similar increase across all prices, following comparable dynamics. Third, the effects of a positive fertilizer price shock on wheat prices remain uncertain.

Our results shows that, despite the inherent heterogeneity of wheat as a commodity, international prices across different varieties exhibit remarkably similar paths in response to global shocks, consistent with the empirical findings of Goodwin (1992).

4.3 Decomposing production into yield and acreage

An accurate estimate of annual price supply elasticity plays a crucial role in understanding wheat price volatility and how prices respond to unexpected fluctuations in harvests and demand. Specifically, the more inelastic the annual supply, the greater the impact of demand and weather shocks on wheat prices (see Haile *et al.*, 2014). Building on this framework, we estimate an augmented version of model (1), referred to as the 6-SVAR model, which incorporates $a_t = \ln(A_t)$ and $y_t = \ln(Y_t)$.

This new model is expressed as a system of six structural equations:

$$a_t = \beta_{ae} e_t + \beta_{ai} \Delta i_t + \beta_{ap} p_t + \tilde{\mathbf{b}}_a' \tilde{\mathbf{x}}_{t-1} + v_t^a, \tag{7a}$$

$$y_t = \beta_{ya} a_t + \tilde{\mathbf{b}}_y' \tilde{\mathbf{x}}_{t-1} + v_t^y, \tag{7b}$$

$$w_t = \beta_{we} e_t + \tilde{\mathbf{b}}_w' \tilde{\mathbf{x}}_{t-1} + \tilde{v}_t^w, \tag{7c}$$

$$e_t = \beta_{ew} w_t + \beta_{ep} p_t + \tilde{\mathbf{b}}_e' \tilde{\mathbf{x}}_{t-1} + \tilde{v}_t^e, \tag{7d}$$

$$\Delta i_t = \beta_{ia} a_t + \beta_{iy} y_t + \beta_{iw} w_t + \beta_{ie} e_t + \beta_{ip} p_t + \tilde{\mathbf{b}}_i' \tilde{\mathbf{x}}_{t-1} + \tilde{v}_t^i, \tag{7e}$$

$$a_t = -y_t + \beta_{qw}^d w_t + \Delta i_t + \beta_{qp}^d p_t + \tilde{\mathbf{b}}_c' \tilde{\mathbf{x}}_{t-1} + \tilde{v}_t^c, \tag{7f}$$

where $\tilde{\mathbf{x}}_{t-1} = (\tilde{\mathbf{y}}_{t-1}, 1)'$ with $\tilde{\mathbf{y}}_t = (a_t, y_t, w_t, e_t, \Delta i_t, p_t)'$. We focus on Equations (7a) and (7b).[13] Equation (7a) models the global acreage curve, capturing farmers' decisions on how much cropland to plant. These planting decisions are influenced by factors, such as energy costs, via parameter β_{ae}, and wheat market conditions, via parameters β_{ap} and β_{ai}. This specification also accounts for the forward-looking nature of wheat production by including inventory changes as contemporaneous variables. The unexpected change

13 Equations (7c) and (7d) model global economic activity and energy-related cost conditions, while Equations (7e) and (7f) represent the inventory and consumption demand equations, respectively.

Table 2. Specification of prior distributions for structural parameters of the 6-SVAR model.

		Student t			
Parameter	Economic interpretation	Mode (c)	Scale (σ)	Dof (ν)	Sign
β_{ae}	Effect of e_t on acreage	0	0.3	3	–
β_{ai}	Effect of i_t on acreage	0	0.3	3	()
β_{ap}	Effect of p_t on acreage	0	0.3	3	+
β_{ya}	Effect of a_t on yield	0	0.3	3	–
β_{we}	Effect of e_t on world industrial production	0	0.3	3	()
β_{ew}	Effect of w_t on fertilizer price index	0	0.3	3	()
β_{ep}	Effect of p_t on fertilizer price index	0	0.3	3	()
β_{ia}	Effect of a_t on wheat inventories	0	0.5	3	()
β_{iy}	Effect of y_t on wheat inventories	0	0.5	3	()
β_{iw}	Effect of w_t on wheat inventories	0	0.5	3	()
β_{ie}	Effect of e_t on wheat inventories	0	0.5	3	()
β_{ip}	Effect of p_t on wheat inventories	0	0.5	3	()
β^d_{qw}	Income elasticity of wheat demand	0.3	0.2	3	+
β^d_{qp}	Price elasticity of wheat demand	-0.2	0.2	3	–

Notes: See Table 1.

in planted acreage, v^a_t, represents an acreage shock. Equation (7b) says that the global yield curve is contemporaneously affected by planting decisions, through the parameter β_{ya}. The term v^y_t represents a yield shock, which is closely linked to weather-related events.

Table 2 reports the priors for the contemporaneous structural coefficients.

To evaluate whether the 6-SVAR model produces results consistent with those of model (1), we begin by analysing the response of global wheat production to each structural shock. This approach allows us to determine whether production reacts differently to acreage and yield shocks. While production is not directly included in $\tilde{\mathbf{y}}_t$, its response to structural shocks can be inferred indirectly as the sum of the responses of the acreage and yield variables to each shock.

Panels 1 and 2 of Fig. 4 illustrate the heterogeneous response of global wheat production to acreage and yield shocks. A negative acreage shock causes an immediate decline in global wheat production, reaching its lowest point 3 years after the shock with a 1.56 per cent reduction, before gradu-

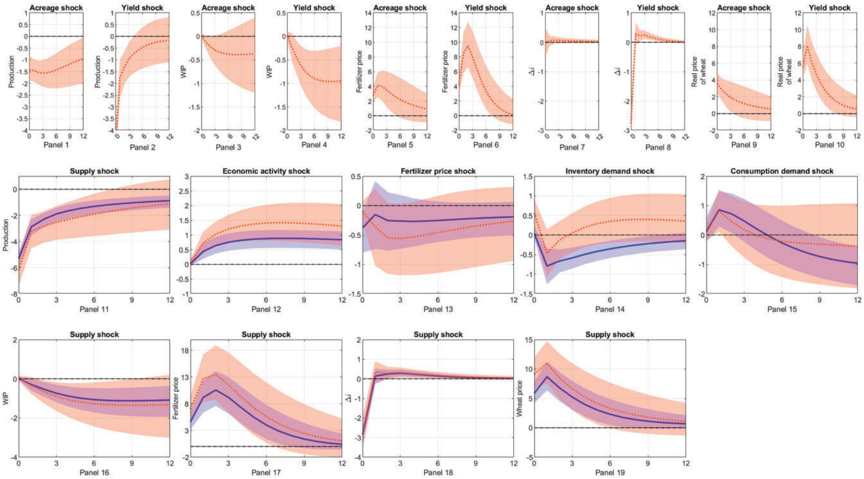

Fig. 4. Impulse response functions of model (1) and the 6-SVAR model. Note: Blue and red lines indicate the posterior median impulse responses to a one-standard deviation structural shock for model 1 and the 6-SVAR model, respectively. Shaded bands indicate the posterior credibility regions at 68 per cent. The wheat supply shock has been normalized to imply an increase in the real price of wheat.

ally returning to equilibrium. This slow and persistent dynamic suggests that acreage shocks are driven by structural and long-term factors. For instance, prolonged price changes may induce farmers to make gradual adjustments in planting decisions, such as adopting crop rotations to prevent soil degradation. Similarly, structural factors like agricultural policies, climate change, urbanization, geopolitical instability or competing land uses (e.g. for biofuels) can contribute to sustained shifts in wheat acreage. In contrast, a negative yield shock reduces wheat production by 4.8 per cent but is absorbed more quickly, typically within one or two growing seasons, as shown in Panel 2 of Fig. 4. Yield shocks are generally associated with short-term disruptions, such as adverse weather, pest outbreaks or fungal infections. Unlike acreage shocks, which involve gradual structural changes, yield shocks represent immediate productivity losses. These short-term disruptions can intensify price volatility, especially when they occur in major wheat-producing regions.

Next, we calculate the supply shock by summing the impulse responses of each variable to yield and acreage shocks, allowing for direct comparison with the supply shock identified in model (1). In the 6-SVAR model, both the supply shock and production responses are derived through an aggregation method, introducing additional uncertainty. The middle and bottom panels of Fig. 4 show that the credible regions for production responses to structural shocks in the 6-SVAR model are wider than those in model (1), reflecting greater estimation uncertainty. Consequently, unless the goal is to distinguish between acreage and yield shocks, the 6-SVAR model offers no clear advantage in identifying supply shocks and calculating production responses. Panels 11–15 illustrate that the impact response of wheat production to a negative supply shock is slightly smaller in the 6-SVAR model compared to model (1). How-

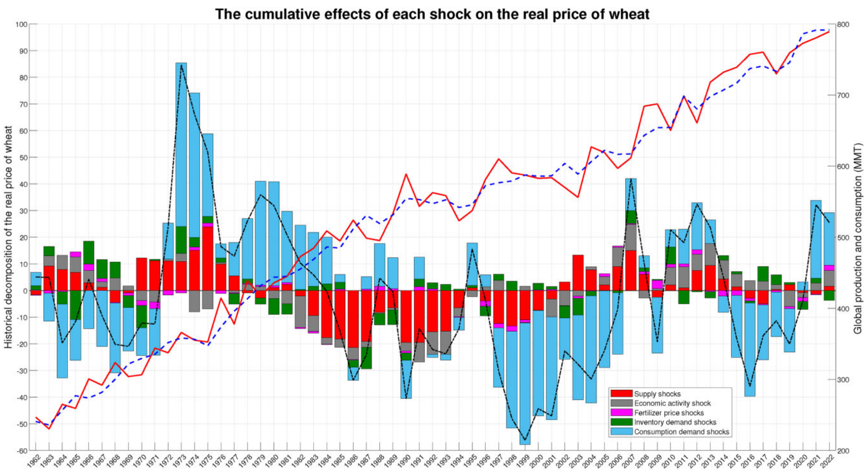

Fig. 5. Historical decomposition of the real price of wheat during the period 1962–2022.
Note: The bars illustrate the contribution of each structural shock to p_t (multiplied by 100). The red and blue lines represent actual data on global wheat production and consumption, measured in MMT, respectively. The black line shows the net effect of all structural shocks on p_t, at each point in time.

ever, the contemporaneous response of production to a positive consumption demand shock is nearly identical in both models.

In summary, while the responses of production and price to each shock in the 6-SVAR model are qualitatively similar to those in model (1), the latter exhibits less uncertainty in estimation, as indicated by its narrower credible regions.

4.4 Historical decomposition

Over the past decades, supply and demand shocks have significantly influenced the global wheat market, with several notable exogenous events between 1962 and 2022, as shown in Fig. 5.[14]

The 1972–1973 Wheat Crisis: Russian Wheat Deal. One of the most significant price shocks occurred in 1972–1973, driven by a combination of adverse weather and geopolitical developments. In 1972, a severe drop in wheat production in the Soviet Union, estimated at 13 per cent, induced the USSR to make unprecedented purchases of US wheat under the ‘Russian Wheat Deal’. These purchases amounted to 30 per cent of the average annual US wheat pro-

14 Fig. 5 plots the historical decomposition (HD) of the real price of wheat. The HD is computed as the product of the relevant row of the impulse response function and the corresponding structural shock, thereby tracing the time-varying contribution of each shock to p_t. Let $\hat{p}_{jt}$ denote the cumulative effect of structural j shock on the log-price, where $j = 1, 2, ..., 5$ corresponds respectively to the supply shock, economic activity shock, fertilizer price shock, inventory demand shock and consumption demand shock. The dashed black line in Fig. 5 represents the net effect of all shocks on p_t, that is, $\hat{p}_t = \sum_{j=1}^{5} \hat{p}_{jt}$. The estimated growth rate of the log-price between periods t and $t-1$ is given by $\Delta\hat{p}_t = \hat{p}_t - \hat{p}_{t-1}$ and similarly for individual shocks, such as, $\Delta\hat{p}_{1t} = \hat{p}_{1t} - \hat{p}_{1(t-1)}$. It follows that $\Delta\hat{p}_t = \sum_{j=1}^{5} \Delta\hat{p}_{jt}$.

duction and coincided with a failed monsoon in South Asia. The combined effect was a sharp global supply shortfall, resulting in a 61 per cent increase in the real price of wheat in 1973. Fig. 5 illustrates that price increase was predominantly driven by consumption demand shocks (48 per cent) and inventory demand shocks (10 per cent), the latter highlighting the importance of panic buying and strategic stockpiling in exacerbating the crisis.

The 1988–1990 Drought and Policy Responses. Global wheat production declined by 6 per cent from 1986 to 1988, and the 1988 drought in the USA marked another major disruption. As one of the worst droughts in US history, it reduced US wheat production by 12 per cent, leading to a sharp price increase. Simultaneously, policy changes—particularly a reduction in land set-aside requirements—facilitated a recovery in 1989. Planting and wheat production increased across all major wheat-producing countries in 1989, including China (6 per cent), France (10 per cent), India (17 per cent), the USA (12 per cent) and the USSR (11 per cent), resulting in a global production increase of 8 per cent in 1989 and an additional 10 per cent in 1990. Fig. 5 shows that while negative supply shocks and positive consumption demand shocks were the primary drivers of price increases in 1988, each accounting for 11 per cent of the price rise, supply shocks reduced prices by 13 per cent and consumption demand shocks by 26 per cent in 1990.

The 1994–1996 Supply Constraints and Subsequent Price Decline. In 1994, global wheat production faced severe constraints due to adverse weather conditions in major producing regions, including the USA and Argentina. Global cereal production fell by 6 per cent, with wheat and maize particularly affected. Fig. 5 reveals that supply shocks were the dominant driver of price increases during this period, contributing 9 per cent, while economic activity shocks added another 5 per cent. In contrast, consumption and speculative demand shocks led to price reductions of 3 per cent and 2 per cent, respectively. In 1995, the price of wheat rose by 30 per cent, driven primarily by consumption demand shocks (21 per cent) and supply shocks (7 per cent). However, a strong recovery in global wheat production in 1996, combined with negative consumption demand shocks, led to a price decline.

The 2006–2008 Global Food Crisis. The 2007–2008 global food crisis was one of the most dramatic episodes of wheat price fluctuations. A combination of droughts in Australia, rising energy prices and positive economic growth drove prices to unprecedented levels. Export restrictions in key wheat-producing countries further constrained supply. Fig. 5 highlights the importance of economic activity shocks during this period, which raised prices by 7 per cent, alongside consumption demand and supply shocks, contributing 41 per cent and 13 per cent, respectively. Interestingly, inventory demand shocks had a relatively minor impact on the price surge (5 per cent), consistent with the view that speculative demand shocks were not the main drivers of the price increase.

The 2010–2012 Droughts and Export Restrictions. The 2010 drought in Russia and Eastern Europe led to one of the most significant wheat price spikes in recent history, widely attributed to unexpected supply disruptions. In this case, the historical price decomposition does not entirely reflect the prevailing market narrative, as it attributes approximately 28 pp of the 33 per cent year-over-year price increase in 2010 to demand shocks, and only 5 pp to supply shocks. This suggests that the model may not fully capture the specific dynamics at play during this episode. However, in the case of the 2012 wheat supply shortfall, the historical decomposition of the real price of wheat attributes the price increase primarily to supply shocks (7 per cent), with consumption demand and inventory demand shocks each accounting for 5 per cent. Taken together, these episodes point out the increasing vulnerability of global food systems to climate-related events.

The COVID-19 Outbreak and the 2021–2022 Geopolitical and Supply Chain Crises. The most recent episodes of wheat price fluctuations occurred during 2018–2019 and 2020–2022, driven by the lingering effects of the COVID-19 pandemic on global supply chains and the geopolitical tensions arising from the Russia–Ukraine war. Fig. 5 shows that the 2019 price drop was primarily explained by economic activity disruptions (8 per cent) and inventory demand shocks (3 per cent). Negative supply shocks contributed to a 2 per cent price increase, while the remaining shocks had negligible impacts on the real price of wheat. Fig. 5 also indicates that the Russia–Ukraine conflict did not significantly affect global wheat production, as negative supply shocks caused only a 1 per cent price reduction between 2020 and 2022. During this period, positive consumption demand and economic activity shocks were the primary drivers of price fluctuations, increasing wheat prices by 36 per cent and 12 per cent, respectively. These findings emphasize the important role of demand-side factors in driving global wheat price dynamics.

5. Policy implications and conclusions

We develop a novel Bayesian SVAR model that incorporates the full endogenous interactions among the key participants in the global wheat market, including producers, consumers and inventory holders. This study offers a more comprehensive perspective on the factors influencing wheat prices, with a particular focus on consumption dynamics. Our approach allows a more precise identification of shocks and elasticities, representing a significant improvement over traditional econometric models that often underestimate the role of demand. Furthermore, we address recent critiques of earlier models concerning the accuracy of demand elasticity estimates (see e.g. Kilian, 2022a, b).

This work provides critical insights into the factors driving global wheat price dynamics, highlighting that demand shocks—particularly those related to consumption—are the primary drivers of price variability, accounting for nearly 70 per cent of price fluctuations. This finding departs from the traditional emphasis on supply shocks, which, while significant, play a secondary role. Supply shocks are often associated with climatic disruptions or long-term structural changes, such as shifts in land use, and their impacts are amplified by the inelastic nature of wheat supply. The limited ability of producers to rapidly adjust production in response to price changes further exacerbates price fluctuations. While inventory adjustments can help stabilize prices in the short term, they are insufficient to offset the larger impacts of significant demand-driven shocks.

We believe that our findings have relevant policy implications, although we recognize that our study does not provide a framework to assess the costs and benefits of specific interventions. Therefore, the identification of supply and demand shocks points to the importance of designing complementary tools to mitigate their effects. In particular, supply shocks could be mitigated through measures, such as international cooperation on emergency stockpiles and investments in climate-resilient agriculture—such as drought-resistant crop varieties and improved irrigation infrastructure (see, for instance, Kalkuhl *et al.*, 2016). While our study does not provide an assessment of the optimal size or cost-effectiveness of such reserves, it highlights their potential role in buffering supply disruptions. Demand shocks, by contrast, reflect unanticipated shifts in consumption patterns, income or expectations. While their timing and magnitude are inherently unpredictable, their market impact depends on the underlying elasticities of demand and supply.

Structural policies that increase the supply response to demand shocks may help limit the extent to which such shocks translate into large price movements. Moreover, greater flexibility in land use policies and agricultural technology adoption could enhance the responsiveness of supply to changing market conditions, especially in the face of unexpected demand shocks. However, such interventions may involve important trade-offs, particularly with respect to environmental sustainability, which lie beyond the scope of this paper. These measures are not intended to eliminate demand shocks, but rather to reduce their pass-through to the real price of wheat, thereby limiting their impact on market volatility and food security.

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Author contributions

Daniele Valenti: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing–original draft. Danilo Bertoni: Data curation Daniele Cavicchioli: Data curation Alessandro Olper: Conceptualization, Validation.

Supplementary data

Supplementary data is available at *ERAE* Journal online.

Conflicts of interest. The authors have nothing to declare.

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