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Shockwaves from Ukraine: Trends and Gaps in Agricultural Commodity Prices

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Keywords: commodity storage, trends, nonstationary models, numerical methods

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Shockwaves from Ukraine: Trends and Gaps in Agricultural Commodity Prices

Olga Bondarenko*

February 6, 2025

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I propose partial-equilibrium models that describe the dynamics of global wheat and corn markets. These models extend the classic competitive storage framework by incorporating nonstationary variables. They are calibrated using data from Ukraine and key importing and exporting countries. The models enable the endogenous estimation of price trends, based on the observed movements in the underlying variables. This framework provides insights into how involuntary reductions in Ukraine's global market presence, triggered by Russia's invasion, could have affected trend prices.

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1 Introduction

Headwinds of 2021-2023 have reminded policymakers in both emerging and advanced economies that commodity prices matter. An agnostic view of commodity price dynamics, typically employing futures prices, can lead to notable inflation forecast errors (Chahad et al., 2023). The issue is especially pertinent for emerging markets (EMs), including Ukraine, where food and energy comprise a substantial portion – sometimes up to 50% – of the CPI basket. In addition, some EMs rely on revenues from commodity exports to maintain their external balance and stability on foreign exchange (FX) market. For instance, in war-torn Ukraine, solely grains (mostly corn and wheat) accounted for 23% of total exports in 2023, up from 18% in 2021. However, existing approaches to analyze and forecast commodity market developments offer little to no reliable guidance on medium- to long-term fluctuations in commodity prices.

In this paper, I propose partial-equilibrium models of global wheat and corn markets that simultaneously estimate grain prices and their trends. To this end, the models include production and storage decisions of key exporting, including Ukraine, and importing countries. Unlike most previous studies, this study uses a nonstationary setting with trending supply and demand variables, following Miao et al. (2011). The models thereby allow for endogenous estimation of price trends, drawing upon the medium-term dynamics of the underlying fundamental forces.

The results offer a novel interpretation of grain price dynamics over the past 40 years. In contrast to trends, such as those obtained with statistical methods, which closely follow the price series, the trend derived from the structural model exhibits larger deviations from the observed data. These deviations often culminate in sharp price spikes or collapses when the production and consumption trends intersect, typically corresponding to local minima in inventories. For instance, during the early 2000s, when demand from emerging markets was gaining pace, real grain prices fluctuated well below the trend. Instead, between 2007 and 2013, corn and wheat prices surged above the trend, alongside other commodity prices, despite trend production growth exceeding consumption. More recently, trend consumption has been growing faster than production, leading to increasingly tight market conditions that make it more vulnerable to large weather or trade shocks. Russia's invasion of Ukraine demonstrated how structural changes in quantities can have a disproportionate effect on price trends. Specifically, a 1% decrease in global harvested areas resulted in a 4% higher price trend, while a 2% decline – in a more than 10% increase in three years, relative to a no-change scenario.

By striking a delicate balance between the transparency of time series models and the structural integrity of large sector-specific models, such a framework might become a valuable addition to policymakers' toolkits. First, its results can be easily incorporated into other forecasting models, including standard Quarterly Projection Models (QPMs), to reflect upon exogenous to these models trends in world prices of selected commodities. Second, in contrast to more sophisticated models operated by specialists (for instance, Aglink-Cosimo by OECD/FAO (2022)), it requires a limited understanding of the market and a small number of assumptions, which can be easily interpreted and communicated. Finally, developing scenarios like those related to climate change becomes more straightforward. A solid understanding of its consequences for commodity prices and inflation might be particularly relevant for central banks that contemplate adding climate change to their mandates.

The rest of the paper is structured as follows. Section 2 reviews the existing literature on selected approaches to analyzing and forecasting commodity prices, emphasizing the underlying price trends. In Section 3, the paper describes the partial-equilibrium model developed for the joint estimation of prices and trends, highlighting its key components and assumptions. The data used in the study is presented in Section 4. Section 5 provides a detailed discussion of the results of applying the model to the corn and wheat markets and develops illustrative scenarios. Finally, Section 6 concludes.

2 Literature review

This paper elaborates upon two major strands of literature on commodity prices.

Forecasting approaches Policymakers worldwide have long regarded futures prices as predictors of future commodity price movements (evidence spans at least from Greenspan (2004) to Lane (2024)). However, futures markets tend to underperform relative to the no-change forecast when the forecast horizon exceeds one year (Alquist et al., 2013). Earlier studies also show that the predictive content of futures prices has been declining since the early 2000s (Chinn and Coibion, 2014). Moreover, except for the upcoming one or two seasons, futures are typically available for only a few months and tend to be thinly traded.

An alternative approach involves the use of standard univariate and multivariate econometric models (Kilian and Murphy, 2014; Baumeister and Hamilton, 2019; Bondarenko, 2023). While these models can provide reasonable price forecasts over short horizons, they rely on linear trends. Given the high volatility in commodity prices, such linear models are less informative beyond 6 to 12 months.

Arroyo-Marioli et al. (2023) identifies consensus forecasts and macroeconometric models, such as the Oxford Economic Model, as the preferred tools for constructing longer-term projections. However, both approaches have certain limitations. Consensus forecasts may lack consistency with other key assumptions, such as on harvests or population growth. This is particularly relevant for Ukraine, given its significant role in global corn and wheat markets. Although Ukraine's production accounted for only about 3-4% of global totals, it was the third-fourth largest exporter of corn and the fifth-sixth largest exporter of wheat in 2014–2023 (on average, about 14% and 9% of global trade, respectively). Additionally, consensus forecasts do not allow for scenario analysis. In turn, large-scale macroeconometric models are costly and complex to operate. This drawback applies to other sophisticated sector-specific models, such as Aglink-Cosimo by OECD/FAO (2022), as well.

Commodity storage model Although primarily used for analytical purposes rather than forecasting, the commodity storage model is a prominent structural model that operates within a partial equilibrium framework. Initially proposed by Gustafson (1958), a theory of optimal storage and price determination was later brought into the empirical domain by Deaton and Laroque (1992, 1995, 1996). In their simulations of the baseline model, authors managed to replicate most of the key features of observed prices, except for the high autocorrelation. Building on their findings, Deaton and Laroque (1996) suggested that the high autocorrelation in prices should be attributed, at least partially, to the properties of the underlying supply and demand forces. However, the role of storage in explaining price dynamics then weakens substantially.

Therefore, the subsequent studies, following the standard approach in macroeconomic modeling, mostly resorted to statistical methods to remove the trend in prices and then analyzed the deviations from this trend with the competitive storage model. The existing body of literature primarily focuses on three distinct types of trends: linear, spline, and stochastic, each of which has its own shortcomings. The classic linear trend in the logarithm of price (Cafiero et al., 2011; Bobenrieth et al., 2013; Guerra et al., 2014) rotates from downward- to upward-sloping depending on the period under consideration (Figure A.1(a) in Appendix). The use of restricted cubic splines (Roberts and Schlenker, 2013; Gouel and Legrand, 2017) involves pre-specifying the knots, with the main issue being how to determine the appropriate number of knots. Depending on this parameter, price volatility in 2022–2024 can be attributed to either trend swings or deviations from the trend, with future forecasts diverging significantly from a downward to an upward trajectory (Figure A.1(b) in Appendix). In addition, just as with the Hodrick-Prescott filter, a modeler working with splines faces the challenge of identifying turning points in the cycle, represented by the knots, in real-time analysis (Figure A.1(c) in Appendix). Osmundsen et al. (2021) questioned the economic logic of separating deterministic trends from the pricing model since predictable income for stockholders has been generated in this setting. The authors then proposed a stochastic trend, but it accounted for the majority of price volatility, leaving the storage model to explain only a minor and often statistically insignificant fraction (Figure A.2 in Appendix).

However, in the standard macroeconomic literature, both the practice of detrending prior to applying a model and the hybrid approach of Canova (2014) are often viewed as inferior to explicitly embedding trends into the model structure (Fernandez-Villaverde et al., 2016). Thus, Bobenrieth et al. (2021) introduced a latent deterministic trend in production, which together with consumer demand of HARA type alters the arbitrage condition of storage. With such a model, the authors were able to generate high autocorrelation and a declining secular trend in prices, but they stopped short of analyzing developments after 2007 (despite having access to more than 10 years of data at the time of publication). The explanation for this may lie in the fact that their model implicitly induces a common trend across production, consumption, and prices, making it difficult to account for the structurally higher demand from EM countries and the US ethanol mandate changes, factors widely cited in the literature as somehow responsible for higher prices between 2007 and 2011 (Trostle, 2008; Trostle et al., 2011).

Instead, Miao et al. (2011) incorporated both supply and demand trends, which made the price trend the outcome of the interaction between the two forces. This nonstationary trend-based model likewise captured most price properties, including high autocorrelation, in simulations with artificially generated shocks to harvest. However, simulations involving actual shocks required further ad hoc adjustments to grain prices to account for the impact of oil prices, as the period under consideration included the energy crises of 1973 and 1979. Despite this shortcoming, the framework of Miao et al. (2011) offers a valuable tool for explaining price trends through economic fundamentals, as opposed to relying on an exogenous trend.

The model developed by Miao et al. (2011) extends Deaton and Laroque (1992), which does not incorporate production decisions. Gouel (2013) shows how to add production decisions and outlines various methods to solve for the optimal price function, including the endogenous grid method. For the sake of experimental rigor, I apply both the original Miao et al. (2011) model and the extended version with production decisions, treating the latter as the baseline.

3 Model

In this section, I develop a competitive storage model in spirit of Miao et al. (2011) and extend it by incorporating the planting decisions of producers, as outlined in Gouel (2013). The model features three types of agents – consumers, producers, and inventory holders – who collectively shape market outcomes, along with a material balance equation. In each marketing year (MY) t, consumer demand for grain is determined by a constant price elasticity demand function with a trend component. Producers decide on acreage to maximize profits from the next harvest. Stockholders optimize storage quantities to maximize profits from selling them at the real price p_{t+1} in the subsequent period. The material balance equation, ensuring supply matches demand, closes the model.

Consumption The consumer sector has a stylized representation, with consumer demand $D(p_t)$ being a continuous function of price that contains a trend λ_t^D, a component with constant price elasticity, and an exogenous demand shock ε_t^d.

$$C_t = D(p_t) = \lambda_t^D p_t^{-\rho} \varepsilon_t^d \tag{1}$$

The trend λ_t^D, which reflects the long-term growth in grain demand, is primarily influenced by two factors: population growth and income growth. Assuming that the consumption patterns of new individuals align with those of the existing population, an increase in the number of individuals would consequently lead to a corresponding rise in the total quantity of grain consumed (Baffes and Nagle, 2022). In turn, as income increases, consumers would be able to afford larger quantities of both grains and meat, thereby enhancing the demand for grain as animal feed, particularly in developing countries (Janzen et al., 2014). Income growth played a lesser role in the case of wheat, where the total quantity consumed has mirrored population growth since 1980. By contrast, the demand for corn has been rising about as rapidly as GDP at market exchange rates, particularly after the global financial crisis (Figure A.3 in Appendix). However, both income and population trends appear only imperfect proxies for consumption trends. Thus, it is more appropriate to use actual consumption data within this framework, leaving alternatives for future research that incorporates more sophisticated demand functions.

Production Each period t, producers make an acreage decision to maximize their expected profits from the harvest H_{t+1} to be collected in the following MY[1]. The total harvest is given by the product of the area planted A_t and the anticipated next-period yield Y_{t+1}, as in $H_{t+1} = A_t E(Y_{t+1})$. Both area and yield can be further broken down into trend and gap (or shock) components, $A_t = \bar{A}_t \varepsilon_t^a$ and $Y_t = \bar{Y}_t \varepsilon_t^y$, respectively.

The yield trend $\bar{Y}_t$ is primarily driven by technological innovations and better managerial practices by producers. Today, it can be argued that worsening weather conditions (including higher temperatures and increased evapotranspiration) may act as a headwind, offsetting technological progress (like drought-resistant seeds and new irrigation systems), potentially causing long-term yields to flatten or decline. In their expectations of next-MY profit, producers rely on the estimates of long-term trend yield $E(\bar{Y}_{t+1})$. Still, they have no control over the final outcome because of the random component in yield, ε_t^y. This gap between actual and expected harvests primarily results from short-term weather fluctuations and the harmful impact of pests. While they are fully exogenous to the model, substantial skill has been achieved in forecasting seasonal mean temperatures and precipitation, especially in the tropics and in regions with strong teleconnections with ENSO[2]. Moreover, there is some evidence of the impact of large-scale circulations, like ENSO, NAO, etc., on crop yield anomalies (Iizumi et al., 2014; Ceglar et al., 2017). Thus, although variability in ε_t^y can be to certain extent predictable well before harvest, I exclude this channel from the farmer's problem for now, deeming it insignificant, – this assumption can be revisited later.

$$\pi_{t+1}^a = \frac{E(P_{t+1}H_{t+1})}{1+r} - c(\bar{A}_t) = \frac{E(P_{t+1}\bar{A}_t\bar{Y}_{t+1}\varepsilon_t^a\varepsilon_{t+1}^y)}{1+r} - \frac{\bar{A}_t^{\alpha+1}}{(1+r)(\alpha+1)} \tag{2}$$

Production involves sowing costs that are modeled by an isoelastic cost function $c(\bar{A}_t)$, where the cost varies with the acreage planted. However, the available data refers to the area harvested, not the one planted. Although the former is often a reasonable approximation for the latter, they differ somewhat in both their absolute levels and short-term fluctuations (see Figure A.4 in Appendix for the U.S., where both series can be obtained from the NASS survey). Therefore, ε_t^a encompasses several important elements that are currently omitted from the cost function, such as expected prices of key inputs (oil/diesel, fertilizers), expected prices of alternative crops, and price risks[3], as well as measurement errors. ε_t^a is realized at the end of the year t, after the sowing decision is done.

The cost function is also normalized by the factor $(1 + r)$, where r denotes a cross-period real interest rate, to ensure that the model's deterministic steady state is normalized to 1 when trends are set to 1.

[1]The marketing year varies slightly depending on the crop, but it usually starts with harvest and ends before the next year's harvest.

[2]Nevertheless, the accuracy of a seasonal forecast is lower than that of a week-ahead forecast.

[3]The gap between expected and realized prices

The solution to the profit maximization problem results in a constant elasticity supply function, with acreage planted $\bar{A}_t$ being a strictly increasing function of the expected per-acre revenue[4].

$$\bar{A}_t = E(P_{t+1}\bar{Y}_{t+1}\varepsilon_t^a\varepsilon_{t+1}^y)^{\frac{1}{\alpha}} \tag{3}$$

Instead, if supply is completely inelastic, harvest is simply the product of trend area planted $\bar{A}_t$, trend yield $\bar{Y}_{t+1}$, and supply shocks ε_t^a and ε_{t+1}^y.

Storage Risk-neutral inventory holders, operating in a competitive market, seek to maximize profits by purchasing grains at a lower price in period t and selling them at a higher price in the subsequent MY.

$$E_t(\pi_{t+1}^s) = \frac{1-\delta}{1+r}E_t(p_{t+1})I_t - p_tI_t - \kappa I_t \tag{4}$$

The costs associated with storage include fixed physical per-unit costs κ, depreciation δ, and the opportunity cost $(1+r)$. Taking into account his expectations of price, the stockholder decides on the amount to store, I_t, subject to the constraint that the quantity I_t cannot be negative. This gives rise to the intertemporal complementarity condition.

$$I_t \geq 0 \perp \frac{1-\delta}{1+r}E_t(p_{t+1}) \leq p_t + \kappa \tag{5}$$

Thus, whenever the expected profit from carrying an additional unit of inventory is positive, stockholders will demand more inventory and bid up prices until the current and expected price, adjusted for carrying costs, converge. Conversely, an expected loss from holding inventories would imply zero holdings in t. Competition guarantees the absence of arbitrage profit from storage.

The market demand curve becomes kinked in the presence of inventory holders, as these agents create additional demand at lower price levels in order to take advantage of cost-effective storage opportunities (Figure 1). For its part, storage plays a crucial role in mitigating price volatility in the event of a negative harvest shock. For instance, a decline in availability from Q_1 to Q_2 would normally cause the price to increase from p_1 to p_2, but in the presence of stored inventories, it rises only from p_1^* to p_2^*.

Material balance Availability Q_t is the sum of the new harvest H_t and quantities stored in the previous period I_{t-1}, subject to a constant linear depreciation rate δ. Q_t can either be consumed or stored for the next period.

$$Q_t = H_t + (1-\delta)I_{t-1} \tag{6}$$

[4]For corn, per-acre revenue was also augmented by the trend in harvested areas, as the model without this trend failed to replicate the steep increase in areas and produced unreasonable parameter values.

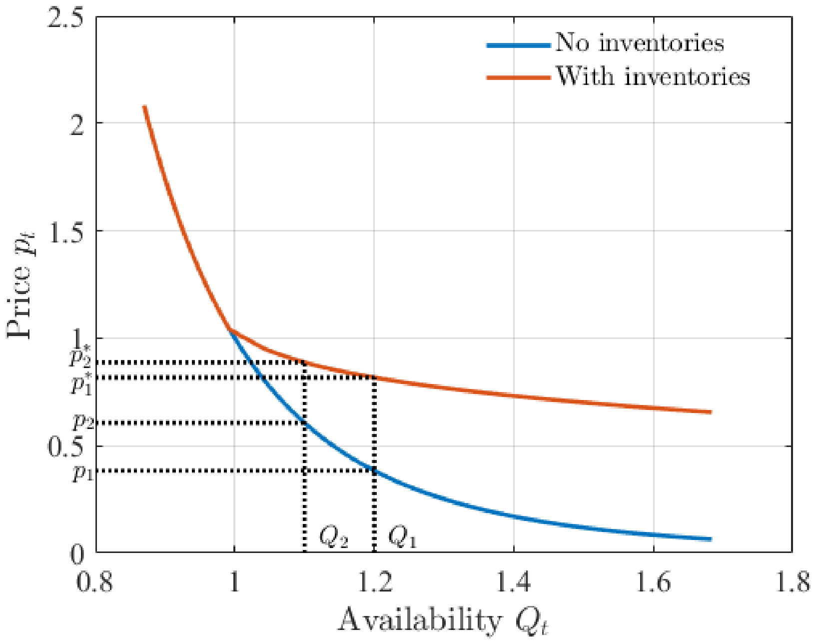


Figure 1: Market demand function with and without storage

Parameter values are $\beta = 0.989$, $\delta = 0.023$, $\rho = 0.19$, and $\kappa = 0$, as estimated in Miao et al. (2011). All trend values are set to 1.

$$Q_t = C_t + I_t \tag{7}$$

This concept corresponds to the balance sheet used by the U.S. Department of Agriculture (USDA) to discipline individual-country estimates of supply and demand (Vogel and Bange, 1999). The balance sheet equation ensures that total grain supply (the sum of production, imports, and beginning stocks) equals total distribution (the sum of consumption, exports, and ending stocks) for each country and marketing year. Since exports and imports largely offset each other, up to a minor discrepancy, related to reporting differences and grain in transit, I currently omit trade in the analysis.

Equilibrium A stationary rational expectations equilibrium (SREE) is a price function f – rather than a single value – that is monotonically decreasing in the state variable, $p_t = f(Q_t)$ (Deaton and Laroque, 1992). When harvest is supplied randomly and inelastically, that is producers assume rather than choose area planted $\bar{A}_t$, it is characterized by the first-order condition (5) and the transition equation (6). If producers optimize with respect to acreage, another condition (3) is added to the system.

Solution The equilibrium price function f lacks an analytical solution and must be solved numerically. For models with inelastic supply, several methods can be used, including the basic fixed-point iteration method outlined in Deaton and Laroque (1992). However, when time-varying parameters are introduced, the grid of states Q_t changes every time period, requiring an increasingly large number of evaluation points and thus increasing computational burden. To handle this, I use the endogenous grid method (EGM) of Carroll (2006), as suggested by Miao et al. (2011), which places a grid on the decision variable I_t. For the model with endogenous production, I enhance the EGM by adding an extra step to solve for acreage A_t using the FOC (3) at each I_t gridpoint every second iteration, as outlined in Gouel (2013).

Parameters I calibrate the models to match moments in the price data, namely coefficient of variation and first two autocorrelations. The model with exogenous areas and i.i.d. harvest shocks has four structural parameters – real interest rate r for time discount factor, demand elasticity ρ, depreciation rate δ, and storage cost κ, – whereas the model with endogenous production includes also supply elasticity α. The parameter r is calibrated as the average 1-year U.S. Treasury yield in 1987/88 MY to 2022/23 MY, adjusted for expected PCE inflation and aggregated on a marketing-year basis for the Northern Hemisphere[5]. As the values are approximately the same, $r = 0.93\%$ in both the corn and wheat models. In line with the USDA data, where ending and beginning stocks are equal, depreciation δ is set to zero.

The remaining parameters are estimated with the simulated method of moments. For each candidate set $\theta = [\rho, \kappa, \alpha]$, I simulate a series of artificial prices for the years 1987 to 2024 using the re-estimated function path along with the actual shocks to production and consumption. Next, the moments obtained from the simulations (i^{th} order autocorrelations $\hat{ac}(i)$ and coefficients of variation $\hat{cv}$) are compared with with those observed in the data (corresponding variables without hats) to choose a set of optimal parameters $\hat{\theta}$ that minimizes the sum of their squared differences.

$$\min_{\theta} \sum_{i=1}^{2} (ac(i) - \hat{ac}(i))^2 + (cv - \hat{cv})^2 \tag{8}$$

When considering exogenous supply, the objective function is initially evaluated on a sparse grid of 1,000 points, where ρ takes values between 0 and 1, and κ varies between 0 and 0.5. The grid is then refined over a narrower set of parameter values, with the maximum values of ρ set at 0.6 and 0.4, and those of κ set at 0.1 and 0.07 for corn and wheat, respectively (see Figure A.6 in the Appendix). Owing to the substantial computational burden, the parameters ρ and α were restricted to the interval $[0, 0.5]$, κ to $[0, 0.25]$ in the endogenous production case. Moreover, several stages of grid refinement, focusing exclusively on areas near the minimum values of the objective function, were necessary to to obtain optimal parameter values with the same level of precision.

The estimated parameters ρ and α in Table 1 show that both demand and supply are relatively inelastic, consistent with previous studies. For instance, Roberts and Schlenker (2013) report demand elasticities for caloric intake (maize, wheat, rice, and soybeans) ranging from -0.05 to -0.08, and higher (in absolute values) supply elasticities of 0.08 to 0.13, with the supply response mainly driven by land area expansion. Gouel and Legrand (2017) finds demand elasticities of -0.03 for wheat and -0.06 for corn, whereas Miao et al. (2011) estimates for wheat

[5]For wheat, July to June; for corn, October to September.

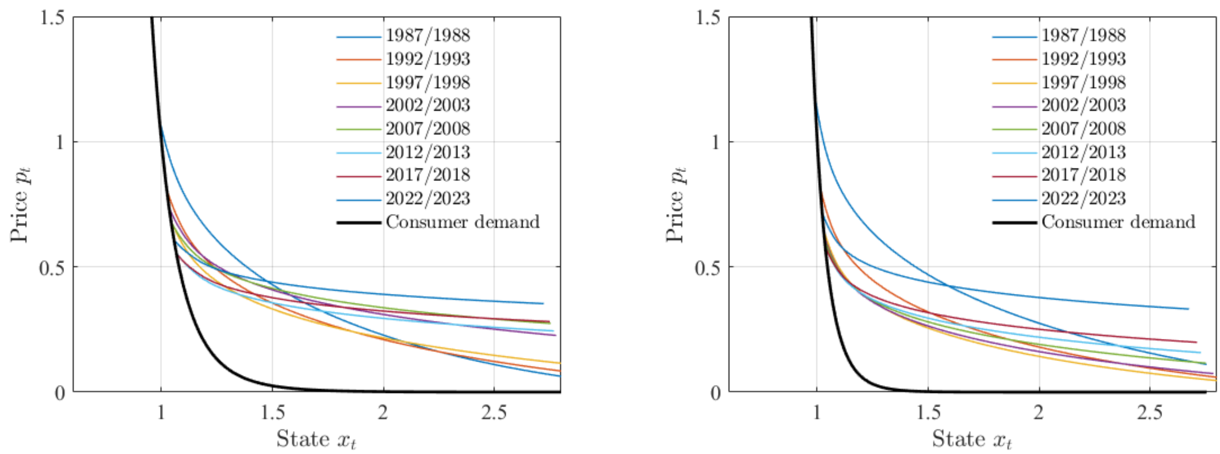
Parameter	r	δ	κ	ρ	α	σ^a	σ^y	σ^d
Corn	0.0093	0	0.062 0.069	-0.11 -0.12	0.015 –	0.0206	0.034	0.0160
Wheat	0.0093	0	0.035 0.042	-0.065 -0.08	0.03 –	0.0186	0.023	0.0143

Table 1: Parameter values

are higher at about -0.19, or within a range of -0.12 to -0.22. By contrast, models focusing solely on consumer demand often report higher elasticity values, with those collected by the USDA for products like wheat, maize, and cereals frequently clustering around -0.3, -0.5, and -0.7 to -0.8. While the fixed storage costs are generally comparable to those reported in Gouel and Legrand (2017), they are slightly higher, likely owing to the lower fixed interest rate of 0.93% in this study, as opposed to the 5% rate used in Gouel and Legrand (2017).

The standard deviations of shocks σ^a, σ^y, and σ^d capture the standard deviations of area, yield, and consumption deviations from their respective trends.

Trends Following Miao et al. (2011), I treat trending variables λ_t^D, $\bar{Y}_t$, and (in the model with inelastic supply) $\bar{A}_t$ as time-varying parameters. This formulation implies that, in contrast to the equilibrium framework of Deaton and Laroque (1992), for each period t, there exist an equilibrium price function f_t rather than a single SREE (Figure 2).



(a) Corn (b) Wheat

Figure 2: Market and consumer demand functions for the baseline model in selected MYs

While this approach offers the advantage of simplicity and lower computational cost by keeping the number of state variables at one, it introduces a trade-off in terms of economic consistency. Specifically, the resulting equilibrium assumes that future price functions will remain unchanged from the present. A more consistent approach – such as constructing an extended function path to account for rational expectations of changes in time-varying parameters, as proposed by Maliar et al. (2020) – is left for future research.

4 Data

This section first describes the price data used to estimate actual moments, which are then compared with simulated moments in the process of model calibration. It then discusses the quantity series used to calibrate the trends and the construction of alternative scenarios.

Prices In the case of traded commodities like wheat and corn, which are generally standardized but still feature some degree of differentiation[6], specific reference or benchmark prices might depend on application. The National Bank of Ukraine relies in its analysis and forecasting processes on the data from the IMF's Primary Commodity Price System, deeming it as the most informative on the evolution of export prices of Ukrainian grains. Thus, this paper also uses benchmarks from the IMF: Kansas City No. 1 Hard Red Winter for wheat and Louisiana No. 2 Yellow for corn. Prices are then adjusted by the U.S. Consumer Price Index (CPI) to account for changes in the general price level over time.

To reconcile the monthly data from the IMF's Primary Commodity Price System with the annual data from other sources, it is necessary to aggregate the price series. However, given the importance of current and expected prices in shaping the decisions of producers and competitive stakeholders, a basic aggregation method, like the calendar average, could prove to be inappropriate. Thus, I compute averages over the marketing year in the Northern Hemisphere[7], while acknowledging that differences in sowing times between hemispheres could lead to divergent price expectations in different regions. This concern is particularly relevant for corn, where the combined exports of the three largest Southern Hemisphere exporters – Argentina, Brazil, and South Africa – accounted for over 40% of global exports in the most recent five-year period, with their combined production comprising around 15% of the world total. However, the development of a multi-region, multi-period model is beyond the scope of this study and is to be addressed in future research.

Consistent with previous studies, the price data exhibits a high degree of autocorrelation at both first and second lags, pointing to a persistence in price movements over time. However, the price data used in this paper, which spans from 1987 onward due to the limited availability of disaggregated production data, shows lower values across all of the presented statistical metrics compared to the longer time series analyzed by Deaton and Laroque (1992) and Miao et al. (2011) (Table 2).

It should also be noted that, at higher frequencies, such as quarterly, relatively large price fluctuations occur more often, consistent with the model of speculative behavior, which leads to increased skewness and kurtosis. Quarterly prices also show higher autocorrelations, where high and low prices tend to be followed by high and low prices, respectively. Therefore, future studies could benefit from incorporating quarterly rather than annual data, though this would require addressing harvest discontinuities.

[6] For instance, USDA and traders distinguish several U.S. grain grades that reflect the general quality and condition of a representative sample, marked by "No. 1", "No. 2", etc.

[7] For wheat, July to June; for corn, October to September.

Statistic	Corn		Wheat		
	DL (1992)	This paper	DL (1992)	MWF (2011)	This paper
Autocorrelation(1)	0.76	0.63	0.86	0.83	0.57
Autocorrelation(2)	0.53	0.29	0.68	0.63	0.20
Coefficient of variation	0.38	0.27	0.38	0.49	0.27
Skewness	1.18	0.90	0.87	1.57	0.36
Excess kurtosis	2.48	0.13	0.61	2.60	-0.92

Table 2: Descriptive statistics

Supply and demand USDA is a widely recognized and reliable source of data on agricultural markets. It provides estimates for key components of the supply and demand equation – including beginning stocks, production, area, yield, imports, exports, consumption, and ending stocks – for most countries, on a MY basis. As per the countries listed below, the balanced panel of series starts in the 1987/88 MY.

In its influential WASDE report, USDA classifies Argentina, Brazil, Russia, South Africa, Ukraine, and the United States as major exporters of corn, and Egypt, European Union (with the UK), Japan, Mexico, Southeast Asia[8], and South Korea as major importers of corn. Japan, Malaysia, and South Korea are excluded from the sample, as their production and areas harvested are comparatively small. To maintain a balanced representation of the global market, Canada, China, India, Angola, Nigeria, Tanzania, and Uganda are incorporated into the analysis. The selected countries and country groups represent, on average, about 82% of corn areas and 92% of global production.

Major wheat exporters, as defined by USDA, consist of Argentina, Australia, Canada, the European Union (with the UK), Russia, Ukraine, and the United States. In contrast, the list of major wheat importers is broader, covering regions such as North Africa[9], the Middle East[10], and Southeast Asia[11], along with countries including Bangladesh, Brazil, China, South Korea, Japan, Nigeria, Mexico, and Turkey. To ensure a relatively stable share for the rest of the world, I include also India, Kazakhstan, Pakistan, Ethiopia, and Uzbekistan. This extensive set of countries covers nearly 95% of the total wheat area harvested and almost 96% of global wheat production.

Each country's acreage and yield series are filtered using the HP filter with a lambda of 100, consistent with standard practice for annual data, to separate long-term trends from short-term fluctuations. The resulting country-specific trends are then aggregated to construct a global trend. The shocks, denoted as ε_t^a and ε_t^y, are calculated as the deviations between the global areas harvested and yields, respectively, and their corresponding trends, which are derived from the country-level filtered data.

[8]Indonesia, Malaysia, Philippines, Thailand, and Vietnam.

[9]Algeria, Egypt, Libya, Morocco, and Tunisia.

[10]Lebanon, Iraq, Iran, Israel, Jordan, Kuwait, Saudi Arabia, Yemen, United Arab Emirates, and Oman. The sample includes only Iraq, Iran, and Saudi Arabia, as other countries produce negligible amounts.

[11]Indonesia, Malaysia, Philippines, Thailand, and Vietnam. No countries produce any relevant output, and thus, they are not explicitly represented in the sample.

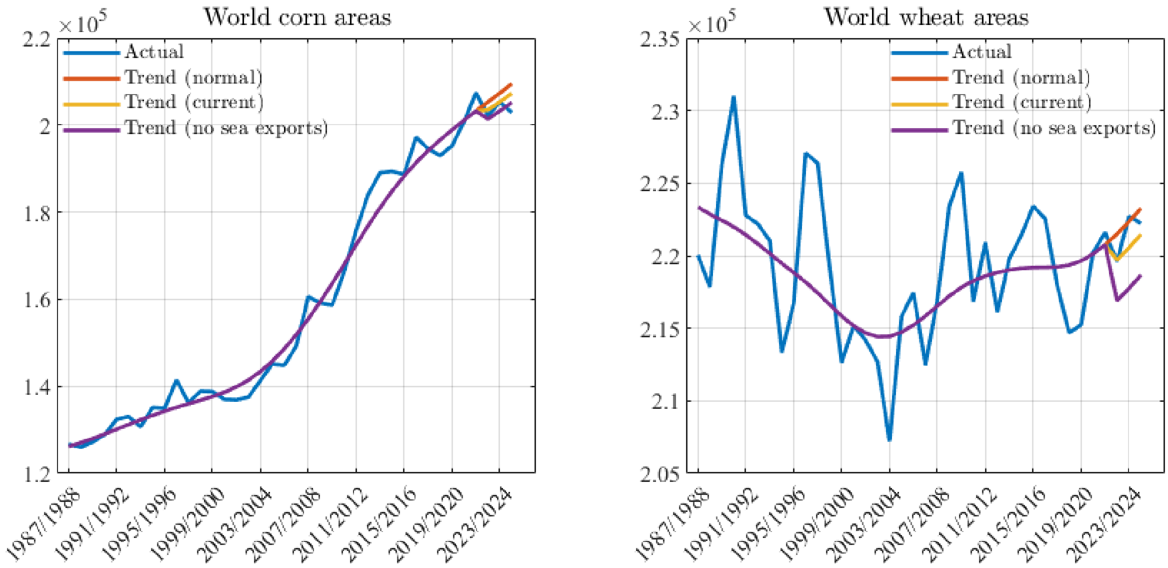


Figure 3: Projected world wheat and corn area under different Ukraine export scenarios

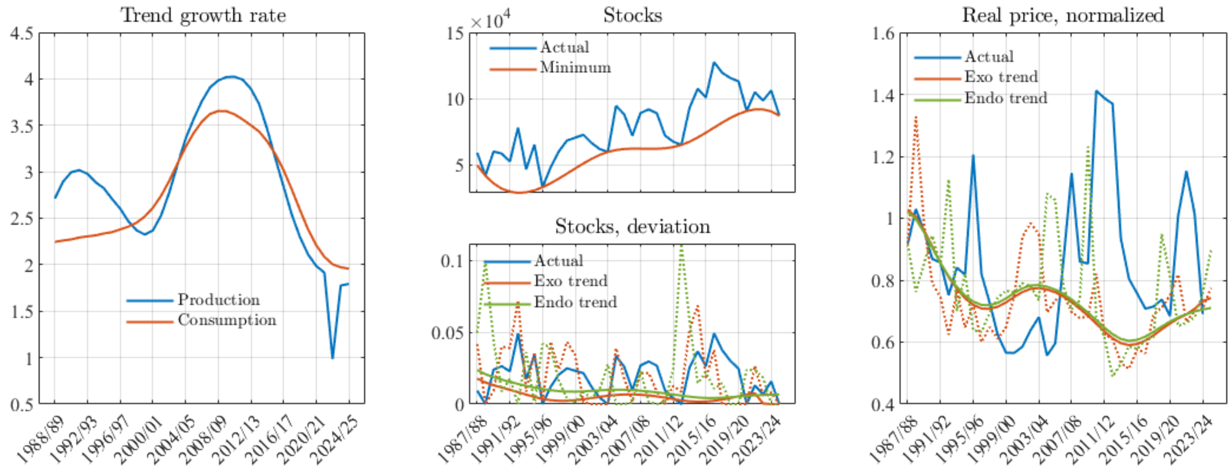
This approach to constructing trends facilitates the analysis of the impact of country-specific events on global yield, harvested areas, and, consequently, price trends. For example, Russia's invasion of Ukraine and the subsequent closure of ports severely disrupted Ukraine's ability to export. Alternative transportation routes, such as railways, roadways, and Danube ports at maximum capacity, were only able to sustain just over half of Ukraine's pre-invasion export volumes, and only around 30% at average capacity. Unless for the successful operations of Ukraine's Armed Forces, which allowed ports to resume operations, this would have further reduced the area planted in Ukraine. As shown in Figure A.5 in the Appendix, there has been no structural break in yields; rather, the impact was absorbed by a reduction in acreage. Instead, had it not been for the invasion, Ukraine's planted areas would have been approximately 30–35% higher. Ukraine's areas represent only 2-3% of global harvested areas, but such a significant change would still result in a 0.8-2% drop in global trend areas, relative to the 'normal' scenario without the invasion (see Figure 3). Ukraine's status as a major exporter would amplify the impact on prices.

Since world consumption of corn and wheat generally exhibits relatively low volatility from year to year, each is treated as a separate global aggregate, simplifying the analysis by omitting a country-by-country breakdown. The shock, ε_t^c, represents the differences between actual consumption series and its smoothed HP-filtered trend, capturing unexpected fluctuations in global consumption patterns for each crop.

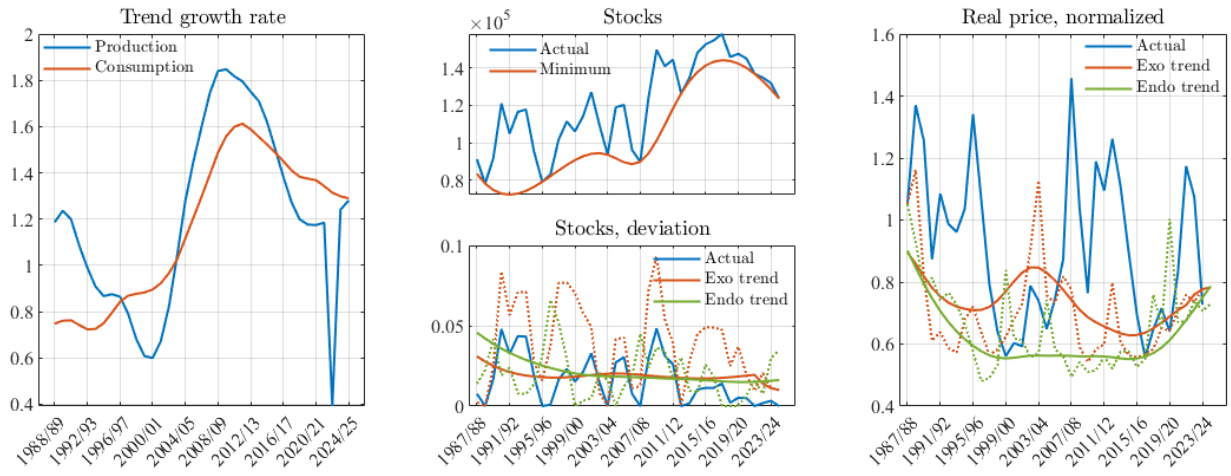
5 Results

The analysis reveals patterns in grain prices that differ slightly from those found with statistical methods. By construction, the interplay between production and consumption trends directly shapes price trends, with periods of stronger production than consumption growth associated with lower prices, and vice versa (Figure 4), in line with economic theory. Before the mid-

1990s, supply outpaced demand, leading to a prolonged decline in price trend that culminated in a sharp price drop by the 2000s. In the early 2000s, however, demand – driven largely by emerging markets amidst globalization and rising incomes – surpassed production growth, before production again took the lead. As a result, price trends peaked several years before the price spikes of 2007–2013, when the prices of major commodities, including corn and wheat, surged. When wheat production is endogenous, this pattern largely disappears, suggesting that fluctuations in planted areas are the primary cause of the volatility[12]. Since 2015, the slowdown in production growth has outpaced that of consumption, contributing to greater upward pressure on prices.



(a) Corn



(b) Wheat

Figure 4: Actual and simulated grain stocks[13]and prices

Prices simulated with shocks ε_t^a, ε_t^y, and ε_t^c are shown with dotted lines.

While the models are calibrated to closely match actual and simulated moments (first two

[12]As Figure A.7 in Appendix shows, the model's trend areas, generated without exogenous inputs, deviate somewhat from actual data.

[13]World stocks, excluding China (assumed to be mostly owned by the government (Deuss and Adenauer, 2020)) and estimated U.S. public stocks until 1988 (according to Zulauf et al. (2021), the 1985 Farm Bill, coupled with the severe 1988 drought, played a key role in reducing public stocks, and the 1996 Farm Bill subsequently eliminated most public stock programs).

autocorrelations and coefficient of variation), the Exo model[14] achieves a better fit. Overall, the three shocks from USDA quantity data are insufficient to fully capture price dynamics. Of the factors identified in Trostle (2008) and Trostle et al. (2011), the model fully or partially incorporates only about half, through either trends or shocks. It notably omits international trade and policies of key exporting and importing countries, which can amplify the effects of regional shocks, such as weather events, on prices. These results align with previous studies, suggesting that unforeseen macroeconomic shocks fail to translate into commodity price fluctuations, with own price movements responsible for the majority of variance in both nominal and real prices (OECD, 1993). Moreover, the models also overlook the relationship between commodities, particularly oil, price of which remained consistently high between 2007 and 2015. Apart from the financialization of commodities (Janzen et al., 2014), the most apparent link between grain and oil prices lies in the production costs. Since oil is an essential input to both the fuel needed for planting and harvesting, and the fertilizers and pesticides required for crop growth, higher oil prices tend to drive up agricultural costs across the board and, as a result, grain prices.

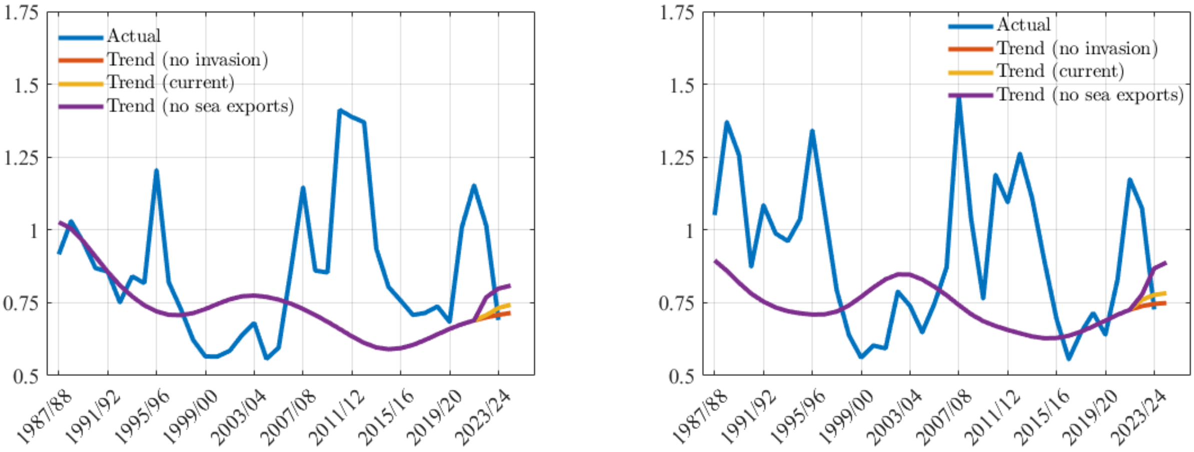
Statistic	Corn			Wheat		
	Actual	Exo mod	Endo mod	Actual	Exo mod	Endo mod
Autocorrelation(1)	0.63	0.61	0.33	0.57	0.60	0.51
Autocorrelation(2)	0.29	0.29	0.14	0.20	0.15	0.39
Coefficient of variation	0.27	0.21	0.22	0.27	0.22	0.22
Skewness	0.90	1.68	0.88	0.36	1.49	0.94
Excess kurtosis	0.13	4.11	0.55	-0.92	1.94	0.34

Table 3: Summary statistics of actual and simulated prices

The models simulate not only prices but also stocks, chosen by the competitive inventory holder. While stock-outs are unlikely in practice due to the need to maintain operational inventories, multi-period stock lows are consistently associated with price spikes. The "Exo" model performs particularly well in tracking the dynamics of stock deviations from these minimums. Notably, these minimums frequently coincide with the intersections of trends in production and consumption.

Russia's invasion of Ukraine, which in the model is reflected solely by a reduction in Ukraine's harvested areas (as international trade is currently omitted), has influenced trend prices, particularly in the Exo model. Relative to a counterfactual scenario without the invasion, corn price trend was just 1% higher in the first year, but the gap widened to around 4% by the current year. For wheat, the effect was more pronounced, with price trends decoupling by 3% to 4.5%. However, these changes remain relatively moderate compared to a scenario of continuous disruption to Ukraine's sea exports, which would have caused trend prices to rise by 13% to 18% by the third year of the war (Figure 5).

[14]Hereafter, the label "Exo" denotes variables produced by the model with an exogenous trend in the area harvested, while "Endo" refers to those generated by the model that incorporate producers' endogenous decisions regarding acreage.



(a) Corn (b) Wheat

Figure 5: Alternative price trends in Exo model after the invasion

6 Conclusions

This paper presents a thorough attempt to reconsider the conventional approaches used to analyze trends in corn and wheat prices, highlighting their limitations, and proposes instead an alternative framework. Rather than relying on econometric techniques such as splines or HP filters, it employs a structural model that builds upon the commodity storage model, incorporating trending supply and demand shifters. These trends are calibrated using comprehensive USDA data on quantities produced and consumed, aiming to ensure a robust connection of prices to real-world market conditions. The structural parameters are then estimated with the method of simulated moments.

The outlined approach provides a more comprehensive understanding of how price trends are influenced by evolving market fundamentals. In this setup, periods where production grows more rapidly than consumption are accompanied by lower prices, and conversely, when consumption growth outpaces production, prices tend to rise. Consequently, real grain prices fluctuated well below the trend in the early 2000s before before surging in 2007-2013, in tandem with rising oil prices, amid a backdrop of declining price trends. Structural breaks in consumption or production, like the reduction in Ukraine's harvested areas, can also have a disproportionately large impact on trends. Specifically, this decline led to a 0.8-1% drop in global trend areas but a roughly 4% rise in global trend prices relative to a counterfactual scenario without the invasion.

In addition, the paper confirms that incorporating trends in fundamental variables can address the long-standing issue of high correlation in commodity prices, which is hard to replicate using storage alone.

Nevertheless, to accurately capture price dynamics, the models would require further extensions, particularly the inclusion of international trade. This addition would allow the models to account for trade shocks, such as export bans or involuntary export cuts under the pressure of exogenous factors, say the blockade of Ukraine's Black Sea ports at the outset of Russia's full-scale invasion. Additionally, the models could also benefit from integrating production and consumption trends as autocorrelated variables, rather than treating them as static parameters. Lastly, incorporating semi-annual data to account for the growing significance of the Southern Hemisphere, especially for corn, or quarterly data to capture intra-season price spikes and align with the standard reporting frequency of policymakers, would enhance the model's applicability.

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A Figures

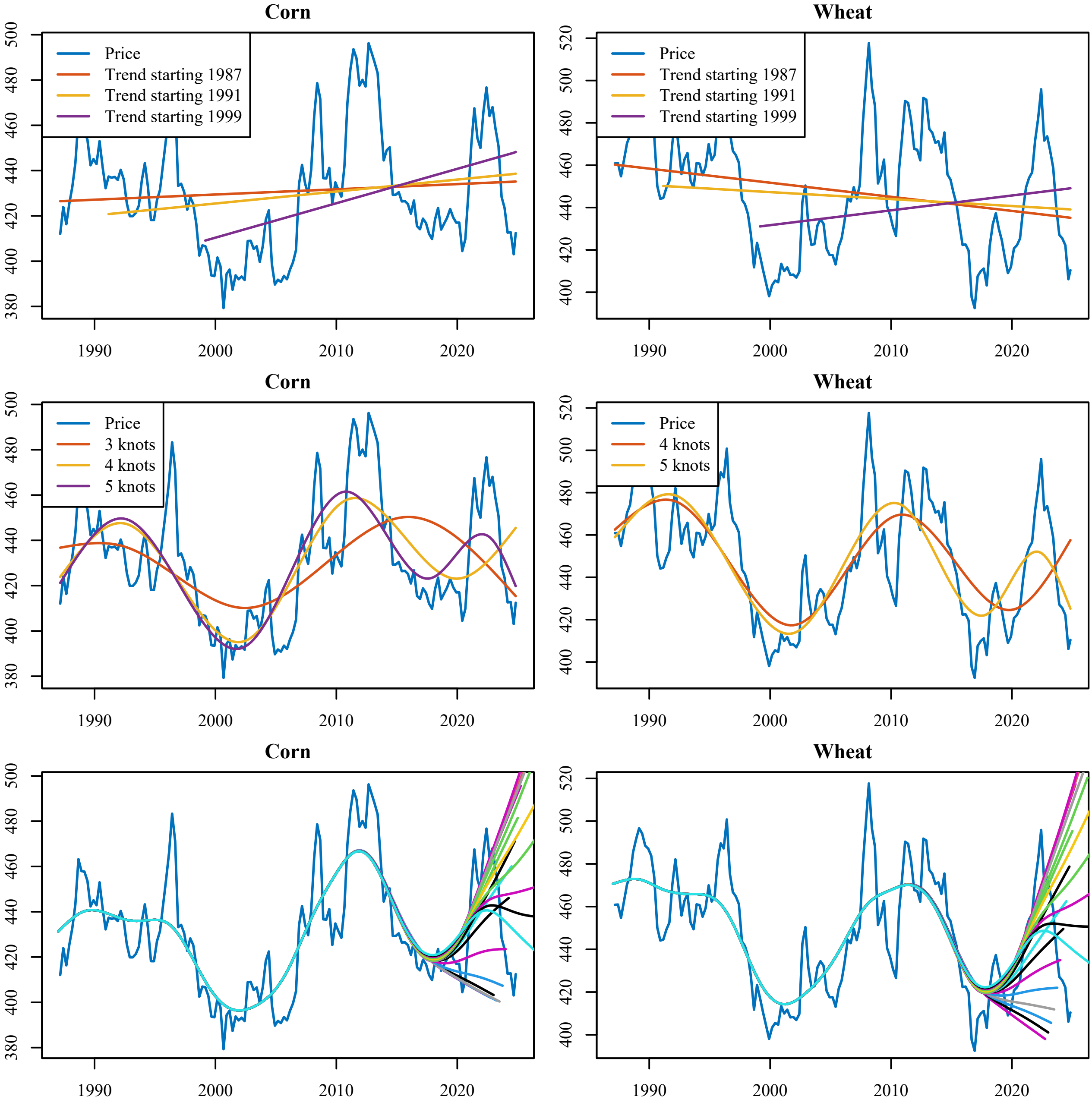


Figure A.1: Logarithm of real prices and alternative trends: (a) linear (top), (b) restricted cubic spline (middle), (c) Hodrick-Prescott filter (bottom)

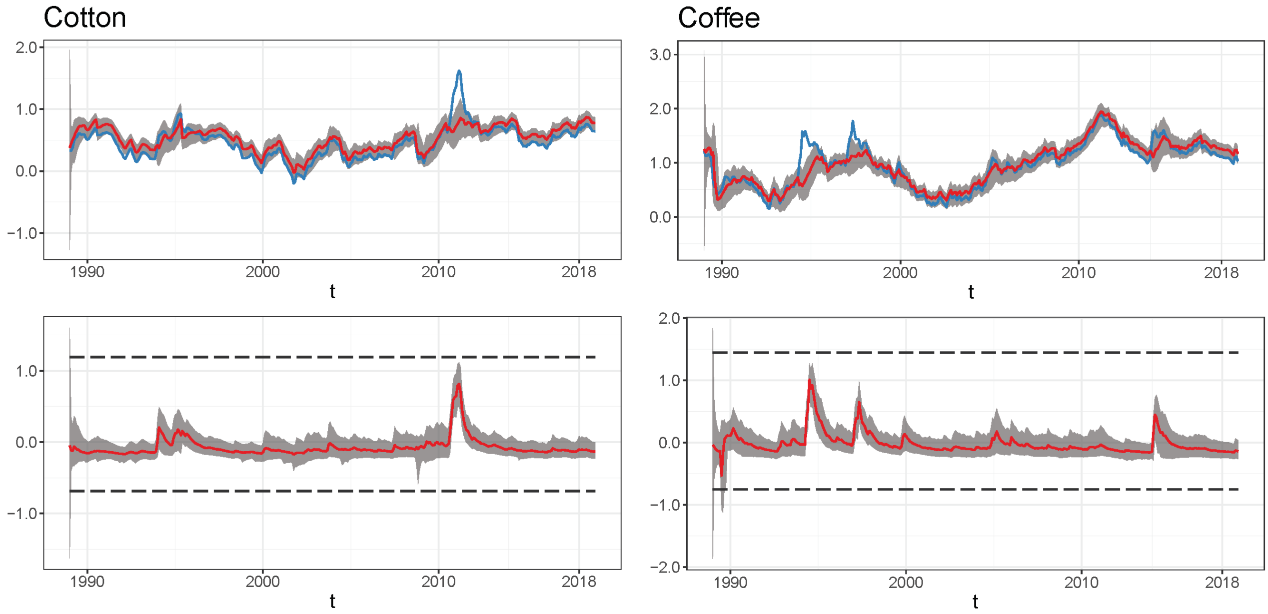


Figure A.2: Commodity prices and filtered price components from Osmundsen et al. (2021): (a) time series plot of the log price in blue and the estimated filtered mean of the stochastic trend component in red (top), (b) time series plot of the estimated filtered mean of the storage model component in red, gray shaded areas indicate the 95% credible intervals under the filtering densities, and the black horizontal lines mark the boundaries of the storage regimes (bottom)

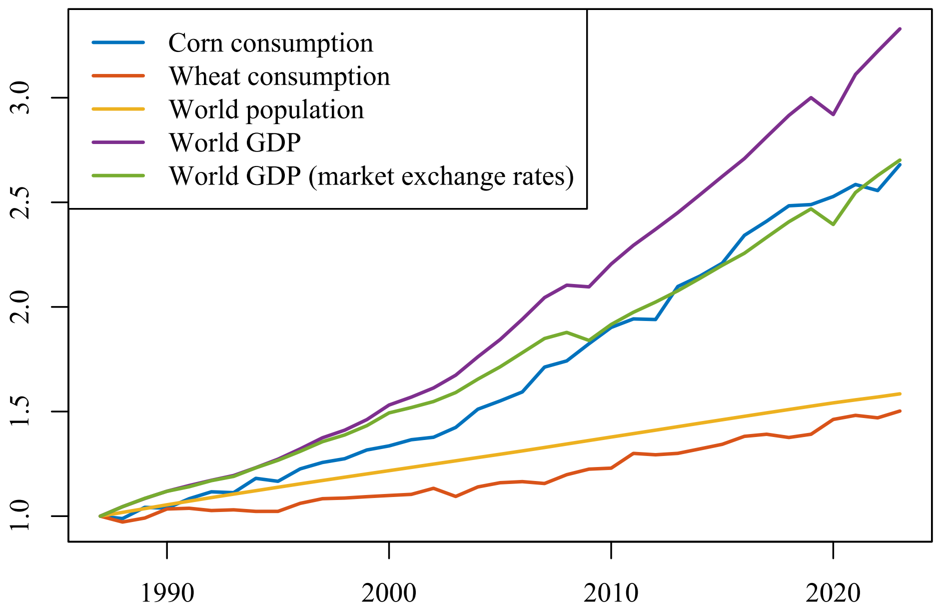


Figure A.3: Indexes of world grain consumption proxies (1987 = 1.0)
Source: USDA, IMF, U.S. Census Bureau International Data Base.

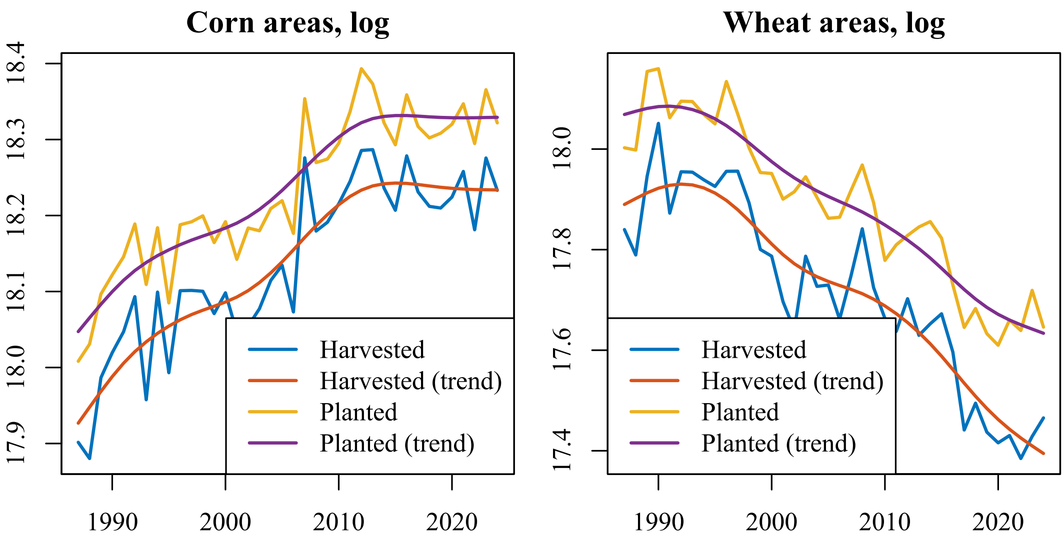
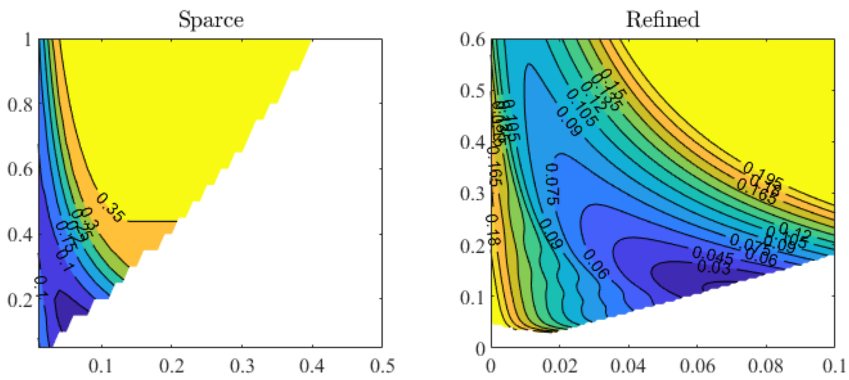
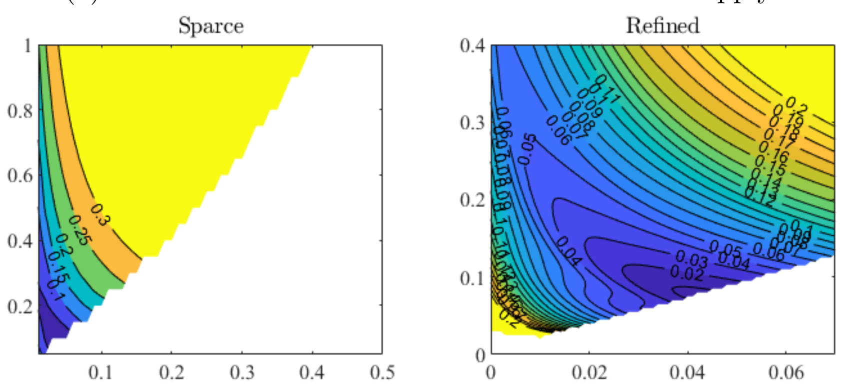


Figure A.4: Harvested and planted corn and wheat areas in the U.S.
Source: USDA National Agricultural Statistics Service.

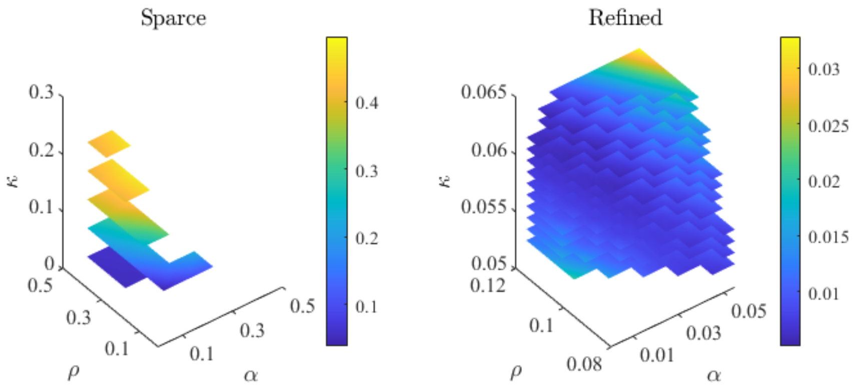
Figure A.5: Corn and wheat areas harvested and yields in Ukraine



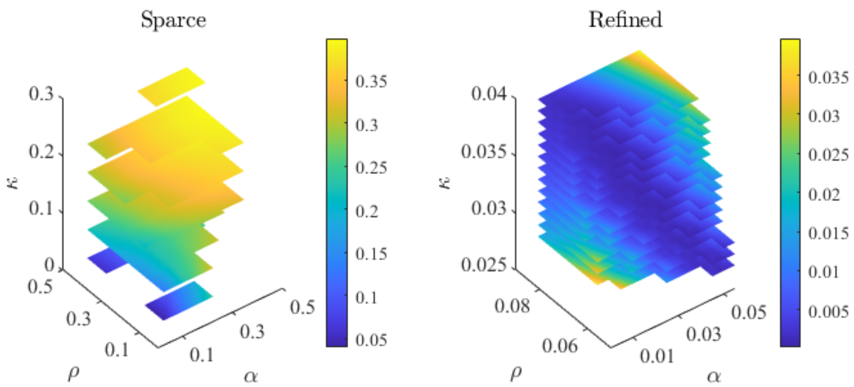
(a) Parameters for the corn model with inelastic supply



(b) Parameters for the wheat model with inelastic supply



(c) Parameters for the corn model with endogenous areas



(d) Parameters for the wheat model with endogenous areas

Figure A.6: Squared difference between simulated and actual moments

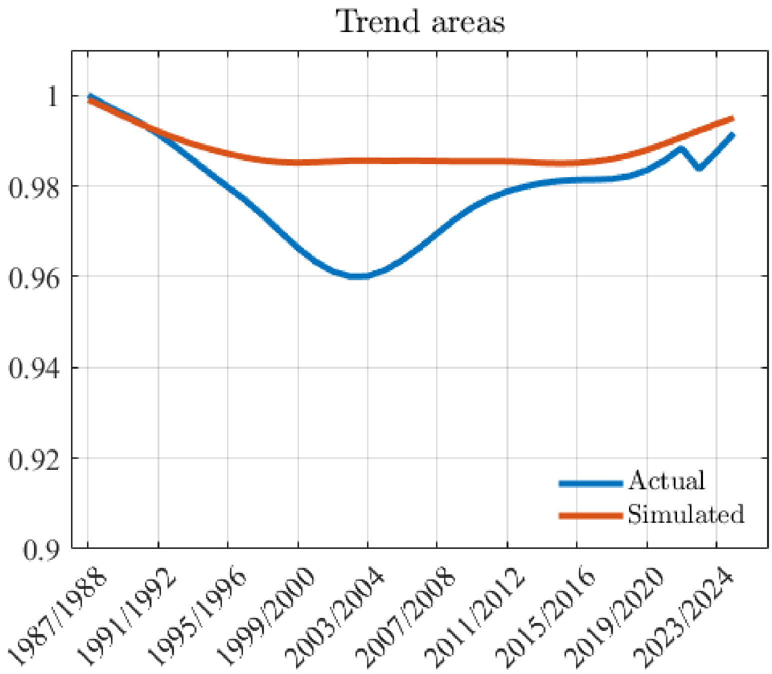


Figure A.7: World wheat areas harvested