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Abstract

Agricultural commodity markets have experienced bouts of significant volatility in recent years, drawing the attention of policymakers all over the world. This paper studies the dynamics of wheat and corn prices since 1999 through the lens of standard BVAR models in the spirit of Kilian (2009) and Kilian and Murphy (2014). I use monthly revisions of the WASDE supply projections to overcome the problem of limited availability of high-frequency data and develop an indicator of aggregate demand for grains, following Baumeister et al. (2020). The estimated elasticities are generally consistent with theory and earlier studies and produce reasonable historical decompositions. Models are helpful in forecasting exercises, including conditional forecasts and alternative scenarios while they perform no better than the random walk in short-term unconditional forecasting.

JEL Classification Codes: C32, C51, Q11.

Keywords: commodity prices, corn, wheat, BVAR models, demand elasticity, supply elasticity, historical decomposition, USDA supply forecasts, WASDE

1. Introduction

International corn and wheat markets got a lot of attention as russia's full-scale invasion of Ukraine broke out in 2022. Active warfare and rocket shelling in the proximity of ports limited Ukraine's export capacity, while sanctions created financing and insurance problems for russia. Grain prices increased substantially on impact, with wheat reaching 500 USD/MT and corn settling above 340 USD/MT for about a month – more than 1.5 times the long-term average. These developments were unsurprising, given that the two countries together accounted for almost 30% of the world's wheat export and about 17% of corn in recent years.

It was not the first time, though, when grain prices rose well beyond their long-term averages. Earlier literature focused on 2006–2008 and 2010–2011 price spikes, proposing competing explanations from weather to biofuel mandates to export restrictions. The truth is likely to lie somewhere in the middle, meaning that all these factors have probably contributed to price increases, at least to some extent. However, attempts to quantify them consistently are relatively scarce, especially at infra-annual frequencies.

Thus, this paper tries to fill the void by developing structural BVAR models for corn and wheat markets, using rather traditional approaches of Kilian (2009) and Kilian and Murphy (2014) for the oil market. Tailoring these methods to the agricultural setup appears to be a nontrivial task. First, a built-in assumption that production and consumption are equal each period is violated in the case of grains, where output is highly seasonal. Second, reliable high-frequency data on monthly grain production and stocks are virtually absent. To overcome both issues, this paper uses supply projections from WASDE reports published by the USDA. Although the values are reported on a marketing-year basis, these reports are updated monthly, closely followed, and considered trustworthy by market participants. Nevertheless, the data requires several adjustments to reflect consistently the USDA revisions across major exporting and importing countries. Since common indicators of aggregate demand may be less indicative of the price pressures associated with a growing economy and income, this paper also develops an alternative demand factor, as in Baumeister et al. (2020).

Structural shocks are identified with sign restrictions, the justification of which comes from competitive equilibrium models with and without storage. Although indirect estimation of the structural matrix does not allow for setting priors, posterior distributions of parameters are generally consistent with theory and earlier studies. The median elasticity of supply is about 0.07 to 0.10, with responsiveness to price stemming from the import component, while beginning stocks and production are largely predetermined. Demand is also inelastic, even if the magnitude of elasticity at 0.5–0.8 is closer to the upper bound of the range of estimates from the literature.

The models generally confirm the earlier readings of price increases in 2006–2008 and 2010–2011. Aggregate demand was more important for corn rather than wheat, given its broader feed and industrial use, including biofuels. Instead, the wheat price was primarily influenced by adverse supply shocks. While the accumulation of inventories drove corn prices upward in 2006–2008 amid expectations of sustained strong demand, their contribution was minor in 2010–2011 for both corn and wheat. When it comes to russia's invasion of Ukraine, a negative supply shock, triggered by sea blockade and export restrictions of alternative suppliers, pushed prices up. Stockpiling, involuntary to some extent (for example, for Ukraine), added to the price pressures while slowing global economic growth was counterbalancing it.

The BVAR models show desirable properties, and it makes them suitable for several forecasting exercises, including conditional forecasts and alternative scenarios. However, the framework presented in the paper is no better than the random walk in making unconditional forecasts of future developments.

The rest of the paper is organized as follows. Section 2 explains the theoretical background, which is vital for systematically building the model. Data and its transformations are described in Section 3. Section 4 shows the estimation methodology, and Section 5 its results. Robustness checks are presented in Section 6. Section 7 concludes.

2. Theoretical Models

A seminal paper by Kilian (2009), with its intuitive supply-demand framework, serves as a basis for numerous commodity price VAR models.[1] It uses three variables: (i) the percent change in global crude oil production; (ii) a global economic activity index derived from bulk dry cargo freight rates; and (iii) the real price of oil. The dynamics of these three variables is modelled jointly as an autoregressive process,

$$A_0 y_t = \alpha + \sum_{i=1}^{24} A_1 y_{t-i} + \varepsilon_t,$$

where $y_t = [\Delta prod_t \quad rea_t \quad rpo_t]'$ and ε_t is the vector of serially and mutually uncorrelated structural shocks. These structural shocks are identified from reduced-form errors ϵ_t with Cholesky decomposition as in

$$\epsilon_t = \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \end{bmatrix} = A_0^{-1} \varepsilon_t = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t}^{oil\ supply\ shock} \\ \varepsilon_{2,t}^{aggregate\ demand\ shock} \\ \varepsilon_{3,t}^{oil-specific\ demand\ shock} \end{bmatrix}.$$

Oil supply shocks $\varepsilon_{1,t}$ reflect unpredictable changes to the current production of crude oil, aggregate demand shocks $\varepsilon_{2,t}$ stand for innovations to global real economic activity that cannot be explained by oil supply shocks, and oil-specific demand shocks $\varepsilon_{3,t}$ represent shifts in the

[1] See Kilian and Zhou (2020) for a comprehensive survey of papers on the oil market.

precautionary demand for oil. Thus, any shortfalls of supply versus demand expected by market participants fall into $\varepsilon_{3,t}$ instead of being modelled explicitly.

The framework proposed by Kilian (2009) is simple and elegant, but it cannot be applied to grain markets straight away. Though the paper does not state it explicitly, this model is, in essence, a VAR representation of the simplest competitive price equilibrium model. Its setup typically consists of two behavioral equations of supply and demand and an identity linking them:

$$Q_t^s = q(P_t, P_{t-1}, \dots)$$

$$P_t = \beta_0 + \beta_1 Q_t^d + \beta_2 Inc_t$$

$$Q_t^s = Q_t^d$$

where Q_t^s and Q_t^d are quantities demanded and supplied, Inc_t stands for income, and P_t is price. Whenever Q_t^s is treated as production only, it implies that the amount of good produced is also consumed during the same period.

If such an approximation could have loosely fitted for the oil market[2], it becomes inapplicable when grain markets are considered. Unlike crude oil, which is extracted continuously throughout the year, grain production is discontinuous. Harvesting lasts, in general, two to four months, so stocks are necessary to match relatively smooth consumption with seasonal production (Figure 1A in Appendix). In addition, international trade in grains also exhibit a seasonal pattern (Figure 2A in Appendix).

Thus, for each period t, the USDA defines the total supply of grains Q_t^s, which is equal to the total distribution Q_t^d, as follows:

$$Q_t^s = I_{t-1} + Prod_t + M_t = X_t + Cons_t + I_t = Q_t^d$$

where $Prod_t$ and $Cons_t$ are production and consumption in the current marketing year, M_t and X_t are aggregate imports and exports, I_{t-1} and I_t are beginning and ending stocks. During the latest five marketing years (2017/2018 to 2021/2022), on average, carryover stocks and imports made up about 30% to 39% of the total supply of corn and wheat, respectively. Consequently, a consistent model of grain markets should include all of its components. In turn, it would ensure that the equality $Q_t^s = Q_t^d$ holds.

2.1. Temporal Dimension

When a commodity is storable, it creates opportunities for inter-temporal arbitrage. While production is predetermined by past sowing decisions, fertilizer inputs, and weather events,

[2] Admittedly, this assumption is relaxed later in Kilian and Murphy (2014).

carryover stocks can augment total supply from one marketing year to the next. By correctly anticipating future shortfalls of supply versus demand, market participants provide sufficient inventories and, hence, moderate price fluctuations. If they are wrong, however, a sequence of unfavorable weather events can result in a significant drawdown of stocks and, consequently, large price spikes. For this reason, researchers sometimes treat intertemporal arbitrage as speculation and demand for inventories as speculative demand (Kilian and Murphy, 2014).

In agriculture, the problem of optimal storage dates back to Gustafson (1958), but the first attempt to confront a storage model with the data was done by Deaton and Laroque (1992). Since the problem has no simple analytic solution, the paper uses a numerical approximation to solve for equilibrium price, and simulates the distribution of prices, given i.i.d. shocks to harvest. Deaton and Laroque (1992) were able to replicate some features of the observed price dynamics but not autocorrelation. As a result, a strand of literature has emerged[3] that focuses on bringing the competitive storage model closer to the data.

While these models are inherently more complex than the VAR framework would allow, they offer an intuition on problem formulation. First, demand consists of two parts, namely consumption demand, and demand from profit-maximizing, risk-neutral stockholders. Second, stockholders try to earn positive returns from storage by buying cheap and selling at higher prices in the next period, which implies an inverse relationship between price and inventories. Third, the availability of storage always dampens the effect of positive output shocks, but not negative ones, which can cause stock-outs and, thus, positive price spikes (Miao et al., 2011).

In line with Deaton and Laroque (1992), supply that contains inventories from the previous period must equal demand, including demand for inventories to hold until the next period, so that,

$$Prod_t + (1-\delta)I_{t-1} - I_t = d(P_t)$$

where δ is a depreciation rate, and $d(P_t)$ is a standard continuous and strictly decreasing function of price. Abstracting from depreciation, this identity is essentially the USDA balance sheet equation if one assumes exports and imports as parts of demand and supply, respectively, so that $Q_t^{ps} = Prod_t + M_t$ and $Q_t^{pd} = X_t + Cons_t$. Then,

$$P_t = d^{-1}\left(Q_t^{ps} + I_{t-1} - I_t\right)$$

If $d(P_t)$ is an isoelastic function, then model variables are usually defined in logarithmic form. Thus, instead of substituting $Q_t^{ps} + I_{t-1} - I_t$ into a linear equation directly, I transform the variables:

[3] Deaton and Laroque (1996), Cafiero et al. (2011), Miao et al. (2011), and Gouel and Legrand (2017) to name a few.

$$\ln(Q_t^{pd}) = \ln(Q_t^{ps} + I_{t-1} - I_t) = \ln\left(Q_t^{ps}\left(1 - \frac{\Delta I_t}{Q_t^{ps}}\right)\right) = \ln Q_t^{ps} + \ln\left(1 - \frac{\Delta I_t}{Q_t^{ps}}\right) = \ln Q_t^{ps} - \frac{\Delta I_t}{Q_t^{ps}}$$

Here, $\Delta I_t / Q_t^{ps}$ is sufficiently small to apply Taylor approximation around zero and simplify $\ln(1-x)$ to $-x$. This ratio is close to a popular concept of the stock-to-use ratio, which shows a relative grain market tightness (see, for example, analysis by Glauber (2023)). The demand equation then reduces to

$$P_t = \beta_0 + \beta_1 Q_t^{ps} + \beta_1\left(-\frac{\Delta I_t}{Q_t^{ps}}\right) + \beta_2 Inc_t$$

To close the model, one should specify an equation for the quasi-stock-to-use ratio. From earlier literature, inventories and stock-to-use ratios are inversely related to price (Bobenrieth et al., 2013). Since I_{t-1} is treated as predetermined and Q_t^{ps} appears in the denominator[4], the ratio is likely to have the same relationship to price. To avoid the presence of a contemporaneous variable in the ratio, researchers tend to substitute it with the previous-period value, e.g. Baumeister and Hamilton (2019). When production is rather smooth, as in the case of oil, it should work well. However, in agriculture, the differences across marketing years can be substantial so that the ratio of stocks to previous MY supply would not reflect the actual market tightness. Thus, the quasi-stock-to-use ratio is expected to depend also on Q_t^{ps}, as in

$$\frac{\Delta I_t}{Q_t^{ps}} = f(Q_t^{ps}, P_t, \ldots)$$

There is an alternative way to define the inventory variable simply as a difference between current and previous inventories in levels, as Kilian and Murphy (2014) and others[5] do. Nevertheless, such an approach tends to worsen model properties and forecasts.

3. Data

Unlike standard macroeconomic models, for which a set of variables is usually well defined, models of commodity markets employ different indicators to decompose shocks and forecast prices. Kilian (2009) and Kilian and Murphy (2014), as well as other papers that adopt a similar approach, use global crude oil production, the index of real economic activity, global crude oil inventories, and the real price of oil. Economou et al. (2017) go one step further by manually disentangling exogenous and endogenous supply shocks for all OPEC producers, the U.S., China, russia, Canada, Mexico, the North Sea, and the rest of the world (as an aggregate). Baumeister and Hamilton (2019) use an extended version of the OECD's index of monthly industrial production

[4] Quantity supplied is directly related to price.
[5] For instance, Baumeister and Kilian (2011), Economou et al. (2017).

as an indicator of global demand. Baumeister et al. (2020) offer an alternative measure of global economic activity, which appears superior to the industrial production index in forecasting oil consumption. Finally, Delle Chiaie, Ferrara, and Giannone (2017) state that the common factor, extracted from the panel of 52 internationally traded commodities, is indicative of global demand pressures and explains a large share of commodity price fluctuations.

However, in either case, authors rely on variables that are available monthly or at higher frequencies. Instead, data availability creates substantial problems for modeling agricultural markets at infra-annual frequencies. The USDA Production, Supply, and Distribution (PSD) Dataset, a credible source of international grain supply and demand data, reports the data only on a local marketing-year (MY) basis. It is worth noting that USDA may specify MY differently than producing countries (Vogel and Bange, 1999), so this paper uses solely USDA's definitions.

Authors employed different strategies to overcome this obstacle. Wang et al. (2014) rely primarily on oil market data and the Kilian (2009) setup, assuming that biofuels connect oil and agriculture markets. McPhail et al. (2012) add ethanol into the system explicitly. Both papers show that fluctuations in oil markets could have caused 15%–17% of forecast errors at the 12-month horizon during 2000–2012 (or even less during the first part of the sample). Qui et al. (2012) use U.S. corn supplies from the USDA's Economic Research Service along with the data on fuels. However, these supplies are provided on a quarterly basis, so authors transform them into monthly with a cubic spline. Whether this interpolation reflects actual data fluctuations, taking into account the seasonal nature of agricultural production, is an open question, but it explains about 5% of forecast error variance in 12 to 60 months. Instead, Janzen et al. (2014) rely on financial market indicators to identify structural shocks, namely the spread between the fifth deferred futures contract price and the nearby futures prices (reflecting a precautionary demand shock). A supply shock in that model is a residual variation in the agriculture commodity price that remains unexplained by the other three shocks. It turns out to be a key driving force behind wheat price fluctuations.

An alternative approach to capture a supply shock is to use changes in projections published in the World Agricultural Supply and Demand Estimates (WASDE). Empirical research (Arnade et al., 2021, Milacek and Brorsen, 2017, Adjemian, 2012 etc.) corroborates an assumption that WASDE reports contain significant nonpublic information that influences prices. It also suggests that the market adjusts its forecast of grain supply-demand balance according to USDA forecasts. Thus, Adjemian and Smith (2012) use monthly WASDE forecasts of crop production in the U.S. from May to January (excluding December; seven observations per year) to estimate the short-run demand flexibility for corn and soybeans. Although researchers in this topic concentrate predominantly on estimates for the U.S., Isengildina-Massa et al. (2008) show that the international situation and outlook have a measurable impact on the corn and soybean futures return variance.

WASDE forecast data seems to have several advantages over alternatives. First, the USDA publishes the report monthly, so one can easily construct a monthly time series, while the PSD

Database contains only annual values. Second, it provides consistent estimates of production, consumption, trade, and stocks that fit the structure of the outlined model well. Third, market participants follow the WASDE report closely, and a series of forecast revisions should mimic the information set that they rely on when they make pricing decisions. Therefore, this paper uses revisions of WASDE projections as a primary tool to capture supply shocks.

3.1. WASDE Supply Estimates

A standard WASDE report includes an analytical section and a set of world and U.S. supply and use tables for several commodities, including wheat and corn. The world supply and use table comprises three parts, corresponding to three marketing years, of which two are tagged with “Est.” and “Proj.” labels. These two labels might be misleading, as some people might treat the data for respective years as estimates for the current MY and projections for the next MY. However, it might not be the case depending on crop, country, and month.

For many crops, including corn and wheat, the marketing year differs from the calendar year and varies by country or region, as it normally starts with the first month of harvesting. Commonly, seasons in the Southern Hemisphere are a mirror image of those in the Northern, and harvesting in Ukraine occurs at about the same time as sowing in Argentina (Figures 3A, 4A, and 5A in Appendix). Although Argentina will collect its crops far later, both October Ukrainian corn and May Argentinian corn correspond to the same MY and, thus, fall into the same world total.

However, such an approach aggregates estimates constructed with unbalanced information sets. For example, USDA grounds its projections of U.S. corn production in May[6], June, and July on NASS estimates of acreage and trend yields since actual ones are unknown before harvest. At the same time, NASS estimates of U.S. winter wheat production, which instead rely on actual information from the fields, become available already in May. Even though Vogel and Bange (1999) do not disclose what methods and when Foreign Agricultural Service (FAS) uses for the foreign crop estimates, common sense suggests that methods and timing should be similar for analogous stages of plant growth in the U.S. and other countries.

It has several important implications for modeling. First, USDA turns out to reveal mainly current-MY estimates for some countries while both next-MY projections and current-MY estimates for others. Assume that in April, weather event damages winter wheat crops in Ukraine, which should be collected in July (already in the next MY). The market is likely to react to the event by adjusting the price (e.g., Guillaume et al., 2019), but the time series of WASDE forecasts will remain unchanged since the next-MY figures for Ukraine are first published only in May. By contrast, if a weather event happens in Argentina in September, the time series will capture it as a revision of WASDE projections.

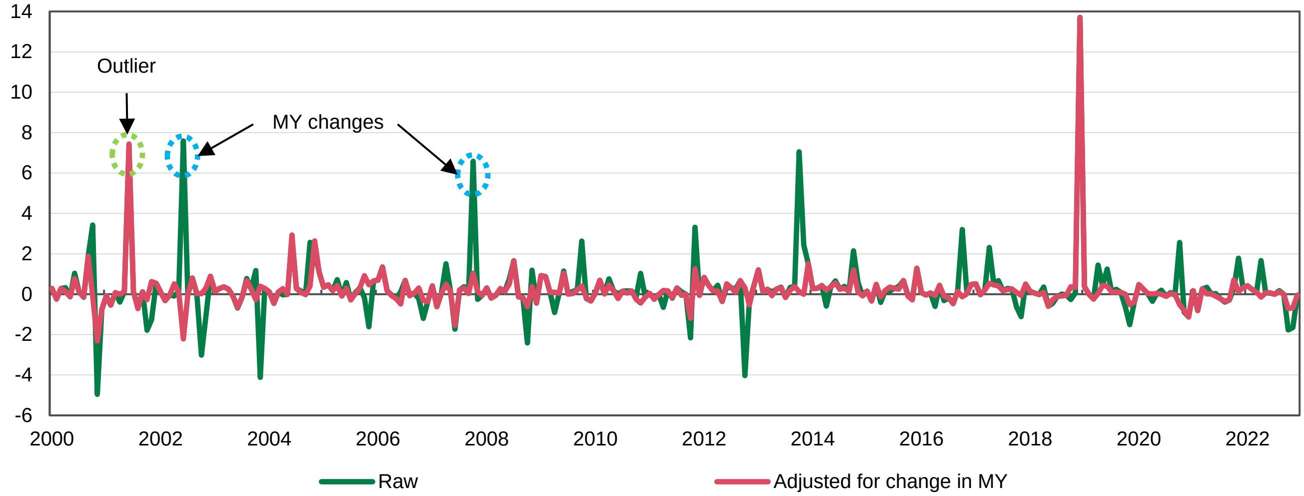
[6] USDA starts a new forecasting cycle each May.

Second, when incoming information for the next MY from countries that collect harvest in the summer months is not incorporated, the production series becomes increasingly less responsive to price. Recall that it takes time to grow crops, and current output results from past decisions (area, fertilizers) and random events (weather, pests). Farmers in Ukraine and other countries can barely adjust their production in May[7], and their elasticity of supply is close to zero. Conversely, farmers in the Southern Hemisphere prepare for sowing so the market price can influence their decisions. Still, crops will be sown in about half a year, and the total elasticity of supply will decline from some positive value at the beginning of the year to zero. Essentially, this elasticity might exhibit seasonality when estimated on raw WASDE report data. In addition, revisions in raw data are different; they are exogenous for countries with approaching harvest and endogenous for others.

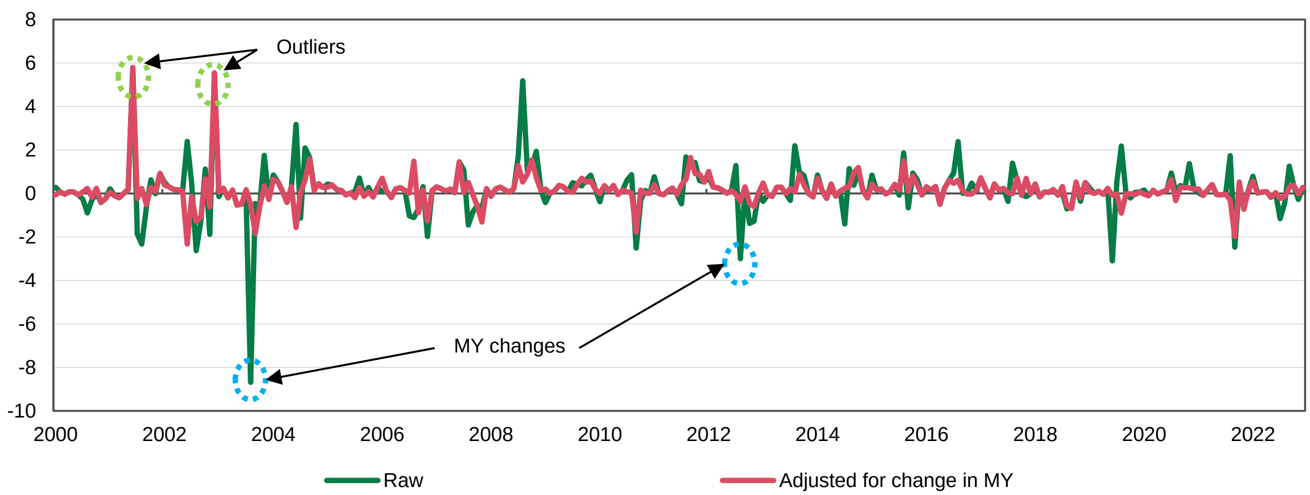
Taking into account the structure of the model, which treats marketing years separately[8], this paper distinguishes between current-MY and next-MY revisions of WASDE forecasts. In each specific month, the time series in levels receives the value from either “Est.” or “Proj.” parts of the table, depending on the current MY in a country.[9] Then it is transformed into revisions by taking the first difference of logarithms. Although formal tests do not find seasonality in the resulting series, one can notice large spikes associated with changes in MY (Figure 1). For instance, the new 2021/2022 MY for wheat in the U.S. starts in June 2021, and if the current harvest differs significantly from the previous one, it will produce a spike in June. Still, projections for 2021/2022 become available from WASDE in May 2021, so the difference between current and previous years[10] can be substituted by the difference between estimates for 2021/2022 released in May and June 2021. The adjusted series no longer exhibits large spikes.

Thorough correction of the supply series for differences in marketing years requires matching revisions with individual countries’ crop calendars. Since global aggregates include countries with different seasonal patterns, as explained above in the example with Ukraine and Argentina, it is virtually impossible to apply all these transformations to totals directly. Nonetheless, it still can be done for countries and regions that regularly appear in WASDE reports (Table 1A in Appendix). The set comprises major exporters and importers that together represent, on average, 90% of the global production of wheat and 88% of that of corn. To construct $Q^{s}_{MY,t}$ and $Q^{ps}_{MY,t}$, I collected separate production, inventory, and import estimates from the WASDE reports, adjusted them to include only current MY values, and then aggregated them into totals.

[7] If the country produces not only winter wheat but also some meaningful quantities of spring wheat, as do the U.S. or russia, unfortunately, it might still be captured in the adjusted series to the extent that the WASDE data-generating process lags actual field progress.
[8] Next marketing year comes through the expectations channel.
[9] Under USDA definitions.
[10] Here, 2021/2022 and 2020/2021. The new series, constructed in the previous step, would contain 2020/2021 value in May and 2021/2022 in June.



a) total supply of corn



b) total supply of wheat

Figure 1. Month-over-Month Changes in WASDE Forecasts

The quasi-stock-to-use ratio also uses data from WASDE reports. It is constructed by dividing the change in ending inventories from the previous MY ($\Delta I_{MY,t} = I_{MY,t} - I_{MY-1,t}$) by the combined value of production and imports in the current MY. Given that the marketing year is not the period t, revisions to the series take the form

$$\Delta \frac{\Delta I_{MY,t}}{Q_{MY,t}^{ps}} = \frac{\Delta I_{MY,t}}{Q_{MY,t}^{ps}} - \frac{\Delta I_{MY,t-1}}{Q_{MY,t-1}^{ps}}$$

It shows a percentage point change in the ratio from one WASDE report to the next that occurs mainly due to variations in the estimates of current-year ending stocks and supply.[11] Countries in the sample hold, on average, 89% of global ending stocks of wheat and 92% of those of corn.

3.2. Consumption and Aggregate Demand

When an aggregate demand indicator is included in a VAR model, it might be perceived as a consumption proxy. If the model behind is a competitive equilibrium model, this perception turns out to be wrong. As the model section shows, consumption is inferred from the identity instead of entering the model directly. The demand equation, however, can take into account demand shifters – factors that influence the level of the curve as opposed to movements along the curve. Models of the oil market commonly use industrial production (Baumeister and Hamilton, 2019) and the index of freight rates (Kilian, 2009) as an indicator of global economic activity that shifts oil demand. Instead, Baumeister et al. (2020) develop a broader measure that reflects some elements of derived demand, such as from the transportation sector.

In agriculture, real income is often considered one of the most important drivers. When consumers earn more, they tend to increase their spending on grains along with adjusting their diets to include more meat, especially in developing countries (Janzen et al., 2014). However, measuring income on a global scale directly can be challenging, as not all countries collect or provide detailed data on individual income. GDP per capita, which shows the average income of a country's citizens, is usually a low-frequency indicator unsuitable for a monthly model. Thus, I construct an alternative proxy in this paper to reflect shifters of grain demand.

Guided by the principles stated in Baumeister et al. (2020)[12], I compile the set of seven variables that correspond to three broad categories: real economic activity, commodity prices, and financial indicators. The number of variables and categories is lower here, given issues with data availability and, in some cases, appropriateness. For example, the weather is a supply rather than a demand factor for grains. Expectations and uncertainty measures are also discarded because a shock to an expectation is an inherent part of inventory demand.

The economic activity block consists of three indicators. The OECD consumer confidence index reveals households' sentiment towards consumption spending, depending on their views of the past and future financial situation. The Conference Board Leading Economic Index shows common turning points in economic data so it can contribute towards gauging changes in income. The OECD+6 industrial production index, which is now maintained by C. Baumeister, is included as a measure of both global economic activity and derived demand for grains from the industrial

[11] Previous-year ending stocks, i.e. current-year beginning stocks, can also be revised, but it happens rarely.

[12] Data should span multiple dimensions; variables should have economic reasoning; coverage in time and space should be the broadest available; the number of variables should be reasonable.

sector, including ethanol. In the U.S., ethanol's share of total use was, on average, 43% in the latest five years.

Ethanol production is also a reason to include oil rather than copper as one of the commodity price indicators. IER's (2007) paper estimates the maximum bidding price for corn and links it to the price of crude oil and dried distillers grains with solubles (DDGS) – a by-product that contains proteins and is used as livestock feed. The nominal price of Brent is deflated by the U.S. consumer price index.

Feed use of grains – about 64% for corn and 19% for wheat – links it to the meat sector. Although having the number of animals (cattle, hogs, and poultry) would be superior to any other approach, this data is rarely available at sufficient precision and frequency. Thus, the FAO real meat price index, which is probably the most timely high-frequency indicator for the sector, is used instead. It covers two poultry, three bovine, three pig, and one ovine meat product, 28 quotations in total.

As commodities are often priced and traded internationally in the U.S. dollar, fluctuations in its exchange rate can have a notable impact on prices in local currencies, affordability of commodities, and, hence, demand. The real trade-weighted U.S. dollar index from the Federal Reserve is chosen as the broadest measure of these developments, as it contains the currencies of 26 economies. In addition to the exchange rate, the financial block includes the MSCI world stock index to reflect the potential influence of higher (or lower) wealth on current household spending, especially in advanced economies.

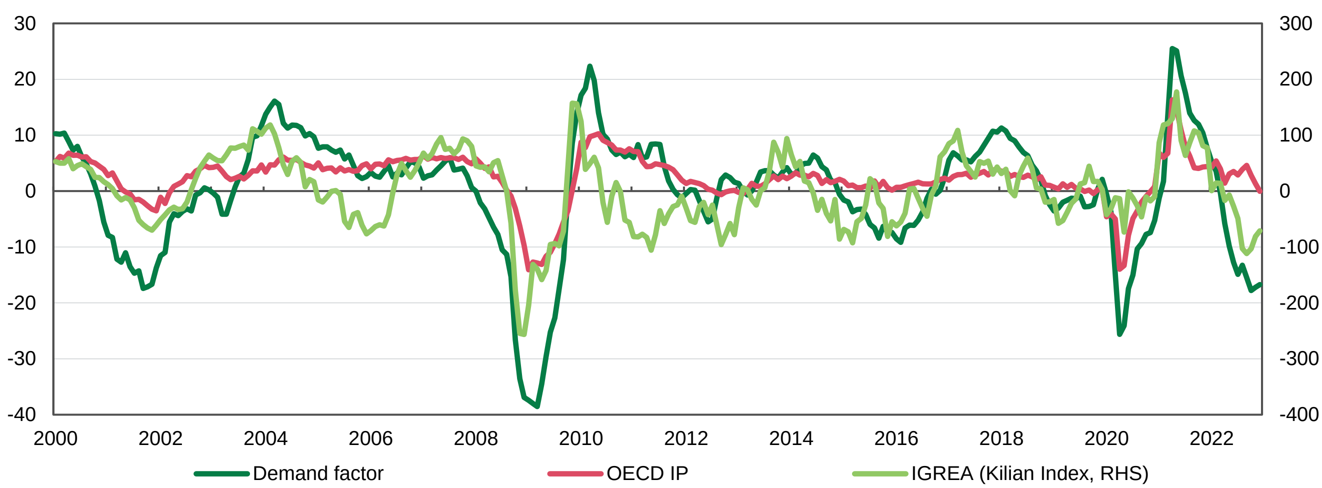


Figure 2. Alternative Aggregate Demand Series, % y-o-y

The aggregate demand factor for grains is estimated as the first principal component from a balanced panel of these seven indicators. It explains about 43% of the variation in the series and exhibits year-on-year dynamics comparable to that of other economic activity gauges exploited in oil literature (Figure 2).

3.3. Prices

Although traded commodities, including wheat and corn, are quite similar in their characteristics, they still feature some degree of differentiation for class and grade. This paper uses U.S. Wheat No. 1 Hard Red Winter and U.S. Maize No.2 Yellow from the IMF Primary Commodity Prices. The series are monthly averages of daily quotes in nominal U.S. dollars, deflated next by the U.S. consumer price index.

4. Estimation

Agricultural models have been mostly estimated with annual data, given the limited availability of high-frequency data, so theoretical models usually assume $MY = t$. This relationship does not hold for monthly models, $MY \neq t$, and t stands for the month, in which projections are released. Thus, for every month t, the balance sheet takes the form of

$$I_{MY-1,t} + Prod_{MY,t} + M_{MY,t} = Cons_{MY,t} + I_{MY,t} + X_{MY,t}$$

Importantly, $I_{MY-1,t} \neq I_{MY,t-1}$. Here, $I_{MY-1,t}$ is usually constant, with some revisions possible for statistical rather than economic reasons. Instead, $I_{MY,t}$ is a choice variable, and $\Delta I_{MY,t}$, which enters the quasi-stock-to-use ratio, is

$$\Delta I_{MY,t} = I_{MY,t} - I_{MY-1,t}$$

The proposed VAR models are specified in revisions, where revision stands for a change in the series from one WASDE report to the next, as in

$$\Delta \ln Q^s_{MY,t} = \ln Q^s_{MY,t} - \ln Q^s_{MY,t-1}$$

This equality holds for all t owing to the adjustments performed during the data preparation stage. The estimation sample spans from January 1999 to December 2019, as Lenza and Primiceri (2022) show that dropping observations after 2020 can be acceptable for estimating the structural parameters. The full sample has been extended beyond 2019 to track and analyze the latest developments.

The models are estimated in the BEAR Toolbox. The values of the hyperparameters are similar to those in the Baumeister and Hamilton (2019) paper: $\lambda_1 = 10\hat{}9$, $\lambda_2 = 1$, $\lambda_3 = 1$, and $\lambda_4 = 100$. Although these values differ somewhat from those used in the macroeconomic literature (see, for example, Canova, 2007), they tend to improve slightly the short-term forecast performance of the model.

4.1. Three-Variable VAR Model

Now consider a structural VAR model with two lags of the form

$$A_0 x_t = A_c + \sum_{i=1}^{T} A_i x_{t-i} + A_D D_t + \varepsilon_t$$

with dummies D_t to correct for outliers and vector $x_t = [\Delta \ln Q_t^s \quad \Delta \ln Inc_t \quad \Delta \ln P_t]'$ of dependent variables, where the first element is the total grain supply ($Q_t^s = I_{t-1} + Prod_t + M_t$), the second is a measure of real aggregate demand, and the third captures the real price of grains. These variables help identify shocks similar to the ones in the original Kilian (2009) paper. It is worth noting, however, that grain supply shocks $\varepsilon_{1,t}$ would show only a joint effect of changes to estimated production, imports, and beginning stocks[13] in the current marketing year.

The model offers an intuitive interpretation of parameters of A_0. For instance, α_{pq} is own-price flexibility, keeping other factors constant. Since substitutes and complements to grains are absent from the model, it is safe to assume that the reciprocal of price flexibility is equivalent to the price elasticity of demand (Houck, 1965). α_{qp} stands for short-term elasticity of supply. It is common to approximate the supply function with a vertical line for infra-annual frequencies since it is assumed that the quantity supplied is slow to react to price changes because of production lags. That argument might hold for production[14] but might not hold for total supply augmented by imports. Importers might be willing to increase purchases swiftly if their expectations of future harvests deteriorate fast or their aggregate income increases substantially. Thus, following Baumeister and Hamilton (2019), assume A_0 takes the form

$$A_0 = \begin{bmatrix} 1 & 0 & -\alpha_{qp} \\ 0 & 1 & -\alpha_{yp} \\ -\alpha_{pq} & -\alpha_{py} & 1 \end{bmatrix}$$

Bearing in mind that the estimation procedure is indirect, i.e. no distributions for elements of A_0 are specified, this matrix is used only to infer and justify sign restrictions on the impact matrix $D = A_0^{-1}$,

$$D = A_0^{-1} = \frac{1}{1 - \alpha_{qp}\alpha_{pq} - \alpha_{yp}\alpha_{py}} \begin{bmatrix} 1 - \alpha_{yp}\alpha_{py} & \alpha_{qp}\alpha_{py} & \alpha_{qp} \\ \alpha_{yp}\alpha_{pq} & 1 - \alpha_{qp}\alpha_{pq} & \alpha_{yp} \\ \alpha_{pq} & \alpha_{py} & 1 \end{bmatrix}$$

[13] Although beginning stocks are predetermined, statistical agencies sometimes revise these estimates, altering the balance in the market.
[14] Still, producers can leave harvests in the fields if farm-gate prices are lower than the costs of harvesting, although these occasions are rare.

If one uses conventional economic wisdom, then the supply curve should have a positive slope ($\alpha_{qp} > 0$), the demand curve a negative one ($\alpha_{pq} < 0$), higher income supports the demand for grains ($\alpha_{py} > 0$), and the higher price reduces real income ($\alpha_{yp} < 0$). Under these assumptions, D will always comply with the following sign restrictions

$$\begin{bmatrix} + & + & + \\ + & + & - \\ - & + & + \end{bmatrix}$$

This approach is somewhat different from Kilian and Murphy (2014), who concentrate on the net effect of change in price on grain supply (d_{qp}).

4.2. Four-Variable VAR Model

Now consider a more sophisticated model that accounts for inter-temporal arbitrage as described in the theoretical section. This VAR includes four variables $x_t = \left[\Delta \ln Q_t^{ps} \quad \Delta \ln Inc_t \quad \Delta \ln P_t \quad \Delta\left(\Delta I_t / Q_t^{ps}\right)\right]'$ that identify four structural shocks $\varepsilon_t = \left[\varepsilon_t^q \quad \varepsilon_t^y \quad \varepsilon_t^p \quad \varepsilon_t^i\right]'$. Inventories are no longer part of the supply shock ε_t^q, so it reflects only unexpected fluctuations in production and imports. The former are most likely related to weather events or plant diseases while the latter may originate from trade restrictions introduced by exporting nations. As previously, changes in grain demand associated with variations in aggregate income fall into the second shock ε_t^y.

The third shock is usually interpreted as a speculative demand shock, following Kilian and Murphy's (2014) definition of anyone buying oil for the future rather than current consumption as a speculator. Then, however, there exist at least two forms of speculation in commodity markets. One is related to the precautionary motive: an agent expects higher prices down the road and accumulates additional stocks. Another may arise because of the financialization of commodity futures markets and the presence of commodity index traders. Unlike agents from the first group, these investors are willing to gain exposure to commodity markets or diversify their portfolios and not strive to guess the correct value of grains in the future (Janzen et al., 2014).

This conceptual difference helps us establish correspondence between variables and shocks. If stockholders start expecting higher prices tomorrow, they start acquiring additional inventories, raising the price until the current price reaches a discounted value of the expected price minus the storage cost. Since these expectations are unobservable for now, they end up in inventory demand shock ε_t^i. This shock is also likely to include involuntary stock accumulation in countries that introduce export bans or become unable to export because of exogenous reasons. For instance, the blockade of Ukraine's Black Sea ports that started from the outset of russia's full-scale invasion caused the USDA to revise estimates of corn exports down by 6 MMT, while those of ending stock, up by 3 MMT. Instead, demand related to a financial activity or other demand not otherwise accounted for goes to ε_t^p, which now stands for "pure" speculation.

Transforming a theoretical model outlined above into a structural VAR, using the same logic as in Baumeister and Hamilton (2019), assume A_0 is

$$A_0 = \begin{bmatrix} 1 & 0 & -\alpha_{qp} & 0 \\ 0 & 1 & -\alpha_{yp} & 0 \\ -\beta & -\alpha_{py} & 1 & \beta \\ -\alpha_{iq} & 0 & -\alpha_{ip} & 1 \end{bmatrix}$$

where $|\alpha_{pq}| = |\alpha_{pi}| = |\beta|$ to adhere to the restriction superimposed by the balance sheet identity. It is also assumed that inventories do not react immediately to changes in aggregate income, $\alpha_{iy} = 0$, as it does not enter the optimization problem of stockholders directly. Therefore, the impact matrix $D = A_0^{-1}$ has the form

$$A_0^{-1} = \frac{1}{\det(A)} \cdot \begin{bmatrix} 1 + \beta\alpha_{ip} - \alpha_{yp}\alpha_{py} & \alpha_{py}\alpha_{qp} & \alpha_{qp} & -\alpha_{qp}\beta \\ \alpha_{yp}\beta - \alpha_{yp}\alpha_{iq}\beta & 1 + \beta\alpha_{ip} - \alpha_{qp}\beta + \alpha_{qp}\alpha_{iq}\beta & \alpha_{yp} & -\alpha_{yp}\beta \\ \beta - \alpha_{iq}\beta & a_{py} & 1 & -\beta \\ \alpha_{iq} - \alpha_{iq}\alpha_{yp}\alpha_{py} + \alpha_{ip}\beta & \alpha_{ip}\alpha_{py} + \alpha_{iq}\alpha_{qp}\alpha_{py} & \alpha_{ip} + \alpha_{iq}\alpha_{qp} & 1 - \alpha_{qp}\beta - \alpha_{yp}\alpha_{py} \end{bmatrix}$$

where $\det(A) = 1 + \beta\alpha_{ip} - \alpha_{yp}\alpha_{py} - \alpha_{qp}\beta + \alpha_{qp}\alpha_{iq}\beta$. Here, one should make two additional educated guesses on the sign of parameters α_{ip} and α_{iq}. The literature on competitive storage highlights an inverse relationship between price and inventories, $\alpha_{ip} < 0$. A non-zero value of α_{iq} is primarily motivated by the presence of contemporaneous supply Q_t^{ps} in the denominator of the quasi-stock-to-use ratio, so its sign is likely to be negative as well. Imagine a positive supply shock: Q_t^{ps} increases, but ΔI_t remains constant on impact[15], so the ratio goes down. Assuming the same signs of remaining slope parameters as before (and $\beta = \alpha_{pq} = -\alpha_{pi} < 0$), the matrix of sign restrictions is

$$\begin{bmatrix} + & + & + & + \\ + & + & - & - \\ - & + & + & + \\ + & - & - & + \end{bmatrix}$$

Although the sign of the element d_{iq} is unidentified in advance without further magnitude restrictions, $\Delta I_t / Q_t^{ps}$ is small enough to produce a positive net response to a positive supply shock whenever at least 4.4% of additional supply ends up in inventories (since 1999, on average, inventories represented about 20% of the sum of production and imports and no less than 12%).

The resulting sign restrictions on the matrix D appear consistent with the general understanding of the way x_t would react to ε_t shocks. In particular, positive but transitory aggregate demand or

[15] Current supply is not directly present in the optimization problem either.

grain-specific demand shocks stimulate stockholders to sell more inventories today (or accumulate less) in the expectation that prices declines tomorrow.

5. Results

The identification strategy outlined in the previous section does not allow for setting specific distributions of underlying structural parameters, but one can still analyze the posteriors. The short-term elasticity of supply appeared at the core of the debate on identification restrictions in the oil literature (see, for example, Baumeister and Hamilton (2019) and related papers). While there is no doubt that supply is inelastic, the magnitude is disputable.

In agriculture, the discussion can be broadly divided into two strands that barely overlap. The first one analyzes the short-term endogenous response of supply to price. As the final production can be hit by numerous exogenous shocks, primarily weather and pests, elasticity is usually estimated with farmers' intended supply approximated by sowing areas. Iqbal and Babcock (2018) rely on panel time-series data to figure out short- and long-run own-price elasticities of several grains, including corn and wheat. Their findings, as well as those of earlier studies mentioned in their paper, generally agree that the magnitude of short-term supply elasticity for corn, wheat, or aggregate of four major crops[16] does not exceed 0.23. Earlier research for the U.S. suggests that the upper bound can be even higher (Lin et al., 2000).

The second strand of literature – especially papers dealing with the data at infra-annual frequencies – tends to assume simply that supply is fixed, i.e. its elasticity to price is zero. This assumption appears to be less controversial in the agricultural setting as opposed to oil because of natural lags in production. Beginning stocks are the outcome of past decisions, so both I_{t-1} and $Prod_t$ are, broadly speaking, predetermined. Then the import component (which is often ignored in other studies) becomes the only source of responsiveness to price.

Let a relevant total supply elasticity $e_{Q^s} = \frac{\partial Q^s}{\partial P}\frac{P}{Q^s}$. Using the sum rule and the balance sheet identity,

$$e_{Q^s} = \frac{\partial I_{t-1}}{\partial P_t}\frac{P_t}{I_{t-1}}\frac{I_{t-1}}{Q_t^s} + \frac{\partial Prod_t}{\partial P_t}\frac{P_t}{Prod_t}\frac{Prod_t}{Q_t^s} + \frac{\partial M_t}{\partial P_t}\frac{P_t}{M_t}\frac{M_t}{Q_t^s} = 0 + 0 + \frac{\partial M_t}{\partial P_t}\frac{P_t}{M_t}\frac{M_t}{Q_t^s}$$

Thus, e_{Q^s} is equivalent to import elasticity adjusted by the share of imports in total supply. On average, imports constituted 7% to 11% of the relevant supply measure[17] of corn and wheat during 1999–2019. It implies that even relatively inelastic imports would be able to generate a slightly positive response of supply to price. The median short-term elasticity of supply α_{qp} in the BVAR

[16] Some authors, e.g. Roberts and Schlenker (2013), use the combined caloric production of corn, wheat, rice, and soybeans.
[17] In the four-variable model, beginning inventories would be excluded.

models is from 0.07 to 0.10, with the four-variable model producing a lower estimate and a less skewed distribution.

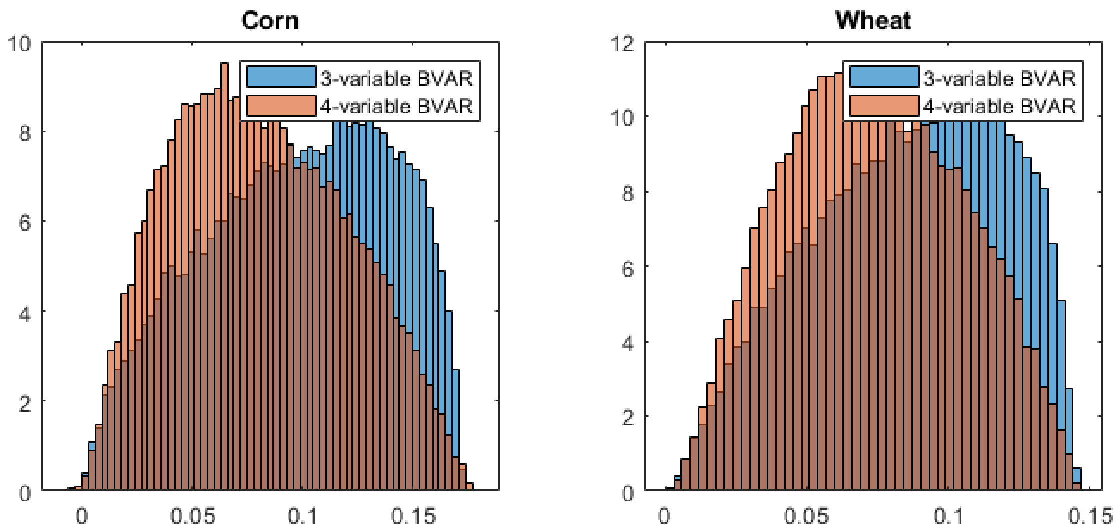


Figure 3. Distributions of α_{qp}

The Baumeister and Hamilton (2019) paper also raises the question of what traditional approaches to identification imply for the elasticity of demand. Authors show that the posterior distribution of α_{pq} for the oil market is rather wide, so the elasticity can exceed 1 or 2 in absolute value more than 90% of the time. The literature, however, usually treats demand for commodities as inelastic, so the distribution is expected to be mostly below these values.

Structural models of grain markets tend to produce rather low estimates of the elasticity. Miao et al. (2011) find that its value should be about 0.19 or within the range of 0.12 to 0.22 to generate a distribution of prices with similar characteristics to the observed one. Instead, slightly more elastic demand (0.5) would imply fewer spikes in prices and fewer stock-outs. Gouel and Legrand (2017) even propose a lower elasticity (in absolute value) of about 0.03 for wheat and up to 0.062 for corn to produce a sufficiently high degree of serial correlation in grain prices. Roberts and Schlenker (2013), who are guided by the competitive storage model but perform the estimation outside of it, still find that the total demand[18] elasticity of caloric intake ranges from -0.08 to -0.05, depending on the method.

In contrast, in empirical models that concentrate solely on consumer demand, magnitudes are often higher. Seale and Regmi (2006) find that the own-price elasticity of bread and cereals range from -0.04 for rich countries (e.g. the U.S.) to -0.49 for poor countries (e.g. Vietnam). A collection of demand elasticities, maintained by the USDA up to 2006, also provides quite a diverse set of values. They span from about -1.95 to -0.18 for Marshallian or uncompensated demand for wheat, maize, grains, cereals, and similar categories. The majority of estimates are still below 1 in

[18] Represented there by the sum of consumption and ending inventories.

absolute value, with magnitudes around -0.3, -0.5, and -0.7-0.8 appearing more frequently. Finally, Adjemian and Smith (2012), who use USDA forecasts to quantify the price flexibility[19] of demand for corn and soybeans for 1981–2010, find that, on average, over that period corn price flexibility was -1.35. This estimate implies an elasticity of -0.74, which is close to the median of the distribution from BVAR. When stocks are lower, however, demand turns out to be more inelastic (0.44 at a stock-to-use level of 0.2).

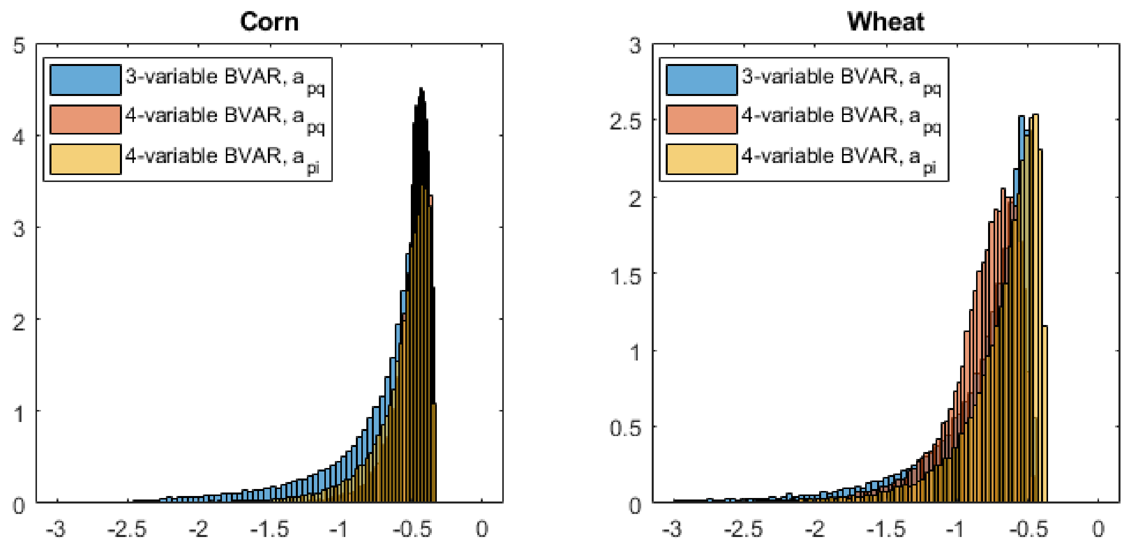


Figure 4. Distributions of α_{pq}

Overall, while the estimates produced by the BVAR models appear closer to the upper end of the range of demand elasticities in the literature, their absolute values are still mostly below 1: the probability of getting elastic demand does not exceed 25%. Unlike other studies, this paper combines consumption with exports, which usually is more elastic (Reimer et al., 2012) and, hence, can somewhat inflate the estimate (in a similar way that import does). It is also nice to acknowledge that distributions of $|\alpha_{pq}| = |\alpha_{pi}| = |\beta|$ are generally consistent despite the absence of any additional restrictions on their magnitudes.

Baumeister and Hamilton (2019) also propose a direct approach to estimating structural parameters. It would allow imposing a sufficiently tight prior to ensure that both demand and supply elasticities are lower in their magnitudes than those estimated with sign restrictions only. At the time of writing, however, this approach has not been implemented in any known toolbox, so direct estimation of structural BVAR is left for further research.

[19] In a single-commodity setting, the price flexibility of demand equals the inverse of the price elasticity of demand (Adjemian and Smith, 2012).

5.1. Impulse Responses

Figures 5 and 6 show the impulse responses to a one-standard-deviation shock in three- and four-variable models. Solid lines and shaded areas represent the median response and the 68% error bands, respectively.

Sign restrictions determine the direction of the contemporaneous response of all variables to all shocks, but further moves are not restricted. Aggregate demand is the only variable that exhibits a kind of exponential decay, while shocks in other variables dissipate quickly. As the elasticity of supply α_{qp} is not zero, higher price still creates some short-lived increase in supply, likely driven by higher imports for precautionary reasons. In turn, supply shocks cause prices to decline, with the cost of wheat going down by more than that of corn. Despite that, positive income response is stronger for corn, which might be associated with higher industrial use of corn (e.g. for biofuels).

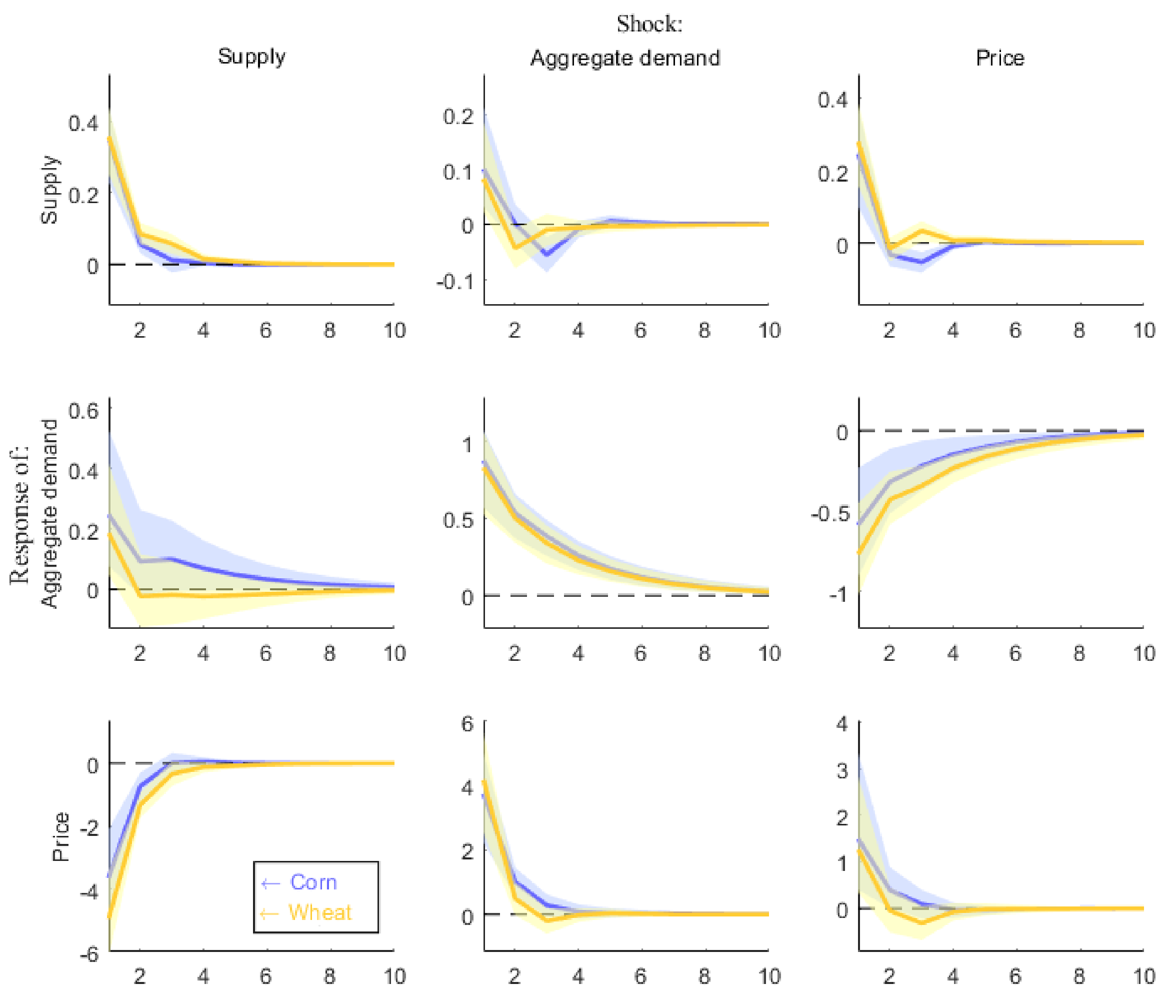


Figure 5. Impulse Responses of the Three-Variable BVAR

Although the dynamic reaction to supply and aggregate demand shocks is similar in both three- and four-variable models, inventories help distinguish between the two different types of speculation hidden in $\varepsilon_{3,t}$ of the Kilian (2009) model. Both do increase prices, but the response of prices to expectations (through inventories) is stronger than to own shocks. These IRFs also assume that stockholders know the "nonfundamental" nature of the shock, so they sell their inventories, expecting prices to be lower next period. Interestingly, fluctuations in aggregate demand cause quite strong and persistent reductions in inventories of corn but not wheat while prices converge to a new level fast. It implies that it is harder to compensate for income shocks in the corn market.

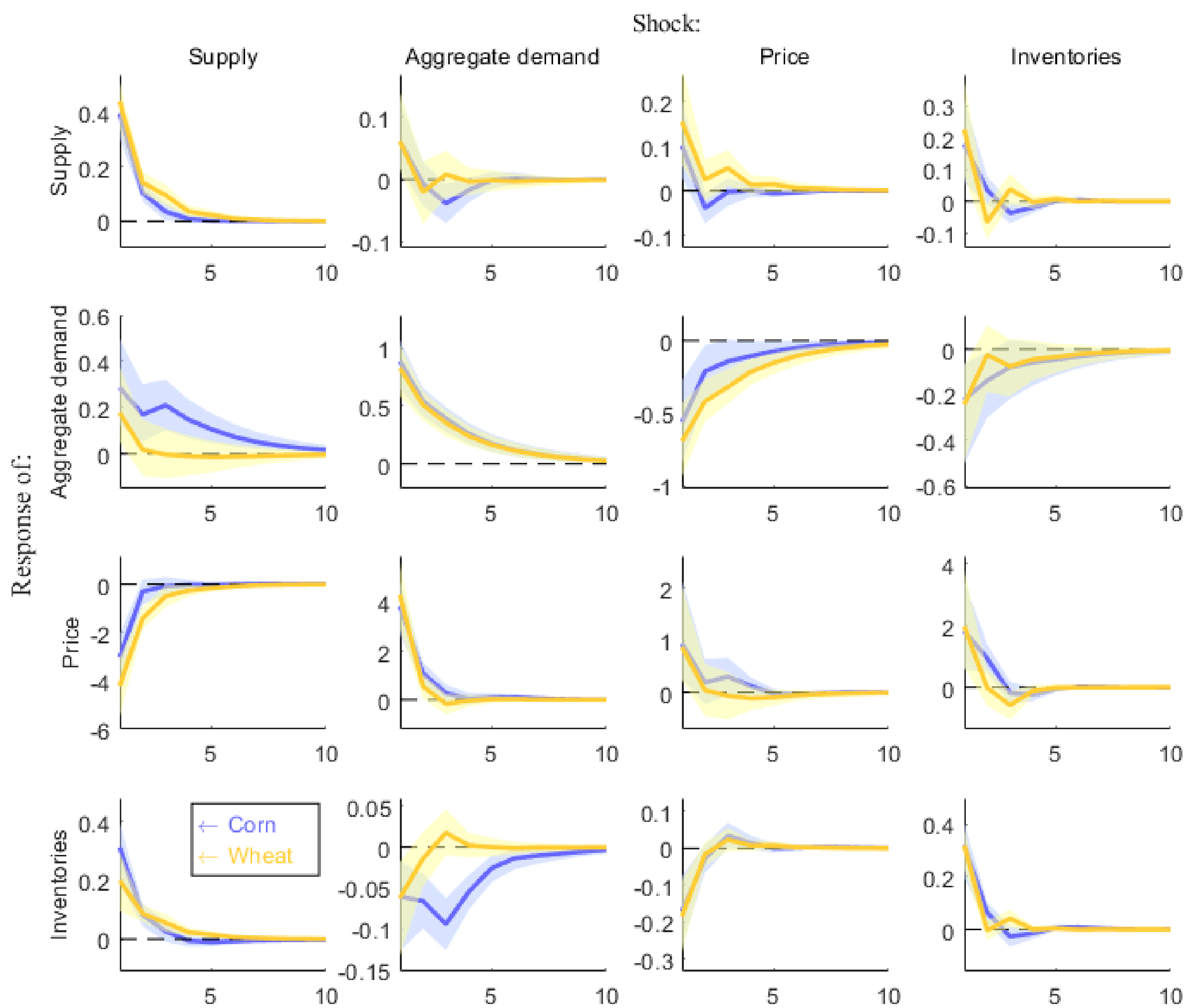


Figure 6. Impulse Responses of the Four-Variable BVAR

Since the models are specified in differences, most of these impulse responses indicate that disturbances tend to have a permanent effect on the levels of variables.

5.2. Forecast Error Variance Decomposition

Table 1 provides a six-month-ahead forecast error variance, attributable to structural shocks identified by structural BVAR models. As shown in rows 3 and 7, own price shocks tend to explain a relatively minor share of variation in prices. Instead, they are dominated by fluctuations in supply and aggregate demand that together contribute from 81% to 95% to variation, depending on model specification. The latter shocks are slightly more important for the corn market, given its tighter connection to oil (ethanol), while the former, for the wheat market.

Table 1. Forecast Error Variance Decomposition 6-month ahead

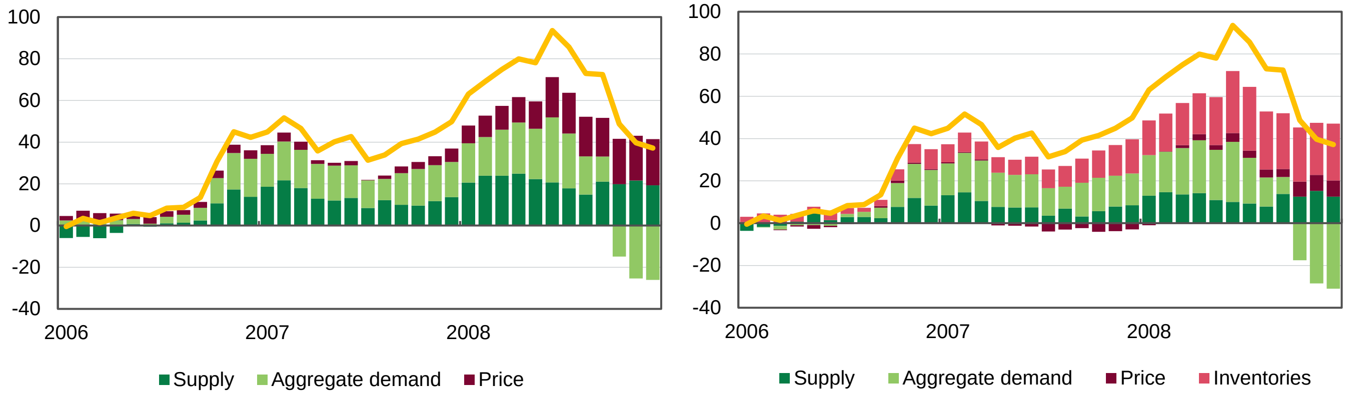
	Shock							
	Corn				Wheat			
	ε_t^q	ε_t^y	ε_t^p	ε_t^i	ε_t^q	ε_t^y	ε_t^p	ε_t^i
Three-variable BVAR								
Supply	60.9	7.9	31.2	n/a	59.6	5.7	34.7	n/a
Aggregate demand	4.8	67.9	27.3	n/a	3.2	52.0	44.8	n/a
Price	43.8	48.1	8.1	n/a	56.9	38.4	4.7	n/a
Four-variable BVAR								
Supply	73.2	4.1	6.5	16.2	69.1	3.1	9.4	18.4
Aggregate demand	10.0	65.7	19.7	4.6	3.1	53.8	38.8	4.2
Price	29.9	51.4	4.3	14.4	44.8	41.7	3.1	10.4
Inventories	38.7	9.1	12.5	39.7	26.5	3.6	18.2	51.7

Grain supply is mostly influenced by own disturbances (about 60%–70% of variation) and inventories (16%–18%), as the four-variable model suggests. In turn, grain-specific shocks tend to exert notable influence on real incomes, especially those stemming from the wheat market. Since wheat is an important staple food for a significant part of the population, higher food prices can lower demand for other goods, in this way depressing economic activity in general. As the last row of Table 1 shows, inventories are mostly driven by changes in expectations; supply shocks account for about 27% and 39% of the forecast error variance in the wheat and corn markets, respectively.

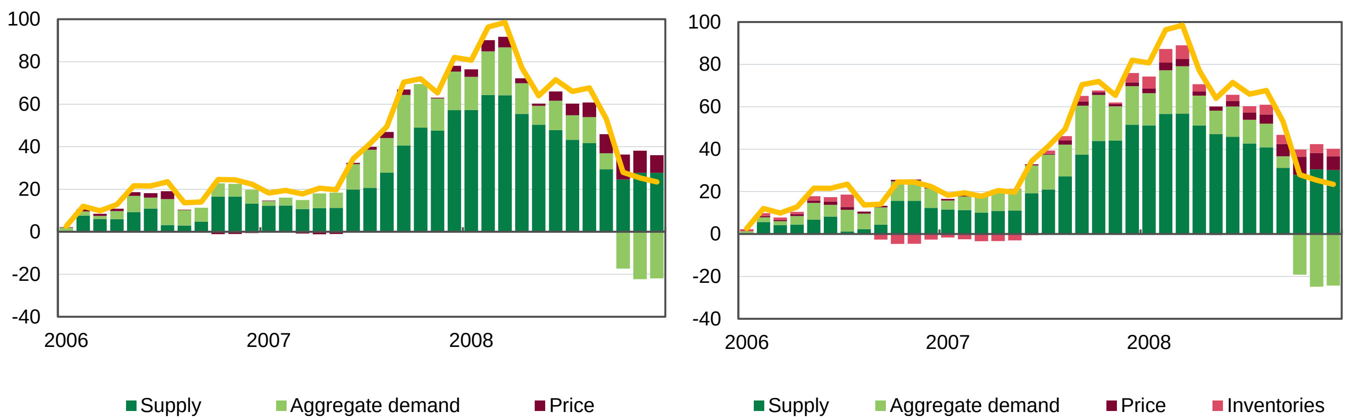
5.3. Historical Decomposition

The forecast error of price series can be recursively decomposed into contributions from each variable in the model, providing insights into the driving forces behind the observed price. Several episodes in the recent history of grain markets have caught the attention of economists and market observers.

One such episode was a sharp – more than twofold – spike in prices of corn and wheat during 2006–2008. Trostle (2008) and other researchers point to several factors that, to varying degrees, contributed to these developments. On the one hand, robust average income growth, especially in emerging markets, supported a shift in diets to include more meat. It also coincided with the expansion of the U.S. ethanol production from corn incentivized by rising oil prices and environmental objectives. As the decomposition in Figure 7 shows, these aggregate demand drivers tend to be more important for corn as opposed to wheat, given its wider feed (demand from China and India) and industrial (biofuels) use.



a) corn price

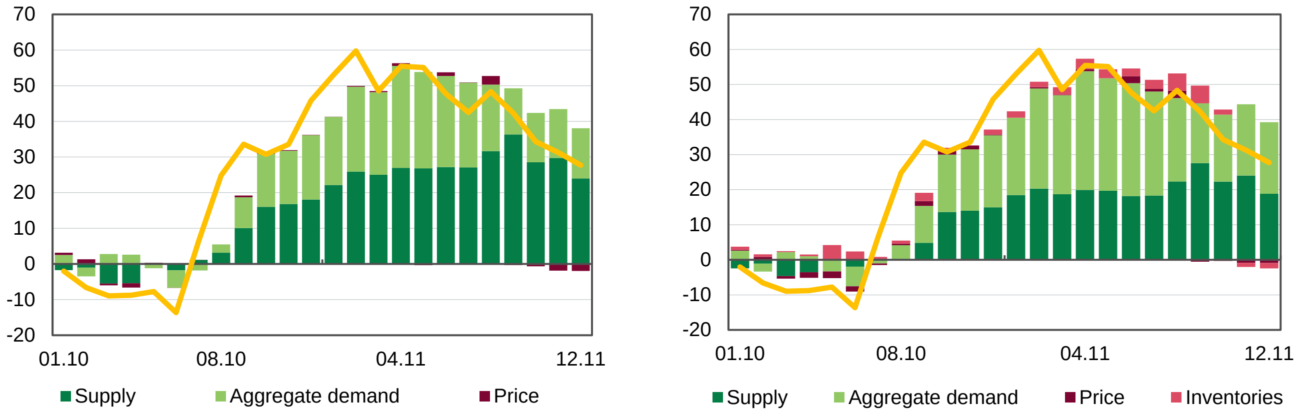


b) wheat price

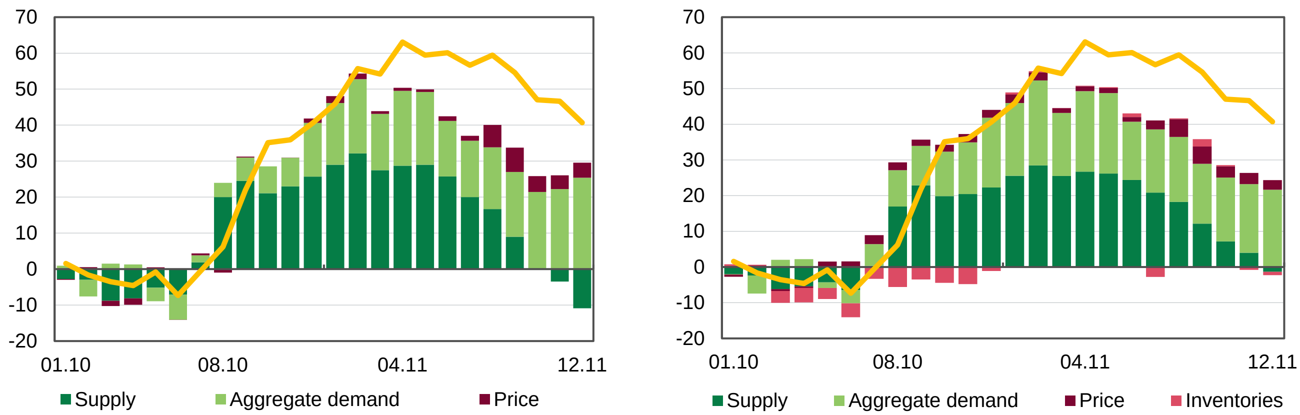
Note: variables are in log changes (scaled by 100) from December 2005. Yellow line shows change in price, which includes also trend and exogenous components.

Figure 7. Historical Decomposition of Prices in pre-GFC and GFC Episode

On the other hand, adverse weather conditions all across the globe in 2007 produced a second consecutive drop in global average yields. On top of it, some countries introduced export restrictions, primarily on wheat, which could have limited opportunities to stockpile in expectation of higher future prices. That can probably explain the difference in the contributions to corn and wheat prices. Janzen et al. (2014), who use financial markets indicators to decompose shocks to wheat prices, also find that net supply influence was the major factor shaping the developments in 2006–2008. According to BVAR models, index trading and demand factors, not otherwise accounted for, played only a minor role.



a) corn price



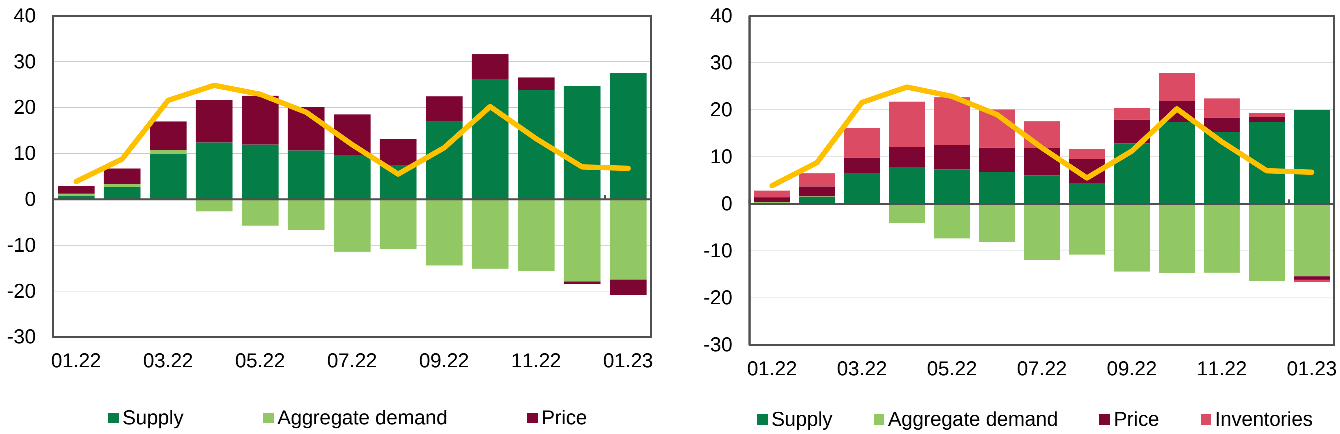
b) wheat price

Note: variables are in log changes (scaled by 100) from December 2009. Yellow line shows change in price, which includes also trend and exogenous components.

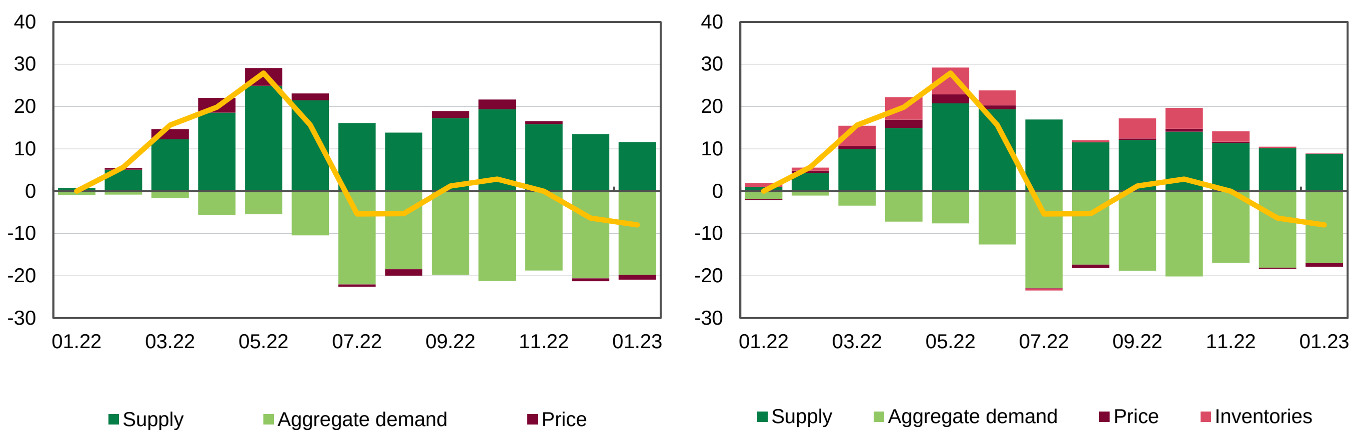
Figure 8. Historical Decomposition of Prices in 2010-2011

By contrast, during the price increase of 2010–2011, both wheat and corn prices were largely driven by two shocks: aggregate demand and supply. The former stemmed from the post-GFC economic recovery, which reinforced the general trend of income growth in emerging markets and shifts in diet. The latter resulted from a number of detrimental weather events during a short period of 10 months (Trostle et al., 2011). Despite trade restrictions introduced by some countries, several importers started hunting for additional import volumes from the remaining sources in late 2010, driven by precautionary motives. It turned the contribution of inventories to wheat prices from negative to slightly positive (compared to December 2009).

Another episode – russia's invasion of Ukraine – happened at a time when grain markets were still grappling with the consequences of the Covid-19 pandemic. Corn and wheat prices have risen already by about 40%–50% since late 2020, driven by a combination of recovering demand, supply chain issues, and growing transportation costs, as well as drought-reduced production.



a) corn price



b) wheat price

Note: variables are in log changes (scaled by 100) from December 2021. Yellow line shows change in price, which includes also trend and exogenous components.

Figure 9. Historical Decomposition of Prices During russia's Invasion of Ukraine

Against this backdrop, a negative supply shock, caused by reduced export from the Black Sea region[20] and alternative exporters (primarily India due to export restrictions), triggered another steep increase in prices. The upward dynamics was reinforced by stockpiling, which, however, was involuntary to some extent. For example, if it had not been for the sea blockade, Ukraine would have exported the additional amounts that ended up in storage. The launch of the Black

[20] The USDA lowered projections of imports for many countries, mainly in the Middle East and North Africa, because of lower Black Sea grain export availability and higher world prices.

Sea Grain Initiative in late July helped reduce supply pressure somewhat, but poor weather in Europe and Argentina outweighed the positive developments. At the same time, the cooling global economy amid an increase in uncertainty, a surge in the cost of living, and a global tightening of monetary policy was keeping prices at bay.

5.4. Out-of-Sample Forecasting Performance

While the models may contribute to the analysis of the market situation, it would also be beneficial if they could produce accurate forecasts. To understand the reliability of the models' predictions, I calculate the out-of-sample root mean squared error (RMSE) at a 36-month horizon for the period of 2011–2019. VARs are trained on trimmed samples, which include only the months preceding the "date of the forecast." For instance, a model estimated in January 2011 uses the data for 1999–2010. Such a long subsample (109 out-of-sample forecasts generated) was chosen intentionally to check models' performance not only during the period of relatively stable prices but also during substantial volatility.

As Table 2 shows, this paper generally confirms earlier studies that forecasting commodity prices is a nontrivial task. Manescu and Van Robays (2014) show that all the individual methods to forecast oil prices, including state-of-the-art VARs, suffer from significant time variations in their performance. This problem emerges in grain markets as well. Figure 6A in the Appendix demonstrates spaghetti graphs of the predicted versus actual price of corn and wheat. One can clearly see that forecasts at horizons of 6+ months in the earlier part of the sample were driven primarily by the wrong long-term upward trend. Instead, when prices returned closer to the long-term average, projections started to resemble the random walk. As for shorter horizons, the models sometimes capture the overall dynamics and turning points quite well but fail in other instances. This might be primarily related to the fact that it is harder for the model to grasp the short-term dynamics of the supply variable, which is heavily hit by exogenous shocks.

Table 2. Out-of-Sample RMSE (lowest values are in black)

	Corn						Wheat					
	Univariate		3-variable		4-variable		Univariate		3-variable		4-variable	
	RW	AR	OLS	BVAR	OLS	BVAR	RW	AR	OLS	BVAR	OLS	BVAR
1	**5.39**	5.44	5.53	5.48	5.49	5.50	6.23	6.23	6.14	**6.13**	6.16	6.17
2	**8.09**	8.27	8.36	8.33	8.35	8.36	9.33	9.47	9.30	**9.30**	9.33	9.37
3	**10.05**	10.43	10.40	10.40	10.39	10.40	**11.38**	11.77	11.52	11.56	11.57	11.62
4	**11.37**	11.88	11.93	11.99	11.92	11.94	**12.52**	13.08	13.27	13.32	13.31	13.37
5	**12.72**	13.52	13.37	13.42	13.44	13.45	**13.76**	14.51	14.80	14.86	14.75	14.81
6	**13.51**	14.62	14.56	14.61	14.71	14.73	**14.68**	15.63	16.19	16.25	16.01	16.07

Although BVAR models do not outperform univariate time series models most of the time, they still provide insights into the underlying relationships between variables and reveal the factors driving changes in prices. Thus, these structural models can be used for conditional forecasting and developing alternative scenarios.

6. Robustness

The results of any VAR model can be sensitive to various assumptions and specifications, such as variable choice and identifying restrictions. That is why the paper also covers robustness checks that show the sensitivity of the results to the use of alternative aggregate demand indicators, zero restrictions on the elasticity of supply, and domestically available supply instead of total.

6.1. Aggregate Demand

As already mentioned in the data section, the literature suggests several alternative aggregate demand indicators. The Kilian index (Index of Global Real Economic Activity or IGREA), maintained by the FRB of Dallas, and the OECD+6 industrial production index, extended by C. Baumeister, are probably the two widely used gauges nowadays. The former is a measure of global demand for industrial commodities based on dry cargo single voyage ocean freight rates (Kilian, 2009). The latter is the monthly index of industrial production in the OECD and 6 major nonmember countries.

To check to what extent the results are sensitive to the choice of aggregate demand variable, all four models were re-estimated with month-on-month change in alternative series instead of the demand factor. All identifying restrictions were the same as previously.

Figure 7A in the Appendix and Table 3 below compare distributions of demand elasticity α_{pq}. In general, both shapes of distributions and the median values are comparable, with the magnitude of α_{pq} being generally lower for the demand factor. The same conclusion can be reached regarding the elasticity of supply α_{qp} (Figure 8A in the Appendix).

Table 3. Comparison of Medians of Distributions of Elasticity of Demand

	Demand factor	IGREA	Industrial production
	Corn		
3-variable BVAR (α_{pq})	-0.6705	-0.7242	-0.7062
4-variable BVAR ($\alpha_{pq} = \beta$)	-0.4693	-0.5149	-0.4799
4-variable BVAR ($\alpha_{pi} = \beta$)	-0.5077	-0.5430	-0.4990
	Wheat		
3-variable BVAR (α_{pq})	-0.7124	-0.7240	-0.7543
4-variable BVAR ($\alpha_{pq} = \beta$)	-0.7676	-0.7634	-0.8381
4-variable BVAR ($\alpha_{pi} = \beta$)	-0.6004	-0.5932	-0.6468

Even though important structural parameters are similar, the choice of variable materially influences the historical decomposition. In the earlier part of the sample, alternative indicators suggested a higher contribution of aggregate demand to corn and wheat prices. By 2005, higher values came mainly from the IGREA, given the smaller decline in freight rates in 2001–2002 amid a slowdown in the growth of advanced economies and a steeper increase afterward. There is evidence (UN, 2005) that a sluggish supply of vessels coincided with faster growth in global trade, particularly with China, driving prices upward. Since 2011, the demand factor produced an approximately average contribution – above that of IGREA and below that of the industrial production index.

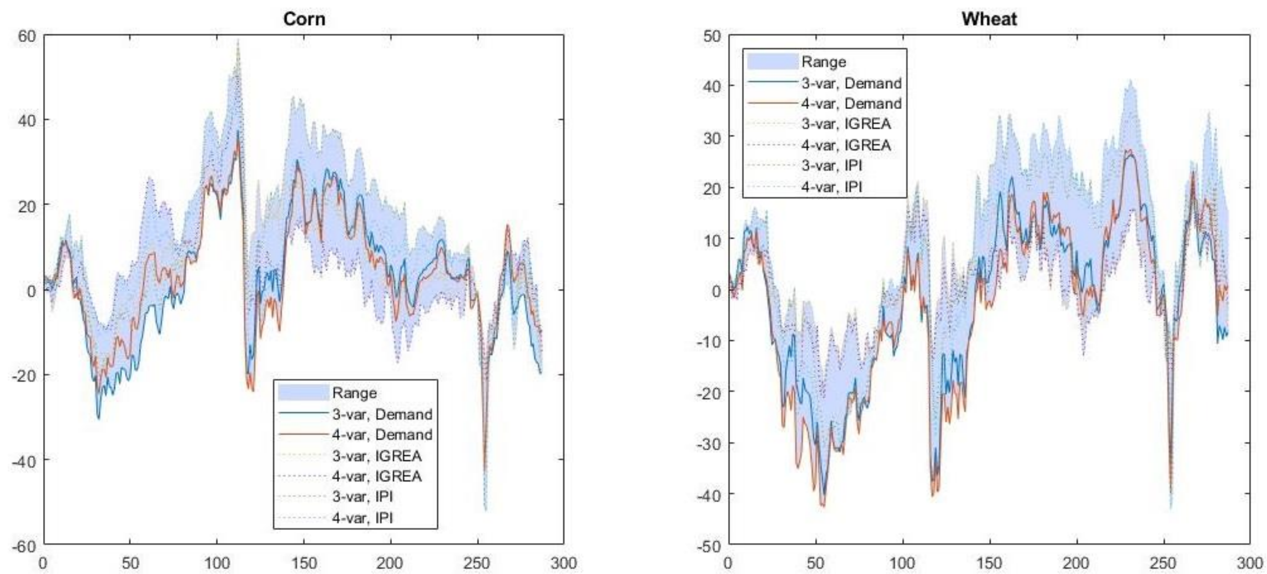


Figure 10. Contribution of Demand Factor to Decomposition of Corn and Wheat Price

The models also demonstrate a rather similar forecasting performance, but BVARs with the OECD+6 industrial production index produce slightly lower RMSE, likely due to lower variability of the index around the linear trend (Tables 2A and 3A in the Appendix).

6.2. Elasticity of Supply

A common assumption used in the papers that omit an import component in their supply series is to set the short-term elasticity of supply to zero. Given lags in production, when areas sown are determined several months in advance, and the static nature of beginning stocks, this assumption is often justifiable. Suppose imports turn out to be very inelastic, and the share in total supply remains low so that it would drive α_{qp} to zero. Then the impact matrix and sign restrictions of the three-variable model would be as follows

$$A_0^{-1} = \frac{1}{1-\alpha_{yp}\alpha_{py}}\begin{bmatrix} 1-\alpha_{yp}\alpha_{py} & 0 & 0 \\ \alpha_{yp}\alpha_{pq} & 1 & \alpha_{yp} \\ \alpha_{pq} & \alpha_{py} & 1 \end{bmatrix} \xrightarrow{yields} \begin{bmatrix} + & 0 & 0 \\ + & + & - \\ - & + & + \end{bmatrix}$$

Analogously, for the four-variable model, matrices take the form

$$A_0^{-1} = \frac{1}{\det(A)} \cdot \begin{bmatrix} 1+\beta\alpha_{ip}-\alpha_{yp}\alpha_{py} & 0 & 0 & 0 \\ \alpha_{yp}\beta-\alpha_{yp}\alpha_{iq}\beta & 1+\beta\alpha_{ip} & \alpha_{yp} & -\alpha_{yp}\beta \\ \beta-\alpha_{iq}\beta & \alpha_{py} & 1 & -\beta \\ \alpha_{iq}-\alpha_{iq}\alpha_{yp}\alpha_{py}+\alpha_{ip}\beta & \alpha_{ip}\alpha_{py} & \alpha_{ip} & 1-\alpha_{yp}\alpha_{py} \end{bmatrix} \xrightarrow{yields} \begin{bmatrix} + & 0 & 0 & 0 \\ + & + & - & - \\ - & + & + & + \\ + & - & - & + \end{bmatrix}$$

Since α_{qp} is now fixed, the remaining parameter to compare is demand elasticity α_{pq}. As Figure 9A in the Appendix and Table 4 show, demand is now more elastic, particularly in the three-variable case, where the median magnitude rises above 2 in absolute value. The discrepancy between $\beta = \alpha_{pq}$ and $\beta = \alpha_{pi}$ has increased for both the corn and wheat four-variable models.

Table 4. Comparison of Medians of Distributions of Elasticity of Demand

	Sign restrictions, $\alpha_{qp} > 0$	Zero restrictions, $\alpha_{qp} = 0$
	Corn	
3-variable BVAR (α_{pq})	-0.6705	-2.4059
4-variable BVAR ($\alpha_{pq} = \beta$)	-0.4693	-0.6040
4-variable BVAR ($\alpha_{pi} = \beta$)	-0.5077	-0.5157
	Wheat	
3-variable BVAR (α_{pq})	-0.7124	-2.8112
4-variable BVAR ($\alpha_{pq} = \beta$)	-0.7676	-1.1964
4-variable BVAR ($\alpha_{pi} = \beta$)	-0.6004	-0.5729

New restrictions also exert considerable influence on the historical decomposition. The contribution of the supply factor drops by more than half (Figure 11), while the impact of other shocks, primarily speculative ones, gets inflated (Figure 10A in the Appendix). However, the competitive storage model shows that current supply shocks play an important role in price determination. Thus, relatively low contributions, especially like the one in the case of corn, are somewhat doubtful.

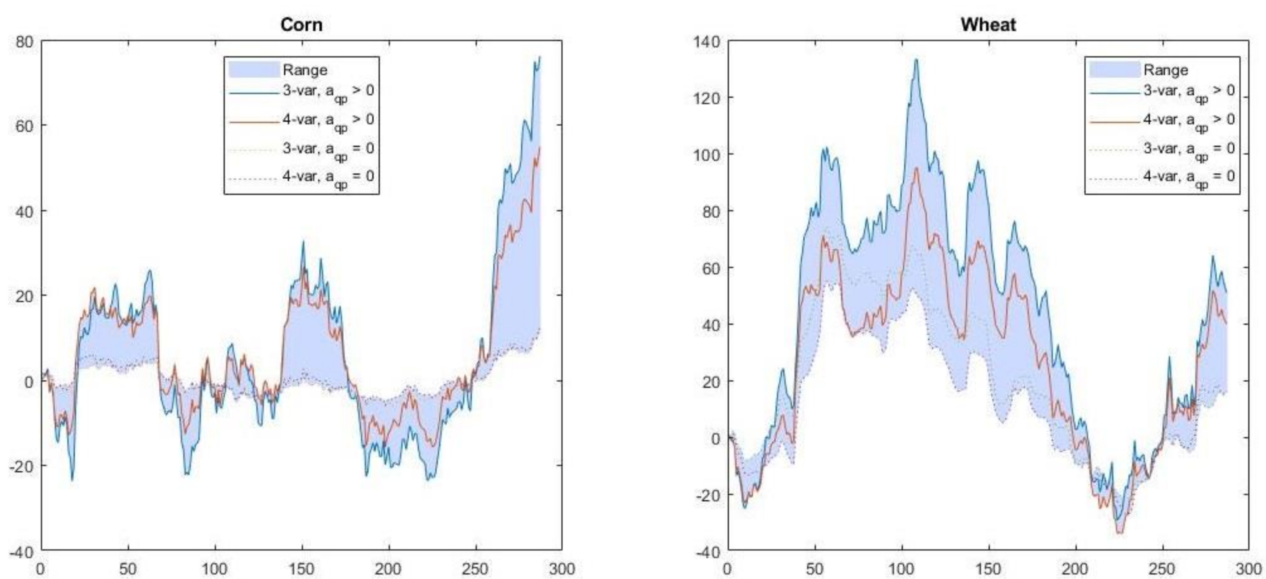


Figure 11. Contribution of Supply Factor to Decomposition of Corn and Wheat Price

6.3. Domestic Supply

The fundamental USDA identity described in Section 2 equates the total supply of grains to the total demand. It is possible, however, to reformulate this equation in terms of domestic supply and demand by netting export and import components of the balance sheet. Then, for each country i, domestic supply $Q_{i,t}^{ds}$ is the sum of beginning inventories, production, and net imports, equal to domestic demand $Q_{i,t}^{dd}$ (consumption and stocks), so that

$$Q_{i,t}^{ds} = I_{i,t-1} + Prod_{i,t} + M_{i,t} - X_{i,t} = Cons_{i,t} + I_{i,t} = Q_{i,t}^{dd}$$

The only difference between the two identities is in the position of exports. Whenever a country is a net importer, additional imports augment production while the domestic supply of a net exporter is reduced. Next, the values are combined across countries to produce world totals. Since exporting countries dominate the sample, the domestic supply is lower than the total supply. Given a nonzero aggregate net import component, the assumption of responsive domestic supply to price is still valid. Nevertheless, there is a difference in the treatment of supply elasticity associated with the domestic supply. Using the same approach as in Section 5,

$$e_{Q^{ds}} = \frac{\partial NM_t}{\partial P_t}\frac{P_t}{NM_t}\frac{NM_t}{Q_t^{ds}}$$

where NM_t stands for net import, and Q_t^{ds} is domestic supply. The ratio NM_t/Q_t^{ds} is negative; it steadily declines from approximately -6% to -10% for wheat and fluctuates around -4% for corn. The relationship between price and net import has become negative as well, reflecting the downward-sloping demand for exports. As a result, the overall supply elasticity remains small and positive.

Table 5 and Figure 11A in the Appendix demonstrate that model properties remain virtually unchanged, even though it could have been expected that all structural parameters would decline in absolute value. The elasticity of demand no longer contains the more elastic export component, but the impact on its magnitude is only marginal. Thus, the estimates remain closer to those of Adjemian and Smith (2012). The distributions of β-equivalent parameters in four-variable models generally remain aligned. Consistency between α_{pq} and α_{pi} is relatively better for wheat and somewhat worse for corn.

The historical decomposition of the wheat price remains rather robust to the change in the supply variable, as shown in Figure 12, except for the three-variable total-supply model that assigns more importance to supply shocks in the earlier part of the sample. The contribution of the demand factor to price increases appears slightly higher in 2002–2008 than in baseline models, while for other variables, changes are relatively minor. The differences are more pronounced in the case of corn, where the impact of supply shocks is reduced markedly. This effect is partially compensated by an increase in the role of own price shocks, especially in the four-variable corn model.

Table 5. Comparison of Medians of Distributions of Elasticity of Demand

	Total supply	Domestic supply
	Corn	
3-variable BVAR (α_{qp})	0.1007	0.1002
3-variable BVAR (α_{pq})	-0.6705	-0.7600
4-variable BVAR (α_{qp})	0.0781	0.0759
4-variable BVAR ($\alpha_{pq} = \beta$)	-0.4693	-0.4378
4-variable BVAR ($\alpha_{pi} = \beta$)	-0.5077	-0.4928
	Wheat	
3-variable BVAR (α_{qp})	0.0882	0.0865
3-variable BVAR (α_{pq})	-0.7124	-0.6909
4-variable BVAR (α_{qp})	0.0725	0.0744
4-variable BVAR ($\alpha_{pq} = \beta$)	-0.7676	-0.6423
4-variable BVAR ($\alpha_{pi} = \beta$)	-0.6004	-0.6571

The models also demonstrate a similar forecasting performance relative to baseline (see Table 4A in the Appendix), with only the four-variable wheat domestic-supply model outperforming its total-supply alternative and the random walk in the first three periods.

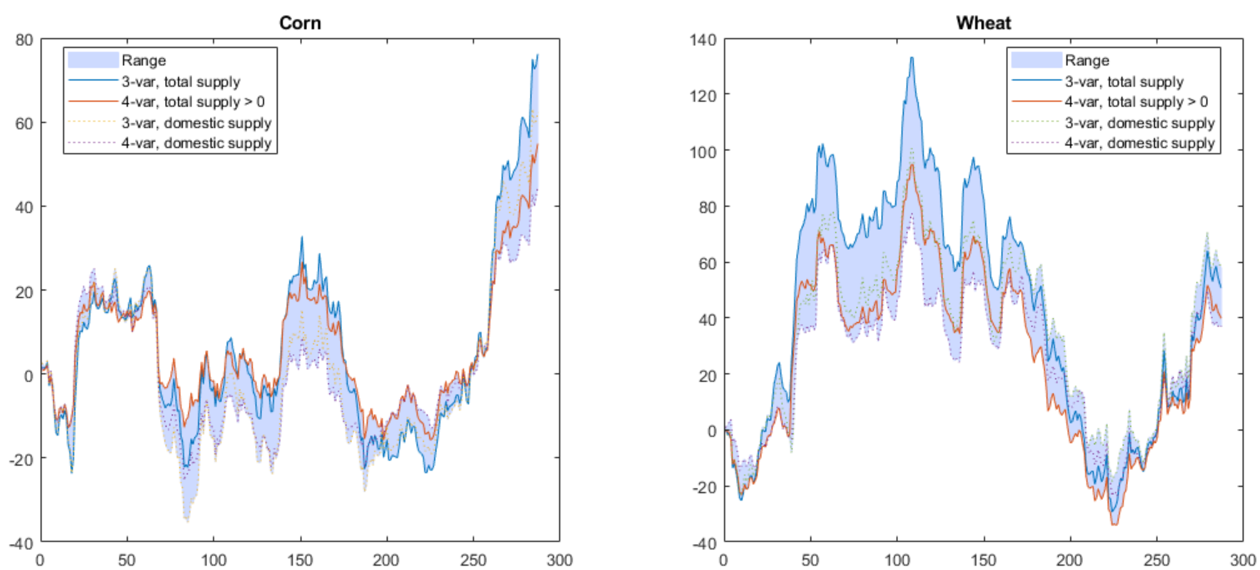


Figure 12. Contribution of Demand Factor to Decomposition of Corn and Wheat Price

7. Conclusions

This paper makes the first known attempt to estimate monthly VAR models for corn and wheat markets that directly account for supply and inventory in a way Kilian (2009) and Kilian and Murphy (2014) do. To overcome the limited availability of high-frequency data on production and stocks, it uses projections of supply variables from the monthly WASDE report. These projections are adjusted to reflect only the current marketing year and then are transformed into revisions. The paper also develops an indicator of aggregate demand for grain markets using an adapted version of the Baumeister et al. (2020) approach.

I estimate the models with Bayesian methods and identify the structural shocks using sign restrictions. Although indirect estimation of the structural matrix does not allow for setting priors, posterior distributions of structural parameters are generally consistent with theory and earlier studies. Both demand and supply functions appear inelastic in the short term, with the elasticity of the former being higher than that of the latter. Future research can elaborate upon these findings and compare the outcomes of the direct estimation of structural matrices, as in Baumeister and Hamilton (2019), with the indirect one. This estimation procedure would allow accounting for parameter restrictions and checking whether it significantly influences model performance.

The models produce quite reasonable historical decompositions of price during important episodes in 2006–2008, 2010–2011, and 2022–2023. Aggregate demand is a more important factor for corn rather than wheat, given its broader feed and industrial use, including biofuels. In addition, the accumulation of inventories played a larger role for corn in 2006–2008 but contributed to both prices in 2022–2023. Instead, the wheat price has been mostly driven by relatively sluggish supply during a considerable part of the sample.

The models can become a valuable tool for the analysis of current developments, as well as for conditional forecasting and building alternative scenarios. At the same time, unfortunately, they do not generate forecasts that would be consistently superior to the random walk.

I also see an attempt to incorporate explicitly next-MY expectations in the models as a prospective avenue for further research. It could shed more light on the stock-building motives of speculators, who can expect higher prices next period because of either supply shortfalls or higher future demand, and improve forecasting performance. Nevertheless, since the WASDE series are incomplete (they cover only part of the next MY, usually 1 to 5 months), one should build another series, which is easier said than done. Although data from weather maps – precipitation, sunlight, or NDVI – can be very informative of future yield developments, a supplementary model is required to transform it into comparable production estimates (e.g., the WOFOST model used by the European Commission). The models could also benefit from a more elaborate treatment of export-import shocks and effects from redistributing stocks across countries, as trade restrictions and disruptions can play increasingly important roles in a fragmented world.

References

Adjemian, M. K., Smith, A. (2012). Using USDA forecasts to estimate the price flexibility of dmand for agricultural commodities. American Journal of Agricultural Economics, 94(4), 978–995. https://doi.org/10.1093/ajae/aas032

Adjemian, M. K. (2012). Quantifying the WASDE announcement effect. American Journal of Agricultural Economics, 94(1), 238–256. https://doi.org/10.1093/ajae/aar131

Arnade, C., Hoffman, L., Effland, A. (2021). The impact of public information on commodity market performance: The response of corn futures to USDA corn production forecasts. Economic Research Report, 293. U.S. Department of Agriculture. Retrieved from https://www.ers.usda.gov/webdocs/publications/101815/err-293.pdf

Baumeister, C., Hamilton, J. D. (2019). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. American Economic Review, 109 (5), 1873–1910. https://doi.org/10.1257/aer.20151569

Baumeister, C., Korobilis, D., Lee, T. K. (2022). Energy markets and global economic conditions. The Review of Economics and Statistics, 104(4), 828–844. https://doi.org/10.1162/rest_a_00977

Bobenrieth, E., Wright, B. Zeng, D. (2013), Stocks-to-use ratios and prices as indicators of vulnerability to spikes in global cereal markets. Agricultural Economics, 44(s1), 43–52. https://doi.org/10.1111/agec.12049

Canova, F. (2007). Methods for Applied Macroeconomic Research. Princeton: Princeton University Press.

Cafiero, C., Bobenrieth H, E., Bobenrieth H., J., Wright, B. D. (2011). The empirical relevance of the competitive storage model. Journal of Econometrics, 162(1), 44–54. https://doi.org/10.1016/j.jeconom.2009.10.008

Deaton, A., Laroque, G. (1992). On the behaviour of commodity prices. The Review of Economic Studies, 59(1), 1–23. https://doi.org/10.2307/2297923

Deaton, A., Laroque, G. (1996). Competitive storage and commodity price dynamics. Journal of Political Economy, 104(5), 896–923. https://doi.org/10.1086/262046

Delle Chiaie, S., Ferrara, L., Giannone D. (2017). Common factors of commodity prices. ECB Working Paper Series, 2112. Retrieved from https://www.ecb.europa.eu/pub/pdf/scpwps/ecb.wp2112.en.pdf

Economou, A., Agnolucci, P., Fattouh, B., De Lipsis, V. (2017). A structural model of the world oil market: The role of investment dynamics and capacity constraints in explaining the evolution of the real price of oil. The Oxford Institute for Energy Studies Paper, WPM 75. Retrieved from https://www.oxfordenergy.org/wpcms/wp-content/uploads/2017/12/A-Structural-Model-of-the-World-Oil-Market-WPM-75.pdf

Glauber, J. (2023). Assessing tight global wheat stocks and their role in price volatility. IFPRI Blog: Issue Post (March 15, 2023). Retrieved from https://www.ifpri.org/blog/assessing-tight-global-wheat-stocks-and-their-role-price-volatility

Gouel, C., Legrand, N. (2017). Estimating the competitive storage model with trending commodity prices. Journal of Applied Econometrics, 32(4), 744–763. https://doi.org/10.1002/jae.2553

Guillaume, P., Trueck, S., D'Ecclesia, R., Montalbano, P. (2019). Wheat and maize futures reaction to weather shocks in Europe. 172nd EAAE Seminar, May 28-29, 2019. Brussels: European Association of Agricultural Economists. Retrieved from https://ageconsearch.umn.edu/record/289704/files/Pierre-European%20grain%20futures%20reaction%20to%20weather%20shocks-127_a.pdf

Gustafson, R. L. (1958). Carryover levels for grains. Technical Bulletin 1178. Washington: US Department of Agriculture. Retrieved from https://naldc.nal.usda.gov/download/CAT87201112/PDF

Houck, J. P. (1965). The relationship of direct price flexibilities and elasticities. American Journal of Agricultural Economics, 47(3), 789–792. https://doi.org/10.2307/1236288

IER (2007). The world biofuel boom and Ukraine – how to reap the benefits. Policy Paper, 7. Kyiv: Institute for Economic Research and Policy Consulting. Retrieved from http://www.ier.com.ua/files/publications/Policy_papers/Agriculture_dialogue/2007/AgPP7_En.pdf

Iqbal, M. Z., Babcock, B. A. (2018). Global growing-area elasticities of key agricultural crops estimated using dynamic heterogeneous panel methods. Agricultural Economics, 49(6), 681–690. https://doi.org/10.1111/agec.12452

Isengildina-Massa, O., Irwin, S., Good, D., Gomez, J. (2008). The impact of situation and outlook information in corn and soybean futures markets: Evidence from WASDE reports. Journal of Agricultural and Applied Economics, 40(1), 89–103. https://doi.org/10.1017/S1074070800027991

Janzen, J. P., Carter, C. A., Smith, A. D., Adjemian M. K. (2014). Deconstructing wheat price spikes: A model of supply and demand, financial speculation, and commodity price comovement. Economic Research Report, 165. Washington: U.S. Department of Agriculture. Retrieved from https://www.ers.usda.gov/webdocs/publications/45199/46439_err165.pdf

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review, 99(3), 1053–1069. https://doi.org/10.1257/aer.99.3.1053

Kilian, L., Murphy, D. P. (2014). The role of inventories and speculative trading in the global market for crude oil. Journal of Applied Econometrics, 29(3), 454–478. https://doi.org/10.1002/jae.2322

Kilian, L., Zhou, X. (2020). The econometrics of oil market VAR models. Working Paper, 2006. Federal Reserve Bank of Dallas. https://doi.org/10.24149/wp2006

Lenza, M., Primiceri, G. E. (2022). How to estimate a vector autoregression after March 2020. Journal of Applied Econometrics, 37(4), 688–699. https://doi.org/10.1002/jae.2895

Lin, W., Westcott, P. C., Skinner, R., Sanford, S., De La Torre Ugarte, D. G. (2000). Supply response under the 1996 farm act and implications for the U.S. field crops sector. Technical Bulletin, 1888. Washington: U.S. Department of Agriculture. Retrieved from https://www.ers.usda.gov/webdocs/publications/47349/32301_tb1888_002.pdf

Manescu, C., Van Robays, I. (2014). Forecasting the brent oil price: Addressing time-variation in forecast performance. Working Paper Series, 1735. Frankfurt am Main: European Central Bank. Retrieved from https://www.ecb.europa.eu//pub/pdf/scpwps/ecbwp1735.pdf

McPhail, L., Du, X., Muhammad, A. (2012). Disentangling corn price volatility: The role of global demand, speculation, and energy. Journal of Agricultural and Applied Economics, 44(3), 401–410. https://doi.org/10.1017/S107407080000050X

Miao, Y., Wu, W., Funke, N. (2011). Reviving the competitive storage model: A holistic approach to food commodity prices. Working Paper, 2011/064. International Monetary Fund. Retrieved from https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Reviving-the-Competitive-Storage-Model-A-Holistic-Approach-to-Food-Commodity-Prices-24720

Milacek, T., Brorsen, B. (2017). Trading based on knowing the WASDE report in advance. Journal of Agricultural and Applied Economics, 49(3), 400–415. https://doi.org/10.1017/aae.2017.8

Qiu, C., Colson, G., Escalante, C., Wetzstein, M. (2012). Considering macroeconomic indicators in the food before fuel nexus. Energy Economics, 34(6), 2021–2028. https://doi.org/10.1016/j.eneco.2012.08.018

Reimer, J., Zheng, X., Gehlhar, M. (2012). Export demand elasticity estimation for major U.S. crops. Journal of Agricultural and Applied Economics, 44(4), 501–515. https://doi.org/10.1017/S107407080002407X

Roberts, M. J., Schlenker, W. (2013). Identifying supply and demand elasticities of agricultural commodities: Implications for the US ethanol mandate. American Economic Review, 103(6), 2265–2295. https://doi.org/10.1257/aer.103.6.2265

Seale, J. L. Jr., Regmi, A. (2006). Modeling international consumption patterns. Review of Income and Wealth, 52(4), 603–624. https://doi.org/10.1111/j.1475-4991.2006.00204.x

Sobolev, D. (2021). Grain and Feed Annual: Ukraine. Report, UP2021-0017. Washington: U.S. Department of Agriculture. Retrieved from https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=Grain%20and%20Feed%20Annual_Kyiv_Ukraine_04-15-2021

Trostle, R. (2008). Global agricultural supply and demand: Factors contributing to the recent increase in food commodity prices. WRS-0801. Washington: U.S. Department of Agriculture. Retrieved from https://www.ers.usda.gov/webdocs/outlooks/40463/12274_wrs0801_1_.pdf

Trostle, R., Marti, D., Rosen, S., Westcott, P. (2011). Why have food commodity prices risen again? WRS-1103. Washington: U.S. Department of Agriculture. Retrieved from https://www.ers.usda.gov/webdocs/outlooks/40481/7392_wrs1103.pdf

UN. (2005). Review of Maritime Transport. UNCTAD/RMT/2005. Retrieved from https://unctad.org/system/files/official-document/rmt2005_en.pdf

USDA. (2022). Grain: World Markets and Trade, February 2022. Washington: U.S. Department of Agriculture. Retrieved from https://downloads.usda.library.cornell.edu/usda-esmis/files/zs25x844t/0p097999b/p8419q779/grain.pdf

Vogel, F. A., Bange, G. A. (1999). Understanding crop statistics. Miscellaneous Publication, 1554. Washington: U.S. Department of Agriculture. Retrieved from https://www.nass.usda.gov/Education_and_Outreach/Understanding_Statistics/pub1554.pdf

Wang, Y., Wu, C., Yang, L. (2014). Oil price shocks and agricultural commodity prices. Energy Economics, 44, 22–35. https://doi.org/10.1016/j.eneco.2014.03.016

APPENDIX A

Tables

Table 1A. Countries and Regions in WASDE Reports

Corn		
Argentina	Egypt	South Africa
Brazil	Japan	South Korea
Canada	Mexico	Ukraine
China	russia	United States
European Union	Southeast Asia***	
Wheat		
Argentina	European Union	russia
Australia	India	Selected Mideast**
Brazil	Kazakhstan	Southeast Asia***
Canada	North Africa*	Ukraine
China	Pakistan	United States

* Algeria, Egypt, Libya, Morocco, and Tunisia.

** Lebanon, Iraq, Iran, Israel, Jordan, Kuwait, Saudi Arabia, Yemen, United Arab Emirates, and Oman.

*** Indonesia, Malaysia, Philippines, Thailand, and Vietnam.

Table 2A. Out-of-Sample RMSE of Models with IGREA as Aggregate Demand Indicator

	Corn		Wheat	
	3-variable BVAR	4-variable BVAR	3-variable BVAR	4-variable BVAR
1	5.59	5.55	6.12	6.18
2	8.40	8.46	9.38	9.45
3	10.46	10.49	11.63	11.75
4	11.93	11.99	13.35	13.43
5	13.34	13.46	14.91	14.91
6	14.55	14.79	16.29	16.16

Source: own elaboration.

Table 3A. Out-of-Sample RMSE of models with industrial production index as aggregate demand indicator

	Corn		Wheat	
	3-variable BVAR	4-variable BVAR	3-variable BVAR	4-variable BVAR
1	5.41	5.40	6.09	6.07
2	8.12	8.12	9.19	9.18
3	10.19	10.14	11.35	11.40
4	11.80	11.67	13.17	13.21
5	13.22	13.18	14.76	14.74
6	14.36	14.38	16.13	15.95

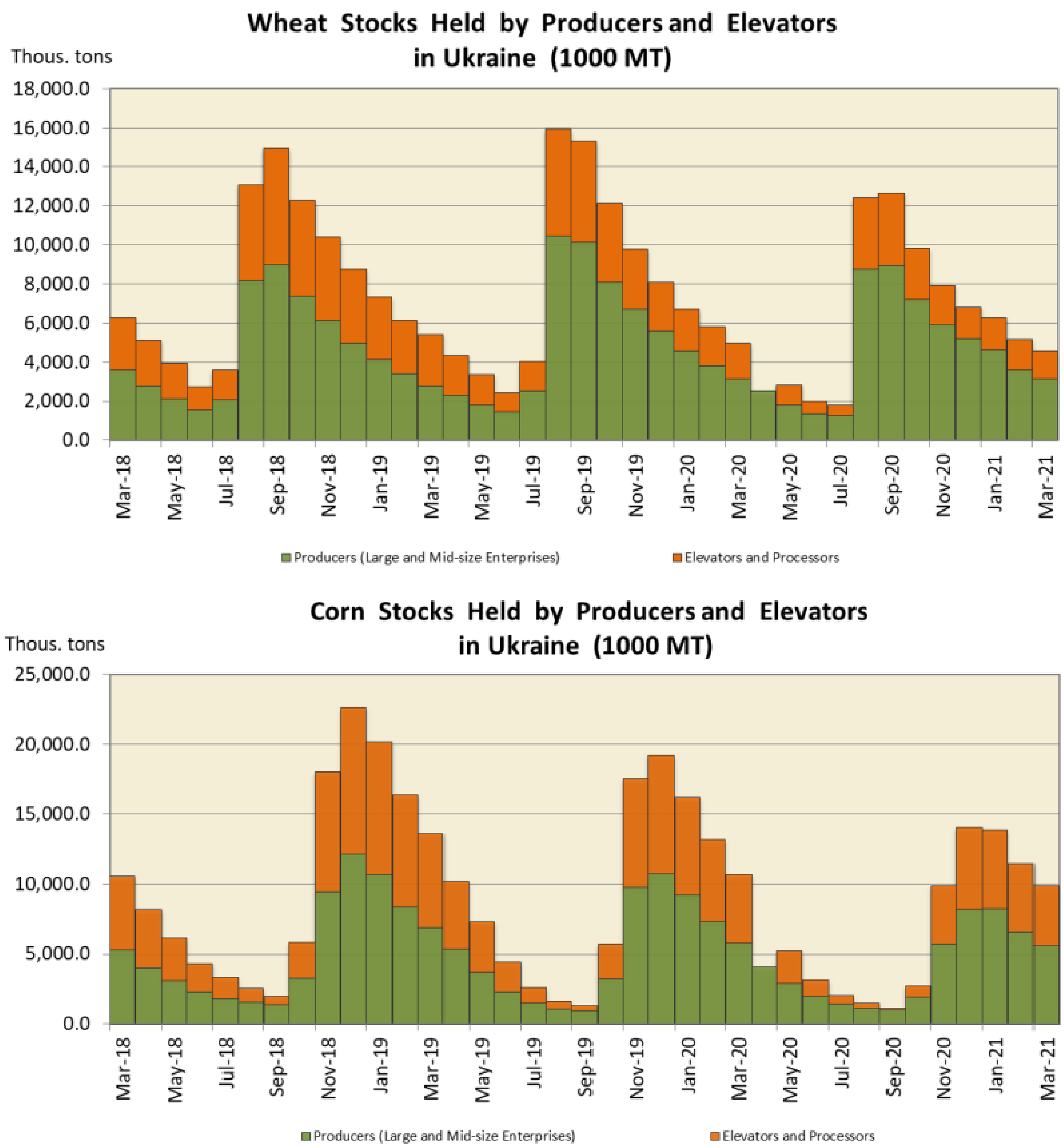
Source: own elaboration.

Table 4A. Out-of-sample RMSE of models with domestic supply

	Corn		Wheat	
	3-variable BVAR	4-variable BVAR	3-variable BVAR	4-variable BVAR
1	5.48	5.52	6.16	6.09
2	8.36	8.39	9.34	9.16
3	10.43	10.35	11.52	11.36
4	12.02	11.80	13.26	13.09
5	13.47	13.28	14.79	14.62
6	14.69	14.48	16.14	15.91

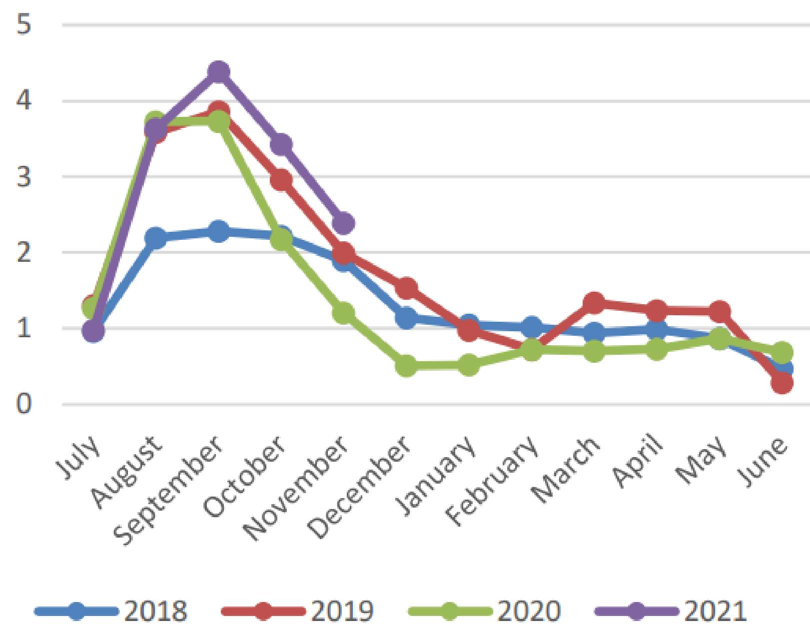
Source: own elaboration.

APPENDIX B. Figures



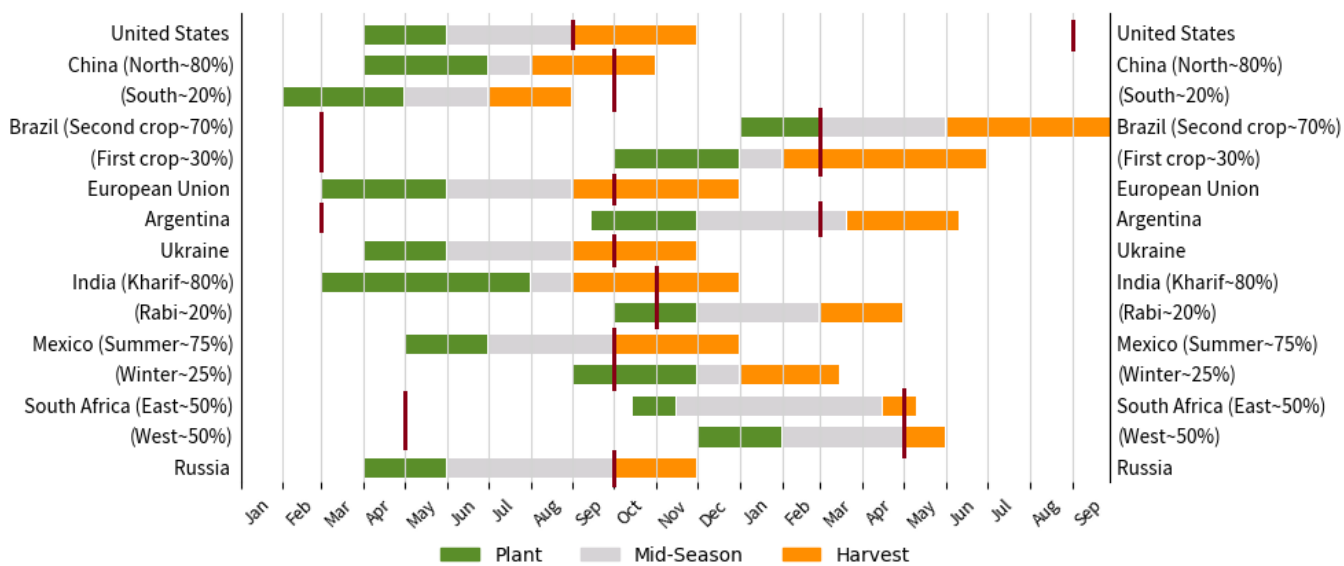
Source: Sobolev (2021).

Figure 1A. Seasonality in Wheat and Corn Stocks on the Example of Ukraine



Source: USDA (2022).

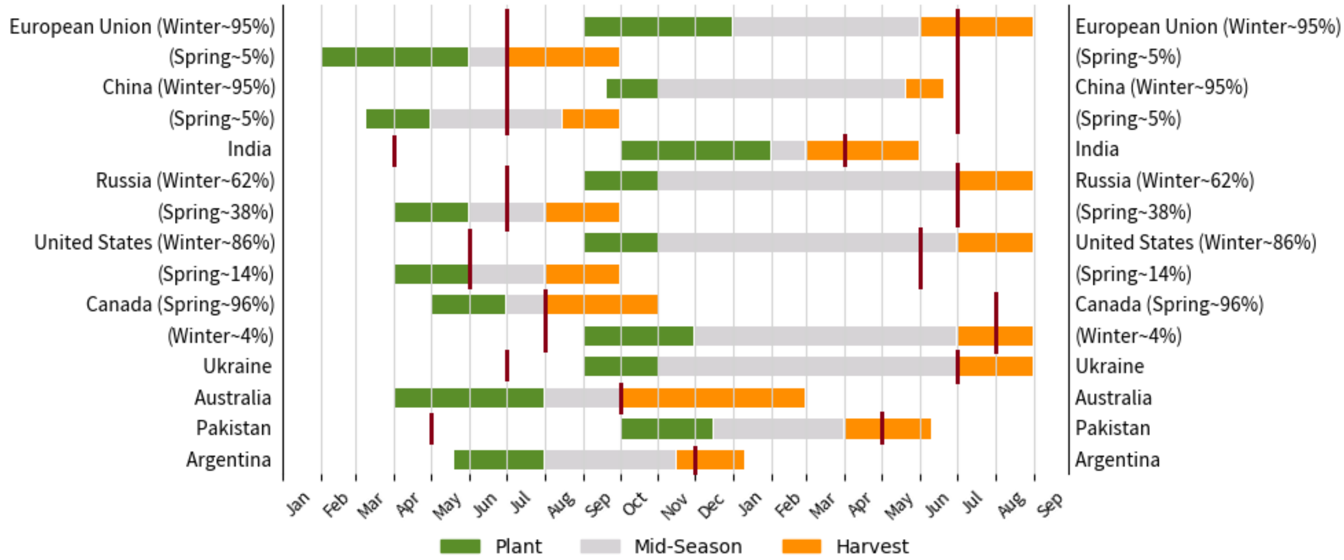
Figure 2A. Seasonality in Wheat Exports on the Example of Ukraine (by month, million metric tons)



Note: burgundy lines were added to the USDA calendar by the author based on PSD definitions of marketing years.

Source: USDA International Production Assessment Division.

Figure 3A. Crop Calendar for Corn (countries ranked by descending production 2021)



Note: burgundy lines were added to the USDA calendar by the author based on PSD definitions of marketing years.

Source: USDA International Production Assessment Division.

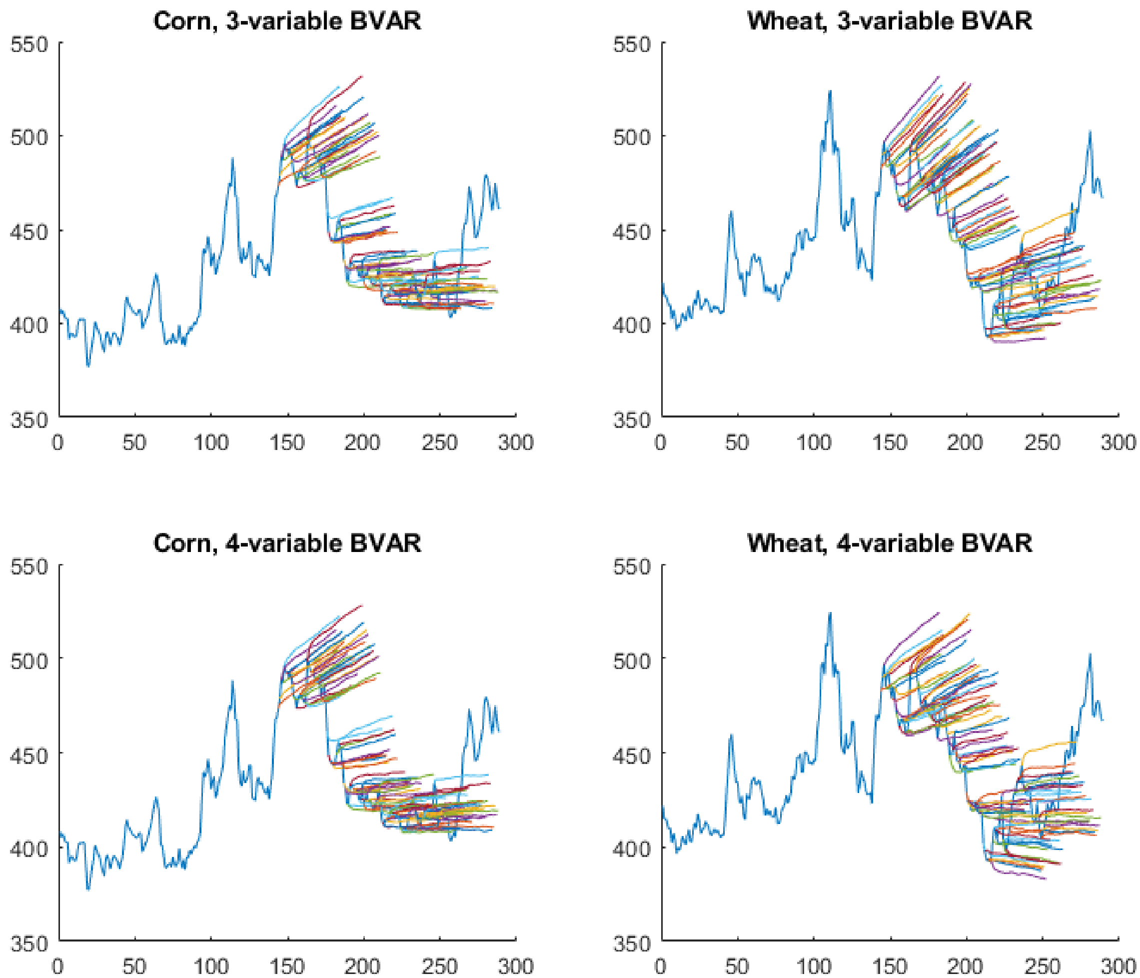
Figure 4A. Crop Calendar for Wheat (countries ranked by descending production 2021)

Publication date	05.21	06.21	07.21	08.21	09.21	10.21	11.21	12.21	01.22	02.22	03.22	04.22
"Proj." MY	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22
MY in the US	20/21	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22
(winter ~68%)												
(spring ~32%)												
MY in Ukraine	20/21	20/21	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22	21/22
Stage of MY												
MY in Argentina	20/21	20/21	20/21	20/21	20/21	20/21	20/21	21/22	21/22	21/22	21/22	21/22
Stage of MY												

Plant Mid-Season Harvest

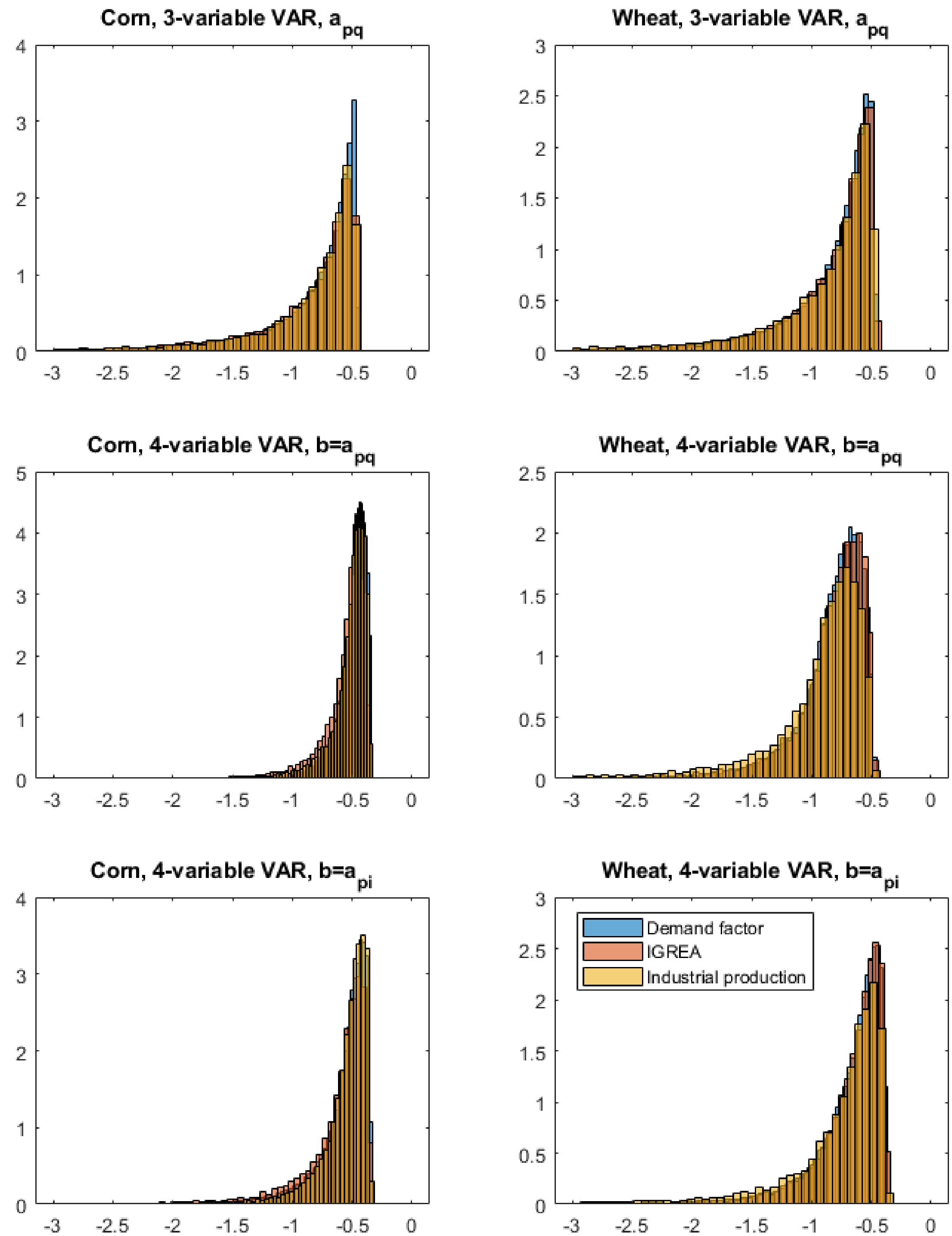
Source: own elaboration.

Figure 5A. Comparison of the Sequences of Wheat Supply Data Release for the U.S., Ukraine, and Argentina



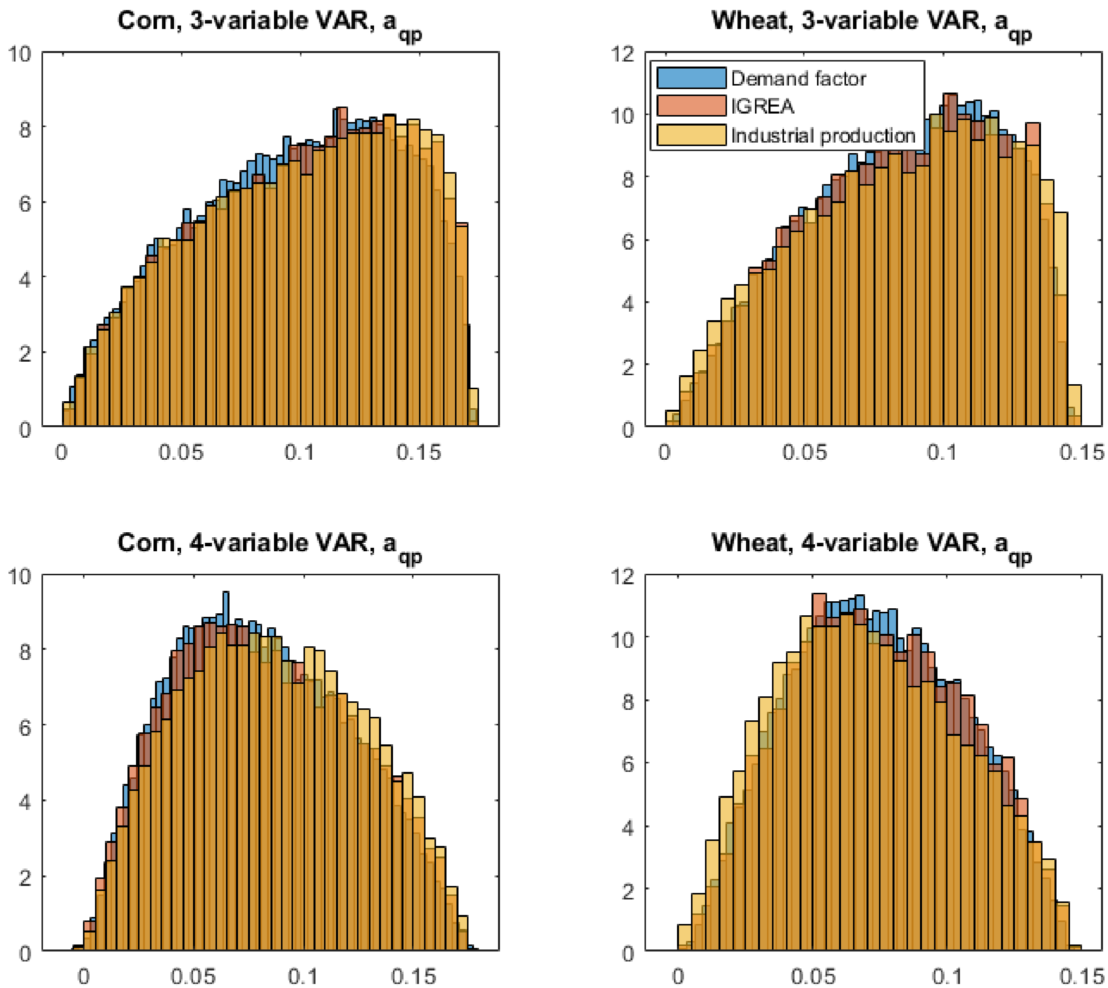
Source: own elaboration.

Figure 6A. Out-of-Sample Forecasts of Corn and Wheat Price



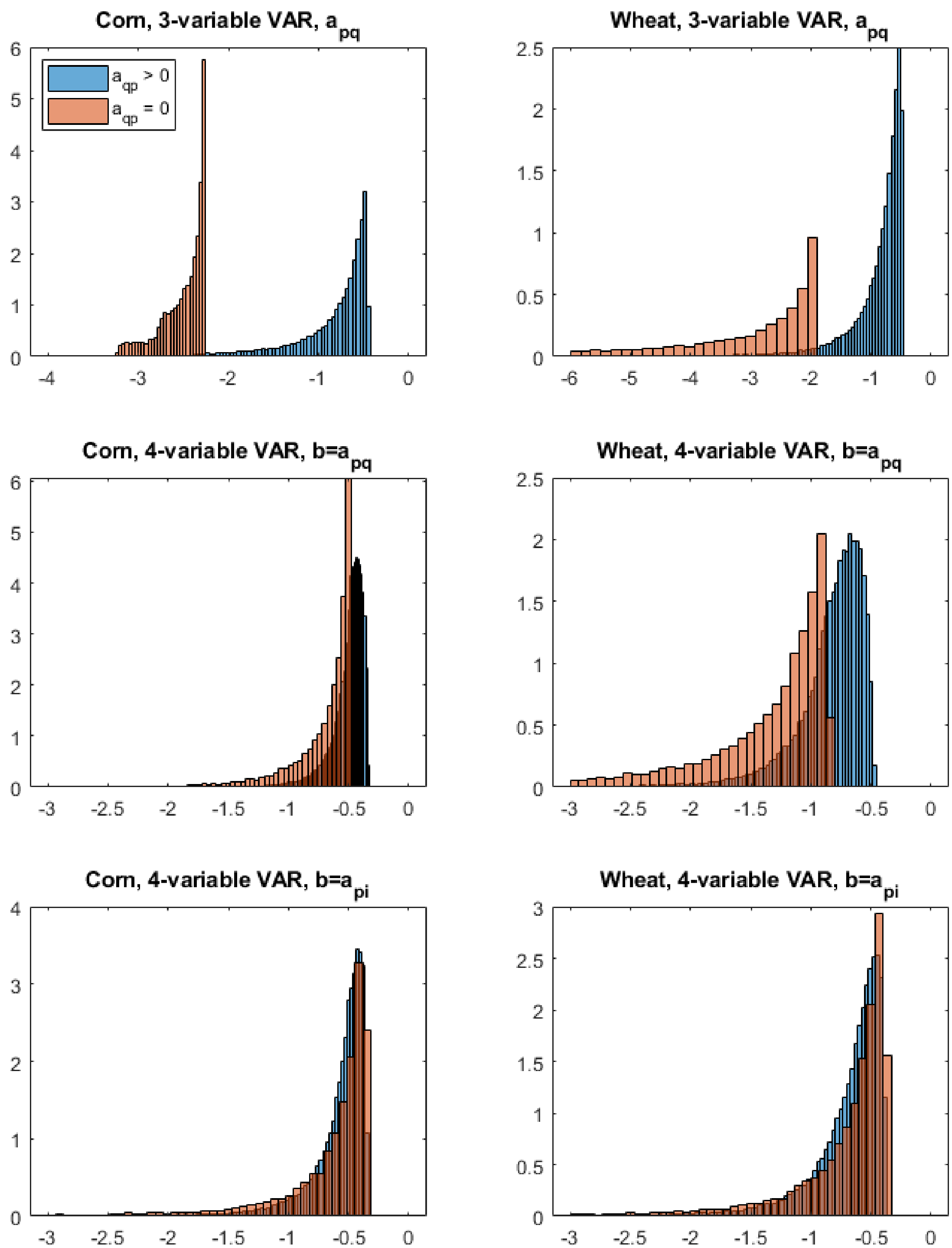
Source: own elaboration.

Figure 7A. Distributions of Elasticity of Demand in Models with Different Aggregate Demand Variable



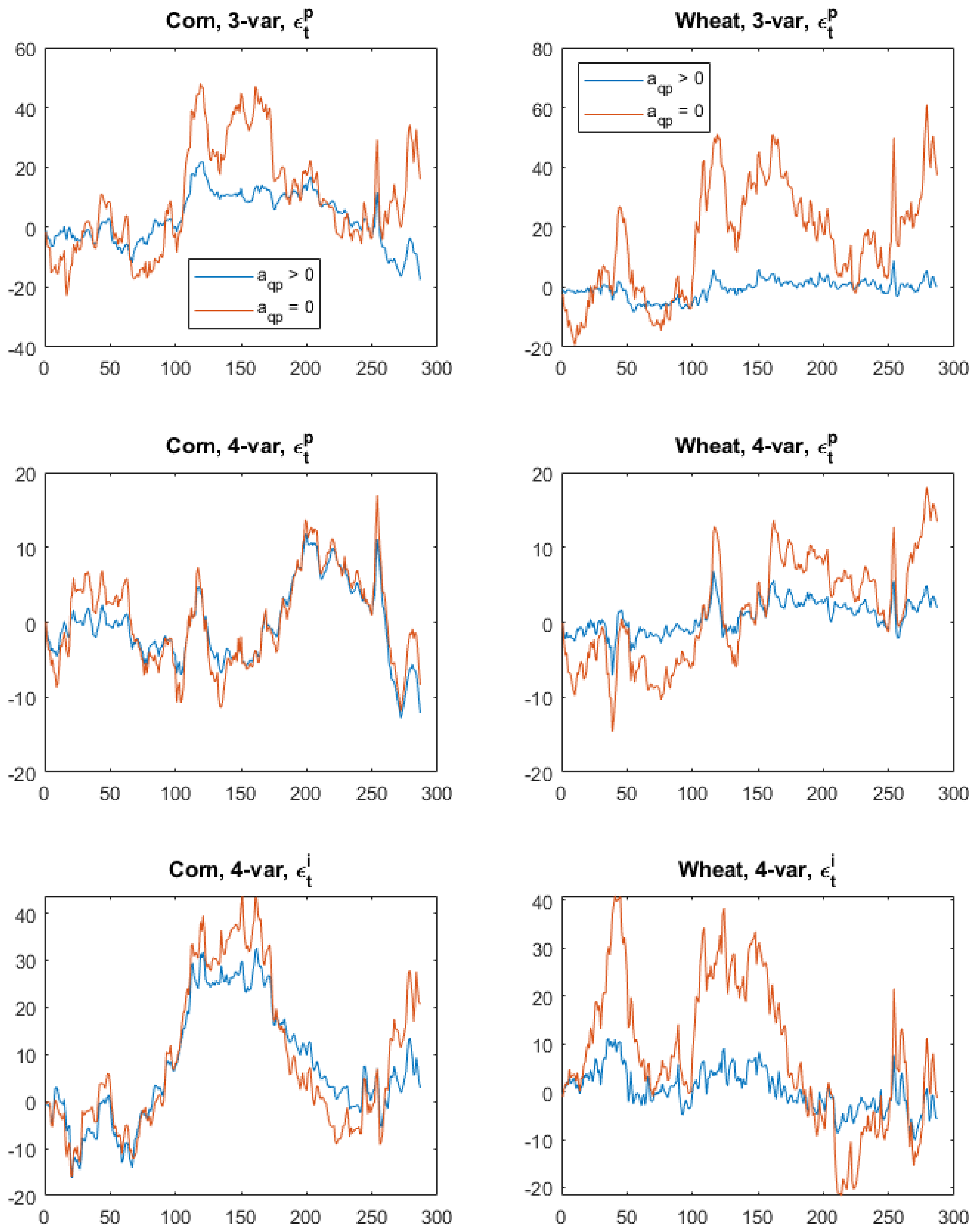
Source: own elaboration.

Figure 8A. Distributions of Elasticity of Supply in Models with Different Aggregate Demand Variable



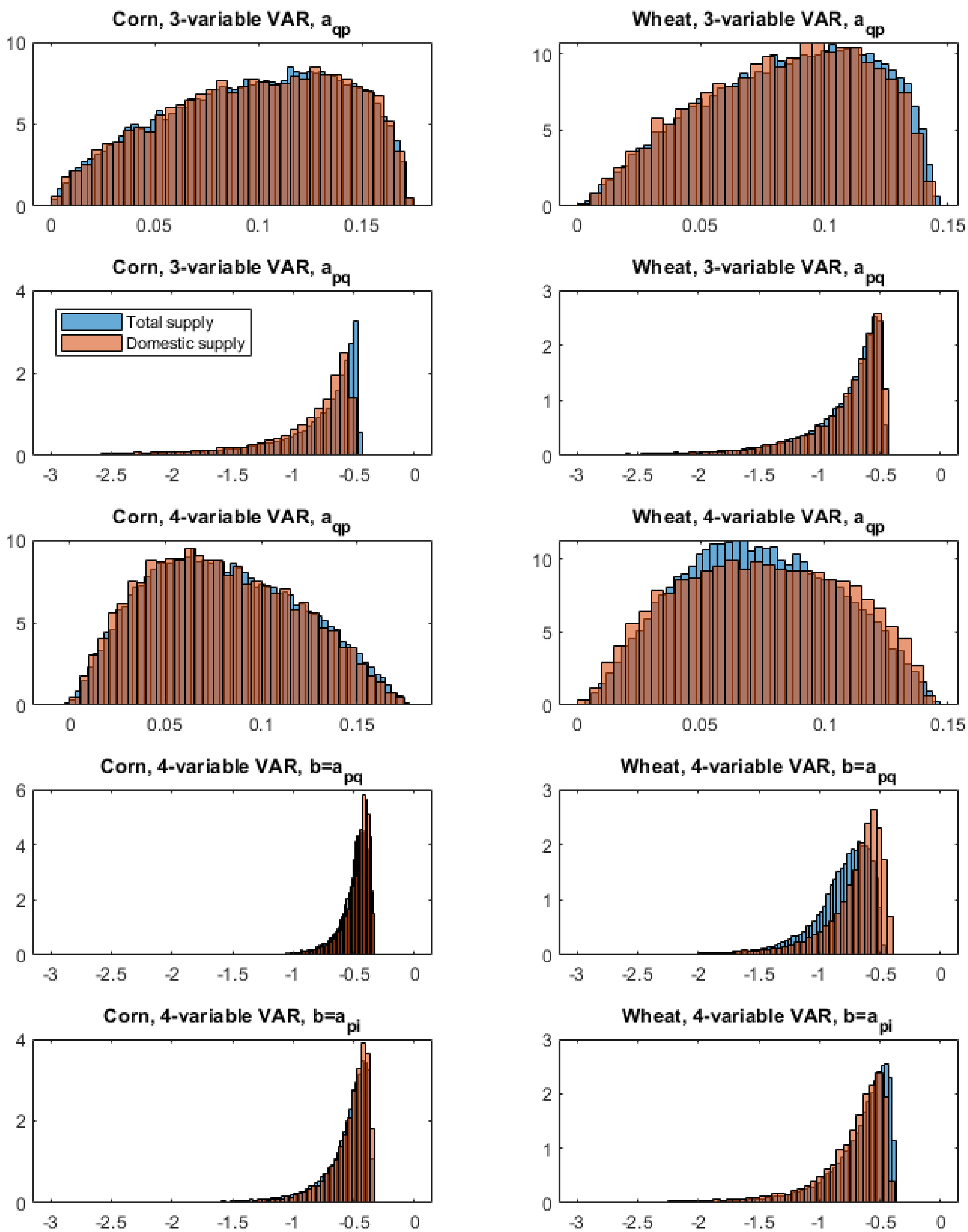
Source: own elaboration.

Figure 9A. Distributions of Elasticity of Demand in Models with Zero Elasticity of Demand



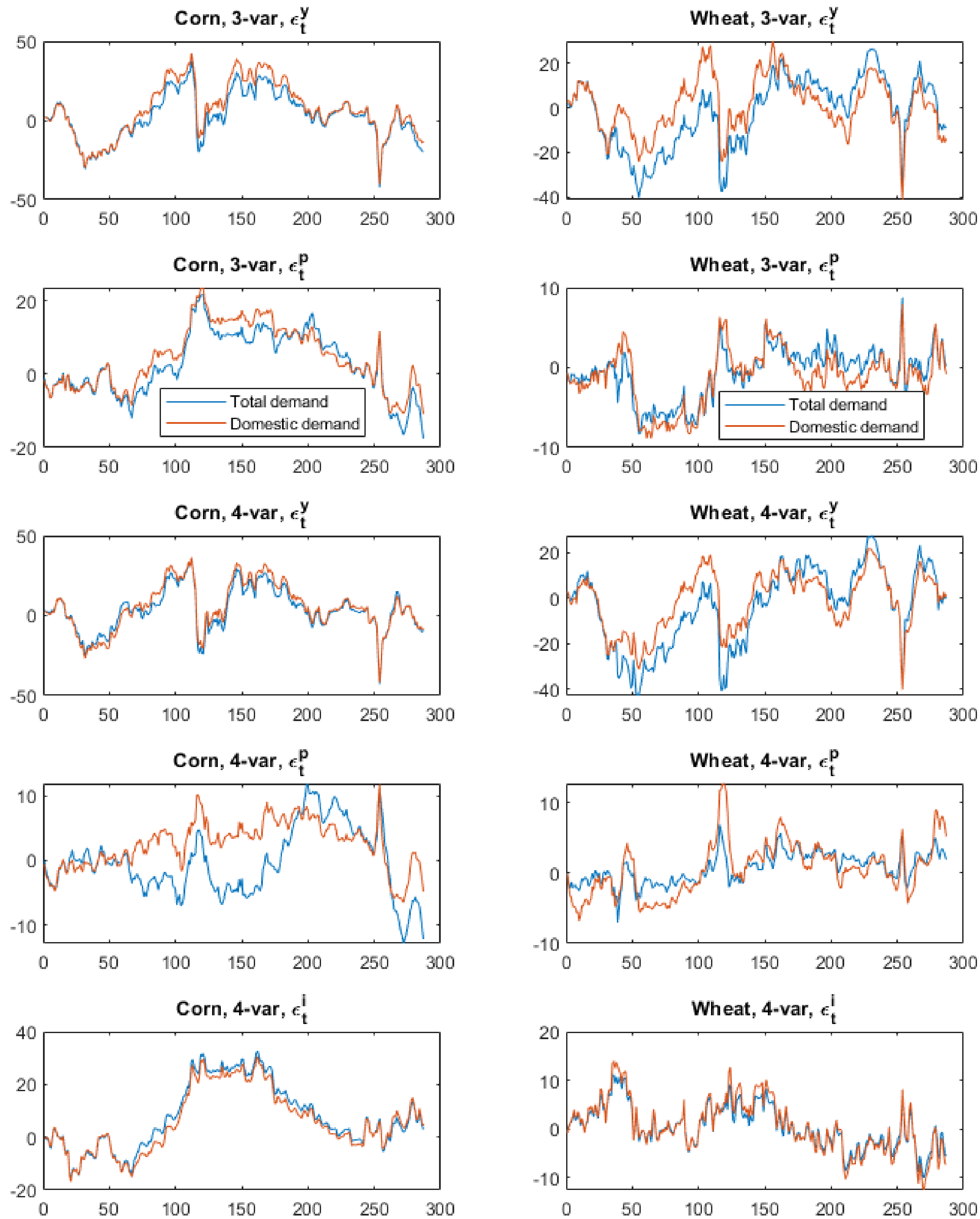
Source: own elaboration.

Figure 10A. Contributions of Speculative Shocks to decomposition of corn and wheat price



Source: own elaboration.

Figure 11A. Distributions of Elasticities of Supply and Demand in Models with Total and Domestic Supply



Source: own elaboration.

Figure 12A. Contributions of Demand and Speculative Shocks to Decomposition of Corn and Wheat Price