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Robuste Versorgungsketten in der Agrar- und Nahrungsmittelwirtschaft

Forecasting Producers Prices for Crops in Austria

Thomas Url (WIFO)

Wissenschaftliche Assistenz: Ursula Glauninger, Cornelia Schobert

Juli 2023
Österreichisches Institut für Wirtschaftsforschung

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Im Auftrag des Bundesministeriums für Land- und Forstwirtschaft, Regionen und Wasserwirtschaft (BML)

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Die Preise von Feldfrüchten sind für Erzeuger und Verbraucher gleichermaßen wichtig. Auf der Erzeugerseite signalisieren Preise das Ausmaß an Knappheit einer Feldfrucht. Bei einer hohen Preiselastizität des Angebots können genaue Preisprognosen für Feldfrüchte den landwirtschaftlichen Betrieben in Österreich ein wertvolles Signal für den Wechsel zu profitableren Kulturpflanzen geben. Damit wird auch die Ernährungssicherheit Österreichs gestützt. Wir wenden drei Typen von Zeitreihenmodellen auf die Erzeugerpreise von vier Feldfrüchten in Österreich an: Mahlweizen, Qualitätsweizen, Raps und Mais. Die Verwendung zusätzlicher erklärender Informationen von Terminmärkten und internationalen Organisationen verbessert die Prognosefähigkeit der Modelle. Der eingesetzte Prognosezyklus beruht auf dem jährlichen Rhythmus der Entscheidungen über Aussaat und Erntezeitpunkt für jede Feldfrucht in Österreich. Wir identifizieren die Mallows Model Averaging-Methode (MMA) als jene mit dem kleinsten durchschnittlichen Prognosefehler. Die Prognosegenauigkeit einer kombinierten Modellprognose aus den eingesetzten Modellen schlägt im Durchschnitt die individuellen MMA-Prognosen und den Preis zeitlich passender Futureskontrakte.

Forecasting Producers Prices for Crops in Austria

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Peer Review: Serguei Kaniovski

Abstract

Prices for agricultural products are critical for producers and consumer alike. On the producer side higher prices signal the degree of scarcity of a crop. Given a high price elasticity of supply, accurate and timely price forecasts for the main crops provide Austrian farmers with a valuable signal to shift land use towards more profitable crops, thus supporting the security of food supply in Austria. We apply three classes of time series models to producer prices of four popular crops in Austria: milling wheat, quality wheat, rapeseed, and maize. Using explanatory variables from futures markets and international organisations improves the model performance. The proposed forecasting cycles reflect the dates of decision making in sowing and harvesting each crop. We find that the Mallows Model Averaging method produces the smallest average forecast error, but a combined model forecast ranks best among all alternatives and beats both, individual model forecasts and the prices of matching futures contracts.

Kurzzusammenfassung

Die Preise von Feldfrüchten sind für Erzeuger und Verbraucher gleichermaßen wichtig. Auf der Erzeugerseite signalisieren Preise das Ausmaß an Knappheit einer Feldfrucht. Bei einer hohen Preiselastizität des Angebots können genaue Preisprognosen für Feldfrüchte den landwirtschaftlichen Betrieben in Österreich ein wertvolles Signal für den Wechsel zu profitableren Kulturpflanzen geben. Damit wird auch die Ernährungssicherheit Österreichs gestützt. Wir wenden drei Typen von Zeitreihenmodellen auf die Erzeugerpreise von vier Feldfrüchten in Österreich an: Mahlweizen, Qualitätsweizen, Raps und Mais. Die Verwendung zusätzlicher erklärender Informationen von Terminmärkten und internationalen Organisationen verbessert die Prognosefähigkeit der Modelle. Der eingesetzte Prognosezyklus beruht auf dem jährlichen Rhythmus der Entscheidungen über Aussaat und Erntezeitpunkt für jede Feldfrucht in Österreich. Wir identifizieren die Mallows Model Averaging-Methode (MMA) als jene mit dem kleinsten durchschnittlichen Prognosefehler. Die Prognosegenauigkeit einer kombinierten Modellprognose aus den eingesetzten Modellen schlägt im Durchschnitt die individuellen MMA-Prognosen und den Preis zeitlich passender Futureskontrakte.

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1. Introduction

Prices for agricultural products are critical for producers and consumer alike because the main signal transmitted through prices is the degree of scarcity of the underlying agricultural product. For farmers prices directly determine their income based on the quantity harvested. At the same time, they provide a signal for future profit opportunities. For consumers, on the other hand, food is a consumption good with a low substitution effect, i. e. the reduction in consumption after a price increase will be small and there are only few opportunities to substitute towards cheaper alternatives. Increasing prices will therefore redistribute income from consumers to farmers and commodity traders.

Typically, the share spend by private households on food consumption will decline with increasing income level, i. e. households in developed countries will spend a larger share of their consumption on food as compared to households living in developing countries. Meade & Rosen (1996) show that low-income countries like Honduras or Tanzania in 1980 spent between 51% and 71% of their income on food, while households from high income countries like the USA (8.7%) or Israel (22.1%) spend a considerably lower share on food consumption. The development of food spending in Austria over time is also instructive: while in the year 1954 Austrian households spent almost half of their consumption expenditures on food (45%), this share dropped to 12.1% in the most recent consumer survey from 2019/2020. Similarly to the international comparison, high income households living in high income countries tend to spend a smaller share of consumption on food. Whitmore Schanzenbach et al. (2016) show this by using the consumption bundles of US-households in 2014. Households belonging to the first income quintile spent slightly less than 16% of consumption expenditures on food, while those in the fifth income quintile spent some 11% on food. Despite the falling share in total consumption spending on food, US-high-income households spent roughly three times as much on food as compared to low-income households.

Similarly, the share of agricultural value added in the total value added of an economy decreases lower over time because growth will be concentrated in new products and services which happen to be provided by manufacturing firms, service providers, and the public sector, rather than farmers. This general pattern suggests that fluctuations in agricultural prices have higher welfare effects in low-income countries. Within a high-income country variation in agricultural prices will affect low-income households more strongly than others. This aspect highlights the distributional consequences of higher agricultural prices at the national level.

Most agricultural commodities are homogenous goods, i. e. the differences with respect to product quality and processing characteristics are small and can be easily measured. The protein content of wheat is a good example for the degree of homogeneity. Milling wheat is defined by a minimum protein content of 12.5% while quality wheat has a minimum of 14%. Due to the extensive international trade in agricultural products, prices formed on local markets are closely linked to what happens in important producer countries. Fluctuations in weather conditions, the effects of natural hazards or of political conflict will spread from large producer countries to the world market. The development of energy prices will also impact on agricultural prices because some farm inputs are energy intensive. Small cross border deviations in crop prices may still arise from conditions of delivery and the costs of transportation. For example, US-wheat prices in the World Bank's Pinksheet define financial delivery conditions like fob (free on board) or cif (cost, insurance and freight) and the relevant ports for shipment. This kind of homogeneity implies that the supply of crops in a particular country can quickly respond to local price signals by redirecting international trade.

Figure 1 shows that prices for the main crops are stable in the long run, when measured in euro per tonne. Some large ups and downs associated with energy price hikes and recently, the attack of Russia on Ukraine, are also visible, but the prices for the three crops tend to return to stable means even after substantial gains. The broad span resulting from these large swings creates a difficult environment for forecasters. For example, the minimum price for wheat recorded between 1960 and 2023 was 86 € per tonne in November 1990 and the maximum was 494 € per tonne in May 2022, cf. Table 1. The dates of recording the minimum or maximum price do not fall into specific periods. For example, the price for soybeans had its minimum in October 1960 and the maximum in June 1973 while maize was cheapest in March 1987 and recorded its highest price in October 2022. Appendix

Table A1 in the appendix shows the statistics by decade. The period from 2019 onwards appears particularly volatile. If crop prices are measured in US-dollar instead of euro, the long-term development is slightly different. Due to the devaluation of the dollar vis-a-vis the euro a long run upward trend in crop prices emerges.

Given that the demand for food has increased substantially since 1960, the long-run stability of commodity prices requires a high enough price elasticity of supply. The world population started at 3 billion people in 1960 and more than doubled towards 8 billion in 2023 (UN-DESA, population division). Per-capita GDP measured in PPP in emerging markets increased by a factor of 8.8 between 1980 and 2022 (IMF-datamapper), and the switch to biofuels added further demand during the last decade. Higher real demand has been met by an expansion of supply due to further cropland being put into use and by applying more efficient agricultural techniques. Currently, commodity markets are strongly affected by Russia's attack on Ukraine. Both countries are among the most important crop exporting countries in the world. Exports by Ukraine were effectively blocked from the world market in March 2022, creating a surge in crop prices (Figure 1). After an agreement to allow bulk shipping from and to Odessa has been brokered by Turkey on June 6th 2022, prices started to edge down. By May 2023, however, crop prices remain elevated.

Figure 1 also shows that none of the crop prices shows a strong seasonal pattern, e. g. due to a lower price during harvest. Table 2 presents the autocorrelation coefficients for the first difference of the crop prices at lags corresponding to the seasonal frequencies of a monthly time series. The values are close to zero. Only for wheat and soybeans at lag 3 we find values significantly different from zero.

Austria as a high-income country should be less affected by large swings in crop prices. Still such swings may have negative welfare consequences resulting either from reduced accessibility of international crop markets by Austrian importers or by high foreign demand absorbing more of Austria's current production or its stocks. Accurate price forecasts for the main crops provide Austrian farmers with a valuable signal to shift land use towards more profitable crops and thus they will also contribute to food supply security in Austria, which was also the topic of a recent analysis by the Austrian Court of Audit. Rechnungshof (2023) documents that the degree of self-sufficiency in Austria varies across agricultural products and over time (2015-2020). For grain the degree fluctuates between 86% and 95% of domestic use; for oilseeds the degree is much lower varying between 45% and 53%.

International organisations and the United States Department for Agriculture (USDA) already make quantity and price forecasts for many internationally traded crops[1]). The forecasts are usually published as the average price over the year and some are updated twice a year. The OECD-FAO uses a structural partial equilibrium model (Aglink-Cosimo) to forecast produced and consumed quantities for 31 individual countries and several regional modules which include the remaining countries (OECD-FAO, 2023B). The model covers over 90 commodities and computes 39 world market-clearing prices. In contrast to this structural approach USDA uses a set of parsimonious time series models to forecast producer prices (MacLachlan et al., 2022). The USDA switched from more structured pass-through models for individual prices to ARIMA based time series models (Enders, 2010). Pass-through models use the information from input prices in agricultural production to forecast the development of the respective output price. MacLachlan et al. (2022) present results indicating a better forecasting performance for time series models; the authors also emphasise the advantage of ARIMA-models in computing confidence intervals.

In this study we will apply three classes of time series models to forecast four Austrian producer prices for crops. The producer prices encompass milling wheat, quality wheat, rapeseed, and maize. The following section will present the data. Then we give a short overview about the time series models applied and motivate the forecasting cycle chosen for each crop. After estimating the models and using them to compute real-time ex-ante forecasts for the years 2018 through 2022, we can present a first impression of the forecasting performance. The final section concludes.

Table 1 - Descriptive statistics of crop prices 1960 through 2023, € per tonne

	Wheat	Soybean	Maize
Mean	160.4	285.8	125.8
Std. Deviation	58.2	96.4	46.4
Min	85.6	166.3	61.8
Max	493.7	716.3	349.6
Span	408.1	550.0	287.9

Source: OECD, Worldbank (Pinksheet). Monthly average price converted to Euro-ATS from January 1960 through May 2023. See Appendix

Table A1 for a division of the total sample by decades.

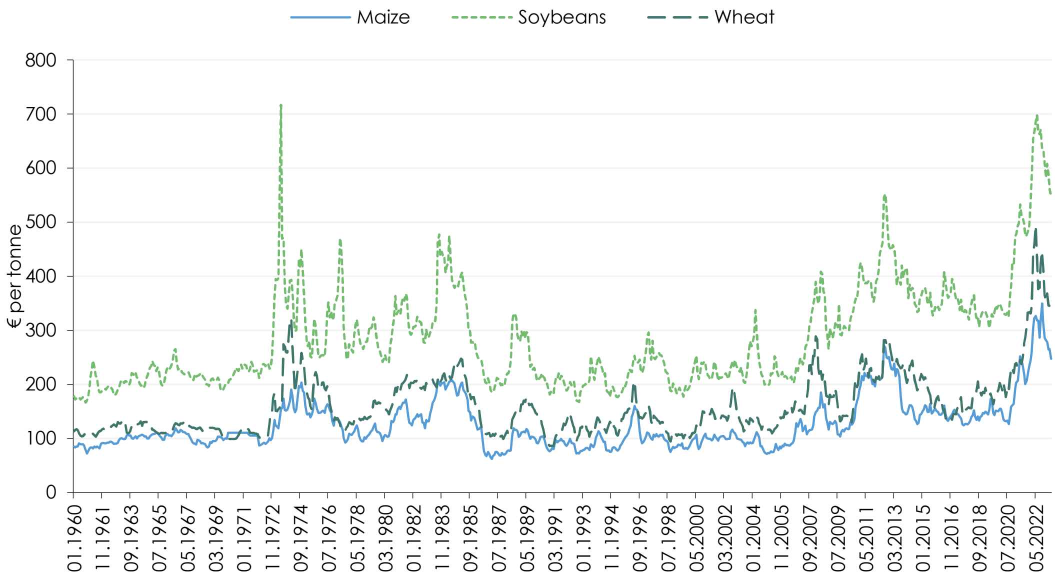
[1]) OECD-FAO (2023A), World Bank Group (2023), and USDA https://www.ers.usda.gov/topics/crops/.

Table 2 - Test on seasonal variation in international crop prices

		Wheat	Soybean	Maize
Autocorrelation at lag	3	– 0.15	– 0.07	– 0.02
	6	0.05	– 0.06	– 0.04
	9	– 0.02	0.02	– 0.02
	12	– 0.04	– 0.05	0.01

Source: Own calculations. – Autocorrelation coefficients for first differences of crop prices based on 760 observations.

Figure 1 - Long-term development of crop prices 1960-2023



Source: OECD, World Bank (Pinksheet) prices are converted to Euro-ATS.

2. Data

We forecast Austrian crop producer prices as published by Statistics Austria on a monthly frequency (cf. Table 3 at the end of this section) and presented in Figure 2 through Figure 4. Additionally, to the Austrian producer prices, each Figure also shows the corresponding US-price transferred from US-dollar into euro-ATS. Due to months without trading activity the Austrian time series for rapeseed frequently has gaps with missing data. We fill the missing observations by using growth rates from the respective international time series.

Wheat and maize prices appear to remain in a stable band between January 1999 and mid-2010. Following the business cycle upturn after the financial market crisis, grain prices became more volatile and the average producer price in Austria was about 50% higher than before. The international acceleration in crop prices during 2021 was also noticeable in Austria and received further stimulus, when Russia attacked Ukraine in March 2022 and blocked shipping traffic from and to Ukrainian Black Sea ports. After an agreement to allow bulk shipping from and to Odessa has been brokered by Turkey on June 6th 2022, prices started to edge down. By

May 2023, however, crop prices still remain elevated. Over time, the dynamics of Austrian producer prices moved closer to the international prices of similar crops. At the end of the sample the matching of price movements is already very close, best seen in Figure 3 for maize. Figure 2 through Figure 4 also show that the year 2019 is the last more or less regular year in the sample, afterwards a steep increase in prices occurred until June 2022, when prices started to drop. The wild and sudden swings in crop prices over this period will provide a challenging sample for ex-ante forecasting tests.

Further leading indicators used to forecast Austrian producer prices are the prices of crop futures with varying maturity, featuring delivery dates between 1 month to 12 months ahead. Futures are forward contracts being initiated at date t and executed at a subsequent time t+h, i. e. the delivery date. The terms of the contract fulfilment are fixed in advance, e. g. the price at which a commodity is exchanged is fixed at the time of initial contracting. Futures have several advantages: they are traded on organised exchanges under standardised contract terms. The fulfilment of a future is guaranteed by a clearinghouse and supervised by an official authority. Contract partners are subject to margin payments to ensure fulfilment of the contract. Futures are useful because they allow to fix the price of a commodity – which is delivered in the future – in advance, i. e. they resolve the uncertainty about the future price of a crop. From the perspective of a farmer, the price for the future harvest can be locked in at the time of sowing, from the perspective of a food manufacturer the price of an important input can be locked in, when contracts with wholesalers or retailers are signed.

Three international institutions collect data relevant for food security. The World Bank monitors information on price developments and publishes data regularly in its Commodity Markets Outlook. The World Bank collects long-term time series in its Pinksheet. The Commodity Markets Outlook is currently published twice a year in April and October.

The Food and Agriculture Organisation (FAO) belongs to the institutions set up by the United Nations. The FAO provides information on agricultural stress indicators for various crops, published 3 times a month. The stress indicators combine satellite data on precipitation and temperature with theoretical plant growth models to estimate the amount of stress on a fine grid across all members of the United Nations. The FAO defines stress as the share of area with a Mean Vegetation Health Index below 35 in percent of the total area under cultivation. We aggregate the agricultural stress level for crop i in country c in month t, ASI_{ict}, of the 20 biggest producers of wheat, rapeseed, and maize into three crop specific monthly stress indicators. Monthly values for ASI correspond to the average of the three measurements within the respective month. The computation uses the share of country c in the total harvest of crop i throughout the 20 biggest producer countries in 2021 as weights, ω_{ic}:

$$ASI_{it} = \sum_{c=1}^{20} \omega_{ic} ASI_{ict} \; .$$

All international data contain comparable values for wheat and maize but no information on rapeseed. As a substitute we use the information provided for soybeans, cf. Figure 4 to get an impression about the relevance of soybean price data from the World Bank (converted into euro-ATS) for Austrian producer prices of rapeseed.

Finally, the Organisation for Economic Cooperation and Development (OECD) teams up with the FAO to produce the Agriculture Outlook, including forecasts of supply and demand for several crops, meat, and fish. The expected quantities produced, consumed, traded across borders, and stored at the end of the year are published for individual countries and at the world level in the annual report published every July. We use the supply and demand data at the world level to compute indicators of scarcity for each crop i. The indicators signal the ratio of production to consumption:

$$PC_{it} = \frac{production_{it}}{consumption_{it}},$$

the ratio of the stock at the end of the previous year to the consumption of the current year:

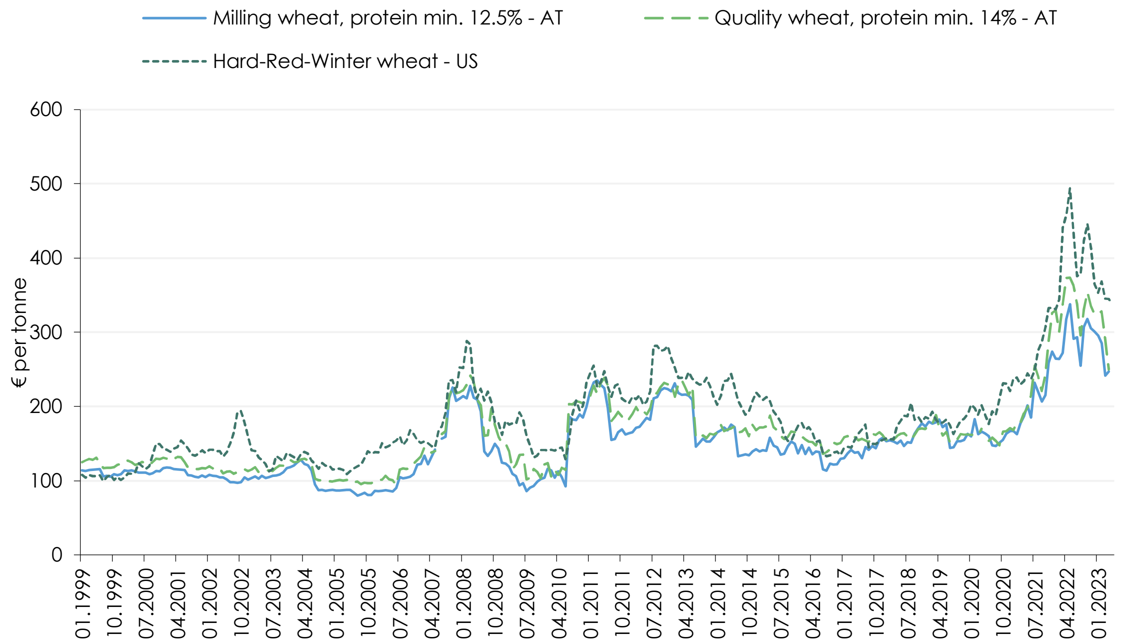
$$SC_{it} = \frac{end\ of\ year\ stockt_{i(t-1)}}{consumption_{it}},$$

and the ratio of stocks carried over from the previous period plus the production of the current period to the consumption of the current period:

$$SPC_{it} = \frac{end\ of\ year\ stockt_{i(t-1)} + productio\ \ _{it}}{consumption_{it}}.$$

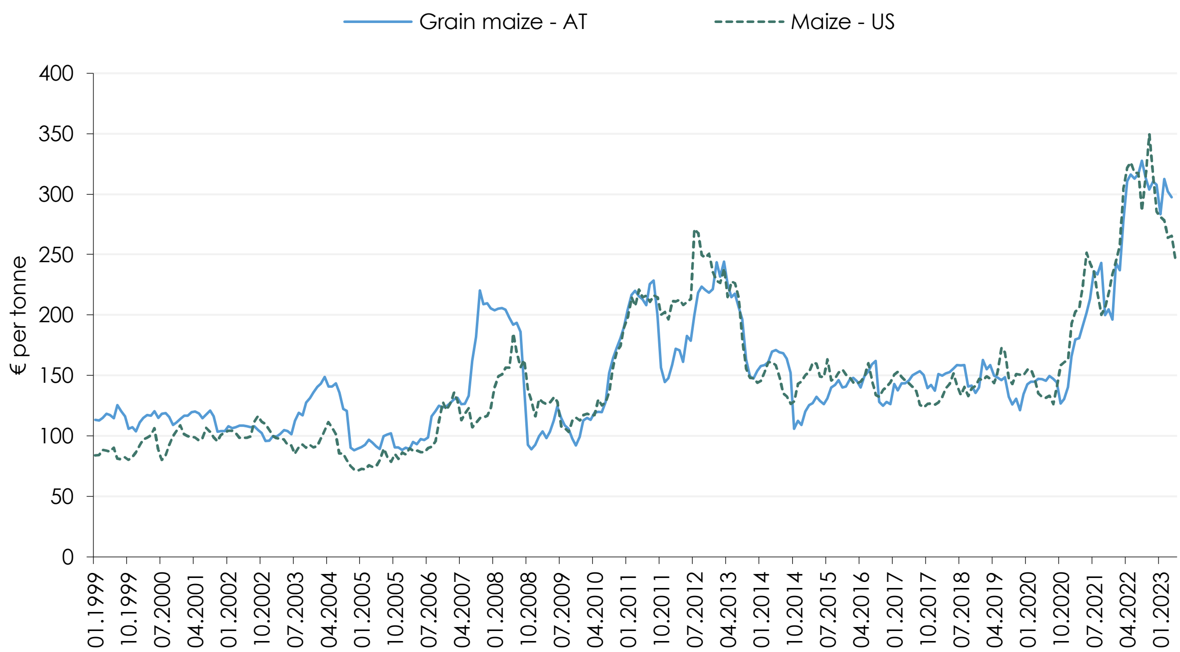
All quantity forecasts by OECD-FAO are at the annual level. Because the price forecasts are based on monthly data, we interpolate the low frequency annual data from the Agriculture Outlook into high frequency monthly data by fitting a local quadratic polynomial for each observation of the low frequency series. Then this polynomial is used to fill in all observations of the high frequency series associated within the period. The quadratic polynomial is formed by taking sets of three adjacent points from the source series and fitting a quadratic such that the average of the high frequency observations over 12 months matches the low frequency data from the Agriculture Outlook. For most points, one point before and one point after the period currently being interpolated are used to provide the three points. The OECD-FAO forecasts extend up to eight years into the future, therefore this procedure avoids an end point problem.

Figure 2 - Prices for milling wheat and quality wheat in Austria, and US-hard-red-winter wheat



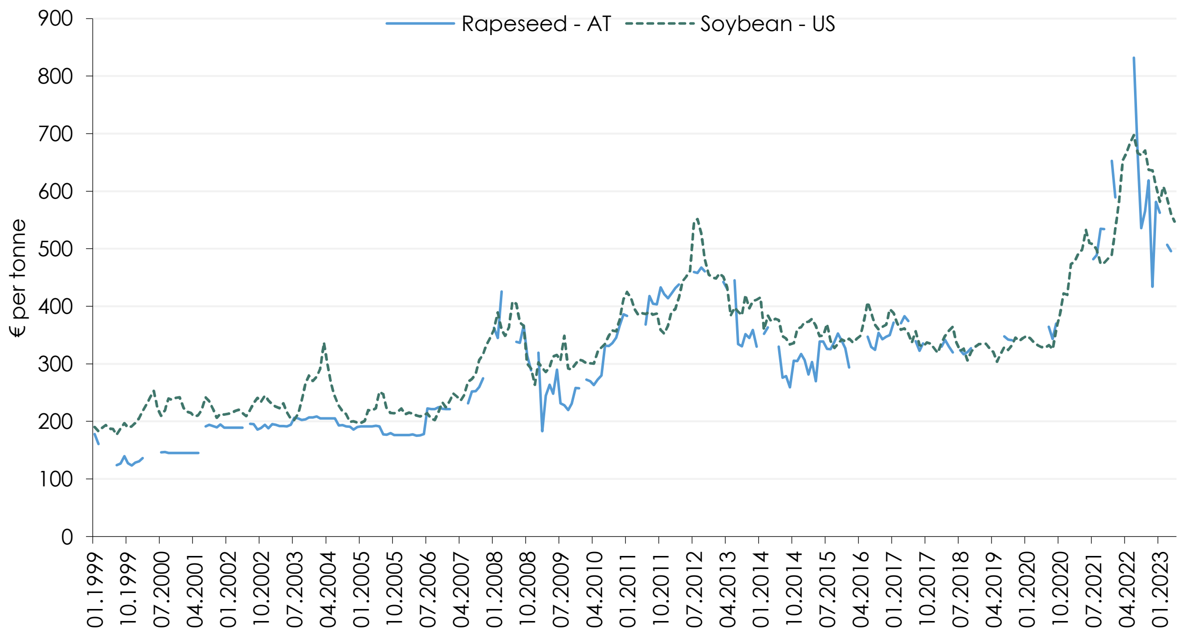
Source: Statistics Austria, World Bank (Pinksheet), OECD. – Monthly prices in euro per tonne, US-Hard-Red-Winter-Wheat in USD per tonne f.o.b. at US-Gulf ports converted to Euro-ATS.

Figure 3 - Prices for grain maize in Austria and US-maize



Source: Statistics Austria, World Bank (Pinksheet), OECD. – Monthly prices in euro per tonne, US-Maize (No. 2 yellow) USD per tonne f.o.b. at US-Gulf ports converted to Euro-ATS.

Figure 4 - Prices for oil rapeseed in Austria and US-soy beans



Source: Statistics Austria, World Bank, OECD. – Monthly prices in Euro per tonne, gaps in timeseries due to lack of trading activity, U.S Gulf Yellow Soybean No. 2, CIF Rotterdam in USD per tonne converted to Euro-ATS.

Table 3 - Description of data and sources

Variable	Unit	Details	Source
Price for grain maize	€ p. tonne		Statistics Austria
Price for US-maize (yellow No. 2)	USD p. tonne	f.o.b. US Gulf ports	World Bank Pinksheet
Price for oil rapeseed	€ p. tonne		Statistics Austria
Price for US-soybeans (yellow No. 2)	USD p. tonne	cif. Rotterdam	World Bank Pinksheet
Price for milling wheat	€ p. tonne	Protein min. 12,5%	Statistics Austria
Price for quality wheat	€ p. tonne	Protein min. 14%	Statistics Austria
Price for US-hard-red-winter wheat	USD p. tonne	Export price delivered at the US Gulf port for prompt or 30 days shipment	World Bank Pinksheet
Price for maize	USD p. tonne	Commodity Market Outlook (CMO), various issues	World Bank
Price for soybeans	USD p. tonne	Commodity Market Outlook (CMO), various issues	World Bank
Price for wheat	USD p. tonne	Commodity Market Outlook (CMO), various issues	World Bank
Exchange rate	USD per €-ATS		OECD
Price for corn-future	€ p. tonne	Euronext Paris Close, various maturities	Macrobond
Price for rapeseed-future	€ p. tonne	Euronext Paris Close, various maturities	Macrobond
Price for wheat-future, milling wheat No.2	€ p. tonne	Euronext Paris Close, various maturities	Macrobond
Maize Agricultural Stress Index (Season 1)	in percent	Stressed area in 20 biggest maize producing countries in percent of total cropland, aggregated by share of country in production, monthly mean. Stress is defined as percent of area with Mean Vegetation health index below 35.	Own computation based on FAO Agricultural Stress Index System (ASIS), http://www.fao.org/giews/earthobservation/
Rapeseed Agricultural Stress Index (Season 1)	in percent	Stressed area in 20 biggest rapeseed producing countries in percent of total cropland, aggregated by share of country in production, monthly mean. Stress is defined as percent of area with Mean Vegetation health index below 35.	Own computation based on FAO Agricultural Stress Index System (ASIS), http://www.fao.org/giews/earthobservation/
Wheat Agricultural Stress Index (Season 1)	in percent	Stressed area in 20 biggest wheat producing countries in percent of total cropland, aggregated by share of country in production, monthly mean. Stress is defined as percent of area with Mean Vegetation health index below 35.	Own computation based on FAO Agricultural Stress Index System (ASIS),

Table 3 - Description of data and sources (continued)

Variable	Unit	Details	Source
Production of maize, world	tonnes	OECD-FAO Agriculture Outlook, estimate from various issues	Macrobond
Consumption of maize, world	tonnes	OECD-FAO Agriculture Outlook, estimate from various issues	Macrobond
Ending stock of maize, world	tonnes	OECD-FAO Agriculture Outlook, estimate from various issues	Macrobond
Production of oil seeds, world	tonnes	OECD-FAO Agriculture Outlook, estimate from various issues	Macrobond
Consumption of oil seeds, world	tonnes	OECD-FAO Agriculture Outlook, estimate from various issues	Macrobond
Ending stock of oil seeds, world	tonnes	OECD-FAO Agriculture Outlook, estimate from various issues	Macrobond
Production of wheat, world	tonnes	OECD-FAO Agriculture Outlook, estimate from various issues	Macrobond
Consumption of wheat, world	tonnes	OECD-FAO Agriculture Outlook, estimate from various issues	Macrobond
Ending stock of wheat, world	tonnes	OECD-FAO Agriculture Outlook, estimate from various issues	Macrobond

3. Models

We use three classes of time series models to forecast producer prices for crops in Austria. The time series models encompass Autoregressive Integrated Moving Average (ARIMA) models, Exponential Smoothing (ETS) models, the Mallows Model Average (MMA) method, and ARIMAX models where explanatory variables provided either by capital markets or by international organisations are added to ARIMA models.

Univariate time series models assume that the future development of a variable can be predicted by using only information about the dynamic behaviour of a variable over the past. This approach uses therefore only information from the past development of the crop price under consideration to make out-of-sample forecasts. Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ETS) models belong to this class. Another model class allowing for the use of additional information from other explanatory variables is the Mallows Model Averaging (MMA) method. The MMA method either selects the optimal model or produces the forecast from a combination of several models. The MMA method can incorporate leading indicators into an autoregressive model, but it uses only past observations of the leading indicators to compute the forecast.

Finally, single equation regression models can use exogenous information on the expected future development of the respective crop price. This information can be provided by financial markets (futures prices) or alternatively by international organisations. For example, the outcome of the comprehensive procedure applied by the OECD-FAO and the World Bank to forecast crop prices and quantities may be helpful to forecast the future development of producer prices in Austria. For this purpose, we complement ARIMA models, which are good on capturing the dynamics of a time series, with explanatory variables. Pokorný & Froněk (2021) provide evidence for a higher predictive performance of some OECD-FAO crop price forecasts compared to naïve extrapolations of the last observed value.

3.1 Autoregressive Integrated Moving Average (ARIMA) models

Univariate ARIMA models are based on the theory of stochastic linear difference equations. The model parameters are estimated from past observations of the target variable, in our case the respective crop price. The stability conditions for these models require that the target variable follows a stationary process, i. e. the variable always converges back to a stable mean and the covariance structure between pairs of observations remains constant over time. The second condition excludes bouts of high volatility in the time series. If these conditions are met, the parameters can be estimated by maximum likelihood and the model selection is based on minimising an information criterion. The information criterion for a model specification will become smaller if the model fits better to the data, i. e. the sum of squared estimation errors (sum of squared residuals) within the estimation sample is smaller. On the other hand, a penalty term for the number of parameters to be estimated will favour parsimonious models over models including more autoregressive and moving average terms. We use the Bayesian Information Criterion (BIC) for model selection because it poses a higher penalty on additional regular and seasonal autoregressive or moving average terms (Enders, 2010).

3.2 Exponential Smoothing model (ETS)

Exponential smoothing models belong to a class of univariate time series models not requiring a constant mean over time, rather they adjust slowly to changes in the mean of a time series because each forecast is a weighted average of past observations and the weights decay exponentially as the observation is more distant from the last observed value. The simplest ETS model is the naïve forecast based on the last realised value of a variable. In this special case all weight is given to the last observation, i. e. it is the only observation that matters for forecasting, while all other previous observations for the crop price are ignored. If we attach larger weights to the more recent observations and smaller weights to the more distant observations, the forecast is a weighted average of past observations. More complex ETS models distinguish between one or more components of a time series, i. e. a level, trend or seasonal component, and the way how these components are aggregated in the forecast equation (additive, multiplicative) (Hyndman & Athanasopoulos, 2014). Hyndman et al. (2002) put the ETS model into a state space form and show how to find the optimal model according to the Bayesian information criterion (BIC). Again, the optimal model structure will be determined by the best fit within the estimation sample, i. e. the sum of squared residuals.

3.3 Mallows Model Averaging (MMA)

The univariate ARIMA model uses only the dynamics observed in the past development of the target variable for a forecast. Richer forecasting models include additional leading indicators which carry a signal about the future development of the target variable. If a leading indicator carries a signal on future values of the target variable, model forecast from the richer model are expected to outperform forecasts based on univariate ARIMA models. The actual set of leading indicators and the number of lags for the target variable as well as the leading indicators, however, are unknown and therefore models with all possible combinations of potential lags of leading indicators with the target variable must be estimated and compared. Because the leading indicators are observable at the time when the forecast is made, we do not need forecasts of them, i. e. only past and current observations are necessary for forecasting.

Hansen's Mallows Model Averaging method searches across all combinations of autoregressive terms of the target variable and the leading indicators. The number of potential models is $2^{L(1+M)}$, where L is the number of all possible combinations of autoregressive lags and M is the number of all possible combination of leading indicators and their lags. The model is optimised for the length of the forecast horizon (h), which is h=12 months in the case of wheat and rapeseed and h=9 months in the case of maize. The Mallows Model Averaging method computes quasi out-of-sample forecasts for each observation in the sample by applying a leave-one-out cross validation technique. This mimics a forecasting situation more closely than the in-sample estimation errors used to compute the BIC criterion. We restrict the number of possible lags in the target variable and the leading indicators to L=6. The optimal model selected by the leave-one-out cross validation approach provides the MMA-selected forecast. Additionally, we use the MMA-combined forecast, which is based on all potential models, but gives forecasts from sub-optimal models lower weights (Hansen, 2007, 2008).

We use two sets of variables as potential leading indicators. First a set of futures prices of each crop with contract length of 1 through 6 months ahead from the last observation in the sample. The market based leading indicators of future crop prices should reflect all information available among traders in each spot and futures market. The alternative set of leading indicators encompasses information provided by institutional forecasters, like the OECD-FAO and the World Bank. These institutions regularly make quantity and dollar price forecasts for the most important crops. The quantity indicators cover the production, the consumption, and the end of period stock for each crop in our sample. This allows for the computation of indicators signalling future scarcity in each market. The price forecasts in US-dollar will be converted into euro by using the current forecast of the dollar per euro exchange rate made by WIFO each quarter. For details of the data cf. Table 3 in the data section.

3.4 Autoregressive Integrated Moving Average models with exogenous variables (ARIMAX)

Finally, we add leading indicators directly into optimised ARIMA models. This approach is very similar to the ARIMA modelling procedure and selects in a first step the optimal lag structure of the explanatory variables by the magnitude of the cross-correlation coefficients between the target variable and the leading indicators. In a second step, we search for the optimal ARIMAX model according to the Bayesian Information Criterion. As leading indicators, we use a combined set of futures prices and the variables provided by international organisations. These variables encompass expected agricultural prices and quantities. Additionally, we add the FAO agricultural stress indicators into the models, which also have a leading characteristic: When sowing starts in Austria, the first season in the southern hemisphere is close to its end. Given the leading indicators, the model with the lowest BIC is chosen. In a second step we re-estimate the optimised model and drop autoregressive, moving average terms, and leading indicators according to t-tests.

4. The forecasting cycle

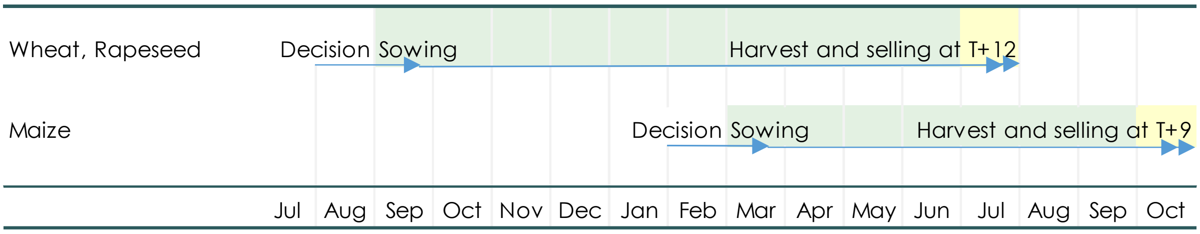
The forecasting cycle is determined by the growing season of each crop in Austria. For example, wheat and rapeseed are planted in late fall, which implies that farmers have to decide on the crop they will sow by August. Both crops will grow over the following winter and spring throughout June and July of the next year, when farmers will harvest and sell their crop at the prevailing price. A price forecast for wheat and rapeseed for July of the next year can add valuable information to the information set of farmers if it is available in August, when the sowing decision is due. This gives rise to a forecast horizon of 12 months based on information available at the end of July. The forecast should be published by mid-August and reach out to the price in July of the next year, cf. Figure 5.

For maize the growing season deviates strongly from this pattern due to a shorter growing period. The decision to plant maize will be made in February and the harvesting season for maize starts in September of the same year, thus farmers will be interested in the expected price of maize in October, giving rise to a forecast horizon of 9 months based on information available at the end of January. The price forecast should be published by mid-February and reaching out to October of the current year.

This peculiar forecast cycle reduces the number of useful forecasts in a comparison of real-time ex-ante forecasting precision of individual models to one forecast per year, i. e. a late summer round for wheat and rapeseed and a winter round for maize. Given the need for a training sample and the missing data from Commodity Market Outlooks published between 2014 and 2017, this precludes a model selection based on statistical tests, rather we will present the results from forecasts starting in late summer 2018 for the price of wheat and rapeseed in July 2019, leaving a training sample of monthly data from January 2000 through July 2018.

The availability of institutional forecasts is also restricted by the forecasting cycle. For example, the forecast in August 2018 can use real time price forecasts for wheat and rapeseed published by the World Bank in April 2018; these forecasts would have covered the period 2019 through 2025. Every forecasting round after mid-summer 2018 will use a correspondingly younger World Bank outlook, e. g. the maize price forecast in February 2019 will use the October 2018 World Bank outlook. A similar schedule holds for the quantity forecasts by OECD-FAO which are published every year in July. Consequently, the production, consumption, and end of year stock forecasts for crops from July can be used for the following two forecasting rounds in August and February.

Figure 5 - Timeline of the growing cycle for wheat, rapeseed and maize in the northern hemisphere



Note: The southern hemisphere's growing season is shifted by 6 months.

5. Results

The optimisation algorithm selects for each crop a separate forecasting model and produces a dynamic forecast starting in T up to the end of the forecasting horizon h. We compare the model forecasts to a naïve no-change forecast, i. e. we use the last observation from period T as the forecast for T+h. Alternatively, we use the price of 9- or 12-months ahead futures as a forecast based on current expectations of participants in crop market trading. For the ARIMA, the MMA, and the ARIMAX models Table 4 provides a simple overview on the final model structures in terms of the number of autoregressive lags (p), the differencing (d), the moving average lags (q), and the seasonal equivalents to these terms (P, D, Q). For the models also using leading indicators Table 4 also shows the number of leading indicators. The leading indicators are either prices from financial markets or variables published by international institutions.

A short list of the explanatory variables for each crop conveys the usefulness of additional information in the forecasting procedure. The final models using leading indicators for milling wheat include the price of a 6-month ahead future, the production-to-consumption ratio, and the expected commodity price by the World Bank. The final models for quality wheat use these variables and additionally include the wheat stress indicator. The models for the price of rapeseed include the prices of 3- and 6-months ahead futures, the rapeseed stress indicator, and the expected commodity price from the World Bank. One model also uses the SPC for rapeseed. The final models for the price for maize depend on the price of 6-months ahead futures, the commodity price outlook by the World Bank, and the SPC for maize. Typically, the final models of the MMA method are very parsimonious at the 9- and the 12-months horizon, using mostly 1 lag of the target variable and one explanatory variable. The ARIMAX models on the other side use between two and four leading indicators.

The ex-ante forecasting cycle starts in August 2018 with a forecast for the prices of milling wheat, quality wheat, and rapeseed in July 2019. The next round is in February 2019 with a forecast for the price for maize in October 2019. The last forecasting round starts in February 2022 and predicts the price of maize in October 2022. For all these forecast horizons we use only information available in the month before the publication of the forecast and compare the predicted with the realised value. The difference between both values is the forecast error for each individual model. Our forecasting cycle allows the computation of four forecast errors for each crop and each model, which clearly falls short of providing enough observations to apply serious forecasting tests. Instead, we provide a graphical analysis of forecasts, and present a model ranking according to the root mean squared forecasting errors (RMSE).

The years 2021 and 2022 have been particularly hard for forecasters because agricultural prices started to increase during spring 2021 and got a strong boost with the start of the attack by Russia on Ukraine. Figure 6 to Figure 9 show the results of the last two forecasting rounds in terms of the dynamic forecasting paths and their final value. The forecasts are compared to the realised prices until May 2023, because the values for July and October 2023 are not yet available. The model forecasts tend to miss the upswing in crop prices in 2021, the only exception being the price of rapeseed, for which many models expect a higher price 12-months ahead as compared to the last observation from July 2021, cf. Table 5. On the other hand, most models expect prices to decline from July 2022 onwards, but the extent will be probably underestimated. The tentative impression from the graphical analysis can be corroborated by computing real time forecasting errors. The difference between realised values and the model forecasts are the 9- and 12-step ahead forecast errors, which can be squared and added to achieve a RMSE. This indicator is smaller if a model produces more accurate forecasts, and it punishes large forecast errors more strongly. We compare the sum of squared forecast errors for each model with two popular naïve forecasts: the last observed price and the price of a 9- or 12-month ahead future in period T. Table 6 presents the RMSE for each crop and each model and the rank achieved by each model for individual crops. The last column of Table 6 shows the sum of ranks over the four crops.

Surprisingly, the forecasts provided by the prices of 9- or 12-months ahead futures produce some of the highest RMSE. The ARIMA-model using levels and the ETS-model show a comparable forecasting performance. On the other hand, the models selected by the MMA method, either based on capital market prices or based on institutional forecasts, are ranked among the top performing models; just the ARIMA-model using annual growth models comes close to this ranking. Relative to the standard deviation of the price for milling wheat, the lower ranked models have a RMSE which is around 2.2-times the standard deviation, while the MMA-based Models show a RMSE 1.7-times the standard deviation. For quality wheat the RMSE of the lower ranked models is 2.6-times the standard deviation, while the MMA-based models have the same precision as for milling wheat. In general, the forecast precision for soybeans is lower: lower ranked models produce a RMSE being 4.4-times the standard deviation, while the MMA-based models show a RMSE of 2.5-times the standard deviation. The forecasting models for maize produce the highest precision and the difference between lowest ranked (0.8-times) and MMA-based models (0.6-times) is small.

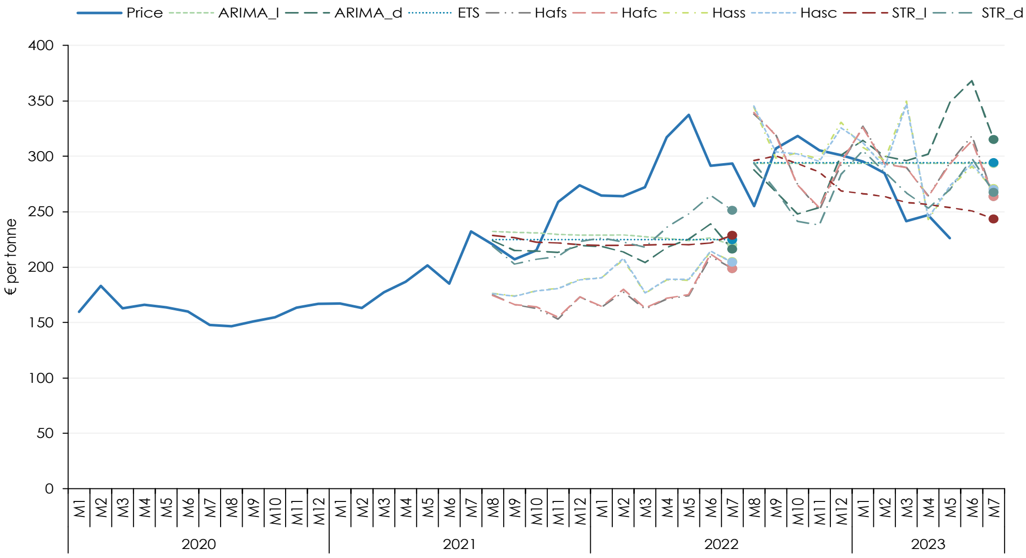
A view on the model ranking for individual crops supports the hypothesis derived from figures Figure 6 through Figure 9: we cannot identify a single optimal forecast model for crop prices. Therefore, we compute a combined forecast as the mean of all forecasts, except the two worst performing models: the ARIMA-model using levels and the ETS-model. This combined forecast stands out as the most accurate model for quality wheat and rapeseed, it ranks third for wheat and sixth for maize. The good performance of the combined forecast results from the different capabilities of each model to process specific aspects of the recent dynamics of the target variable or the predictive power of leading indicators. For example, using the combined forecast for rapeseed brings a reduction in the root mean squared forecast error (against the naïve forecast and the 12-month futures price) by roughly 50 percent, for quality wheat the reduction is 30%, and for wheat it is 24%. With respect to maize, the reduction in the RMSE in comparison to 9-months futures prices is 25%. Only with respect to the no change forecast for maize a combined model forecast shows no advantage.

Table 4 - Number of explanatory variables, autoregressive and moving average lags in optimised model

	p	d	q	P	D	Q	Explanatory Variables.
				Milling wheat			
ARIMA, level	0	1	0	0	0	0	-
ARIMA, annual growth rate	1	0	0	0	0	0	-
MMA based on futures	1	1	-	-	-	-	1
MMA based on inst. forecasts	1	1	-	-	-	-	1
ARIMAX, level	4	0	0	0	0	0	2
ARIMAX, annual growth rate	3	0	0	0	0	0	3
				Quality wheat			
ARIMA, level	0	1	0	0	0	1(12)	V
ARIMA, annual growth rate	1	0	0	0	0	0	-
MMA based on futures	2	1	-	-	-	-	1
MMA based on inst. forecasts	1	1	-	-	-	-	1
ARIMAX, level	3	0	0	0	0	0	4
ARIMAX, annual growth rate	3	0	2	0	0	0	2
				Rapeseed			
ARIMA, level	1	1	0	0	0	2(12)	-
ARIMA, annual growth rate	2	0	0	0	0	0	-
MMA based on futures	1	1	-	-	-	-	1
MMA based on inst. forecasts	1	1	-	-	-	-	1
ARIMAX, level	3	0	4	0	0	0	2
ARIMAX, annual growth rate	3	0	1	0	0	0	2
				Maize			
ARIMA, level	3	1	0	0	0	1(12)	-
ARIMA, annual growth rate	3	0	0	0	0	0	-
MMA based on futures	2	1	-	-	-	-	1
MMA based on inst. forecasts	2	1	-	-	-	-	1
ARIMAX, level	1	0	2	0	0	0	3
ARIMAX, annual growth rate	3	0	0	0	0	0	2

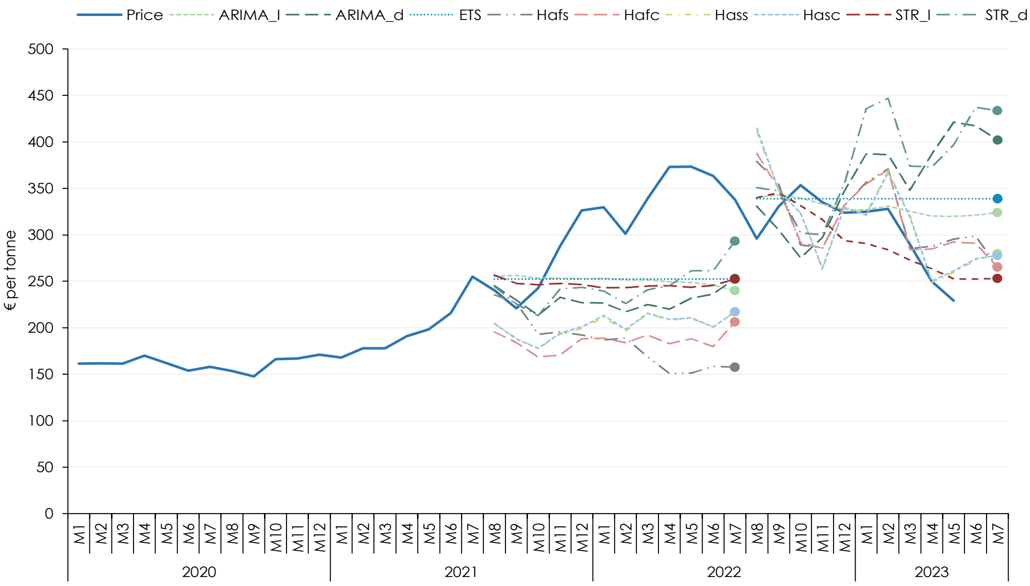
Source: Own calculations. – See Section 2 for a description of individual models. p: number of autoregressive lags, d: number of differences, q: number of moving average lags. P, D and Q represent the seasonal equivalents of the terms p, d and q.

Figure 6 - Comparison of price forecasts for milling wheat for July 2022 and 2023 from various models



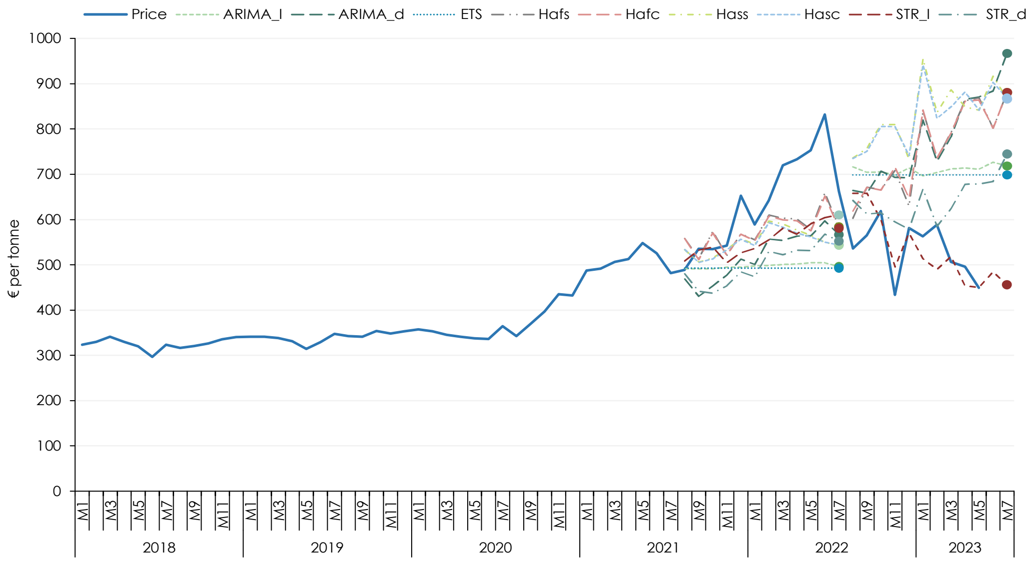
Source: Statistics Austria, Macrobond, own calculations. – Dots indicate the value at the final month of the forecast rounds in 2021 and 2022. ARIMA: Autoregressive Integrated Moving Average Model, ETS: Exponential Smoothing Modell, MMAs: Mallow Model Average selected using futures, MMAc Mallow Model Average combined using futures, STR: ARIMAX using institutional forecasts. The extension _l indicates a models based on levels and the extension _d indicates a model based on annual differences.

Figure 7 - Comparison of price forecasts for quality wheat for July 2022 and 2023 from various models



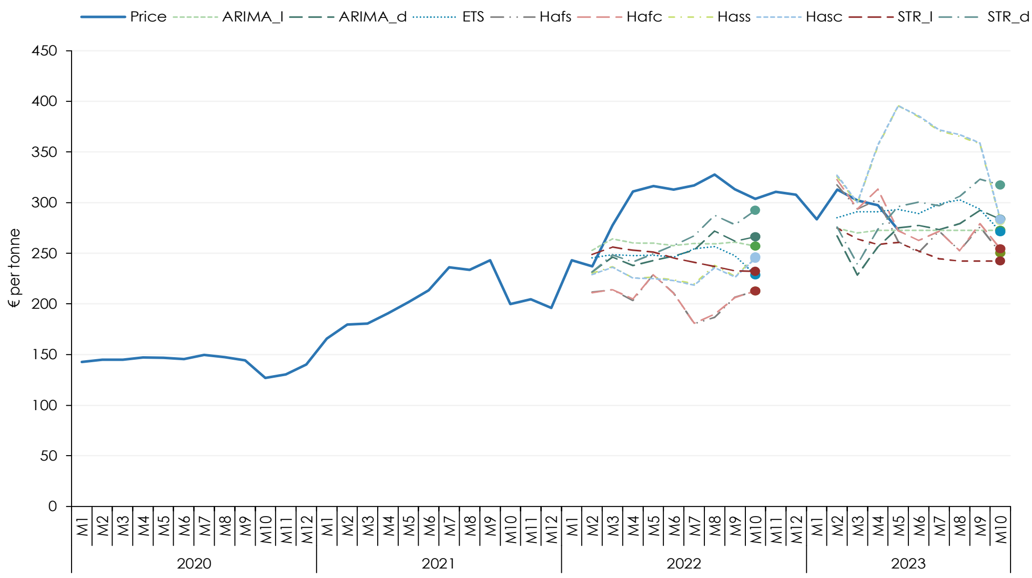
Source: Statistics Austria, Macrobond, own calculations. – Dots indicate the value at the final month of the forecast rounds in 2021 and 2022. ARIMA: Autoregressive Integrated Moving Average Model, ETS: Exponential Smoothing Modell, MMAs: Mallow Model Average selected using futures, MMAc Mallow Model Average combined using futures, STR: ARIMAX using institutional forecasts. The extension _l indicates a models based on levels and the extension _d indicates a model based on annual differences.

Figure 8 - Comparison of price forecasts for rapeseed for July 2022 and 2023 from various models



Source: Statistics Austria, Macrobond, own calculations. – Dots indicate the value at the final month of the forecast rounds in 2021 and 2022. ARIMA: Autoregressive Integrated Moving Average Model, ETS: Exponential Smoothing Modell, MMAs: Mallow Model Average selected using futures, MMAc Mallow Model Average combined using futures, STR: ARIMAX using institutional forecasts. The extension _l indicates a models based on levels and the extension _d indicates a model based on annual differences.

Figure 9 - Comparison of price forecasts for grain maize for October 2022 and 2023 from various models



Source: Statistics Austria, Macrobond, own calculations. – Dots indicate the value at the final month for the forecast rounds in 2021 and 2022. ARIMA: Autoregressive Integrated Moving Average Model, ETS: Exponential Smoothing Modell, MMAs: Mallow Model Average selected using futures, MMAc Mallow Model Average combined using futures, STR: ARIMAX using institutional forecasts. The extension _l indicates a models based on levels and the extension _d indicates a model based on annual differences.

Table 5 - Comparison of last available price for each crop, realised price at the end of the forecast horizon, and the combined forecast

Forecasting round August 2021	€ per tonne				change to … in €	
	mean	last obs.	realised	combined forecast	realised	combined forecast
Milling wheat	149.9	232.1	293.5	214.7	61.4	– 17.4
Quality wheat	163.7	255.0	338.1	228.2	83.1	– 26.8
Rapeseed	310.4	481.7	663.0	568.8	181.3	87.1
Maize	150.9	243.1	303.8	243.9	60.7	0.9

Forecasting round August 2022	€ per tonne				change to … in €	
	mean	last obs.	realised[1])	combined forecast	realised[1])	combined forecast
Milling wheat	271.4	293.5	226.3	270.6	– 67.3	– 22.9
Quality wheat	286.4	338.1	229.0	311.0	– 109.0	– 27.0
Rapeseed	766.9	663.0	449.2	809.0	– 213.7	146.0
Maize	265.2	283.6	272.9	273.4	– 10.7	– 10.2

Source: Statistics Austria, World Bank, Macrobond, own calculations. – Mean from January 1999 through May 2023. Last observation corresponds to July of the previous year for wheat, quality wheat, and rapeseed; it corresponds to January of the current year for maize. - [1]) Preliminary value based on most recent realisation in May 2023.

Table 6 - Forecasting quality of models for four forecasting rounds starting in August 2018 through February 2022

Model	Root mean squared forecasting error in €				Rank				
	Milling wheat	Quality wheat	Rapeseed	Maize	Milling wheat	Quality wheat	Rapeseed	Maize	Total
ARIMA, level	101.1	108.9	117.6	64.2	12	12	10	8	42
ARIMA, annual growth rate	121.0	152.7	221.9	87.0	7	7	3	2	19
Combined Forecast	83.4	93.3	111.1	77.8	3	1	1	6	11
Exponential Smoothing, level	112.2	140.2	222.7	95.5	10	10	11	9	40
Futures, 12 months ahead	116.5	140.3	242.0	103.4	11	11	12	11	45
Mallow model avg., comb., futures	82.4	97.9	137.1	77.3	2	5	7	5	19
Mallow model avg., comb., institutions	92.4	95.2	121.7	64.5	4	3	5	3	15
Mallow model avg., sel., futures	82.0	97.2	138.4	77.1	1	4	8	4	17
Mallow model avg., sel., institutions	92.7	95.1	121.6	63.6	5	2	4	1	12
Naive no change	104.6	127.9	218.0	78.3	8	8	9	7	32
ARIMAX, level	99.9	106.8	115.8	140.8	6	6	2	12	26
ARIMAX, annaul growth rate	106.8	131.2	122.8	101.4	9	9	6	10	34

Source: Statistics Austria, World Bank, Macrobond, own calculations. – Compare Section 2 for a description of the models and Figure 5 for the forecasting cycles of each crop.

6. Conclusions

Accurate and timely forecasts for crop prices provide valuable information for farmers and facilitate the decision on which crop to plant in the next growing season. Because the growing season varies across crops, farmers will reduce their opportunity set by both a definitive decision on sowing a crop as well as a decision to postpone sowing due to unsatisfactory price expectations. On the one hand, the decision to sow prevents the use of the cropland for alternative crops. On the other hand, postponing the decision on sowing excludes crops with longer growing period from use during this season. From a risk management perspective, the decision for sowing a crop will always include aspects of diversification. Furthermore, positive price signals will induce other farmers to adjust their sowing decision in the same direction. Due to the length of the growing period this will have a negative feedback effect on prices. A well-known example for this feedback loop is the pig cycle. Therefore, farmers are likely to respond to positive price forecasts by marginally increasing the share of cropland devoted to crops with high price expectations.

Farmers can use several sources to build their own expectations on future prices. For example, they may rely on the last observed price in their home market or the perception on excess supply or demand observed for a certain crop. Alternatively, for homogenous crops traded on liquid markets they may use prices of futures with adequate delivery dates. Euronext-MATIF is an example in Europe. They may also respond to news about poor or plenty harvests in other countries, e. g. in the southern hemisphere. The United States Agriculture Department makes crop price forecasts for the US-market. Three international organisations provide public forecasts on the expected quantities (produced, consumed, and internationally traded) for a broad set of crops (OECD-FAO Agriculture Outlook) or for their prices (World Bank Commodity Market Outlook).

In this paper, we apply three classes of time series models to producer prices of four popular crops in Austria: milling wheat, quality wheat, rapeseed, and maize. We concentrate on a forecasting cycle which mirrors the times of decision making in sowing and harvesting. For wheat and rapeseed, we use information available up to the end of July to make a price forecast which can be published by mid-August and refers to the crop price in July of the next year. For maize, we use the information available up to the end of January to make a price forecast which can be published by mid-February and refers to the price of maize in October of the same year. The relevant target month for the price forecast of each crop corresponds to the harvest season, when crops will be sold by farmers.

The time series models encompass Autoregressive Integrated Moving Average (ARIMA) and Exponential smoothing (ETS) models, the Mallows Model Averaging method, and ARIMAX models using futures prices, agricultural stress indicators, and price and quantity forecasts by international institutions. Due to limited data, we are restricted to make ex-ante crop price forecasts through four forecast cycles starting in August 2018 for wheat and rapeseed and ending in October 2022 for maize. The resulting small number of forecasting errors excludes a statistically robust model selection test, but our results provide reliable evidence that forecasts based on models selected by Mallows Model Averaging method provide on average smaller forecast errors than naïve forecasts using the last observation or the price of a 12-months ahead future available at the publication date of the forecast. Moreover, the combination of forecasts based on the mean of individual model forecasts appears to generate an even higher precision throughout a period with extraordinary high price volatility.

At the beginning of the most recent forecast cycle in August 2022 and February 2023, respectively, crop prices have been in the upper range of historical values. Consequently, the combined forecasts point towards a reduction for milling wheat from 294 towards 271 € per tonne. The price of quality wheat is expected to decline by 27 € towards 311 € per tonne, and the price of maize will fall from 284 to 273 € per tonne. Only the combined forecast for rapeseed of 809 € per tonne in August 2023 indicates further price pressure against the 663 € per tonne observed in July 2022. Given available realisations up to May 2023 the reduction in prices will be stronger than expected, and the forecasted further surge in prices for rapeseed is unlikely to be realised. The decline in crop prices will reduce inflationary pressure throughout 2023.

A promising extension for future research includes the use of multivariate models for forecasting crop prices. Ahumada & Cornejo (2016) mention the high correlation among crop prices and see some potential for error correction models and vector autoregressive models in first differences.

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Appendix

Table A1 - Descriptive statistics of crop prices 1960 through 2023 by decades

Decade		Wheat	Soybean	Maize
			€ per tonne	
1960-1969	Mean	117.8	209.0	97.9
	Std. Deviation	8.3	18.5	9.5
	Min	98.6	166.3	71.8
	Max	134.0	265.0	118.3
	Span	35.4	98.8	46.5
1970-1979	Mean	156.3	298.6	126.6
	Std. Deviation	51.1	79.5	27.9
	Min	98.6	202.2	86.9
	Max	320.8	716.3	203.6
	Span	222.2	514.1	116.6
1980-1989	Mean	172.0	299.9	132.0
	Std. Deviation	41.3	71.7	42.8
	Min	98.8	184.9	61.8
	Max	247.6	476.8	208.4
	Span	148.8	291.9	146.7
1990-1999	Mean	123.5	211.5	93.9
	Std. Deviation	21.4	27.1	16.8
	Min	85.6	167.0	71.8
	Max	205.5	295.8	160.0
	Span	119.9	128.8	88.1
2000-2009	Mean	152.0	252.3	105.0
	Std. Deviation	36.3	50.5	21.8
	Min	104.4	197.4	71.3
	Max	288.2	408.2	184.6
	Span	183.8	210.8	113.3
2010-2019	Mean	193.6	369.9	164.8
	Std. Deviation	38.0	47.9	37.1
	Min	129.2	300.3	117.0
	Max	281.8	551.6	271.1
	Span	152.6	251.4	154.1
2019-2023	Mean	299.8	506.5	228.0
	Std. Deviation	90.7	118.7	66.4
	Min	176.3	325.1	126.3
	Max	493.7	697.6	349.6
	Span	317.4	372.5	223.4

S: OECD, Worldbank (Pinksheet). Monthly average prices converted into Euro-ATS per tonne.