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Forecasting Wheat Commodity Prices using a Global Vector Autoregressive Model

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Summary

In this paper the performance of a Global Vector Autoregression model in forecasting export wheat prices is evaluated in comparison to different benchmark models. Forecast evaluation results are based on different statistics including RMSE, MAPE, the Diebold-Mariano (DM) tests and turning points forecast accuracy. The results show that the GVAR forecasts tend to outperform forecasts based on the benchmark models, emphasizing the interdependencies in the global wheat market.

Keywords: forecasting, global dynamic models, price analysis, wheat market.
JEL Classification codes: G14, Q14, C12, C15

Introduction

An accurate prediction of agricultural commodity price movements can be invaluable for crop producers, agribusiness industries and also for government agencies and food aid programs because price fluctuations have an important impact on poverty and food insecurity across the world. This is especially true for wheat. Wheat is the most important protein source and provide around 20% of global calories for human consumption. More than 215 million hectares are planted annually and with around 130 million tonnes, annual global wheat trade is higher than that of maize and rice combined. Thus, it is not surprising that a large space has been attributed to the study of wheat price forecasts in order to get fair decisions.

Forecasting wheat prices has a long-lasting tradition and a large number of studies have proposed worldwide models for the analysis of this topic. In his seminal work, Bosland (1926) introducing the problem of wheat forecasting stresses: "Forecasting of prices involves knowledge of the forces or factors that cause prices to change and. a study of wheat prices must be a study that is worldwide in its scope."[1] Working (1927), in the conclusions to his speech at the 70th of the American Farm Association, argues: "Practical forecasting of prices of wheat requires consideration of a great variety of influences bearing on price. Among the most important of these are the fundamental demand and supply (*domestic and worldwide*[2]) conditions."[3] The previous considerations explain why many efforts have been directed to the implementation of large scale multi-country agro-economic models with the intent to provide baseline forecasts for wheat, as for other commodities, prices and yields.[4]

In this paper we follow a worldwide approach but, differently from the previous literature, try to exploit the relevance of recent time series analysis, specifically the Global Vector AutoRegressive (GVAR) model proposed by Pesaran, Schuermann and Weiner (2004) and Dées et al. (2007), to predict wheat commodity prices of the six main exporting countries: the United States, Argentina, Australia, Canada, Russia (including Ukraine and Kazakhstan), and the EU.

We analyze the forecasting performance of the GLObal Wheat Market Model (GLOWMM) presented in Gutierrez et al. (2014), for studying wheat price movements. The model allows for the dependence of each country's commodity price on all other countries' commodity prices and on fundamental real and financial drivers, such as supply and demand factors, exchange rates, and oil prices.

There are reasons why the GVAR model may be useful for analyzing and predicting worldwide wheat prices. First, the model is specifically designed to analyze market fluctuations and interactions between countries. Secondly, the GVAR lets us model the dynamism in wheat export prices caused by the effects of country-specific and foreign-specific variables. Thirdly, the GVAR model has proven to be especially useful for describing the dynamic behaviour of economic and financial time series, di Mauro and Pesaran (2013).

[1] Bosland (1926) pg. 149.
[2] In italics, our note based on Working's (1927) discussion.
[3] Working (1927) pg. 287.
[4] Focusing only on the set of stochastic model, we can cite the AGLINK-COSIMO (OECD-FAO) model, the FAPRI (FAPRI-UMC) model and the ESIM (Hohenheim University-IPTS) model.

Fourth, the model is mainly based on Vector Autoregression methodology which has usually been known as a natural tool for forecasting, e.g. Lütkepohl (2005).

The article is organized as follows. In Section 2 we provide a brief, not exhaustive survey, on the topic of forecasting agricultural prices. The survey is useful in introducing the motivation and describing the GVAR econometric model in Section 3. In Section 4 we present the forecasting performances of the GVAR model and compare them with the forecasts obtained by using other univariate and multivariate models. Finally, Section 5 concludes.

1. A brief survey on forecasting agricultural prices

Forecast of agricultural production and prices are largely used by farmers, agribusiness industries and governments due to the high risks and uncertainty in the agricultural sector connected to uncertain production and a low price elasticities of demand. In this condition, price forecasts are critical to decision makers and market participant within the supply chain. Further, policy makers involved in defining commodity programs and specific interventions, need information about future outcome and prices (Allen, 1994). Considering the importance of agricultural prices and the need in reliable forecasts, it should be not surprising that commodity price forecasting is a topic of great interest for economists and statisticians. Economic forecasting in agricultural sector has some features in common with business forecasting and macroeconomic forecasting but, over time, it has developed a own literature strand.

Moore (1917), recognized as the founder of statistical economics, presents the first econometric forecast of an agricultural commodity. Using regressions of cotton yield on rainfall and temperature in selected months, the author was able to provide better forecasts compared with those obtained by USDA forecasts which were only based on crop reports. After Moore's (1917) contribution, statisticians and agricultural economists estimated several single equation forecasting (between the others Sarle (1925), Ezekiel (1927) for the hog price; Hopkins (1927) for the cattle prices).

Bosland (1926) highlights the need to include as much as forces or factors that may affect commodity prices. He underlines how any attempt to forecast price must be based on the knowledge of factors affecting supply and demand. Working (1927) reinforced Bosland's (1926) argument underlying that forecasting of wheat price needs knowledge of a large number of factors affecting prices mostly related to fundamental demand and supply conditions.

In line with this effort, dynamic supply response approach became the main application of time related single equation work as in Cox and Luby (1956) for the hog price and the more sophisticated model used by Nerlove (1961). In the meanwhile, thanks to the greater computing power, larger multi-equation analysis was developed allowing for the use of multiequations model, see Allen (1994). Sectoral models are basically multiequation models since they contain at least a supply equation and a demand equation for a single commodity. In addition, if the commodity considered is a storable one, they include an inventory demand

equation.[5] Moreover, in presence of trade between countries or regions import supply and export demand equations should be added. There are now a large number of sectoral model in agricultural economics literature, most of them produced in the late 70s. [6]

Spatial equilibrium and interregional competition models have been also proposed to forecast agricultural prices. They had a surge of popularity in the mid 1970s thanks to the work of MacAulay (1978) who proposed a forecasting model for the Canadian and US pork sectors, and Martin and Zwart (1975) who introduced a spatial and temporal model of the North American pork sector for the evaluation of policy alternatives. These models try to solve some of the critical aspects of the sectoral model. Penson and Hughes (1979) and Freebairn, Rausser and de Gorter (1982) distinguish three classes of models within this group. The first class model, or first generation model, considers agriculture as a separate entity such as in Egbert (1969) with a dynamic long run model of the livestock-feed sector, Quance and Tweeten (1972) and Yeh (1976). This class of models are small, strongly aggregated, stand alone models. They use estimates of elasticities and rates of growth and inflation from other studies. They are used with the mainly aim to achieve agricultural output and price projection under different policy proposals. For this reason, forecasting is not the main issue. Within this first class of models it should be considered a second group characterized by large scale multisector models. They may also thought as a larger version of the sector models (see also Maki, 1963 for a livestock supplies and prices forecasting; Crom and Maki, 1965 with a semi annual model of the beef-pork sectors). A mention should be done for Cromarty's model (1959) generally considered the first large scale econometric model of agriculture using an annual 12 products agricultural sector model linked to Klein-Goldberger macro-model with non feedbacks. In second class models, or second generation models, the macromodel is used to forecast a set of variables that are exogenous to the agricultural sector such as average income, interest rates, and the consumer price index. Then, these forecasted variables are used to solve the agricultural system. Examples for second generation models are Chen (1977) and Roop and Zeitner (1977) between others. Penson and Hughes (1979) describe the last class of aggregate and large scale models called also third generation models. The main feature of this class is that the models have direct or indirect accounting of capital accumulation and financing. Example includes Freebairn, Rausser and de Gorten (1982). They describes a quarterly third generation model with 87 equations covering three crop and six livestock groups simply having better linkages between the domestic macroeconomy and the international economy or the agricultural sector.

Agricultural applications of modern time series methods did not appear until the early 1970s. Jarrett (1965) forecasted Australian wool prices using an exponential smoothing method. This work is commonly considered the first application of modern time series methods to agriculture. Moreover, at the begin of 1970, Schmitz and Watts (1970) illustrated the Box-Jenkins and exponential smoothing methods in forecasting

[5] Many "storage models" have been proposed after the works of Gustafson (1958a, 1959b) Wright and Williams (1982), Deaton and Laroque (1992) and more recently Cafiero et al. (2014).

[6] A well known sectoral model for U.S. farm prices for corn and wheat, largely used by USDA, is that proposed by Westcott and Hoffman (1999).

wheat yield marking the era of time series analysis. Bourke (1979) analysed the beef forecasting price by applying Box-Jenkins methodology for the period 1966 to 1975. In the 1980s, multivariate time series analysis appeared. Shonkwiler and Spreen (1982) used a transfer function estimation of hog slaughter to analyse the relation between the number of hogs slaughtered in the US and the hog-corn price ratio.

Finally, at about the same time, more sophisticated efforts were made in order to develop different forms of composite forecasts from vector autoregression (VAR) model. Bessler (1984) introduced VAR to the agricultural economics profession with an application to the US hog market. After that a series of articles introduced various parameter reduction methods. Examples include Brandt and Bessler (1984) that illustrated an empirical study using US hog prices with first differenced data; Bessler and Hopkins (1986) and Bessler and Kling (1986).

A survey of forecasting commmodity prices cannot exclude some comments on the forecast models based on information provided by future market prices. There is a large strand of literature concerning this topic. Just and Rausser (1981) present a complete survey on future price used in forecasting. The authors report that a part of the literature on futures markets challenges the quality of futures prices as forecasts. Examples are Working (1942), Tomek and Grey (1970), Labys and Granger (1970). On the opposite side, much of the conceptual work on futures markets views futures prices as rationally based expectations such as, between others, Danthine (1978), Peck (1976), Feder et al.(1977), Holthausen (1979), Turnovsky (1978), Anderson and Danthine (1978). Peck (1976) and Gardner (1976), cited by Just and Rausser (1981), suggest that future prices play an important role in the formation of producer price expectations.

2. Forecasting wheat prices with a GVAR model

In following we will present a Global Vector Autoregression model (GVAR) which can be included in the modern time series approaches but, differently from the previous one proposed in literature, it allows for the dependence of each country's commodity price on all other countries' commodity prices and on fundamental real and financial drivers, such as supply and demand factors, exchange rates, and oil prices.

There are reasons why the GVAR model may be useful for analyzing and predicting worldwide wheat prices. First, the model is specifically designed to analyze market fluctuations and interactions between countries. Secondly, the GVAR lets us model the dynamism in wheat export prices caused by the effects of country-specific and foreign-specific variables. Thirdly, the GVAR model has proven to be especially useful for describing the dynamic behaviour of economic and financial time series, di Mauro and Pesaran (2013). Fourth, the model is mainly based on Vector Autoregression methodology which has been seen as a natural tool for forecasting, see Lütkepohl (2005).

Here we will provide a briefly introduction to the Global Vector Autoregressive Model (GVAR). *The interested reader can consult* Dées et al. (2007) seminal paper, di Mauro and Pesaran (2013) recent book on GVAR modelling and Gutierrez et al. (2014) for a more complete review of this important research field.

The specification of the GVAR model proceeds in two stages. The first stage is the estimation stage of a Vector AutoRegressive model with exogenous, X, variables, labelled VARX(*p*,*q*), where p is the number of lags of the endogenous variables and q is the lag order of the exogenous variables. This model is estimated for each country or region *i*. In the second stage all individual country VARX models are stacked and linked using a weight matrix.

Specifically, in the first step, each country is modelled as a VARX(*p*,*q*),

$$\phi_i(L,p_i)y_{it} = a_{i0} + \Lambda_i(L,q_i)y_{it}^* + \Psi_i(L,q_i)d_t + \varepsilon_{it} \quad i = 1,...,N; t = 1...T, \tag{1}$$

where a_{i0} is a $(K_i \times 1)$ coefficient vector of the deterministic intercept; y_{it} is a $(K_i \times 1)$ vector of country specific (domestic) variables and corresponding $(k_i \times k_i)$ matrices of lagged coefficients, denoted by $\phi_i(L,p_i)y_{it} = I - \sum_{p=1}^{p_i}\phi_i L^i$, where L is the lag operator. The variable y_{it}^* is a $(k_i \times 1)$ vector of trade-weighted foreign variables and corresponding $(k_i \times k_i^*)$ matrix lag polynomial denoted by $\Lambda_i(L,q_i)$. $\Psi_i(L,q_i)$ is a matrix lag polynomial associated to the global exogenous variables d_t. The distinction between foreign variables y_{it} and the global exogenous variable d_t is relevant for the analysis of the dynamic properties of the global model but it is not important for the estimation of the country specific variables. For this reason, d_t and y_{it} will be combined and considered both as weakly exogenous variables, see Pesaran et al. (2004).

Finally ε_{it} is a $(k_i \times 1)$ vector of zero mean, idiosyncratic country-specific shocks, assumed to be serially uncorrelated with a time invariant covariance matrix Σ_{ii} i.e. $\varepsilon_{it} \sim iid(0,\Sigma_{ii})$.

The GVAR model assumes, for inference and estimation purpose, the weak exogeneity assumption of y_{it}^*, rules out long run feedbacks from y_{it} to y_{it}^*.

To show how the global model is constructed let's consider a generic country *i* in (1) with p_i and q_i equal to 2.

$$y_{it} = a_{i0} + \Phi_{i1}y_{it-1} + \Phi_{i2}y_{it-2} + \Lambda_{i0}y_{it}^* + \Lambda_{i1}y_{it-1}^* + \Lambda_{i2}y_{it-2}^* + \varepsilon_{it}. \tag{2}$$

According to Pesaran's notation (2004): Φ is a $k_i \times k_i$ matrix of lagged coefficients, $\Lambda_{i0,}\Lambda_{i1,}\Lambda_{i2}$ are $k_i \times k_i^*$ matrices of coefficients associated with the foreign specific variables constructed as weighted averages, with country/region specific weights, ε_{it} is a $(k_i \times 1)$ vector of zero mean, idiosyncratic country-specific shocks, assumed to be serially uncorrelated with $E(\varepsilon_{it}) = 0$ and a time invariant covariance matrix Σ_{ii}, i.e. $\varepsilon_{it} \sim iid(0,\Sigma_{ii})$.

Looking at (2) the GVAR allows for interactions among the different countries included in the model through three separate but interconnected channels. Firstly the contemporaneous dependence of the country specific variables on the foreign specific variables; secondly through the dependence of the country-specific variables on common global exogenous variable; and finally, "nonzero contemporaneous dependence of shocks in country *i* on the shocks in country *j*, measured via the cross-country covariances, Σ_{ij}."

To define the GVAR model from the VARX country specific model, the first thing to do is to construct the $(k_i + k_i^*) \times 1$ vector grouping both the domestic and foreign variables for each country:

$$z_{it} = \begin{pmatrix} y_{it} \\ y_{it}^* \end{pmatrix}, \tag{3}$$

Therefore each country VARX model (2) becomes

$$A_i z_{it} = a_{i0} + B_{i1} z_{it-1} + B_{i2} z_{it-2} + \varepsilon_{it}, \tag{4}$$

where

$$A_i = (I_{K_i}, -\Lambda_{i0}),\ B_{i1} = (\Phi_{i1}, \Lambda_{i1}),\ B_{i2} = (\Phi_{i2}, \Lambda_{i2}). \tag{5}$$

Note that A_i and B_i are both $k_i \times (k_i + k_i^*)$.

In the next step a vector of *global* variables is created. It means that the countries specific variables can be all written in terms of y_t

$$y_t = \begin{pmatrix} y_{0t} \\ y_{1t} \\ \vdots \\ y_{Nt} \end{pmatrix}, \tag{6}$$

and using the weight matrix W_i constructed for example from the export weights of each country permits to obtain the following identity

$$z_{it} = W_i y_t,\ \ \forall i = 0,1,...,N. \tag{7}$$

It should be clear that W_i represents a $(k_i + k_i^*) \times k$ matrix of fixed constants defined in terms of the country specific weights. Using Pesaran et al.'s words (2004:132), "W_i can be viewed as the link matrix that allows the country specific models to be written in terms of the global variable vector , y_t". This is the fundamental device through which each country model is linked to the global GVAR model. Using now the identity (7) and (4) we obtain

$$A_i W_i z_{it} = a_{i0} + B_{i1} W_i z_{it-1} + B_{i2} W_i z_{it-2} + \varepsilon_{it}, \tag{8}$$

where $A_i W_i$ and $B_i W_i$ are both $k_i \times k$-dimensional matrices.

Finally by stacking each country-specific model in (8), we end with the Global VAR for all endogenous variables in the system, y_{it},

$$Gy_{it} = a_{i0} + H_1 y_{it-1} + H_2 y_{it-2} + \varepsilon_t \tag{9}$$

where

$$G = \begin{pmatrix} A_0 W_0 \\ A_1 W_1 \\ \vdots \\ A_N W_N \end{pmatrix}, H_1 = \begin{pmatrix} B_{01} W_0 \\ B_{11} W_1 \\ \vdots \\ B_{N1} W_N \end{pmatrix}, H_2 = \begin{pmatrix} B_{02} W_0 \\ B_{12} W_1 \\ \vdots \\ B_{N1} W_N \end{pmatrix}, a_0 = \begin{pmatrix} a_{00} \\ a_{10} \\ \vdots \\ a_{N0} \end{pmatrix}, \varepsilon_t = \begin{pmatrix} \varepsilon_{0t} \\ \varepsilon_{1t} \\ \vdots \\ \varepsilon_{Nt} \end{pmatrix}.$$

The **G** matrix is a $k \times k$ -dimensional matrix, of full rank and, for these reasons, it is non singular. Hence, **G** can be inverted obtaining the Global VAR model in its reduced form

$$y_t = b_0 + F_1 y_{t-1} + F_2 y_{-2} + v_t \tag{10}$$

where

$F_1 = G^{-1} H_{1,}\ F_2 = G^{-1} H_{2,}\ b_0 = G^{-1} a_0,\ v_t = G^{-1} \varepsilon_t.$

The GVAR model (10) can be easily used to compute recursively point forecasts of the endogenous variables $\hat{y}_{t+h}$ *h*-steps ahead

$$\hat{y}_{t+h} = \hat{b}_0 + \hat{F}_1 \hat{y}_{t+h-1} + \hat{F}_2 \hat{y}_{t+h-2},\ h = 1, 2... \tag{11}$$

and initial values equal to the effective values $\hat{y}_t = y_t$ and $\hat{y}_{t-1} = y_{t-1}$.

Gutierrez et al. (2014) propose a GVAR model for the analysis of wheat export prices for the main six export regions: Argentina, Australia, Canada, EU, Russia and the United States. An additional Rest of World region is included in order to account for the effects exerted by all the other countries. For each region a VARX model is estimated including as variables the wheat export prices p_{it}^e quoted in U.S. dollars, the wheat stock-to-use ratio z_{it}, computed as the fraction of the stocks to total consumption, the nominal exchange rate e_{it} given by the bilateral exchange rate of the local currency in region *i* per unit of U.S. dollar. The fertilizer price p_{it}^f expressed in local currency and the index of consumer food prices p_{it}^c have been also included. This latter variable is introduced as a benchmark of food inflation in each region *i*. All the variables, with the exception of z_{it}, are log of indexes with base year July/2000-June/2001. Each country's system of variables can be also influenced by global variables such as the world price of oil, p_t^o, whose importance is common to all countries.

The foreign variables denoted in equation (2) y_t^* are constructed as a geometric average of the country-specific variables, using as weights the wheat export-country shares. The foreign variables are the average

competitors' prices $p_{it}^{e*} = \sum_{j \neq i} w_j p_{jt}^{e}$, the average stock-to-use ratio $z_{it}^{*} = \sum_{j \neq i} w_j z_{jt}$, the effective exchange rate, $e_{it}^{*} = \sum_{j \neq i} w_j e_{jt}$, and the average of the food prices $p_{it}^{c*} = \sum_{j \neq i} w_j p_{jt}^{c}$.[7] The choice of trade weights was based on the rationale that exogenous shocks, such as stock reduction or exchange rate devaluation, could be passed on the export prices in all countries through the trade channel. Fixed trade-weights given by the average of the years 2008-2010 were used in the GVAR model.

The rank of cointegration space for each region was analyzed for equation (1) and for Argentina, Australia, Canada and ROW countries two cointegration relationships were suggested by Johansen's cointegration tests, while for Russia, EU and USA one cointegration relationship was revelead. Given these results equation (1) was estimated for each region in its Vector Error Correction (VEC) form, and the estimates, after some reparametrization[8], were used to build the GVAR model and to compute wheat price forecasts.

3. The GVAR Forecast evaluation

Forecasts obtained[9] from the GLOWMM GVAR model have been compared with the forecasts obtained from four different benchmark models: two univariate model, i.e a pth autoregressive order, AR(p), model with drift and an AR(p) model with linear trend,

$$y_t = \alpha + \beta t + \sum_{i=1}^{p} \gamma_i y_{t-i} + \varepsilon_t, \tag{12}$$

where in case of an AR(p) with drift $\beta = 0$, and two multivariate models, specifically a Vector autoregressive VAR(*p*) model and a VECMX(*p*,*q*) model. The first two models have been included because is well know that univariate models are usually very hard to beat using multivariate models (Stock and Watson (2008) and Smith (2013) among others). The two multivariate VAR and VECM models have been proposed in order to appreciate the advantages of using a global (multicountry) GVAR model to forecast wheat prices with respect to single country VAR(*p*) and VECMX(*p*,*q*) models. The VAR model includes the set of variables $y_{it} \sim \left(p_{it}^{e}, z_{it}, e_{it}, p_{it}^{f}, p_{t}^{c}, p_{t}^{o} \right)$, and the VECMX model $y_{it} \sim \left(p_{it}^{e}, z_{it}, e_{it}, p_{it}^{f}, p_{it}^{c} \right)$ and as exogenous X variable $x_t \sim p_t^{o}$. Note that these models do not contain the foreign variables y_{it}^{*} and thus, by definition and differently from a GVAR model, they do not take into account the market fluctuations and interactions between countries.

[7] Each foreign variable is computed under the constraint that $\sum_{j \neq i} w_j = 1$.

[8] See Gutierrez et al. (2014) for a step by step analysis on how the GVAR model was derived by stacking the single region VECM equations.

[9] GLOWMM's econometric routines, including the forecast routines, have been written using GAUSS 11.0.

For all models, the estimation period covers July/2000 - January/2012 for a total of 139 months. This is the same sample used to estimate the GVAR model presented in Gutierrez et al. (2014). We evaluate the out-of-sample for the period February/2012 – June/2014 for a total of 29 months. For each model the out-of-sample month is forecasted by using a rolling window method and the maximum amount of data available. This means for example that for the one-step February/2012 out-of-sample prediction all the data July 2000 - January 2012 have been used. To predict March/2012 the start data of the estimation sample is moved forward by one month and thus the estimation period is given by September/ 2000-February/2012. Using a rolling window method instead of a recursive method where the starting date does not move forward, may allow to take into account for possible structural breaks.[10] Beside the one-month-ahead forecast we also compute forecasts, two, three, six, twelve, eighteen and finally twenty-four months ahead. This means that we end with 29 forecasts that can be evaluated at one-month-horizon and only 6 in case of the twenty-four-ahead forecasts. Because the VECMX and GVAR models contain an exogenous variable, the oil price, it must be predicted. To this end, we use an AR(p) with two lags and a drift to predict the oil price variable. Other models, which include additional lags or linear trend, do not alter the final results. Finally, forecast performance of each models, GVAR and benchmark models, have been synthesized by using the root mean-squared forecast error (RMSFE) and the mean absolute percentage error (MAPE) statistics.

Due to space constraints we will present only a selected set of results. In Table 1, Table 2, Table 3, Table 4 and Table 5 we show the MAPE statistics for one-month-ahead, three-months-ahead, six-months-ahead, twelve-months-ahead and finally twenty four-months-ahead.

Looking at the average values, the last rows of the Tables, it can be seen that the GVAR model generally works well with a MAPE lower than the other benchmark models. However, the two autoregressive models have a smaller MAPE for h=3,6,12. This last result is not new in literature (see among others Stock and Watson, 2008 and Smith, 2013). Univariate parsimonious models are usually difficult to beat and produce better forecasts than multivariate models.[11].

Secondly, comparing GVAR, VAR and VECMX statistics, can be highlighted the role played by the foreign country variables and also the relationships among countries. The GVAR MAPE statistics are always lower than the VAR or VECMX statistics. Since the latter models are estimated using a single country model hypothesis, i.e. none of the foreign variables have been included in the matrix of data, it emerges the important role carried out by the export relationships among countries. Note that the improvements in the GVAR MAPE statistics are not only at aggregated level but also , with only some exceptions, for single

[10] The recursive window method implies that the starting data of estimation does not change. We verify the forecasting properties of the recursive method and we find out that it provides poorer forecasting results than the rolling window method for all the model proposed.

[11] However from the other side, univariate models, differently from GVAR or VAR, and VECM models, do not permit structural analysis, such for example to analyse the impact of an increase of oil price or an exchange rate devaluation on wheat prices, see for this analysis Gutierrez et al. (2014).

country wheat forecasts. To compare the forecast performances of various models is useful to produce not only statistics but also statistical tests of possible equal forecasts among models.

To this end, we have carried out the Diebold-Mariano (1995) test for the significance of the differences in mean squared errors of competing forecasting models. Suppose we want compare two series made of *n* forecasts and let $\{e_{kit}(h)\}_{t=1}^{n}$ and $\{e_{kjt}(h)\}_{t=1}^{n}$ be the forecast errors respectively of model *i* and of model *j* for each country *k* and *h* horizon. We define $z_{kt}(h) = g\left[e_{kjt}(h)\right] - g\left[e_{kjt}(h)\right]$, where $g(\cdot)$ is an arbitrary function. The null hypothesis of the test will be that $E\left(z_{kt}(h)\right) = 0$, i.e. the difference in the forecasting performance of the two tests is statistically insignificant. Provided that $\{z_{kt}\}_{t=1}^{n}$ is covariance stationary, Dielbold and Mariano (1995) proved that, given the observed value $\overline{z}$, we have: $\sqrt{n}(\overline{z} - \mu) \xrightarrow{d} N(0, 2\pi f_z(0))$. Where μ is the population mean, and $f_z(0)$ is the spectral density of z_t at frequency zero.

Accordingly, Diebold and Mariano (1995) suggest to use the following test:

$$DM_k(h) = \frac{\overline{z}_k(h)}{\sqrt{\hat{V}(\overline{z}_k)}}, \tag{13}$$

which, under the null hypothesis and provided that $\hat{V}(\overline{z}_k)$ is a consistent estimate of the $\overline{z}_k$ variance $V(\overline{z}_k)$, is asymptotically distributed as $N(0,1)$. For one month ahead forecast no adjustments for serial correlation are needed, since we can assume that z_k are not correlated. However this hypothesis is not correct for $h > 1$. To take into account for serial correlation a Newey-West estimator of the variance $V(\overline{z}_k)$, as suggested in Diebold and Mariano (1995) has been used. We adopted as $g(\cdot)$ function the mean square error (MSE). To evaluate forecasting performance we also use the panel version of Diebold and Mariano test computed as

$$DM(h) = \frac{1}{\sqrt{K}} \sum_{k=1}^{K} DM_k(h), \tag{14}$$

where *K* is the total number of countries. The panel test has a standard normal limiting distribution.

In Table 6 and 7 we provide the DM statistics for *h*=1 and *h*=12 forecasts to test whether the differences between the GVAR and the four specifications are in fact statistically significant.

Looking at last row of Table 6, i.e. the panel test, it seems that, with the exception of the VECMX model, predicting with the GVAR model provides statistically significant (the test statistics are lower than the 5% critical values for a standard normal distribution), and better (the values of the test are all negative) forecasts than the other models. The null hypothesis is not rejected for the VECMX model. In Table 7 we provide same statistics but for *h*=12 months. The AR model seems to be superior while the null hypothesis of equal

predictions is not rejected for the ARt model. The GVAR model provides statistically better forecasts than the VAR and VECMX models. In fact, the test statistics are lower than the negative 5% critical value, -1.956, of the normal distribution.

Finally, we evaluate the GVAR and benchmarks forecasting models in terms of their ability to predict the occurrence or non-occurrence of turning points. Specifically, we observe the ability of the models in forecasting three types of turns: peak, troughs and no turns. We use the same procedure as in Brandt and Bessler (1981) and Kaylen (1986). The results presented in Table 8 reports the percent of correct direction of movements for each model using the one-step ahead, h=1, forecast. In synthesis, the GVAR seems to be superior to the other models in predicting peaks, troughs or no turns. On average it correctly predicts the direction of the movements 62% of times. Similar results are obtained for different values of h.

4. Conclusions

In this paper we assess the forecast performance of a Global Vector Autoregression (GVAR) model to predict wheat prices and we compare it with a set of benchmark models. There are reasons why the GVAR model may be useful for analyzing and predicting worldwide wheat prices. First, the model is specifically designed to analyze market fluctuations and interactions between countries. Secondly, the GVAR lets us model the dynamism in wheat export prices caused by the effects of country-specific and foreign-specific variables. Thirdly, the GVAR model has proven to be especially useful for describing the dynamic behaviour of economic and financial time series, di Mauro and Pesaran (2013). Fourth, the model is mainly based on Vector Autoregression methodology which has usually been known as a natural tool for forecasting, e.g. Lütkepohl (2005).

The results show that the GVAR model generally produces more precise forecasts than univariate autoregressive processes or vector autoregression models which only focus on domestic economies. Thus it seems that there is an advantage in modelling the interdipendencies among the main export countries in forecasting and predicting turning points of wheat prices.

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Tab.1 MAPE statistics for one-month-ahead, *h*=1, forecasts

COUNTRY	GVAR	AR	ARt	VAR	VECMX
Argentina	4.713	9.566	9.194	5.549	5.963
Australia	6.662	13.642	13.529	12.244	6.905
Canada	5.864	8.429	9.326	5.056	4.653
Russia	6.600	11.272	10.682	6.218	8.409
EU	6.190	9.981	9.249	9.985	8.611
USA	5.674	9.943	10.308	20.453	7.600
AVG	5.950	10.472	10.381	9.917	7.023
WAVG	6.151	10.537	10.411	10.264	7.418

Note: The mean-absolute-percentage error (MAPE) of a given model is computed as $100\sum_{t=T}^{T+n-1}\left|\left(A_{t+h}-\hat{F}_{t+h|t}\right)/A_{t+h}\right|$ where *h* is the forecast horizon, *n* is the size of forecast evaluation sample, A_{t+h} and $\hat{F}_{t+h|t}$ are respectively the actual value and is corresponding forecast formed at time *t* *h*-months ahead. AVG is the MAPE sample average of 6 countries, and WAVG is the MAPE weighted average, with weights given by the export quotes of the 6 countries. The AR model contains a drift constant and *p=2*, the ARt model contains a linear trend and *p=2*, the VAR model and VECMX model contain the same number of *p* and *q* (for the VECMX model) lags as in the GVAR model, see Table 3. in Gutierrez et al. (2014) for their values.

Tab.2 MAPE statistics for three-months-ahead, *h*=3, forecasts

COUNTRY	GVAR	AR	ARt	VAR	VECMX
Argentina	11.014	13.212	9.407	18.520	15.097
Australia	16.732	17.364	16.825	34.389	16.551
Canada	12.575	10.274	13.972	10.863	9.793
Russia	17.559	12.290	10.788	10.746	15.213
EU	14.673	13.230	11.092	31.081	24.491
USA	13.827	9.886	12.174	54.479	15.169
AVG	14.396	12.709	12.376	26.680	16.052
WAVG	15.141	12.288	12.257	26.319	16.154

Note: See Note Table 1.

Tab.3 MAPE statistics for six-months-ahead, *h*=6, forecasts

COUNTRY	GVAR	AR	ARt	VAR	VECMX
Argentina	17.769	17.686	10.909	20.216	19.611
Australia	25.635	19.520	19.989	49.038	28.775
Canada	15.776	9.064	22.568	13.363	13.205
Russia	24.892	14.832	12.523	16.688	18.340
EU	20.613	17.121	14.374	40.314	33.851
USA	19.588	15.592	15.388	67.853	21.933
AVG	20.712	15.636	15.959	34.579	22.619
WAVG	21.428	15.170	15.781	34.647	22.283

Note: See Note Table 1.

Tab.4 MAPE statistics for twelve-months-ahead, *h*=12, forecasts

COUNTRY	GVAR	AR	ARt	VAR	VECMX
Argentina	19.946	19.564	7.695	24.995	26.964
Australia	33.820	23.540	15.813	44.975	38.037
Canada	19.878	9.298	42.417	25.516	25.722
Russia	19.842	10.318	18.481	18.262	20.844
EU	16.925	12.555	19.411	53.470	49.377
USA	18.071	12.131	16.866	69.289	23.534
AVG	21.414	14.568	20.114	39.418	30.746
WAVG	20.606	12.867	21.232	39.353	29.446

Note: See Note Table 1.