Evaluating forecasts of Feed Barley Hamburg FOB Prices using Vector Autoregression*

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Abstract

We compare the accuracy of vector autoreggresive models in first differences in forecasting feed barley Hamburg fob prices when using a set of futures, such as MATIF wheat, MATIF corn and CME soy-meal as well as other macroeconomic and financial variables. Using CME soy-meal and MATIF corn futures as well as barley prices and ifo business climate index in first differences results in the best model when minimizing the average root mean square error. This model tends to outperform the naive random walk model in short and medium run forecasts (one to six months), but does not reject the null hypothesis of the Diebold-Mariano-Test for equality of forecasting accuracy against the benchmark model (random walk) in every period. We also compare two models solely built on either futures (futures model) or macroeconomic and financial variables (macroeconomic-financial model) to the random process and to each other. We arrive at the conclusion, similar to the literature, that the futures model tends to outperform the macroeconomic-financial model.

Keywords: vector auto regression, random walk, commodity prices, forecasting

JEL Codes: C22, c63, c87, E3, Q10

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1 Introduction

The high volatility of crude oil in recent times has received much attention from financial market participants, economists and policy makers. Whereas, the agricultural industry, which is controlled by few companies, received comparatively less media coverage. Even though, grain prices have fallen from their peaks, they remain quite high, given the fact that they correspond to staple food around the world. Multiple price driving factors have been analyzed, such as, climate change, oil price, speculators and other financial factors (Ke and Xiong, 2012 and Chiaie, Ferrara, and Giannone, 2017). Forecasting such prices is of great interest for various players, such as farmers, policy makers, speculators and even governments, as a stable food supply is of highest importance for national security. Stevenson and Bear (1970) show that in highly competitive agricultural commodity markets predictions based on the random walk model surpass the forecast accuracy of time series models. In theory, when the random walk model holds, past price information does not have any significance in predicting future prices, thus we speak of an "efficient" market. Hence, a new form of a forecasting approach, the fundamental analysis (Fama, 1995), has aroused. This approach depends on the potential of the commodity, which is based on weather, future supply, demand and ending stock to name a few. In addition, since grains are highly substitutable, prices are driven and influenced by supply and demand not only of the grain of interest, but the whole grain industry, thus high price correlations are regarded as "normal", especially when it comes down to barley, soy-meal and corn, given its primacy in the feed market (Chambers, 2004).

This paper presents the results obtained form a systematic comparison of multivariate time series models in terms of accuracy of an out-of-sample, rolling window forecast for Hamburg feed barley free on board prices, as a representative for different barley prices, due to the fact that the barley market is relatively unregulated. We aim to contribute to the literature on feed barley and grain price forecasting (Just and Rausser, 1981, Cuaresma, Hlouskova, and Obersteiner, 2017, Kenneth Rogoff and Rossi, 2010 or Houthakker, 1957) by looking at various unrestricted and restricted first difference vector auto regressive model. Vector error correction models and structured/unstructured vector autoregressions are not considered, due to the issue of co-integration and overshooting this bachelor thesis. The outcome of such an exercise is appealing, both as an instrument for possible trading strategies and as a source of knowledge.

The paper is structured the following way: Section two describes the specifications of the different VAR models and the economic framework. The results of the forecasting exercise of feed Hamburg barley FOB prices and its commentary can be viewed in section three. Section four summarizes the main findings and concludes. Section 5 provides some further remarks. Tables and Information on data used can be viewed in the appendix (section 6).

2 Economic Framework

There is a number of theoretical frameworks showing that future prices contain useful information for predicting commodity price developments (Just and Rausser, 1981). However, more recent studies (Gargano and Timmermann, 2014) have indicated that the information content of both macroeconomic and financial variables are leading commodity price drivers and thus improve forecast accuracy, since prices depend on the state of the economy. Bowman and Husain (2004) show on the basis of 15 different commodities, that models based on future prices tend to have a stronger predictive ability than those solely built on spot prices or on judgment. Thus we try to combine these approaches and find the best fitting model. However, due to the size and nature of the commodity market, we could not use the interpolated monthly data of the fundamental (macroeconomic) variables, such as EU/World barley production, domestic barley consumption and EU/World barley ending stock as only yearly data was available. After Just and Rausser (1981) futures play an important role in forming the price expectations of producers, hence we include the futures of MATIF wheat (W), MATIF corn (C) and CME soy-meal(S), due to the high correlation they have with barley. In addition, we include other financial variables, such as the business climate index for Germany (B) - as the barley price of interest is German barley - EuroStoxx50 (E) and the industrial Production Index for the Euro-zone (I). All the variables of interest are analysed using first differences, as the Dickey-Fuller-Test (Dickey and Fuller, 1979) suggests taking the first difference to make these time series stationary. Our set of forecasts includes multivariate model structures where the commodity price is assumed to depend on its own and other potential parameters' past values. Hence, we follow a vector autoregression forecasting methodology similar to Crespo Cuaresma, Hlouskova, and Obersteiner (2017) and Crespo Cuaresma, Fortin, and Hlouskova (2004).

In our multivariate time series specification we consider the price of barley at time t to be p_t and an element of the vector x_t, which includes futures, feed barley prices as well as financial and macroeconomic variables . Moreover, the vector x_t is assumed to be depended on its past values and on a multivariate normal random shock, so that the model is given by

$$x_t = \phi_0 + \sum_{l=1}^{n} \phi_l x_{t-l} + \epsilon_t, \epsilon_t \sim \boldsymbol{NID}(0, \Sigma_\epsilon) \qquad x_t = [P_t, W_t, C_t, S_t, B_t, E_t, I_t]' \tag{1}$$

where ϕ_l for *(l=1,...,n)* are coefficient matrices and ϕ_0 is the vector of the intercept terms. After performing the Dickey Fuller Test we arrive at the conclusion, that we can assume a relation in differences rather than in levels. Hence, there is a linear connection in first differences of the variables. Thus, the corresponding model would look like this

$$\Delta x_t = \omega_0 + \sum_{l=1}^{p} \omega_l \Delta x_{t-l} + \xi_t, \qquad \xi_t \sim \boldsymbol{NID}(0, \Sigma_\xi) \tag{2}$$

After Fair (1979) unrestricted VARs are known to over fit parameters and hence forecast only poorly, we can optimize the forecast quality by limiting some of the linear combinations of the variables in the vector autoregression to a certain constant. The restrictions which need to be taken can either be coming from available economic theory, such as the above mentioned, or based on empirical findings, such as Kunst and Neusser (1986), meaning that the unrestricted model is estimated and insignificant parameters and lags are excluded from the new model.

2.1 Estimation and Forecasting Comparison

A systematic approach for all models and forecasting exercises has been followed (see Appendix for data set characteristics and tables). Models were estimated in first differences only. The Akaike Information Criterion (AIC) has been evaluated for each VAR specification and lag length l=1,...,6 in order to select the significant lag length which corresponds to the minimum value of the information criterion in the model.

Taking the restricted models into account, we exclude those parameters which t-test statistic's fall within the 90% region of the T-distribution in the VAR estimation of the original in-sample period.

The estimation for the parameters of the model in question is done using available data from 2003.09 up to 2017.04. The periodicity of the data is monthly, fundamental variables are not included as interpolating yearly data led to messy outcomes. For every model forecasts for twelve periods (twelve months) were calculated. We use a rolling window forecasting approach, which means adding a new observation (the one that correspondents to 2017.05) to the sample, re-estimate the model and compute new forecasts which are then compared to realised values. This is done all over again until the last observation has been used. Lastly, we compute the RMSE (Root Mean Square Error) as well as the mean absolute error (MAE) for the model bench-marking exercise, which compares the best model forecasts to the random walk.

$$RMSE(k) = \sqrt{\sum_{j=0}^{N_k-1} \frac{[F_{t+j+k} - A_{t+j+k}]^2}{N_k}}$$

$$MAE(k) = \sqrt{\sum_{j=0}^{N_k-1} \frac{|F_{t+j+k} - A_{t+j+k}|}{N_k}}$$

where k=*1,...,12* corresponds to the forecasting step, N_k is the total of k-steps ahead forecasts for which the actual value of the barley price A_t is known and F_t is the forecast for the barley price.

The Diebold-Mariano Test (Diebold and Mariano, 1995) is applied to compare the accuracy of models against random walk predictions. In this exercise we try to compare our computed models with the random process, hence the question arises whether the results obtained from model A (our best model) are significantly more accurate than the forecasts of model X (random walk), in terms of a given loss function f(.) - here we will be using both the RMSE and MAE. The null hypothesis of the Diebold-Mariano-Test is that both expected forecasts have the same accuracy, whereas the alternative hypothesis states that they differ and hence one of the two models performs better than the other in terms of predictive accuracy. Hence, the null hypothesis can be written in the following way,

$$d_t = E[g(e_t^A) - g(e_t^X)] = 0 \tag{3}$$

where e_t^i corresponds to the forecasting error of model i when forecasting h-steps ahead. In order to test for *(3)*, the Diebold-Mariano-Test uses the auto-correlation-corrected mean of d_t, thus, with n observations and forecasts the test statistics is

$$S = [\hat{V}(\bar{d})]^{-1/2}\bar{d},$$

where

$$\hat{V}(\bar{d}) = \frac{1}{n}[\hat{\gamma}_0 + 2\sum_{k=1}^{h-1}\hat{\gamma}_k],$$

and

$$\hat{\gamma}_k = \frac{1}{n}\sum_{t=k+1}^{n}(d_t - \bar{d})(d_{t-k} - \bar{d})$$

S is under the null hypothesis of equal forecast accuracy asymptotically normally distributed.

3 Results of Forecasting Exercise

Table 1 shows the ratios of the RMSE (MAE) statistics for the best model, which is identified by the smallest average RMSE for the out-of-sample forecast, and the random process as well as the RMSE (MAE) ratios of direct comparisons of the futures and macroeconomic-financial model. Table two presents the results obtained when these models are not compared to each other but to the random walk for feed barley prices . In addition, the results of the Diebold-Mariano-Test are also included in both tables. Thus, the tables summarise the main findings: the ratios of forecasting errors for one two twelve months ahead predictions as well as the average prediction error of all the models for the prediction period.

The RMSE/RMSE(RW) (MAE/MAE(RW)) column corresponds to the ratios between the root mean square error (mean absolute error) of the model of interest and the that of the random walk for feed barley prices as well as for the direct comparison. The best model, which has the smallest average RMSE, is the one with only four variables, namely CME soy-meal, MATIF corn, feed barley Hamburg prices and ifo business climate index for Germany in first differences (in a sense it is a restricted VAR in first differences, average RMSE corresponds to 3,991). Needlessly to say the same model just without the macroeconomic variable (ifo business climate index) achieved a slightly larger average RMSE (4,149) and just did not make the cut. This is a great example that macroeconomic variables increase forecasting accuracy and hence the literature is partly confirmed.

The results of the comparison exercise between the best model and the random walk show that our model performed better than expected. In three cases (periods one, three and six) it rejects the null hypothesis of equal forecasting accuracy when bench-marked with the simple random walk model using root mean square error as a loss function. Hence our best model is significantly better in terms of forecasting accuracy than the random process, also taking into account that the average RMSE of the best model is lower than that of the random process. The naive random walk model surpasses the complex model significantly when RMSE is used as a loss function in period nine only. When MAE is applied we can reject the Diebold-Mariano-Test in three cases.

We clearly see that the futures model rejects the null hypothesis of equal forecasting accuracy when compared to the macroeconomic model in three instances when using the RMSE as a loss function, all in the medium term (five to seven months). The macroeconomic-financial driven model tends to be better in either the short (one and two months) or long run (twelve months), however not significantly. This result is also confirmed in the case of the indirect comparison (table 2) between the futures model and the macroeconomic-financial model, where each of them is compared to the naive random walk model. Only the futures model surpasses the naive random process significantly, in period 4, even though the average RMSE for the macroeconomic driven model is smaller than that of the futures model. In the case of the random walk model, it rejects the null hypothesis for both models in three cases when RMSE is used as a loss function. It seems like the literature (Just and Rausser (1981)) is partly confirmed and that future prices provide good information for commodity forecasting. This might be due to the high correlation of barley prices with different grain futures as well as the fact that weather and demand/supply shocks have greater impact on grain prices rather than region-specific macroeconomic factors.

To summarize, the forecasting exercise delivers interesting results concerning the predictability of feed barley hamburg prices. Using CME soy-meal and MATIF corn futures as well as Hamburg prices and ifo business climate index tend to surpass the random walk model in the short and medium term (one, three and six periods ahead). In the case of the long run (over six months ahead) the null hypothesis is not rejected. The literature is partly confirmed, as the futures model surpasses the macroeconomic-financial model in terms of forecasting quality when bench-marking both to the random process and to one another, as there are other grain specific macroeconomic/fundamental variables driving such prices even more (that were not considered here) and future prices tend to include those in their pricing. Nonetheless, adding a macroeconomic component to the model tends to increase the forecasting accuracy, as happened to our best model when a macroeconomic variable was added.

4 Summary and Conclusion

A set of various time series models has been compared to the simple random walk model in respect to forecast accuracy in the prediction of feed barley Hamburg prices. The results confirm to an extend the conclusion obtained by Kingsley (2011), that commodities do not follow a random process, and future movements can be predicted by past information, as indicated by the average RMSE ratio of the best and random walk model. However, what we also see, is that the naive random walk performs as well as more complex models in the case of medium term forecasts (period nine). Nonetheless, overall, multivariate time series models present a better forecasting precision than the random process.

5 Remarks

As this paper was written as part of the undergraduate program, more complex vector auto regressive models, such as vector error correction models and structured vector autoregressions were not considered, due to complexity. Moreover, important fundamental variables could not be used as interpolating over 90% of a time series tends to be an issue with huge implications.

The next step would be using seasonality filters with fundamental variables, as new crop and different harvesting seasons around the world effect barley prices differently. Other factors that were not accounted for in this paper, are for instance the role Saudi Arabia and China play as world leading importers of barley (*Barley Imports All Countries* n.d.) and how prices are affected when new tenders are opened. In addition, the shipping and insurance market are also subject to volatility, especially in times with growing uncertainty; this also could be taken into account in future examinations. Another aspect could be considering harvesting seasons for the forecast exercise as well as model averaging. Moreover, adding various weightings to parameters, as every variable effects prices differently, might also increase forecasting accuracy.

It remains a challenging and exciting exercise to keep trying to find the right approach and model which allow to consistently beat the random walk and the market. Nowadays this is considered the alchemy that only a hand full of people master.

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6 Appendix

All the variables are of monthly periodicity (September 2003 to May 2018) and have been gathered from Thomson Reuters and Bloomberg. The variables used are:

- Matif wheat future
- Matif corn future
- CME soy-meal future
- Output: Industrial production index for the Eurozone
- Leading indicator for Germany as a proxy for Europe (since Germany is the leading barley producer in Europe): ifo index
- Stock market index for Eurozone: EuroStoxx50
- Feed barley Hamburg FOB USD/metric tonnage

Table 1: Out of Sample forecast Performance for barley price: Best over all model vs random walk and macroeconomic-financial vs futures model - RMSE and MAE: *** and *** represent rejection of null hypothesis of equal forecasting accuracy at 1% and 5%. Source: Author's calculation

	Best model		Macroeconomic-financial vs Futures model	
Horizon	RMSE/RMSE(RW)	MAE/MAE(RW)	RMSE(m)/RMSE(f)	MAE(m)/MAE(f)
1 month	**0,4820*** **	0,4820	0,1340	0,1340
2 months	1,1696	1,3482	0,1186	0,1208
3 months	**0,5348*** **	0,6583	1,1405	0,7510
4 months	0,6072	**0,8210*** **	1,2649	**0,9697*** **
5 months	0,9344	**1,0059*** **	**1,0277*** **	**0,9268*** **
6 months	**0,9257*** **	0,9749	**1,0585*** **	1,0102
7 months	0,9700	1,0540	**1,0304*** **	0,9602
8 months	1,0400	1,1810	1,0120	0,9085
9 months	**1,1161** **	**1,2071** **	1,0959	0,9908
10 months	0,9558	1,0442	1,0089	0,9095
11 months	0,9780	1,0440	1,0705	0,9713
12 months	1,0031	1,1234	1,0545	0,9215
Average	0,9951	0,9953	0,9180	0,7979

Table 2: Out of Sample forecast Performance for barley: Macroeconomic-Financial and Futures model vs Random Walk model- RMSE and MAE: *** and ** represent rejection of null hypothesis of equal forecasting accuracy at 1% and 5%. Source: Author's calculation

	Futures model		Macroeconomic-financial model	
Horizon	RMSE/RMSE(RW)	MAE/MAE(RW)	RMSE(m)/RMSE(f)	MAE(m)/MAE(f)
1 month	1,4990	1,4990	0,2009	**0,2009*** **
2 months	3,1189	3,6889	0,3699	0,4458
3 months	0,8930	1,2238	**1,0184*** **	0,9191
4 months	**0,9350*** **	**1,3383*** **	1,1826	1,2977
5 months	**1,2505*** **	1,4601	1,2851	**1,3533*** **
6 months	1,2244	**1,3545*** **	1,2960	**1,3683*** **
7 months	**1,2541*** **	1,4069	**1,2922*** **	**1,3508*** **
8 months	1,2708	**1,4484*** **	1,2861	1,3159
9 months	**1,2016*** **	**1,3462*** **	**1,3169*** **	**1,3338*** **
10 months	1,0829	**1,2179*** **	1,0925	1,1077
11 months	1,0082	1,1269	1,0792	1,0945
12 months	1,0235	**1,1883** **	1,0793	1,0950
Average	1,3135	1,5249	1,0416	1,0736