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On the Forecastability of Agricultural Output

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The disruption of supply chain due to Covid-19 and the war in Ukraine, render the prediction of agricultural output a determinant factor of economic life. We consider the predictability of agricultural output based on a set of explanatory variables, that include agricultural input, prices and consumer demand among others, for Greece and explore the usefulness of these variables compared to standard, univariate, forecasting methods. We evaluate the impact of using combined information in the form of principal components, and the use of averaging for producing accurate forecasts. Our results indicate that agricultural output is predictable and, moreover, we identify the factors that, for the case of Greece, lead to such predictability. Our outcomes can be used in a variety of ways, the least of which can be scenario analysis that might be very useful in real-world policy making.

Keywords: forecasting, predictability, principal component analysis, explanatory variables, agricultural output.

JEL Classifications: C51, C52, C53, Q10, Q11

1 Introduction

The disruption of supply chain due to Covid-19 and the war in Ukraine, render the prediction of agricultural output a determinant factor of economic life. Agricultural output does generally

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vary with global economic trends and is believed to influence price levels more broadly and thus is of interest to central banks, policy makers, firms, consumers and of course farmers (Groen and Pesenti, 2011). On the other hand, agricultural productivity is very vulnerable generating important economic problems for the farmers and the consumers (Kyriazi et al., 2023). Thus, it is of considerable interest to examine how we can achieve forecastability of agricultural output. The magnitude of this issue is to ensure that there will be knowledge for the governments to implement appropriate trade policies as well as for the farmers adequate market information.

In this paper we consider the forecastability of agricultural output based on a set of explanatory variables, that include agricultural input, prices and consumer demand among others, for Greece. As a small open economy, with limited fiscal freedom and a very large dependence on tourism, Greece is a prime example of how one should monitor, via forecasting, the agricultural markets. In the paper we explore the usefulness of explanatory variables compared to standard, univariate, forecasting methods, the impact of using combined information in the form of principal components, and the use of averaging for producing accurate forecasts. Our results indicate that agricultural output is predictable (Midmore, 1993) and, moreover, we identify the factors that (for the case of Greece) lead to such forecastability. Our results can be used in a variety of ways, the least of which can be scenario analysis that might be very useful in real-world policy making. Furthermore, along with emphasizing on the forecasting accuracy of our models, we also seek to establish inferential relationships relevant for policy and decision making.

The remainder of the paper is organized as follows: in section 2 we review some related literature for forecasting commodity prices and output; in Section 3 we present our data and explain all the useful transformations; in section 4 we introduce our methodology, while in section 5 we discuss our empirical results; finally, in section 6 we offer some concluding remarks and potential extensions for future research.

2 Literature Review

In this section, we review some of the literature on commodity price and output forecasting. We use this review to direct our work and help us understand and interpret our results later on. Forecasting the indices of agriculture, estimating their elasticities, and predicting prices is an issue of considerable practical significance as the volatile nature of agricultural products makes them responsive to a higher level of variability. Therefore, forecasts of agricultural production and prices have become pivotal for researchers, and policymakers (Allen, 1994). Still, central banks, the agribusiness sector, and consumers, whose choices are based on their projections of future inflation, will also find them valuable (Groen & Pesenti, 2011), since agricultural output usually shifts with economic and financial trends worldwide. (Zhang, Lohr, Escalante, & Wetzstein, 2009) . Furthermore, governments have made an effort to measure and regulate agricultural output because a stable food supply is crucial to maintaining national security and driving sustainable management (Kechagia and Kyriazi, 2021). Due to this higher degree of uncertainty, an understanding of the interactions between the various components of an agro-system is necessary, taking into account human factors, natural resources, and agricultural production. For these reasons, models are required in order to comprehend and forecast the overall performance of agriculture (Jones et al., 2017) guiding decisions and policies. This higher volatility across space and time suggests that forecasts and all additional tools and information required to interpret and convey the outcomes of agricultural analysis can be used as part of agricultural monitoring systems (Atzberger, 2013). Thus, the question of the forecastability of agricultural output is extremely intriguing, and the volatile nature of the products suggests a number of explanatory variables that could be used for the generation of such forecasts.

Commodity forecasting goes back to the first half of the 20th century (Sarle, 1925; Cox et al. 1956; L'Esperance, 1964). However, it wasn't until the 1970s oil crisis that forecasting agricultural output and prices were thoroughly examined. A vast number of studies documented the fact that futures markets appear to offer the most reliable price predictions when they are readily available (Just & Rausser, 1981; Tomek, 1996;). Later landmark studies revealed the use of the out-of-sample predictability of commodity prices, like Gargano and Timmermann (2014) or Ahumada & Cornejo, (2016), indicating futures prices as the best available "predictors" of future spot prices. In the same vein of the literature is the work of Fowowe (2016) documenting the fact that agricultural prices are neutral to global oil prices in both the short and long run. Furthermore, Nazlioglou and Soytas (2012) provide compelling proof of how shifts in the price of 24 agricultural commodities are affected by changes in the value of the US dollar in a panel setting.

Other literature that is related to our work includes the following. Kyriazi et al. (2019) introduced a new methodological approach to forecasting agricultural time series[1]. Ramirez and Fadiga (2003) developed an asymmetric-error GARCH model for forecasting agricultural time series and generating solid confidence intervals for these forecasts. Onour and Sergi (2012), declared that there is a mean-reverting trend to the volatility of food commodity prices, which is symbolized by intermediate and short-memory behaviors. Gan-qiong et al. (2012) used a quantile regression approach to show that their VECM-MSVR method is a promising alternative for forecasting interval-valued agricultural commodity futures prices. In a related work, De Nicola (2016) provided an in-depth analysis of the degree of co-movement (measured by correlation coefficients) between the nominal price returns of eleven important commodities related to agriculture, food, and energy. This is in line with the finding that related commodities

[1] For some other forecast methodology, see Kyriazi and Thomakos, 2020, 2020 and Tarani & Kyriazi, 2024

usually have close substitutes in the market. In addition, Law (2023) considered a structural VAR approach to examine the demand shocks of the financial crisis and the structural break in energy prices, indicating a new regime post the financial crisis period. That is an important consideration, especially when modeling periods that do not correspond to normal market conditions. Noor and Erickson (2023) highlight the importance of achieving long-run economic stability to protect against relevant unexpected economic downturns. Especially when aiming to draw inferences and not only to achieve high forecasting accuracy, there is always a tradeoff between including data anomalies and reflecting the long-run average of the data generating process.

3 Data

Our dataset stems from the official website of the Greek Statistical Authority (ELSTAT), a national independent organization of Greece, which is responsible, among other operations, for the construction and the provision of various economic statistical reports of the Greek market. Due to the aforementioned responsibility of ELSTAT, we rely on its reports to employ the economic variables necessary for our empirical investigation.

Gathering data from the press release on input and output price indices of the Greek agricultural market, we selected the following economic variables: The Total Agricultural Output, Total Agricultural Input, Retail Sales Turnover, and Volume.

The purpose of the Total Agricultural Output, the dependent variable, is to measure the relative changes in prices received by producers in the agriculture-livestock sector when selling their agricultural products. The selected explanatory variables correspond to the Total Agricultural Input and Retail Sales Turnover. The purpose of the Total Agricultural Input is to measure the relative changes in prices paid for the acquisition of consumable means, goods, and services used in the production process. Additionally, transactions involving olive oil and wine, which fall under the manufacturing sector, are also covered by the Total Agricultural Output/Input, specifically when their processing or production is carried out by agricultural enterprises and is considered an activity of the agricultural sector. Moreover, the agricultural and livestock production sector is characterized by seasonality, resulting in certain products not being available in the market every month of a calendar year. For this reason, the weighting factors of output products vary monthly throughout the year. Breaking down the index of the Total Agricultural Output, we can further utilize its sub-components to provide more explainability in our empirical research. The Gross Agricultural Output is comprised of the Agricultural Output (Plant based production) and the Animal Output (Livestock production). The most significant component with respect to the weighted factors of the Agricultural Output is the produce of fruits, olive oil, and vegetables, playing a pivotal role in the Greek market and contributing substantially to its agricultural economy and consumer demand. On the other hand, Animal Output consists of the production of livestock and other animal products such as beef, poultry, and dairy products. Furthermore, the Gross Agricultural Input is comprised of the Consumables Input and Fixed Capital Input. More specifically, Consumables are primarily attributed to the consumption of energy and fuels, followed by animal feed, while Fixed Capital Input is fundamentally driven by the capital expenditures on machinery and equipment used for agricultural production. The compilation of the Total Agricultural Output/Input indices in the Agricultural market in Greece is based on voluntary agreements between the member states of the European Union (EU) and Eurostat. The foundations for these agreements were laid in the early ’70s. Thus, the compilation process and methodology are common across member countries of the European Union (EU). Moreover, they are fixed-base indices with a base year of 2015=100.

To ensure the robustness of our analysis and filter the signal from the overall noise present in most time series we undertake a thorough process of variable inspection and transformation. That is by involving logarithmic, first differences, and seasonal differences transformations. By taking the natural logarithm of each variable under consideration, we aim to address heterogeneity and scale the non-linear structure that is commonly encountered in economic time series. Thus, the logarithmic transformation helps stabilize the variance of our sample and makes the relationship between observations of our data series more linear. Therefore, once we make our variables more linear, we can employ regression parameter estimation techniques such as OLS. Following the logarithmic transformation, we compute the first differences for each logged variable. That is, in order to remove trends and address issues of non-stationarity, making the data suitable for certain econometric frameworks that assume stationarity (e.g., ARIMA models). Moreover, by transforming our data series into the log returns setting, we can leverage the nice property of the time-additive compounded returns. This allows us to obtain the return over a period of lower frequency (e.g., quarterly returns, yearly returns) by simply adding up the monthly log returns within the specified window. Additionally, as already mentioned dealing with seasonality is a common challenge for the agricultural and livestock production sector. That is because the dynamics of supply and demand for several agricultural commodities are heterogeneous. Thus, we apply seasonal difference transformation to each log returns variable, intending to eliminate the presence of seasonality. That is, we correct/transform our sample data to ensure capturing underlying trends and patterns, while removing seasonal noise. In addition, although we are not working in high-dimensional spaces, we aim to incorporate a degree of data aggregation through dimensionality reduction, by implementing PCA analysis on all available explanatory variables. The objective is to evaluate the performance of a compressed version of a handful of variables by capturing the important information, translated into variance in their respective data generating processes, simultaneously. For simplicity, we utilize the first three principal components that capture the highest degree of variance among the explanatory variable, as well as we enrich our employed dataset by including lagged versions of the corresponding principal components. As expected from Figure 3 it can be derived that the first principal component is more volatile than the other components, thus capturing the highest degree of information. However, that does not necessarily mean that it is the most appropriate predictor by design. Empirical analysis on the forecastability of low signal principal components (i.e., ”weak factors”) has demonstrated the importance of including them in our pool of explanatory variables (Giglio & Xiu and Zhang, 2023).

As the data frequency plays an important role in determining price transmission (Nazlioglou, 2011) and the selected economic variables are available at a monthly frequency, we constrain ourselves to the use of monthly observations that span the period 2000 to 2019. We choose to exclude the most recent observations that correspond to the Covid-19 period. That is, due to the irregular economic disruptions during that time that could lead us to misunderstand the underlying trends. By excluding the Covid-19 period, we aim to develop models that lead to more reliable predictions. Thus, we consider economic cycles that include one financial crisis and correspond to a mix of good/bad periods. Additionally, due to data length constraints, we use two rolling windows of 36 and 60 for estimating the parameters of our models. Finally, all variables employed in our empirical investigation enter the analysis as monthly growth rates (log returns). We aim to provide forecasts starting from the first month of 2017 until the end of 2019, using the rest of the observations in our training set.

Table 1: Summary Statistics

Variable	**Mean**	**Median**	**S.D.**	**Min**	**Max**
Total Output	85.94	91.50	13.64	53.20	104.2
Agricultural Output	83.83	88.35	16.10	47.60	113.3
Animal Output	93.44	96.75	7.755	75.10	105.8
Total Input	89.75	95.60	14.17	62.70	106.9
Consumables Input	87.74	94.60	16.68	58.00	109.0
Fixed Capital Input	94.46	99.55	8.423	73.80	102.8
Retail Sales Turnover	114.8	106.0	19.87	80.89	161.5
Retail Sales Volume	127.0	124.7	24.14	94.16	176.7

Figure 1: Temporal Evolution of Greek Agricultural Time Series

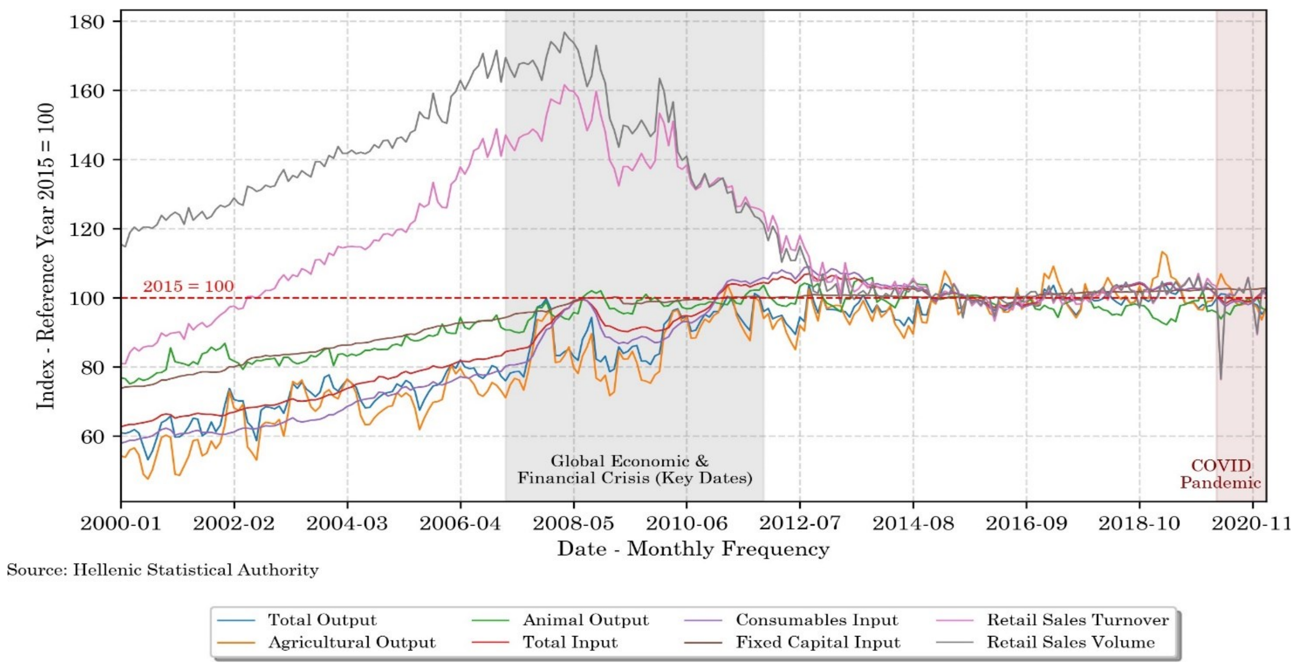


Figure 2: Temporal Evolution of Transformed Greek Agricultural Time Series

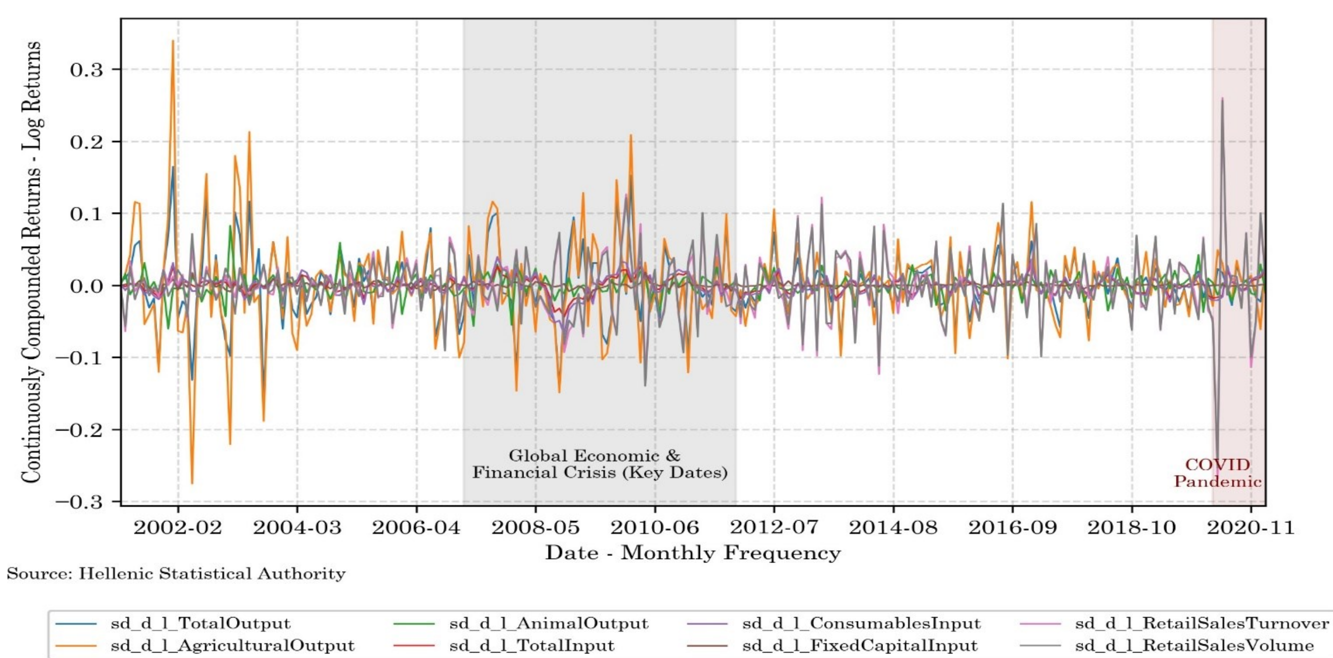
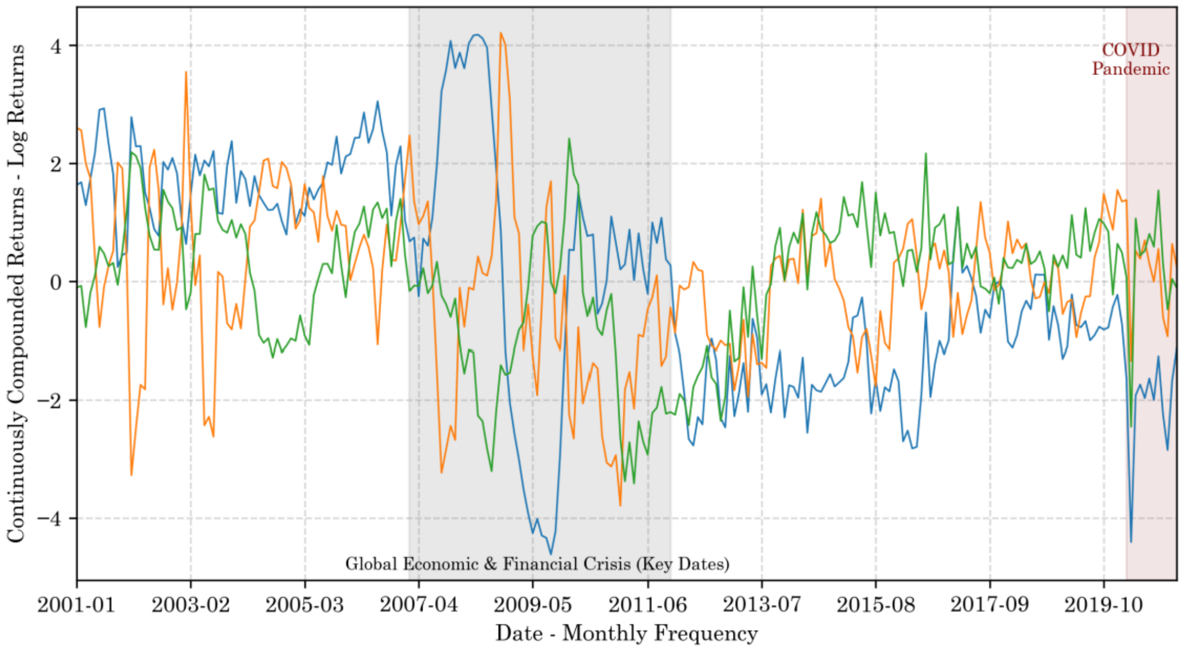


Figure 3: Extracted PCA Factors of the Transformed Greek Agricultural Time Series



Note: PCA factors that are used as explanatory variables

1st Principal Component (F1) — 2nd Principal Component (F2) — 3rd Principal Component (F3)

4 Methodology

In this section, we describe the methodology we followed for our analysis. There are two main concepts that we consider when constructing and testing our forecasting models: model significance and model/dimension reduction. Let $\{Y_t, \mathbf{X}_t\}$ be the dependent and explanatory variables of interest, where $\mathbf{X}_t$ is considered a vector. As the data in their original levels are both non-stationary and devoid of practical meaning (in their original units of measurement), we will work with the growth rates of the variables thus defining $y_t = \Delta \log(Y_t)$ and $\mathbf{x}_t = \Delta \log(\mathbf{X}_t)$. For the case of model reduction, we shall consider the principal components (factors) of the explanatory variables which we shall denote by $\mathbf{f}_t = PCA(\mathbf{x}_t)$. For convenience of notation in what follows, we concentrate the explanatory variables into the vector $\mathbf{z}_t = [\mathbf{x}_t, \mathbf{f}_t]^T$. This technique of dimensional reduction allows us to leverage the signal included in the available variables by identifying characteristics with higher variance, circumventing manual selection. Through PCA, we aim to enhance the efficiency of information representation by compressing the available explanatory variables through Singular Value Decomposition (SVD). Therefore, we not only utilize the extracted principal components (factors) in their standard form but also make use of their versions considering lags up to three month period.

Our main vehicle for estimation and forecasting is the class of *ARMAX*(*P, Q, K, S*) models, where p denotes the number of autoregressive lags, q the number of moving average lags, K denotes the number of explanatory variables entering the model and s denotes the number of lags of the explanatory variables (i.e., Total Agricultural Input, and Retail Sales Turnover). We thus write:

$$y_t = \phi_0 + \sum_{p=1}^{P} \phi y_{t-p} + \sum_{q=1}^{Q} \theta_j \epsilon_{t-q} + \sum_{k=1}^{K} \sum_{s=1}^{S} \beta_{ks} z_{k,t-s} + \epsilon_t$$

where by appropriate parametric restrictions we can nest all kinds of different models, including the standard *ARMA*(*P, Q*) class, regressions, and their combinations - we have also considered models that include seasonal moving average components but for brevity and compactness we do not write it in the above form. This addition of seasonal moving average components is used to enable the models to capture and respond to excess seasonal variations. Table 2 has the description of our modeling framework and the various combinations that stem from it; Table 3 has all models considered with an ID, model category, and model form for easier reference when discussing the results.

We consider both rolling (36 and 60 month-windows) and recursive estimation windows, on which the factors are also computed.[2] The selection of 36 and 60-month rolling windows allows us to capture mainly short-term trends of the agricultural market, utilizing more recent observations that are more relevant to the current conditions of the market.

Table 2: Description of Modeling Frameworks

Model	**Explanation**
AR(i)	The AR(i) forecast, with i = 1, 2, 3, 4
AR(p)	The AR(p) forecast, p by the AIC
MA(j)	The MA(j) forecast, with j = 1, 2, 3, 4
ARMA(i,j)	The ARMA(i, j) forecast
ARMA(i,j)xSMA(p)	The ARMA(i, j) forecast with Seasonal MA(p)
ADL-NS	The adaptive learning forecast, no smoothing
ADL	The adaptive learning forecast, with smoothing
TI(p)	Total Agricultural Input with p lags
RS(p)	Retail Sales Turnover with p lags
CONSI(p)	Consumables Input with p lags
FCI(p)	Fixed Capital Input with p lags
Fj(p)	jth Principal Component Factor with p lags

Table 3: Overview of Employed Forecasting Models

ID	Model Category	Model Form
A01	AutoRegressive	AR(i)
A02	AutoRegressive	AR(i)/TI(p)
A03	AutoRegressive	AR(i)/CONSI(p)
A04	AutoRegressive	AR(i)/FCI(p)
A05	AutoRegressive	AR(i)/TI(p)/RS(p)
B01	Moving Average	MA(i)
B02	Moving Average	MA(i)/TI(p)
B03	Moving Average	MA(i)/CONSI(p)
B04	Moving Average	MA(i)/FCI(p)
B05	Moving Average	MA(i)/TI(p)/RS(p)
C01	AutoRegressive Moving Average	ARMA(i,j)xSMA(p)
C02	AutoRegressive Moving Average	ARMA(i,j)xSMA(p)/TI(p)
C03	AutoRegressive Moving Average	ARMA(i,j)xSMA(p)/CONSI(p)
C04	AutoRegressive Moving Average	ARMA(i,j)xSMA(p)/FCI(p)
C05	AutoRegressive Moving Average	ARMA(i,j)xSMA(p)/TI(p)/RS(p)
D01	AutoRegressive with Factors	AR(i)/Fj(p), where $j=1$
D02	AutoRegressive with Factors	AR(i)/Fj(p), where $j=2$
D03	AutoRegressive with Factors	AR(i)/Fj(p), where $j=3$
D04	AutoRegressive with Factors	AR(i)/Fj(p), where $j=1,2$
D05	AutoRegressive with Factors	AR(i)/Fj(p), where $j=1,2,3$
E01	Moving Average with Factors	MA(i)/Fj(p), where $j=1$
E02	Moving Average with Factors	MA(i)/Fj(p), where $j=2$
E03	Moving Average with Factors	MA(i)/Fj(p), where $j=3$
E04	Moving Average with Factors	MA(i)/Fj(p), where $j=1,2$
E05	Moving Average with Factors	MA(i)/Fj(p), where $j=1,2,3$
F01	AutoRegressive Moving Average with Factors)	ARMA(i,j)/Fj(p), where $j=1$
F02	AutoRegressive Moving Average with Factors	ARMA(i,j)/Fj(p), where $j=2$
F03	AutoRegressive Moving Average with Factors	ARMA(i,j)/Fj(p), where $j=3$
F04	AutoRegressive Moving Average with Factors	ARMA(i,j)/Fj(p), where $j=1,2$
F05	AutoRegressive Moving Average with Factors	ARMA(i,j)/Fj(p), where $j=1,2,3$
G01	Model Averaging of top 3 RMSE Forecasts	ModelAvgRMSE
G02	Model Averaging of top 3 MAE Forecasts	ModelAvgMAE

[2]Note that all factor calculations are in-sample and are not forward-looking; once the model is estimated we then add the new observation, on which the forecast is to be evaluated, compute the forecast errors and only then update the factors.

On the other hand, the selection of a recursive window facilitates a continuous adaptation to evolving market conditions, incorporating all the available information captured in the agricultural sector. Each model is estimated and then the corresponding one-month ahead forecast is computed and stored for post-processing later. Our forecasting strategy considering projecting the future value of the Total Agricultural Output one month ahead, aims to capture short-term fluctuations so as to account for timely market responses. Once all forecasts are available, we compute the forecast errors and descriptive measures of forecast evaluation, the root mean-squared (RMSE) and the mean-absolute (MAE) forecasting errors. We sort the forecasting results and we report the top three models of each forecasting window category regarding the minimum RMSE and MAE accordingly. The rationale for reporting the results of these two performance metrics is due to the fact that RMSE focuses on penalizing larger errors, while MAE considers the absolute magnitude of errors and thus offers a more balanced view. Based on these measures we perform two additional steps: first, we re-forecast the top-performing models using the adaptive learning method of Kyriazi et al. (2019), to examine if further performance enhancements could be affected and, second, we compute the Diebold-Mariano (DM) test of equal forecasting performance. The DM test compares the forecasting performance between two non nested models, evaluating whether one statistically outperforms the other, taking into account the underlying loss function and sampling variation in the average losses. The test provides p-values indicating the significance of differences in forecasting accuracy. Thus, the rejection of the null hypothesis suggests a statistically significant distinction in the predictive performance of the models. (Diebold and Mariano, 1995). Additionally, we consider a version of the Diebold & Mariano Test that incorporates small-sample corrected degrees of freedom adjusted t-statistics, to ensure the robustness of the results (Harvey et al., 1997).

5 Results

We start off our discussion with some general remarks on the three presented tables (i.e., Table 6, Table 9, and Table 12). The tables focus on the relative performances of the top three models/methods based on the RMSE and MAE rankings in each forecasting window category. In addition, we generate two additional forecasts, by employing an averaging approach on the top 3 RMSE and top 3 MAE forecasts, assigning equal weights to each model. By utilizing the model averaging framework, we look forward to mitigating the impact of individual model idiosyncrasies, thereby testing the effectiveness of ensembling on forecasting performance. To facilitate the discussion of the results, we rank the top-performing models based on RMSE and MAE into two distinct tables (Table 4 & Table 5), accompanied by an indicator of whether the model is causal or not and a ”*” indicator highlighting whether a model rejects the Null hypothesis of the Diebold and Mariano (DM) test (i.e., not statistically equivalent). Overall, estimating and comparing a total of 527 models across different frameworks and variable combinations, our empirical analysis highlighted the following results:

In the recursive window setting, key models such as MA(2)/TI(1)/RS(1) and MA(2)/TI(1) underscore the significance of the Total Agricultural Input (TI) and Retail Sales Turnover (RS) as explanatory variables in our models, as well as the moving average setting which is present in the top 3 models. More specifically, the inclusion of Retail Sales Turnover (RS) slightly improves the forecasting performance, showcasing MA(2)/TI(1)/RS(1) as the best individual

Table 4: Model Ranking based on RMSE

Window	ID	Model	RMSE	Causal	DM
Recursive	G01	ModelAvgRMSE	0.874	N	-
Recursive	B05	MA(2)/TI(1)/RS(1)	0.885	Y	-
Recursive	B02	MA(2)/TI(1)	0.885	Y	-
Recursive	E02	MA(2)/F2(*p*), where *p=1,2,3*	0.891	N	-
Rolling 36	G01	ModelAvgRMSE	0.889	N	-
Rolling 60	G01	ModelAvgRMSE	0.906	N	-
Rolling 60	C04	ARMA(1,1)xSMA(1)/FCI(1)	0.908	Y	-
Rolling 60	C02	ARMA(1,1)xSMA(1)/TI(1)	0.912	Y	-
Rolling 36	A05	AR(2)/TI(1)/RS(1)	0.913	Y	-
Rolling 60	A05	ARMA(1,1)xSMA(1)/CONSI(1)	0.914	Y	-
Rolling 36	A05	AR(3)/TI(1)/RS(1)	0.915	Y	-
Rolling 36	B02	MA(2)/TI(1)	0.923	Y	-

Table 5: Model Ranking based on MAE

Window	ID	Model	MAE	Causal	DM
Recursive	G02	ModelAvgMAE	0.591	N	*
Recursive	B04	MA(2)/FCI(1)	0.644	Y	-
Recursive	A02	AR(1)/TI(1)	0.659	Y	-
Recursive	C04	ARMA(2,2)xSMA(1)/FCI(1)	0.660	Y	-
Rolling 36	G02	ModelAvgMAE	0.883	N	-
Rolling 36	C02	ARMA(1,1)xSMA(1)/TI(1)	0.892	Y	-
Rolling 36	C04	ARMA(1,1)xSMA(1)/FCI(1)	0.892	Y	-
Rolling 36	C03	ARMA(1,1)xSMA(1)/CONSI(1)	0.896	Y	-
Rolling 60	G02	ModelAvgMAE	0.898	N	-
Rolling 60	C04	ARMA(1,1)xSMA(1)/FCI(1)	0.906	Y	-
Rolling 60	C02	ARMA(1,1)xSMA(1)/TI(1)	0.909	Y	-
Rolling 60	C03	ARMA(1,1)xSMA(1)/CONSI(1)	0.913	Y	-

Table 6: recursive window: Top 3 models for RMSE & MAE

ID	Model	RMSE	ADL-RMSE
G01	ModelAvgRMSE	0.874	-
B05	MA(2)/TI(1)/RS(1)	0.885	-
B02	MA(2)/TI(1)	0.885	-
E02	MA(2)/F2(*p*), where *p=1,2,3*	0.891	-
ID	**Model**	**MAE**	**ADL-MAE**
G02	ModelAvgMAE	0.591	-
B04	MA(2)/FCI(1)	0.644	-
A02	AR(1)/TI(1)	0.659	-
C04	ARMA(2,2)xSMA(1)/FCI(1)	0.660	-

Table 7: Diebold & Mariano Test of Equal Forecasting Accuracy
(recursive window)

ID	B05	B02	E02	B04	A02	C04	G01	G02
B05	-	0.9196	0.91	0.7011	0.3194	0.3194	0.5312	0.3686
B02	0.9196	-	0.9188	0.719	0.3411	0.7088	0.5662	0.3674
E02	0.91	0.9188	-	0.9264	0.275	0.7232	0.6324	0.3314
B04	0.7011	0.719	0.9264	-	0.4128	0.7653	0.38	0.366
A02	0.3194	0.3411	0.275	0.4128	-	0.9396	0.1594	0.0942
C04	0.3194	0.7088	0.7232	0.7653	0.9396	-	0.6609	0.37
G01	0.5312	0.5662	0.6324	0.38	0.1594	0.6609	-	0.4334
G02	0.3686	0.3674	0.3314	0.366	0.0942	0.37	0.4334	-

H0 - Null hypothesis: Forecasts are equally accurate
Note: The reported values are the p-values of the DM test

model regarding the minimum RMSE. In the case of MAE, again the use of the moving average framework outperforms the rest of the models, aligning with the model selection based on the minimum RSME.

Therefore we can observe that when utilizing the recursive window setting (i.e., full sample and thus more observations), moving average models with additional explanatory variables tend to outperform. Notably, model averaging proved the most effective in both MAE and RMSE settings, producing the most accurate projections. That emphasizes the importance of employing generalization approaches when dealing with uncertainty.

Another prominent feature is the appearance of the factor-based forecasting model in the top 3 RMSE-based forecasts. The respective model interestingly makes use of the second principal component extracted by PCA, which incorporates the second highest degree of information/variance. That indicates the importance of lower signal PCA factors used for tackling uncertainty. The factors were computed by using the signals from all the available variables employed in our empirical examination (i.e., Agricultural Output, Animal Output, Total Input, Consumables Input, Fixed Capital Input, Retail Sales Turnover & Volume).

For the rolling window setting of 60 periods, ARMA(1,1)xSMA(1)/FCI(1) consistently demonstrates strong performance across both minimum RMSE and MAE. Once again, including exogenous variables improves the forecasting accuracy. More specifically, the inclusion of Fixed Capital Input (FCI) enhances the forecastability of Agricultural Output more than Agricultural and Consumables Input do, indicating Fixed Capital Input (FCI) as the strongest predictor when using the ARMA framework. Additionally, the use of Total Agricultural Input (TI) and Consumables Input (CONSI) as predictors separately demonstrates a positive contribution to the forecastability of the Total Agricultural Output. Moreover, the performance of model averaging further justifies the reliability of generalization techniques, outperforming every model employed in both RMSE and MAE.

Table 8: Diebold & Mariano Adjusted Test of Equal Forecasting Accuracy (recursive window)

ID	B05	B02	E02	B04	A02	C04	G01	G02
B05	-	0.9185	0.9088	0.6971	0.3127	0.3127	0.5255	0.3619
B02	0.9185	-	0.9176	0.7151	0.3344	0.7049	0.5608	0.3607
E02	0.9088	0.9176	-	0.9253	0.2683	0.7195	0.6276	0.3247
B04	0.6971	0.7151	0.9253	-	0.4063	0.762	0.3734	0.3593
A02	0.3127	0.3344	0.2683	0.4063	-	0.9387	0.1537	0.0899
C04	0.3127	0.7049	0.7195	0.762	0.9387	-	0.6564	0.3634
G01	0.5255	0.5608	0.6276	0.3734	0.1537	0.6564	-	0.427
G02	0.3619	0.3607	0.3247	0.3593	0.0899	0.3634	0.427	-

H0 - Null hypothesis: Forecasts are equally accurate

Notes: Small-sample corrected degrees of freedom adjusted t-statistics
The reported values are the p-values of the DM test

Figure 4: recursive window Forecasts: Top 3 RMSE models

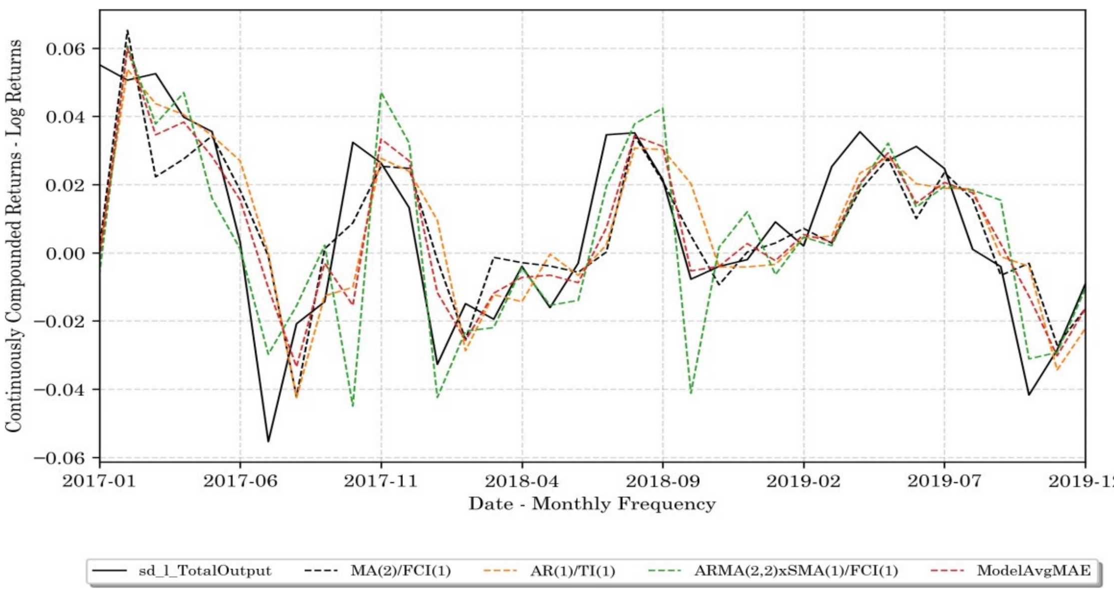


Figure 5: recursive window Forecasts: Top 3 MAE models

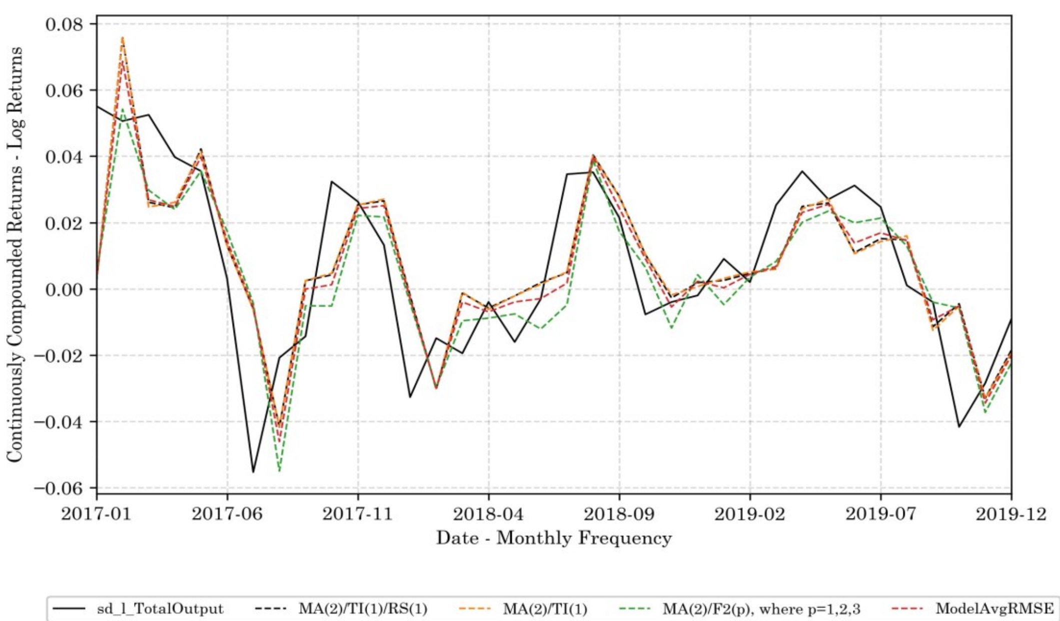


Table 9: rolling window 60: Top 3 models for RMSE & MAE

ID	Model	RMSE	ADL-RMSE
G01	ModelAvgRMSE	0.906	0.900
C04	ARMA(1,1)xSMA(1)/FCI(1)	0.908	0.904
C02	ARMA(1,1)xSMA(1)/TI(1)	0.912	0.904
C03	ARMA(1,1)xSMA(1)/CONSI(1)	0.914	0.909
ID	**Model**	**MAE**	**ADL-MAE**
G02	ModelAvgMAE	0.898	0.894
C04	ARMA(1,1)xSMA(1)/FCI(1)	0.906	-
C02	ARMA(1,1)xSMA(1)/TI(1)	0.909	0.901
C03	ARMA(1,1)xSMA(1)/CONSI(1)	0.913	0.901

Table 10: Diebold & Mariano Test of Equal Forecasting Accuracy (rolling window 60)

ID	C04	C02	C03	G01/02
C04	-	0.8812	0.8188	0.2558
C02	0.8812	-	0.8787	0.4755
C03	0.8188	0.8787	-	0.3352
G01/02	0.2558	0.4755	0.3352	-

H0 - Null hypothesis: Forecasts are equally accurate
Note: The reported values are the p-values of the DM test

Table 11: Diebold & Mariano Adjusted Test of Equal Forecasting Accuracy (rolling window 60)

ID	C04	C02	C03	G01/02
C04	-	0.8795	0.8163	0.2493
C02	0.8795	-	0.877	0.4693
C03	0.8163	0.877	-	0.3285
G01/02	0.2493	0.4693	0.3285	-

H0 - Null hypothesis: Forecasts are equally accurate
Notes: Small-sample corrected degrees of freedom adjusted t-statistics
The reported values are the p-values of the DM test

Figure 6: rolling window 60 Forecasts: Top 3 RMSE & MAE models

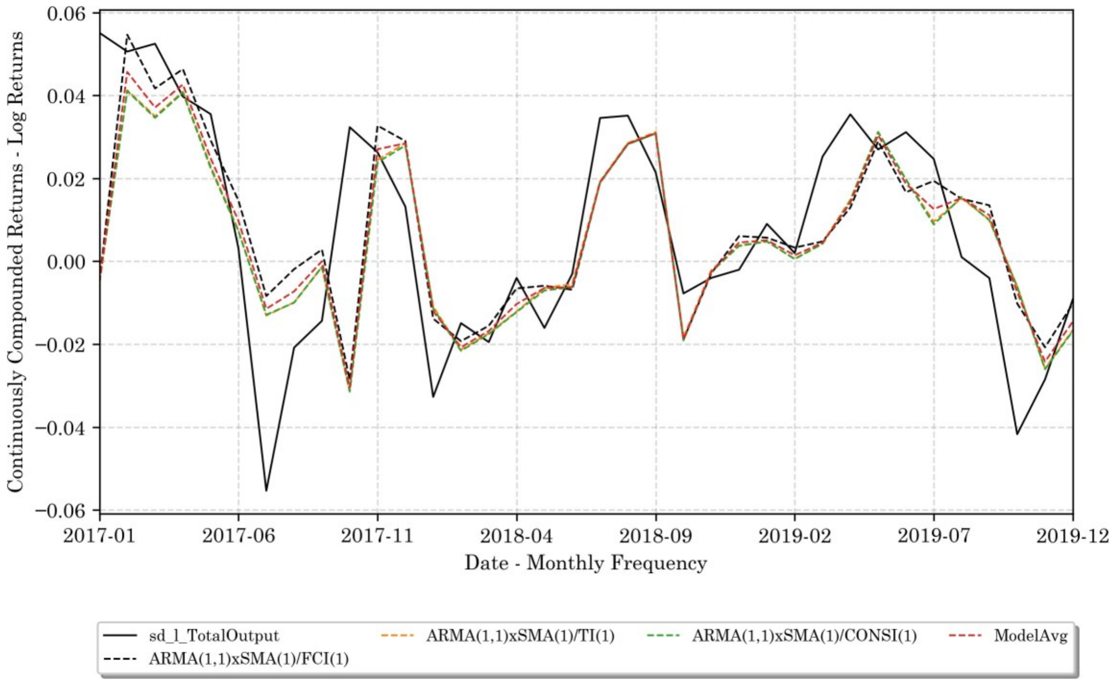


Table 12: rolling window 36: Top 3 models for RMSE & MAE

ID	Model	RMSE	ADL-RMSE
G01	ModelAvgRMSE	0.889	-
A05	AR(2)/TI(1)/RS(1)	0.913	-
A05	AR(3)/TI(1)/RS(1)	0.915	-
B02	MA(2)/TI(1)	0.923	0.922
ID	**Model**	**MAE**	**ADL-MAE**
G02	ModelAvgMAE	0.883	0.880
C02	ARMA(1,1)xSMA(1)/TI(1)	0.892	-
C04	ARMA(1,1)xSMA(1)/FCI(1)	0.892	0.886
C03	ARMA(1,1)xSMA(1)/CONSI(1)	0.896	0.892

Table 13: Diebold & Mariano Test of Equal Forecasting Accuracy (rolling window 36)

ID	A05(i=2)	A05(i=3)	B02	C02	C04	C03	G01	G02
A05(i=2)	-	0.932	0.8354	0.7801	0.5395	0.5395	0.6766	0.3057
A05(i=3)	0.932	-	0.8782	0.8031	0.5607	0.7948	0.7102	0.3268
B02	0.8354	0.8782	-	0.8226	0.5386	0.814	0.7344	0.2741
C02	0.7801	0.8031	0.8226	-	0.3365	0.2483	0.7426	0.685
C04	0.5395	0.5607	0.5386	0.3365	-	0.3532	0.4405	0.457
C03	0.5395	0.7948	0.814	0.2483	0.3532	-	0.2979	0.5033
G01	0.6766	0.7102	0.7344	0.7426	0.4405	0.2979	-	0.6175
G02	0.3057	0.3268	0.2741	0.685	0.457	0.5033	0.6175	-

H0 - Null hypothesis: Forecasts are equally accurate
Note: The reported values are the p-values of the DM test

Table 14: Diebold & Mariano Adjusted Test of Equal Forecasting Accuracy (rolling window 36)

ID	A05(i=2)	A05(i=3)	B02	C02	C04	C03	G01	G02
A05(i=2)	-	0.9311	0.8331	0.7771	0.5338	0.5338	0.6723	0.299
A05(i=3)	0.9311	-	0.8765	0.8003	0.5552	0.792	0.7063	0.32
B02	0.8331	0.8765	-	0.8201	0.5329	0.8114	0.7308	0.2675
C02	0.7771	0.8003	0.8201	-	0.3298	0.2418	0.7391	0.6808
C04	0.5338	0.5552	0.5329	0.3298	-	0.3465	0.4341	0.4507
C03	0.5338	0.792	0.8114	0.2418	0.3465	-	0.2912	0.4973
G01	0.6723	0.7063	0.7308	0.7391	0.4341	0.2912	-	0.6126
G02	0.299	0.32	0.2675	0.6808	0.4507	0.4973	0.6126	-

H0 - Null hypothesis: Forecasts are equally accurate

Notes: Small-sample corrected degrees of freedom adjusted t-statistics
The reported values are the p-values of the DM test

Figure 7: rolling window 36 Forecasts: Top 3 RMSE models

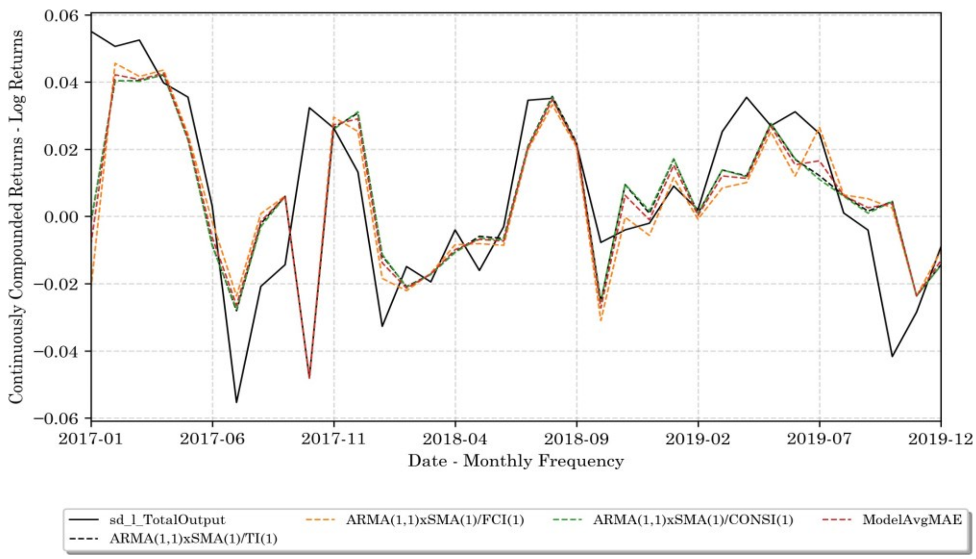
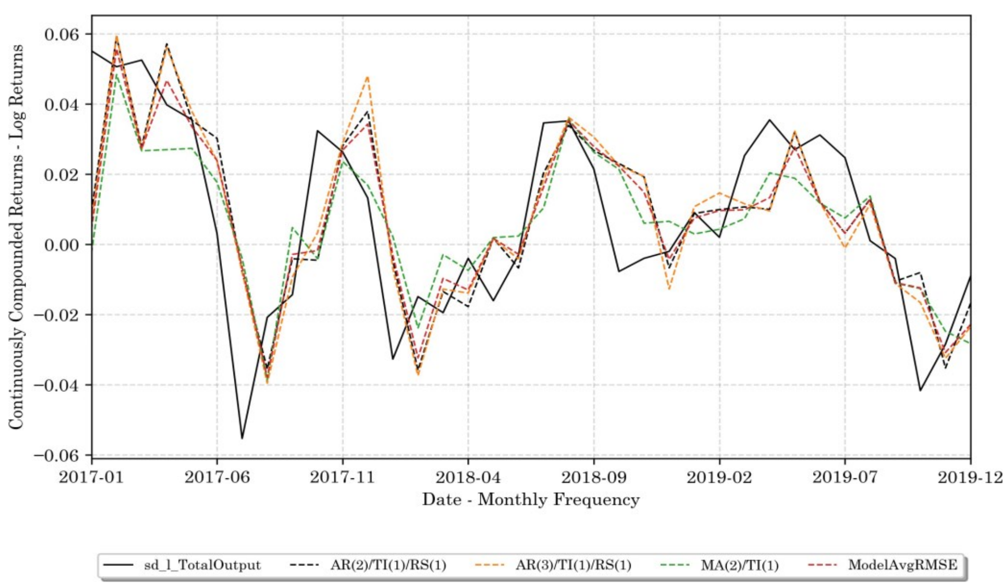


Figure 8: rolling window 36 Forecasts: Top 3 MAE models



For the rolling window of 36 periods, the RMSE-based forecasts indicate model specifications such as AR(2)/TI(1)/RS(1) and AR(3)/TI(1)/RS(1), highlighting the influence of autoregressive structures and the significance of Total Agricultural Input (TI) and Retail Sales Turnover (RS) as exogenous predictors. In the case of the MAE-based forecasts, the highlighted models are similar to the case of the rolling window of 36 periods setting. That is, models the ARMA(1,1)xSMA(1)/TI(1) and ARMA(1,1)xSMA(1)/FCI(1) specifications, which once again highlight Total Agricultural Input (TI) and Fixed Capital Input (FCI) as strong predictors. Moreover, the model averaging framework once again dominates the forecasting landscape, yielding the highest accuracy in both RMSE and MAE model selection scenarios.

Overall we observe that model averaging strategies dominate in all the forecasting scenarios considered, achieving stability and recommending parsimonious ensemble models for informed decision-making. Across the RMSE-based forecasts, the MA(2)/TI(1) model emerges as a strong performer, showcasing its resilience in both the recursive window and the rolling window of 36 periods settings.

In contrast, MAE metric forecasts underscore the prevalence of the ARMA(1,1)xSMA(1)/TI(1) and the ARMA(1,1)xSMA(1)/FCI(1) models, highlighting their reliability in capturing forecast deviations. Notably, Fixed Capital Input (FCI) and Total Agricultural Input (TI) consistently feature in our top-performing models. These consistent findings across metrics highlight the reliability and importance of specific models and variables, providing valuable insights for decision-makers.

Also, a notable insight is that the recursive window forecasts tend to outperform the rolling window setting forecasts. In the recursive window approach, the forecasting model is updated with the addition of each new observation, allowing it to capture evolving patterns and trends in the data over time. This adaptability can result in more accurate predictions as the model continuously incorporates the most recent information. In contrast, a rolling window setting maintains a fixed sample size, potentially leading to the exclusion of informative data as the window shifts. That may correspond to the model's ability to effectively adapt to evolving patterns, explaining the comparatively better performance of the recursive window forecasts.

In addition to producing our point estimate forecasts, we consider a meta analysis of the top performing forecasting models of each window setting. Therefore, we utilize the adaptive learning forecasting methodology to improve our forecasts by subjecting them to post-estimation forecast error learning. By adjusting and testing the relative learning rate we produce re-calibrated forecasts, and our results support the effectiveness of the forecastability of agricultural prices. Although we achieve better forecasts for both rolling window settings, adaptive learning is ineffective for the recursive window. Moreover, despite the improvement in the rolling window adaptive learning forecasts, they do not surpass those produced by the recursive window.

Furthermore, by examining the results of the DM tests across all window settings, we can infer that in most cases the null hypothesis which corresponds to the equality of the forecasting accuracy of the models is not being rejected. That signals the presence of model equivalence and model indeterminacy, where distinct models produce practically statistically similar forecasts. That contributes to the lack of statistical distinctions, except in only one case where the null hypothesis is being rejected, and thus AR(1)/TI(1) model forecasts are being favored against the model averaging forecasts.

In exploring the implications of model equivalence, it is important to consider the interplay between model parsimony and the selection of explanatory variables. Model equivalence complicates the process of model selection, highlighting the importance of understanding the relative performance of models beyond statistical significance alone. The results of our recursive window forecasts in Table 6 indicate that model equivalence is present in our empirical investigation not only in terms of the Diebold & Mariano tests but also regarding the forecasting performance of the models. The top-performing models of the recursive window setting are all nested under the Moving Average process with a lag of 2 months. Consequently, the relatively identical forecasting performance of these models makes it challenging to distinguish one that stands out. The inclusion of Total Agricultural Input (TI) may capture broader trends in agriculture, while Retail Sales (RS) might reflect its specific impact on consumption patterns, influencing forecastability differently. However, based on our empirical findings, there is no statistically significant distinction between whether Model B05 or B02 is more relevant and appropriate for drawing inferences. What is evident is the interplay between model parsimony and the addition of more explanatory variables. The least effective model in terms of RMSE is the less parsimonious Moving Average model, highlighting the trade-off between model complexity and predictive accuracy. Therefore, while Principal Component Analysis (PCA) may capture the most important information from the input variables, it does not necessarily imply that the compressed information may not contain some degree of noise, enough to penalize model performance compared to more parsimonious model specifications. This emphasizes the importance of balancing explanatory power with model simplicity. Therefore, overly complex models may introduce unnecessary noise without significantly improving forecasting performance.

Thus, in that case, it is indicated that we make context-based decisions regarding model selection. To achieve greater forecasting accuracy one may select the model averaging compositions of the recursive window forecasts which outperform the rest of the considered models. However, decision and policy makers tend to prefer more parsimonious and explainable model specifications. Thus, to draw inferences policy makers might account for the trade-off between the accuracy and explainability of the model and potentially select models that illustrate statistically equivalent forecasts such as MA(2)/TI(1)/RS(1) and/or MA(2)/FCI(1). In that way we can draw inferences about the impact of Agricultural Input (TI), Retail Sales Turnover (RS), and Fixed Capital Input (FCI) on the relative change in wholesale prices of agricultural products, as well as the impact of the historical white noise error terms of the regressand (i.e., Moving Average process).

6 Conclusions

In our empirical investigation, our primary objective is to identify the most impactful drivers of the Greek agricultural market's output. Specifically, we aim to uncover the factors that influence the relative change in wholesale prices of agricultural products. Thus, in addition to examining relevant drivers of the agricultural market employed in the existing literature, we assess the forecastability of the Greek market output with regard to the local market trends. Along with focusing on the forecasting accuracy of our models, we also aim to establish inferential relationships useful for policy and decision making.

In all the evaluated scenarios we observe that the model averaging framework provides significant enhancements in both RMSE and MAE based forecasts, showcasing as the strongest forecasting modeling method in our toolbox. Thus, by mitigating the impact of errors in any single model, ensemble methodologies (i.e., model averaging) lead to more robust and reliable forecasts. That is by leveraging the strengths of multiple individual models exhibiting a remarkable ability to generalize well to different scenarios of unseen data. Furthermore, model averaging tackles over fitting by promoting a balance between bias and variance in the overall prediction.

Moreover, we can further extend our analysis by considering alternative directions. Given that the compilation of the Total Agricultural Output/Input indices is similar across the member states of the European Union (EU), we can consider expanding our analysis to other EU countries and potentially consider examining the spillover effects of price transmission between the EU member countries. This approach can provide insights into how pricing dynamics and economic factors in one country may influence neighboring EU countries. By examining the relevant spillover effects, we can aim to enhance our understanding of the interconnectedness within the EU agricultural sector, facilitating more informed decision-making and policy recommendations on a broader scale.

A plausible alternative direction could also refer to the expansion of our modeling techniques by increasing the dimensionality (including more variables) in our analysis. By utilizing the power of shrinkage estimators (e.g., Ridge/Lasso Regression) we can uncover the most important in-sample factors. Then, the selected factors can then be integrated into a second-stage estimation, complementing our classical auto-regression frameworks. Additional variable selection techniques based on information criteria (e.g., AIC, BIC) can be also employed to support the analysis. We can further enrich our empirical investigation by comparing our causal models to more complex modeling techniques (e.g., Neural Networks) that have been used to predict price fluctuations in the commodity markets (Stathakis, Papadimitriou & Gogas, 2021). That is, to further explore the tradeoff between the bias and variance of our models and assess how much predictive accuracy we may sacrifice to maintain causal relationships. Finally, since agricultural commodities play an instrumental role in the financial landscape of Greece, it would be of great interest to investigate how financial market mechanics impact agricultural prices. That is, to evaluate the effect of sovereign bond yields, which are main determinants of the risk profile, and the lending/investment capacity of a country, on the interconnectedness of the financial market and agricultural sector within Greece's economy.

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