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Investigation note

Modeling of nominal *vs* real price predictors applied to corn, wheat and barley in Mexico

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Abstract

In agricultural production, the lag in time between the time resources are allocated and resources are obtained makes it necessary to generate a prediction at time t (sowing), of the current price in t + j (sale). However, in the presence of inflation, the decision maker may choose to make a prediction in nominal terms or discount such inflation. With monthly prices, under a time series approach and after fitting an IMA (1, 1) model, this dilemma was studied for the case of corn, wheat and barley in Mexico. After comparing six goodness-of-fit criteria for each prediction alternative in each crop for the analyzed period 2002 to 2019, it is found that the use of nominal or real data is indifferent in the construction of the price predictor.

Keywords: arima model, goodness of fit, unit root.

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Agricultural production is characterized by committing resources at a moment of time, either before or at the time of sowing, and after the agricultural cycle, obtaining resources through the sale of the product; due to the time lag between expenditure and income, in the administration of agricultural production, price forecast is an option. The latter because at the time resources are allocated, there is uncertainty about the price that will be received later.

The problem in making agricultural investment decisions is the uncertainty in profit expectations generated by an uncertain price at the time of sale. Therefore, the problem is summarized in trying to build a signal or a prediction of the price at time t that will be received at time t+j; call this: $tE(P_{t+j})=\hat{P}_{t+j}$, the price expectation in t of the current price in t+j. A tool in decision-making is the prediction of prices of the products that are sold (Marroquin and Chalita, 2011; Luis *et al*., 2019).

Nevertheless, in the presence of inflation, there is the dilemma of discounting the effect of inflation and producing a price forecast in real terms (Ceballos and Pire, 2015; Jadhav *et al*., 2017) or, alternatively, a forecast can be made with the series in nominal terms (Marroquín and Chalita, 2011; Samuel *et al*., 2019). In order to explore both possibilities, prices of three agricultural products are fitted here in both nominal and real terms.

The objective of the present work is to compare the predictive goodness of time series models applied to three agricultural prices in Mexico, namely: corn, wheat and barley, when taken in nominal terms compared to them in real terms, the period considered was from 2002 to 2019 at a monthly frequency. Given these two forecast possibilities, the hypothesis that the predictive capacity under both approaches is the same is examined.

Average rural prices for corn, wheat and barley obtained from June 2002 to December 2020 are examined, the frequency of the data is monthly-.https://wwwindexmundicom/es/precios-de-ercado/?mercancia=cebada&meses=300&moneda=mxn consulted in July 2020. To convert price data to real prices, the national consumer price index reported by INEGI was used. INEGI BIE: economic indicators of the economic situation> price indices> national consumer price index. Base second half of July 2018=100> monthly> general index (base index second half of July 2018= 100) monthly (April: 2020).

Therefore, two types of series were used: Pn_{it} and Pr_{it}. Where: the first is the nominal price of product i= corn, wheat and barley and the second is defined as $Pr_{it}=(Pn_{it}/CPI_t)\times100$, which is the real price for product i; with CPI_t consumer price index. Therefore, the interest is to fit a time series model for both the nominal price and the real price, once the model is identified, predictors are obtained and from there goodness-of-fit measures in the predictors are contrasted to generate a criterion of discrimination between both options.

A methodology to generate predictors is the approach of Box and Jenkins, which is summarized in three steps, identification, estimation and forecasting, recent examples of its use (Broz and Viego, 2014; Ceballos and Pire, 2015; Jahdav *et al*., 2017). For this methodology to be applicable, the series examined must be stationary, which implies that the first moment of the series does not change in time, the same is required for the second moment; if, in addition, there are decreasing autocorrelations and they are a function only of the temporal distance between the time series itself at time t and its lags t-j for j= 1,2, then a series with these characteristics is called weakly stationary (Greene, 2014).

A graphic examination (Figure 1) shows that both the mean and the variance change for the price of corn (pesos per tonne), both in nominal and real terms. To save space, only the case of corn is presented developed, but the same type of analysis was done for barley and wheat, both nominal and real. Developments of the other two crops are available with the author for correspondence. The real value is the lesser of the two, shown in green. This can be seen since the series first shows an increasing trend and then changes, which is symptomatic of a change in mean, this necessarily entails an effect on variance.

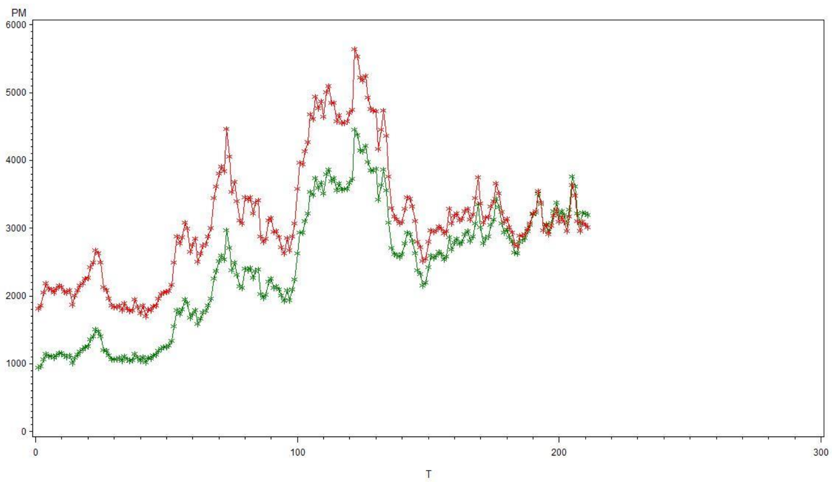

Figure 1. Nominal and real price of corn.

With respect to variance stabilization, each series was transformed to logarithms, which is a particular case of the Box-Cox transformation (Judge *et al*., 1985).

With the transformed series, we proceeded to contrast by the presence of unit root in each series under the criteria suggested by Dickey and Fuller (1981). In the six cases examined (three of real prices and three of nominal prices), the hypothesis that the data contain a unit root was not rejected, so the series were processed in first difference (Luis *et al*., 2019), even so, it was corroborated that first-order difference series rejected the unit root hypothesis so they are suitable for time series analysis (ARIMA procedure, Instituto SAS, 2014).

Table 1 shows that the null hypothesis of unit root existence using the series in levels is not rejected. On the other hand, in first difference, the null is rejected, obtaining stationarity in that case.

Table 1. Augmented dickey-fuller unit root test.

	Lag	Tau	Pr < Tau	F	Pr > F
		Nominal corn price			
Intercept	0	-1.84	0.3621	2.64	0.3987
	1	-1.85	0.3576	2.38	0.4646
	2	-1.62	0.4724	1.95	0.575

	Lag	Tau	Pr < Tau	F	Pr > F
Intercept and trend	0	-1.8	0.7024	2.11	0.7562
	1	-2.06	0.567	2.46	0.6864
	2	-1.84	0.6818	1.94	0.7899
		Real corn price			
	Lag	Tau	Pr < Tau	F	Pr > F
Intercept	0	-2.05	0.2638	2.27	0.4915
	1	-2.19	0.2108	2.51	0.4322
	2	-1.93	0.3186	1.94	0.5767
Intercept and trend	0	-1.81	0.6972	2.11	0.756
	1	-2.07	0.5572	2.48	0.682
	2	-1.85	0.6798	1.94	0.7902
		Nominal corn price differential			
	Lag	Tau	Pr < Tau	F	Pr > F
Intercept	0	-12.55	<0.0001	78.71	0.001
	1	-10.12	<0.0001	51.23	0.001
	2	-7.85	<0.0001	30.83	0.001
Intercept and trend	0	-12.56	<0.0001	78.93	0.001
	1	-10.13	<0.0001	51.33	0.001
	2	-7.85	<0.0001	30.86	0.001
		Real corn price differential			
	Lag	Tau	Pr < Tau	F	Pr > F
Intercept	0	-12.55	<0.0001	78.71	0.001
	1	-10.12	<0.0001	51.23	0.001
	2	-7.85	<0.0001	30.83	0.001
Intercept and trend	0	-12.56	<0.0001	78.93	0.001
	1	-10.13	<0.0001	51.33	0.001
	2	-7.85	<0.0001	30.86	0.001

From the analysis of the correlograms of the series in nominal and real terms (Figure 2), which highlight the first autocorrelation as significant, alternatives of ARIMA models (1, 1, 1), (0, 1, 1) (1, 1, 0) were tested. Based on the Akaike fit criterion and Schultz's statistics, the best representation of the data was obtained with the ARIMA (0, 1, 1) or IMA (1, 1) model, this selection strategy is analogous to that implemented in Jadhav *et al*. (2017); Luis *et al*. (2019).

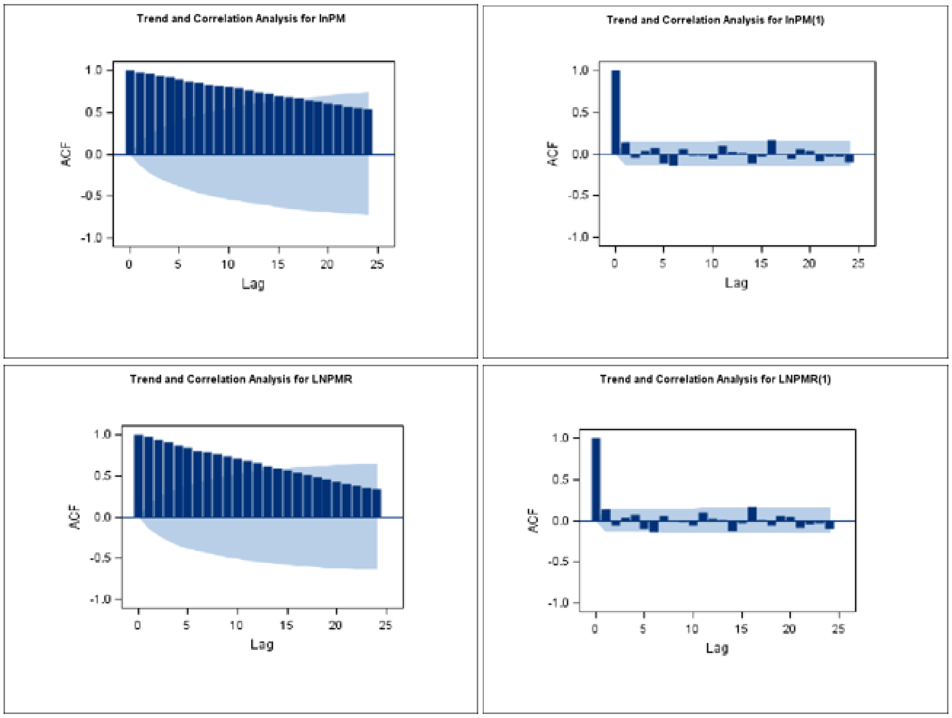

Figure 2. Autocorrelation function and autocorrelogram for nominal and real price of corn in levels and first difference.

It is anticipated that this last result is anticipated as a fit model by Franses (2019), who argues that the IMA (1, 1) model has a higher fit than the random walk model since the latter is a particular case of the IMA (1, 1) model (Table 2).

Table 2. Models tested.

ARIMA(0 1 1)		ARIMA(1 1 0)		ARIMA(1 1 1)	
		Nominal price corn model			
AIC	-578.054	AIC	-577.52	AIC	-576.477
SBC	-574.707	SBC	-574.172	SBC	-569.783
		Real price corn model			
AIC	-578.932	AIC	-578.317	AIC	-577.451
SBC	-575.584	SBC	-574.97	SBC	-570.756

The series were fitted with conditional least squares, which eliminates having to depend on the possible normality of the data during the estimation, as required by maximum likelihood. Once the models were fitted, predictions within the sample were given, since conditional least squares were used, these predictions are conditional on the substitution of the mean as the beginning of the iterated predictions. These predictions were used to calculate the following six statistics (Department of treasury, 2008; Jadhav *et al*., 2017) shown in Table 3.

Table 3. Statistics of goodness of fit of the prediction.

Mean squared error MSE	Mean percentage error MPE	Mean absolute error MAE
a) $\frac{1}{n}\sum_{t=1}^{n}\left(Y_t-\widehat{Y}_t\right)^2$	b) $\frac{1}{n}\sum_{t=1}^{n}\frac{\left(Y_t-\widehat{Y}_t\right)^2}{Y_t}$	c) $\frac{1}{n}\sum_{t=1}^{n}\left\|\left(Y_t-\widehat{Y}_t\right)\right\|$
Mean absolute percentage error MAPE	Theil's U1 statistic	Theil's U2 statistic
d) $\frac{1}{n}\sum_{t=1}^{n}\frac{\left\|\left(Y_t-\widehat{Y}_t\right)\right\|}{Y_t}\times 100$	e) $\frac{\sqrt{\sum_{t=1}^{n}\left(Y_t-\widehat{Y}_t\right)^2}}{\sqrt{\sum_{t=1}^{n}Y_t^2}+\sqrt{\sum_{t=1}^{n}\widehat{Y}_t^2}}$	f) $\sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{\widehat{Y}_{t+1}-Y_{t+1}}{Y_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{Y_{t+1}-Y_t}{Y_t}\right)^2}}$

These statistics focus on the distance between the prediction and the observed value in different ways, i.e., the direct distance between the predicted and the observed in b). Since there are positive and negative distances, a solution is the absolute value as in c) and d) or use the square as in a); e); and f).

Since the models will be compared in nominal and real terms, which may imply an effect in units of measurement, emphasis is placed on the average absolute percentage error, as well as on the two statistics U1 and U2. With respect to U1, values close to zero imply better predictive capacity, considering that U1 is bounded between 0 and 1. With respect to U2, the mark to consider is the value of 1, if U2 is greater than 1, the prediction is bad, if it is equal to 1, it is indifferent to predicting the lagging value, while, if it is less than 1, there is a good predictive process (Table 4).

Table 4. Results of the statistics of goodness of fit.

	MSE	MPE	MAE	MAPE	U1	U2
Nominal corn	26030.77	-0.186	117.5349	4.762	0.031	0.9824
Real corn	42044.6	-0.1851	150.9543	4.7406	0.0315	0.9874
Nominal barley	12872.73	0.0794	80.1353	4.2807	0.028	0.9412
Real barley	22565.65	-0.2313	105.1972	4.2623	0.0287	0.9403
Nominal wheat	45276.82	-0.2655	157.4357	5.0745	0.0332	0.979
Real wheat	80161.98	-0.2659	207.3332	5.0704	0.0346	0.9832

MSE= mean squared error; MPE= mean percentage error; MAE= mean absolute error; MAPE= mean absolute percentage error; U1= Theil's U1 statistic; U2= Theil's U2 statistic.

With three products and six goodness-of-fit statistics, the comparison makes a total of eighteen possible pairs of comparisons between a prediction model with nominal data in relation to one in real terms. A sign test was used to determine if there is a difference (Wackerly *et al*., 2008), under the hypothesis that the predictive capacity is the same against the alternative that they differ, a total of 12 negative (or six positive) differences were found, which with an approximate probability value of 10% the rejection region is 0 to 5 and 13 to 18, negative (nominal minus real). Therefore, the hypothesis of equality of predictive power in nominal models compared to real ones is not rejected.

Conclusions

It is found that in the problem of making a prediction using nominal data or real data for corn, wheat and barley, in Mexico, there is no statistically significant difference between both types of data. This implies that for a decision maker in the construction of predictors, they can do so via nominal or real data indistinctly. This can be useful depending on the objective either to refer to a base period or in different periods.

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