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Effect of Production Costs on the Price per Ton of Sugarcane: The Case of Brazil

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Abstract

The costs of agricultural inputs added to those of labor represent almost a third of the total cost of Brazilian sugarcane production. This study analyzes the behavior of the price per ton of sugarcane in Brazil, relating it to the main production costs of this cultivation. Twelve price indicators from January 2015 to December 2020 were evaluated. First, the data were adjusted to a multiple linear regression model to identify the significant variables on variation in the price per ton of sugarcane. Then, the Monte Carlo simulation was used to measure the level of certainty of occurrence of these variables, and forecasts were obtained from the adjustment of ARIMA models. The results showed the influence of the costs of diesel oil, two agricultural pesticides, and daily laborers on the price of sugarcane, besides an increasing trend of its, providing relevant short-term projections for decision-making about investments in the agribusiness sector.

Keywords: Brazilian agribusiness, sugarcane production, linear regression, Monte Carlo simulation, ARIMA models

1. Introduction

In the last four decades, the cultivation of sugarcane has had great advances in Brazilian agriculture due to the climatic conditions and characteristics of the sugar cycle ideal production (Bigaton et al., 2017; Amorim et al., 2019). Currently, the country is a world reference in sugarcane production technologies and also stands out in the production of sugar and the biofuel ethanol, representing a constantly expanding market (Gilio & Moraes, 2016; Demczuk & Padula, 2017; Rodrigues & Rodrigues, 2018) being one of the examples of partial or total substitution of oil in the world (Chico, Santiago & Garrido, 2015).

Brazil produced about 657 million tons of sugarcane processed in the 2020/2021 harvest (with average productivity of 76 tons per hectare), of which 92% is accounted by the Center-South region of the country (which includes the states of the South, Southeast and Midwest regions), while the remaining 08% fall to the states of the North-Northeast region (UNICA, 2021). The highest concentration of this cultivar is in the state of São Paulo, followed by the states of Goias and Minas Gerais.

Also in 2020, Brazil was the world's largest producer of sugar, with 38 million tons, and the second largest producer of ethanol, with 35 billion liters (UNICA, 2021). Occupying the first place as the world's largest producer of ethanol are the United States of America, a country that uses other production technologies based on the cultivation of corn as a raw material, which is less efficient in terms of rational use of the land and energy spent in the process of transforming raw material into ethanol.

Therefore, the crop of sugarcane corroborates in a relevant way for the development of Brazil, being considered "a commodity valued by the capacity that it has to generate clean and renewable energy and to replace part of the global energy matrix, currently focused on the use of hydrocarbon fuels of fossil origin" (Farias, 2009, p. 420).

However, the sugar and alcohol sector has been experiencing economic and financial instability in the last harvests. One of the factors attributed to this is the high level of the world sugar stock and also the price of hydrated ethanol in the domestic market (Novacana, 2018; Oliveira & Andrade, 2020). In this sense, other countries such as Thailand have been growing significative way in sugar exportation, so there is increasing competition in the world market (Kotyza et al., 2021). These indicators, in the view of Demczuk and Padula (2017), contribute to the indebtedness of this sector and have implications for production costs.

Some characteristics affect the production cycle and productivity of sugarcane, such as: technology used, choice of cultivar variety, genetic improvement, soil preparation, planting techniques, agricultural management, pest and disease control, crop treatment, harvesting and sugarcane field reform (Bigaton et al., 2017; Amorim et al., 2019).

In this regard, the use of agricultural inputs, such as diesel oil, fertilizers, correctives (limestone and plaster), herbicides, fungicides, and insecticides have become essential in the stages of planting and in the cultural treatments in order to guarantee the productivity of this crop (Bigaton et al., 2015; Bigaton et al., 2017; Amorim et al., 2019).

The average productivity of sugarcane in Brazil in 2020 was 76 tons per hectare (CONAB, 2020). However, when the correct management is adopted (liming, fertilization, crop treatments and irrigation), productivity can reach rates above 150 tons per hectare (Oliveira et al., 2012). In this case, by carrying out all stages of planting and cultural treatments, the sugarcane producer would have a higher cost (40% on average) (Bigaton et al., 2017), since the highest production costs of this crop are with agricultural inputs (Oliveira et al., 2012). On the other hand, Bigaton et al. (2015) state that the costs of agricultural inputs added to those of labor represent, on average, 30% of the total cost of sugarcane production. Colaço and Molin (2017) and Amorim et al. (2019) indicate that the use of a variable rate, that is, the application of corrective measures according to each point analyzed by management area, can reduce the use of inputs.

In this sense, several studies have been carried out on the production costs of the main inputs for the production of sugarcane (Bigaton et al., 2015; Zilio & Lima, 2015; Gilio & Moraes, 2016; Martins et al., 2018; Rodrigues & Rodrigues, 2018; Amorim et al., 2019; Amorim et al., 2020). However, there is a gap with respect to the variation of the main costs of production of this raw material (inputs and labor), as well as the impact of such costs in the variability of the price per ton of sugarcane, which are latent issues for the sugar-energy sector. A search in two existing scientific databases that are most popular in Brazil, SciELO and Scopus, pointed out that there were no studies that investigated these indicators in a comparative and detailed way, for the last ten years.

In Brazil, the price paid for sugarcane (US$ / ton) is defined by São Paulo State Sugarcane, Sugar, and Ethanol Producers Council (Consecana), an association built by the Organization of the Center-South Sugarcane Planters (Orplana) and by Sugarcane Industry Union (UNICA), which aims to support the relationship between sugarcane producers and the industries that buy and process this raw material.

The price per ton of sugarcane is obtained based on the quality of the raw material, that is, of Total Recoverable Sugar (TRS), and is calculated from the amount of TRS in kilogram (kg), per ton of sugarcane, multiplied by the TRS price (US$ / kg of TRS). To estimate the price of the TRS, it is obtained a weighted average of the value (received by the mill) of nine products sold in the domestic and foreign markets. These products are: white sugar from the domestic market; white sugar from the foreign market; Very High Polarization (VHP) sugar for export; anhydrous fuel ethanol; hydrated fuel ethanol; industrial anhydrous ethanol; hydrated industrial ethanol; anhydrous export ethanol, and hydrated export ethanol.

Given the relevance of sugarcane crop to Brazilian agribusiness, the aim of this work is to analyze the behavior of the price per ton of sugarcane in this state, relating it to the main production costs (inputs and labor) associated with this cultivation. Specifically, it is intended to identify which variables, from their costs, significantly have influenced the price variation per ton of sugarcane, to measure the level of certainty associated with the occurrence of these variables, and to obtain forecasts for each of them from adjustment of Autoregressive Integrated Moving Average (ARIMA) models, in order to understand the fluctuations in the prices.

As it occurs under conditions of uncertainty, this activity requires tools, from decision-makers, to better assess which inputs to use in the production of sugarcane, ensuring lower cost and greater financial return. Thus, in addition to the ARIMA models, the Monte Carlo Simulation stands out as a viable tool to be used to measure the level of certainty of certain production costs relevant to the price of this crop (Silva et al., 2019), the which can be previously identified through regression models.

2. Method

This is descriptive research, in terms of objectives, with a quantitative approach. The events that took place are investigated by means of 12 variables or indicators related to the main production costs of sugarcane (diesel oil, limestone, fertilizers, insecticides, fungicides, herbicides, daily laborer, and tractor driver), described in Table 1.

To mitigate the effect of serial autocorrelation, average monthly values, both for a ton of sugarcane than production costs, were used, regarding the state of São Paulo, Brazil, during the period from January 2015 to December 2020. Data were made available by the Brazilian Institute of Agricultural Economics (IEA, 2021).

First, the data for the variables in Table 1 were analyzed descriptively, that is, by means of graphs, tables, and descriptive measures. Then, a linear regression model was adjusted from the dependent variable (response) Sugarcane_price, as a function of the other independent (or explanatory) variables described in Table 1.

2.1 Multiple Linear Regression Model

Suppose that a dependent variable (response) Y is related to a set of $k$independent variables (explanatory or predictive) $\boldsymbol{X} = (X_1, X_2, \dots, X_k)$, which can be numeric or not, and that a function relates these variables. Thus, a multiple linear regression model is given by:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon \tag{1}$$

where ϵ are random variables (random error) with zero mean and variance σ^2. The errors, by hypothesis, must be normal and not correlated.

Table 1. Codes and description of the surveyed variables

Code	Variable Type	Description of the variable
Sugarcane_price	Dependent	Average monthly price of the sugarcane (in the field) in the state of São Paulo (US$/ton)
DO	Independent	Average monthly price of the diesel oil (US$/liter)
Limestone	Independent	Average monthly price of the dolomitic limestone (US$/ton)
Ferti1	Independent	Average monthly price of the fertilizer 04-20-20 (US$/ton)
Ferti2	Independent	Average monthly price of the fertilizer 20-05-20 (US$/ton)
Insecti1	Independent	Average monthly price of the insecticide Tiametoxam [141 grams / liter] (US$/liter)
Insecti2	Independent	Average monthly price of the insecticide Imidacloprid [700 grams / kg] (US$/kg)
Fungi1	Independent	Average monthly price of the fungicide Piraclostrobin [250 grams / liter] (US$/liter)
Fungi2	Independent	Average monthly price of the fungicide Tebuconazol [200g/l] + Trifloxistrobin [100 grams / liter] (US$/liter)
Herbi1	Independent	Average monthly price of the herbicide Dimethylammonium [806 grams / liter] (US$/liter)
Herbi2	Independent	Average monthly price of the herbicide Paraquate [200 grams / liter] (US$/liter)
DL	Independent	Average price paid to the daily laborer (US$/day)
TD	Independent	Average price paid to the tractor driver (US$/month)

Source: Prepared by the authors (2022).

The values of the coefficients or parameters $\beta_0, \beta_1, \beta_2, \dots, \beta_k$ can be estimated by the method of ordinary least squares, which obtains estimates $b_0, b_1, b_2, \dots, b_k$, respectively, that minimize the sum of the squares of the residuals (Oliveira & Andrade, 2020).

Then, the significance of the model is tested through the hypothesis test for the existence of linear regression. As α is the level of significance of the test, it is concluded that the model can explain and predict the variable Y if the probability of significance obtained through the data (p-value) is less than or equal to α (Jobson, 1991).

Similarly, the process of selecting independent variables for the adjusted regression model is performed by testing hypotheses for the existence of parameters $\beta_0, \beta_1, \beta_2, \dots, \beta_k$. For a significance level α, the hypothesis Ho $(\beta_i = 0), i = 1,2, \dots, k$, is rejected if the p-value of the test is less than or equal to α (Oliveira & Andrade, 2020).

Once the model has been defined and its parameter estimates have been obtained, the quality of its fit to the data must be evaluated using the multiple determination coefficient (R-sq) and adjusted multiple determination coefficient (R-sq-adjust), where R-sq and R-sq-adjust vary between 0% and 100%. The closer R-sq and R-sq-adjust is to 100%, the better the adequacy of the model to the data (Jobson, 1991).

Three auxiliary measures are also considered to verify the assumptions of the regression: I) For the diagnosis of multicollinearity (cross-correlation between independent variables), the Variance Inflation Factor (VIF) statistic was used, which is calculated by estimating each independent variable as if it were dependent, regressing it in relation to the others. If $\text{VIF} < 1$, there is no multicollinearity; $1 \leq \text{VIF} \leq 10$, multicollinearity is acceptable; $\text{VIF} > 10$, multicollinearity is problematic (Oliveira & Andrade, 2020); II) The analysis of the serial autocorrelation is performed using the Durbin-Watson (DW) test. As α is the level of significance of the test, it is concluded that there is no serial autocorrelation of the residuals if the DW statistic is close to 2.0. The normality of the residues is also verified by the Anderson-Darling test, which concludes that the distribution of the residues is normal if p-value > α (Jobson, 1991).

The systematization and statistical analysis of the data were performed using the Minitab software. For all the tests described above, a significance level of α at 5% was considered.

2.2 Monte Carlo Simulation (MCS)

To identify the probability (or level of certainty) of the occurrence of average costs considered significant in the regression model, as well as the average price per ton of sugarcane, the cumulative frequency generated from the MCS was used in the Oracle Crystal Ball software, an extension of Excel*,* in order to provide estimates using a stochastic approach (Abreu & Amorim, 2017).

MSC is a numerical method that uses random numbers to solve mathematical problems for which an analytical solution is not known. MCS uses models capable of generating possible results from a range of values, in the form of a probability distribution, in which there is inherent uncertainty. The lower and upper values used in the ranges are obtained from the standard deviation (obtained from the descriptive analysis of the simulated data), identifying the level of certainty of occurrence of the variable of interest (Silva et al., 2019; Abreu & Amorim, 2017).

All assumptions (input variables) were made using the normal probabilistic model due to the low dispersion of the values presented in the descriptive analysis. In this way, the possible values for the variable of interest are simulated using resampling and the average result of the process is given by:

$$a_j = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

where $a_j, j = 1,2,\ldots,m$ is the average MCS result for the j_th variable a of interest, m is the number of variables considered, $x_i, i = 1,2,\ldots,n$ is the individual result of the i_th iteration, and n is the number of simulations or iterations. Thus, 50,000 iterations were performed (maximum number of iterations that the Crystal Ball software permits).

2.3 Autoregressive Integrated Moving Average (ARIMA) Models

Finally, to make forecasts for the price per ton of sugarcane and for the production costs, considering a horizon of twelve months, the parametric models of Box and Jenkins, also called Autoregressive Moving Average [ARMA(p,q)] models, were used, where p stands for the order of the auto regressive process and q is the order of the moving average process. The ARMA(p,q) models are given by (Morettin & Toloi, 2004):

$$\phi(B)z_t = \theta(B)a_t \tag{3}$$

wherez_t is the price on the period t, $\phi(B) = (1 - B\phi_1 - B^2\phi_2 - \cdots - B^p\phi_p$ and $\theta(B) = (1 - B\theta_1 - B^2\theta_2 - \cdots - B^q\theta_q$. The terms $\phi(B)$ and $\theta(B)$ are polynomial functions of delay operator B, such that $Bz_t = z_{t-1}$ and $Ba_t = a_{t-1}$ and that represent the autoregressive component and the moving average component, respectively. It is assumed, therefore, that such processes are stationary and invertible, that is, that the roots of $\phi(B)$ and $\theta(B)$ are outside the circle of unit radius. It is further assumed that $\{a_t, t \in Z\}$ is a white noise, that is, a normally distributed random variable with zero mean and constant variance σ^2, and not correlated (Box et al., 1994).

When series are not stationary, one or more differentiations allow them to become. The differentiated series are called Autoregressive Integrated Moving Average [ARIMA(p,d,q)] models, where d is the number of differentiations performed until the series becomes stationary.

In general, the model construction strategy consists of an iterative cycle composed of three stages: identification, estimation and diagnosis. Estimates of these parameters must be obtained through some numerical procedure. In this work, such estimates were determined using Minitab software.

The significance of the terms (autoregressive and/or moving average) of the ARIMA(p,d,q) models is identified through the hypothesis test to verify the existence of each term. As α is the level of significance of the test, it is concluded that the term is not null if p-value is less than or equal to α (Box et al., 1994).

To verify the adequacy of the model's fit to the data, the Akaike information criterion (AIC) was used. The AIC is a model selection criterion proposed by Akaike (1974) given by:

$$\text{AIC} = -2\ln(L) + 2k \tag{4}$$

where $\ln(L)$ = log-likelihood function and k= number of parameters. The model with the maximum likelihood is the one that fits the data the best. Then, the best model is the one that has the lowest AIC value (Oliveira & Andrade, 2012).

To determine whether the chosen models satisfy the assumptions that the residuals are independent, the Box-Pierce Chi-Square statistic (Ljung-Box) was used. In the latter case, considering a significance level α for the test, if p-value is greater than α, it is possible to conclude that the residuals are uncorrelated (Morettin & Toloi, 2004).

For all the tests described above, a significance level of α at 5% was considered.

3. Results and Discussion

Figure 1 illustrates the fluctuations in the average monthly price of sugarcane (US$ / ton) and of the variables corresponding to the main production costs in the period from January 2015 to December 2020.

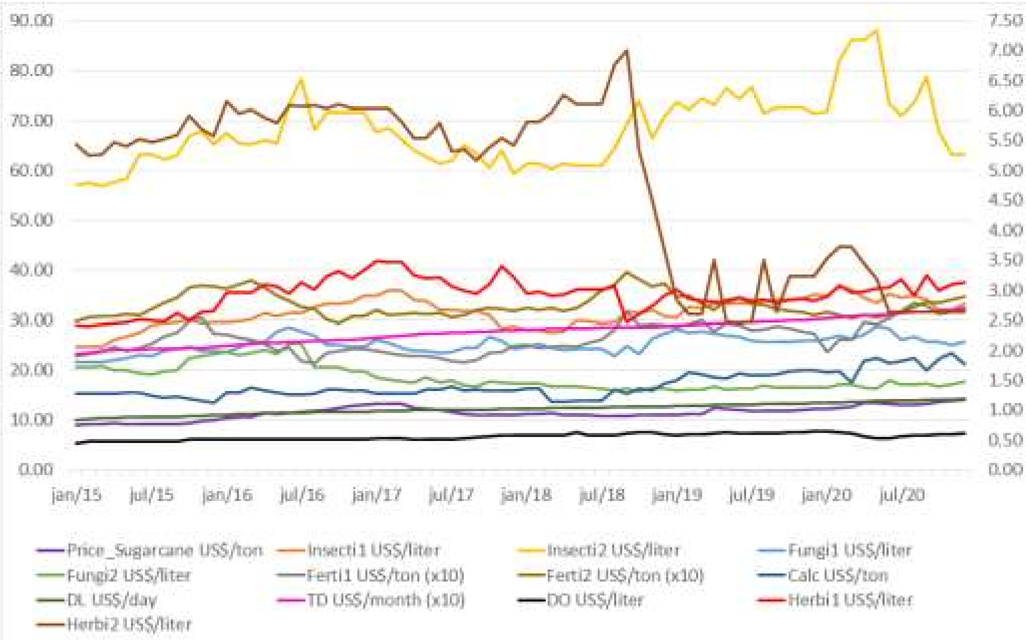


Figure 1. Evolution of the average monthly price of sugarcane (US$/ton) and production costs from January 2015 to December 2020

Source: Brazilian Institute of Agricultural Economics (IEA, 2021)

It should be noted that the average monthly price per ton of sugarcane started to rise in late 2015, remaining so until January 2017. From then on, it suffered a sharp drop in 2017, stabilizing during 2018. In 2019, it started to rise up again, having a significant increase in 2020, when the health crisis started (Covid-19 pandemic).

To show in more detail the degree of variation of the variables observed in Figure 1, a descriptive analysis is presented in Table 2, which shows the average monthly values of the variables, as well as their respective dispersion measures.

Table 2 shows a moderate price dispersion of the average monthly prices of the herbicide Paraquate (Herbi2). On the other hand, the fungicide Piraclostrobina (Fungi1) and the fertilizer 20-05-20 (Ferti2) had the smallest relative price variations. None of the inputs showed high relative price dispersion in the analyzed period. Even with an important exchange rate fluctuation (the rise of the US Dollar against the value of the Brazilian Real) in this period, inputs showed a trend opposite to that predicted in the literature (Oliveira & Andrade, 2020).

Dimethylammonium (Herbi1) is used to control broadleaf *dicotyledonous* weeds, and Paraquat (Herbi2) is used to control narrowleaf weeds or *monocotyledonous* grasses. It is observed that only the average monthly price of the Herbi2 had an important change in level over time. It peaked in September 2018 and then showed a significant reduction of almost 60%. This is due to the entry of similar products on the Brazilian market, which resulted in price competition. Herbi1 presented prices with a relative dispersion considered low, that is, with little variation around the average value.

Table 2. Descriptive measures referring to indicators related to the price and cost of production of sugarcane in the period from January 2015 to December 2020

Variable	Average value	Standard deviation	Minimum value	Maximum value	Coefficient of variation*
Price_Sugarcane (US$/ton)	11.52	1.32	9.04	14.09	11.4%
DO (US$/liter)	0.56	0.05	0.45	0.65	9.4%
Limestone (US$/ton)	17.01	2.53	13.45	23.52	14.9%
Insecti1 (US$/liter)	31.57	2.87	24.68	36.75	9.1%
Insecti2 (US$/liter)	68.02	6.96	56.87	88.08	10.2%
Fungi1 (US$/liter)	25.26	1.70	21.63	28.74	6.8%
Fungi2 (US$/liter)	18.51	2.54	15.75	25.39	13.7%
Herbi1 (US$/liter)	2.93	0.27	2.40	3.48	9.1%
Herbi2 (US$/liter)	4.80	1.40	2.45	7.01	29.2%
Ferti1 (US$/ton)	264.27	31.01	213.76	335.21	11.7%
Ferti2 (US$/ton)	330.16	23.47	294.88	395.71	7.1%
DL (US$/day)	12.28	1.10	10.12	14.22	8.9%
TD (US$/month)	277.51	24.40	233.11	321.93	8.8%

*The coefficient of variation (CV) measures the relative dispersion of the data around the mean. Variation field: CV ≤ 15% (low dispersion); 15 < CV ≤ 30% (moderate dispersion); CV > 30% (high dispersion) (Jobson, 1991).

Source: Prepared by the authors (2022)

Insecticides are responsible for eliminating the main pest insects in sugarcane production, such as sugarcane borer (*Diatraeasaccharalis*), sugarcane weevil (*SphenoforusLevis*), leafhopper root (*Mahanarvafimbriolata*), Migdólus beetle (*Migdolusfryanus*), ants (*Atta laevigata, Atta bisphaerica* and *Atta capiguara*) and termites (*Hetterotermes tenuis, Hetterotermeslongiceps* and *Procornitermestriacifer*) (Dinardo Miranda et al., 2012). It should be noted that, in the analyzed period, the variations in the average monthly price of Imidacloprid (Insecti2) were greater than the oscillations observed in the average monthly price of Tiamethoxam (Insecti1). However, the two products showed similar growth and decrease trends. The control of insect pests is essential for a high productivity of the sugarcane crop (Oliveira et al., 2012), in a way that the prices of these inputs can substantially affect the cost of production of this crop and others, because they are sensitive to the supply and demand of the product.

The prices of fertilizers 4-20-20 (Ferti1) and 20-5-20 (Ferti2) had low dispersion in relation to their average values (mainly Ferti2), when compared to the prices of other inputs used in the production of sugarcane over the analyzed period. In addition, the prices of the two fertilizers showed very similar trend movements (Figure 1), with some seasonal periods of increase, especially between the months of May and November, which are periods of harvest and management of crop treatments for new crops in Brazil. Fertilizers have the greatest impact on the production costs of sugarcane (Rossi & Fernandes, 2020). and an alternative to reduce costs with the application of fertilizers is to use the variable rate system (TV). Colaço and Molin (2017) and Baio et al. (2018) report that this technique has been shown to be more advantageous within precision agriculture, providing a reduction in the use of inputs. The fertilizers are applied in order to satisfy crop needs in terms of nitrogen (N), phosphorus (P) and potassium (K) (Chico, Santiago & Garrido, 2015).

Fungicides are used to combat fungal diseases, such as pineapple rot, red rot, *Fusarium fusariose* rot and rust, caused by *Ceratocystis paradoxa*, *Colletotrichum falcatum* and *Fusarium moniliforme,* and *Puccinia melanocephala*, respectively. When compared to the other inputs, the prices of the fungicides Pyraclostrobin (Fungi1) and Tebuconazol+Trifloxystrobin (Fungi2) showed low relative dispersions in the analyzed period (mainly Fungi1). Together with fertilizers, fungicides had the smallest relative variations.

Limestone is important for sugarcane because it increases the exploitation of water and soil nutrients, helping the plant to tolerate drought (Caldeira & Casadei, 2010). In addition, some authors claim that there is a positive relationship between the dosage of limestone and sugarcane productivity (Caldeira & Casadei, 2010; Silva et al., 2014). Although a non-significant relative variation was observed during the analyzed period, since 2018, the average monthly price of limestone has remained on the rise.

On the other hand, the average monthly price of diesel oil (DO), which had been on the rise since 2015, fell by almost 20% from January to May 2020, mainly as a result of the beginning of the Covid-19 pandemic, when the barrel of oil reached the lowest recorded price, for the last twenty years (Torquato, Sachs & Nachiluk, 2020). In sugarcane crop, the greatest consumption of DO occurs in the planting and harvesting processes.

With regard to labor costs for daily laborers (DL) and tractor drivers (TD), even with low relative dispersions, that is, with little variation around the average costs, these remained on the rise with considerably similar fluctuations throughout the analyzed period.

In order to show how much of the variation in the average monthly price paid per ton of sugarcane is due to the set of independent variables described in Table 1, a multiple linear regression model was adjusted from the sample data. Thus, the regression model obtained is given by:

$$\text{Sugarcane\_price} = -3.900 - 7.520\ \text{DO} + 0.144\ \text{Insecti1} + 1.710\ \text{Herbi1} + 0.818\ \text{DL} \quad (5)$$

Table 3 shows a summary of the regression results and an analysis of the adequacy of the model adjusted to the data. As for the significance of the regression model (ANOVA with p-value = 0.001 < 5%), there is that the adjusted model can explain and predict the average monthly price per ton of sugarcane. Likewise, the parameters of four variables were confirmed to be significant to the model (p-values = 0.000 < 5%), and acceptable multicollinearity (VIF< 10) was obtained for them.

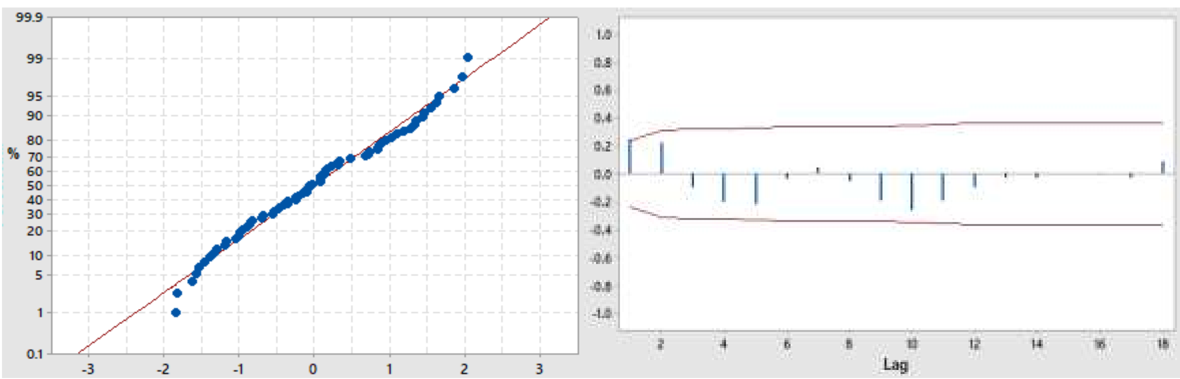
Table 3. Summary of the results of the multiple linear regression (average monthly price per ton of sugarcane)

Predictor	Coefficient	p-value	VIF	
Constant	-3.900	0.001	-	
DO	-7.520	0.001	3.26	
Insecti1	0.144	0.001	2.18	
Herbi1	1.710	0.001	1.55	
DL	0.818	0.001	4.43	
S = 2.336	R-sq = 90.69%	R-sq-adjust = 90.13%		
Analysis of Variance (ANOVA)				
Variation	Degrees of freedom	Sum of squares	Mean squares	p-value
Regression	4	3559.2	889.79	0.001
Residual Error	67	365.6	5.46	
Total	71	3924.8		
Residual normality test p-value (Anderson-Darling) = 0.379			D-W Statistics = 1.695	

Source: Prepared by the authors (2022)

The degree of adjustment of the model based on the multiple determination coefficient (R-quad in Table 3) also established that almost 90% of the variation in the average monthly price per ton of sugarcane can be explained by the independent variables considered significant.

In addition, the Anderson-Darling test (p-value = 0.379 > 5%) confirmed the normality of the residuals, while the Durbin-Watson statistic (DW = 1.695) showed that these are not autocorrelated, according to Figure 2.



(a) (b)

Figure 2. Normal probability (a) and autocorrelation function (b) plots for residuals (95% confidence limit for autocorrelations)

Source: Prepared by the authors (2022)

Thus, it was ensured that the independent variables DO (Average monthly price of the diesel oil, in US$ / liter), Insecti1 (Average monthly price of the insecticide Tiametoxam 141 g/l, in US$ / liter), Herbi1 (Average monthly price of the herbicide Dimethylammonium 806 g/l, in US$ / liter) and DL (Average price paid to the daily laborer, in US$ / day) were the ones that, in fact, most associated with the behavior of the price per ton of sugarcane, respectively.

The variables Insecti1, Herbi1, and DL presented positive coefficients, that is, these variables move (individually) in the same direction as the price per ton of sugarcane, when the other variables are kept constant.

In fact, Oliveira and Andrade (2020) show an increasing trend in the General Price Index paid, by farmers from the state of São Paulo, for pesticides since 2015, following the rise of the average monthly price per ton of sugarcane in the same state, mainly in the last two years. The control of insect pests and weeds is critical to achieving high productivity in the fields of sugarcane (Oliveira et al., 2012). Therefore, the prices of these inputs tend to influence the marketing value and the profitability of this crop.

With regard to daily laborer, the results of this work differ from those obtained by Bigaton et al. (2015), who observe a reduction in the number of employees at the expense of increasing the mechanization of this crop and decreasing production costs. In this case, the positive variation in daily laborer value caused by the wage increase implied a positive variation in production costs and, consequently, in the price per ton of sugarcane. Therefore, it can be deduced that, during the analyzed period, temporary labor has been used more than fixed labor, which, according to Bigaton et al. (2017), has a relevant impact on the costs involved in the stage of sugarcane cultivation.

On the other hand, the diesel oil (DO) variable appeared with a negative coefficient, indicating that this variable moves in the opposite direction to the price per ton of sugarcane, when the other variables are kept constant. However, the rise of the US Dollar against the value of the Brazilian Real drives the demand for ethanol (Demczuk & Padula, 2017; Oliveira & Andrade, 2020), decreasing the demand and the price of other fuels, among them, DO. Besides, DO is a substitute good for ethanol, and an increase in the price of DO should lower its demand and increase the demand for ethanol thus raising its price. Therefore, when diesel oil price increases, two forces should push the prices of sugar cane up a cost component and a demand component.

In order to understand the certainty levels associated with the average price per ton of sugarcane, results of the MCS are presented, summarized in the cumulative frequency graph in Figure 3.

The simulation results in Figure 3 show that the range between US$ 10.36 and US$ 12.66 contains the average prices paid per ton of sugarcane with a certainty level of 68.13%, for an average of US$ 11.51, and standard deviation of US$ 1.15.

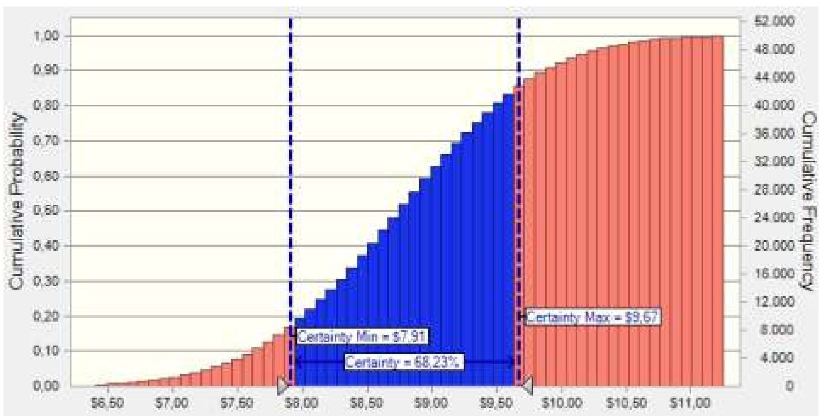


Figure 3. Cumulative frequency graph for Sugarcane_price (US$ / ton)
Source: Prepared by the authors (2022)

These results provide information, based on the history of analyzed prices, which can minimize uncertainties and base decisions on pricing and risking in product transactions, giving indications of the revenue to be obtained through the cultivation of sugarcane.

To analyze the levels of certainty associated with the main average costs of production of this crop (considered significant by the regression model), the other MCS results are presented, summarized in the cumulative frequency graphs in Figures 4 to 7, below.

Figures 4 to 7 show the cumulative frequency graphs referring to the average monthly prices of the diesel oil (DO), the average monthly prices of the insecticide Tiametoxam (Insecti1), the average monthly prices of herbicide Dimethylammonium (Herbi2) and the average monthly prices paid to the daily laborer (DL), respectively.

The simulation results indicated that:

- The range between US$ 0.50 and US$ 0.62 contains the average prices of the DO with a certainty level of 71.74%, for an average of US$ 0.56, and a standard deviation of US$ 0.06;
- The range between US$ 61.26 and US$ 74.86 contains the average prices of Insecti1 with a certainty level of 68.62%, for an average of US$ 68.06, and a standard deviation of US$ 6.80;
- The range between US$ 2.61 and US$ 3.23 contains the average prices of Herbi1 with a certainty level of 67.66%, for an average of US$ 2.94, and a standard deviation of US$ 0.29;
- The range between US$ 11.05 and US$ 13.51 contains the average prices of the DL with a certainty level of 68.52%, for an average of US$ 12.28, and a standard deviation of US$ 1.23.

When the level of uncertainty is high and its causes varied, seemingly simple pricing problems can quickly become unmanageable. In this case, knowledge based on the relative frequency of occurrence of the main average sugarcane production costs is appropriate for decision-making in risky situations, since the economic/financial viability of the sugarcane crop is associated with the price paid to inputs and labor used in the production process of this crop.

Figure 4. Cumulative frequency graph referring to diesel oil (US$ / liter)
Source: Prepared by the authors (2022)

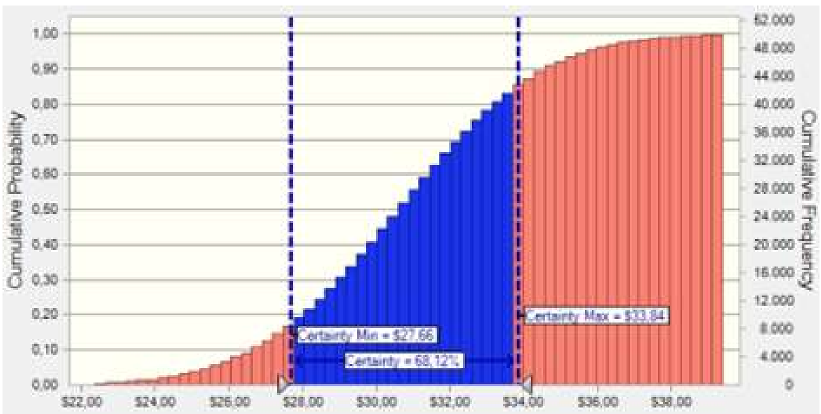


Figure 5. Cumulative frequency graph referring to Insecti1 (US$ / liter)
Source: Prepared by the authors (2022)

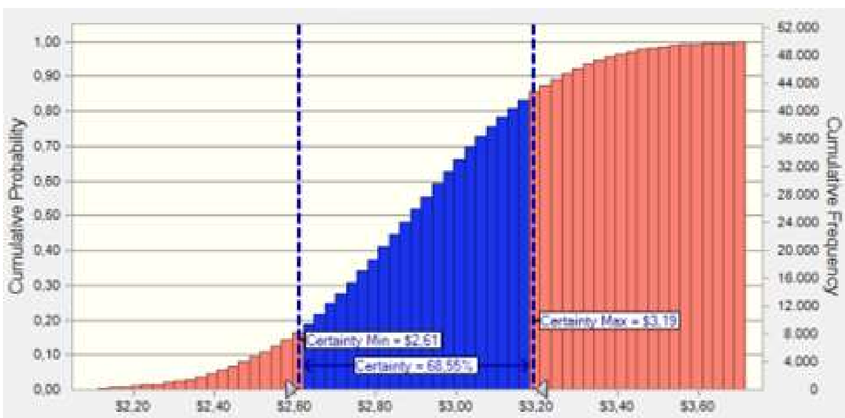


Figure 6. Cumulative frequency graph referring to Herbi2 (US$ / liter)
Source: Prepared by the authors (2022)

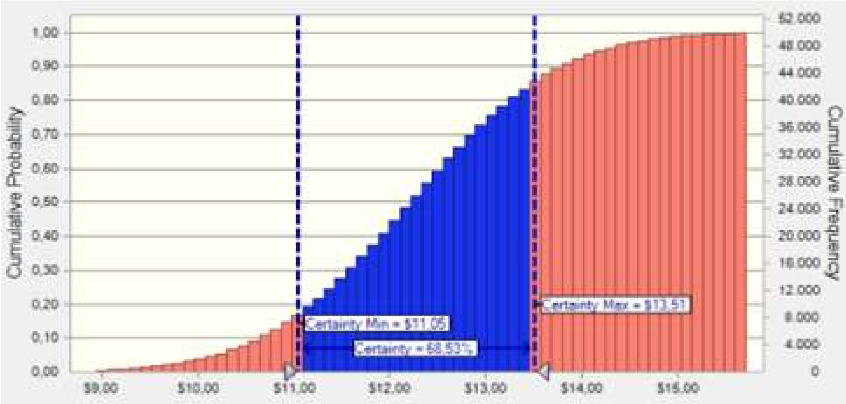


Figure 7. Cumulative frequency graph referring to daily laborer (US$ / liter)
Source: Prepared by the authors (2022)

Finally, ARIMA models were adjusted to the data and forecasts obtained for a 12-month horizon (January 2021 to December 2021). Table 4 and Figure 8 summarize the models obtained and show the adjusted values for each variable, respectively.

The results in Table 4 indicate that all adjusted ARIMA models fulfill the assumptions and are adequate to predict the prices of the variables under study and Figure 8 shows that the predicted values by the models follow the movements of the real prices series.

Table 4. Summary of the adjustment of the ARIMA models from January 2015 to December 2020

Variable	Adjusted Model	Coefficient	Standard error	Coefficient (p-value)	AIC	Ljung-Box Statistics (p-value)
Sugarcane_price	ARIMA (1,1,1)	$\phi_1 = 0.721$	0.208	0.001	−2.612	Lag12 = 0.956 Lag24 = 0.540 Lag36 = 0.805
		$\theta_1 = 0.436$	0.267	0.007		
DO	ARIMA (2,1,0)	$\phi_1 = 0.419$	0.118	0.001	−2.624	Lag12 = 0.388 Lag24 = 0.390 Lag36 = 0.681
		$\phi_2 = -0.242$	0.118	0.044		
Insecti1	ARIMA (1,0,0)	$\phi_1 = 0.985$	0.004	0.001	−2.594	Lag12 = 0.861 Lag24 = 0.656 Lag36 = 0.703
Herbi1	ARIMA (1,0,0)	$\phi_1 = 0.983$	0.006	0.001	−2.604	Lag12 = 0.861 Lag24 = 0.656 Lag36 = 0.703
DL	ARIMA (1,1,0)	$\phi_1 = 0.892$	0.037	0.001	−2.588	Lag12 = 0.547 Lag24 = 0.372 Lag36 = 0.659

Source: Prepared by the authors (2022)

Figure 8. Prices and adjusted values (AV) for each variable from ARIMA models from January 2015 to December 2020
Source: Prepared by the authors (2022)

Table 5 shows the forecasts (with confidence limits at 95%) and real values for the prices per ton of sugarcane and the production costs considered significant, respectively, for the period from January 2021 to December 2021.

Table 5. Forecasts with confidence limits at 95% (in black) and real values (in red) for the price per ton of sugarcane and the production costs from January 2021 to December 2021

	Sugarcane_price ARIMA (1,1,1)	DO ARIMA (2,1,0)	Insecti1 ARIMA (1,0,0)	Herbi1 ARIMA (1,0,0)	DL ARIMA (1,1,0)
Jan/21	14.204 (13.74) [13.696; 14.711]	0.618 (0.64) [0.589; 0.648]	33.273 (34.96) [31.409; 35.138]	3.129 (3.09) [2.846; 3.412]	14.279 (14.28) [14.240; 14.319]
Feb/21	14.284 (14.13) [13.458; 15.110]	0.617 (0.69) [0.566; 0.668]	33.267 (35.13) [30.629; 35.903]	3.127 (3.09) [2.728; 3.527]	14.340 (14.34) [14.252; 14.428]
Mar/21	14.342 (14.43) [13.222; 15.462]	0.615 (0.74) [0.550; 0.679]	33.260 (35.04) [30.031; 36.489]	3.127 (2.99) [2.637; 3.616]	14.401 (14.40) [14.253; 14.548]
Apr/21	14.384 (14.70) [12.989; 15.779]	0.614 (0.73) [0.540; 0.687]	33.253 (35.79) [29.525; 36.982]	3.125 (3.77) [2.561; 3.690]	14.461 (14.45) [14.245; 14.675]
May/21	14.414 (17.44) [12.762; 16.066]	0.614 (0.78) [0.533; 0.695]	33.246 (38.40) [29.078; 37.414]	3.124 (3.25) [2.493; 3.756]	14.520 (14.67) [14.230; 14.810]
Jun/21	14.436 (18.51) [12.543; 16.329]	0.614 (0.79) [0.526; 0.703]	33.239 (37.46) [28.674; 37.805]	3.123 (3.48) [2.432; 3.815]	14.579 (14.67) [14.207; 14.951]
Jul/21	14.452 (20.80) [12.332; 16.571]	0.614 (0.80) [0.519; 0.710]	33.233 (37.63) [28.302; 38.164]	3.122 (3.63) [2.375; 3.869]	14.637 (14.88) [14.177; 15.098]
Aug/21	14.463 (20.34) [12.131; 16.795]	0.614 (0.80) [0.513; 0.716]	33.226 (37.94) [27.955; 38.497]	3.121 (4.05) [2.323; 3.919]	14.695 (14.99) [14.142; 15.249]
Sep/21	14.471 (20.54) [11.938; 17.004]	0.614 (0.82) [0.507; 0.722]	33.219 (38.08) [27.629; 38.810]	3.121 (4.27) [2.273; 3.966]	14.753 (15.09) [14.101; 15.406]
Oct/21	14.477 (21.61) [11.755; 17.199]	0.614 (0.88) [0.501; 0.728]	33.212 (37.25) [27.321; 39.104]	3.119 (4.61) [2.226; 4.011]	14.810 (15.20) [14.054; 15.566]
Nov/21	14.481 (22.01) [11.579; 17.383]	0.614 (0.93) [0.496; 0.733]	33.206 (39.92) [27.027; 39.384]	3.117 (6.38) [2.182; 4.053]	14.867 (15.30) [14.002; 15.731]
Dec/21	14.484 (22.22) [11.411; 17.558]	0.614 (0.93) [0.491; 0.738]	33.199 (40.70) [26.746; 39.652]	3.116 (6.39) [2.139; 4.093]	14.923 (15.30) [13.946; 15.900]

Source: Prepared by the authors (2022)

The forecasts in Table 5 indicate an increasing trend in the prices per ton of sugarcane (about 2.0%) and in daily labor costs (approximately 4.5%) from January 2021 to December 2021. As for the prices of DO, insecti1 and herbi1, the models point to a small drop of 0.4% (on average). However, it can be noted that the adjusted models partially reproduced the behavior of the real prices in 2021, and underestimated them mainly in the second half of the year. Only daily labor costs remained within the confidence limits at 95% established by the adjusted model.

According to Oliveira et al. (2012), "forecasts with many steps forward and using the same adjustment model are not recommended". As data are updated, the adjustment model should be revised in order for the forecasts to be more accurate (Oliveira & Andrade, 2012). In this case, one can observe a need for the models to be updated in about six months (from June 2021).

Table 5 indicates that, in monetary terms, the price per ton of sugarcane would be greater than the increase in production costs in 2021. In fact, the adverse weather conditions affected the summer crop and led to a relevant loss in production, rising the sugarcane price. Furthermore, as a result of the Covid-19 pandemic which had an impact on inflation, the costs of agricultural inputs (most of them are imported) also increased and reduced the profit margins of the sugarcane suppliers and mills. In this sense, organizations have been facing a much more agile and competitive environment which demands new techniques of competition, market attitudes, and production models (Abreu & Amorim, 2018).

Kotyza et al. (2021) point out that the global financial crisis and the Covid-19 pandemic caused a substantial increase in stock market volatility. This fact hit both the supply and the demand in the sugar market, resulting in stock changes. In addition, the conflict between Russia and Ukraine, which began in 2022, also impacted the prices of all classes of commodities in emerging economies, reducing international trade and hampering the normalization of supply chains.

4. Concluding Remarks

The costs of production associated with the price per ton of sugarcane can provide an understanding of oscillations that have occurred over time.

According to the statistical model, the importance of agricultural inputs in sugarcane production costs was evidenced, in particular, the insecticide Tiamethoxam, the herbicide Dimethylammonium and the daily laborer, whose values had the same variation as the price per ton of sugarcane, and also the diesel oil, whose values presented opposite variation.

Among the inputs that most impacted sugarcane production costs, fertilizers 04-20-20 (planting) and 20-05-20 (cultural treatments) stand out. Despite not having been considered significant to the average price paid per ton of sugarcane (by the regression model) and not having presented values with significant relative dispersion, the prices of such inputs show a seasonal pattern of fluctuation. In this sense, using the variable rate fertilizer application system, satisfactory results can be obtained in terms of cost reduction with such inputs.

Based on the methodology used in this work, it was observed that the adjusted models provide relevant short-term projections for decision-making about investments in the agribusiness sector. In a similar way, it is possible to evaluate and associate the price behavior and production costs considering other crops.

The analyzed period, January 2015 to December 2020, included the shock of unexpected disruption to markets during the COVID pandemic. In this sense, a comparison with a more stable period of similar duration could be considered in future works.

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