

EDA and Prediction of International Coffee Prices with a Variety of Algorithms of Machine

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Links

GitHub Link

<https://github.com/montwa/Ryerson>

Data Set Link

<https://federaciondecafeteros.org/app/uploads/2020/01/Precios-%C3%A1rea-y-producci%C3%B3n-de-caf%C3%A9-3.xlsx>

Excel Sheet: 6. Precio OIC Mensual

Abstract

Coffee is one of the greatest drinks that humanity could have ever discovered. The prices of coffee are expressed in US cents per pound of green coffee and many factors affect the prices. The ICO (International Coffee Organization), will collect daily prices from the New York, Germany, and France futures exchanges and will set up a price based on these factors and a variety of conditions.

The idea of this project and after doing an exploratory analysis of the data is to predict the prices of the ICO market given the prices in Europe, more exactly in the countries of Germany and France, as well as in the United States of America of a different variety of Coffee that is grouped as follows: Colombian Mild Arabicas (Colombian Excelso UGQ screen size 14, Colombian Excelso European preparation screen size 15), Other Mild Arabicas (Costa Rica hard bean, Mexico Prime washed, Honduras high grown, Guatemala prime washed, El Salvador Strictly High grown, Guatemala hard bean, Honduras High grown European preparation) Brazilian (Brazil Santos $\frac{3}{4}$ screen size 14/16, Brazil Santos $\frac{2}{3}$ screen size 17/18, Brasil Santos $\frac{3}{4}$ screen size 14/16) and Robustas (Vietnam grade 2, Indonesia EK grade 4, Uganda Standard, Côte d'Ivoire grade 2).

All data for this project comes from Federación Nacional De Cafeteros de Colombia (The Colombian National Coffee Growers), which is the only authorized entity by the government of

Colombia, that is responsible for exporting, buying, and setting the prices of coffee, the website (<https://federaciondecafeteros.org/wp/coffee-statistics/?lang=en>), section Coffee prices, area, and production have an excel file with the data required during this project. The data will be cleaned and checked for any inconsistencies or errors that can alter our results, after that, there will be an Exploratory Data Analysis to check the behavior of the time series data, and to possibly discover new information that could help find important and relevant information about our study. Through a variety of different Machine Learning regression algorithms like linear regression, SVM (Support Vector Machine), KNN regressor (K-Nearest Neighbors), Decision Tree regressor, and Neural Networks, I will intend to predict the future price of the coffee set by the International Coffee Organization.

A variety of tools will be used for this project: Jupyter Notebook, Python, R studio, Microsoft Excel, Github, and Google Documents.

During this project, a variety of questions have to be formulated in order to obtain the best answer to our results. An example of these questions, among many others, are: which is the most accurate algorithm to predict the ICO prices of coffee and why the selection of this algorithm? What will be the future price in the short term given that the model has been adequately trained and formulated? Why is this investigation relevant to the student and how it can help to develop his knowledge not only in exploratory data analysis but as well in machine learning algorithms?

Keywords: coffee, exploratory data analysis, regression analysis, prediction, machine learning algorithms

Literature Review

Coffee has been the most important agricultural product in Colombia, providing livelihood for around two million Colombians (Sanz Uribe et al., 2021, 35). Linear regression has many applications in life, one of them, and the one that I am going to be applying is predicting the price of coffee based on different inputs or variables, this has been already tried by a variety of people using different linear models, Neural Networks, and Support Vector Machines, like in a case study made in India, to forecast Indian green coffee, a study made in Brazil to predict as well the value of the grain using Neural Networks, (Deina et al., 2021, 2)

But why would we want to predict the coffee price? What would be the advantage of doing this? Well, just imagine if coffee growers had been prepared by 2020 when the price of coffee was the highest on the New York stock exchange at US\$1.10 per pound instead of selling the coffee in the harvest of 2019 when prices were below US\$ 1 per pound, (Diario el Mundo, 2021), this fluctuation in prices could have been a great opportunity to growers, and perhaps if is seen from the client or purchaser side, it could be argued that they would want to buy at the lowest prices, creating perhaps a balance in the economy as both ends won't be able to take advantage from each other.

One important factor to be analyzed would be the market size and the demographic impact on different societies around the world, with emerging markets like China, India, and Brazil that constitute 36% of the global GDP (Li et al., 2022, 1) is in these countries where tea consumption is superior to coffee, with the exception of Brazil, and is in these countries where customers would pay a premium price for the symbolic western experience at stores like Starbucks (Li et al., 2022, 2) just for a cup of coffee.

Just imagine for a moment, if the regression analysis to predict the prices is combined as well with an algorithm for coffee selection based on its quality using different techniques like k-Neighbours, Decision Tree, SVM Support Vector Machine, Logistic regression, or Neural Networks, and having these results or classification of superior quality as independent variables in the price regression, and not depending solely on other factors that are not quality, luckily there are new studies that are already doing the first step, like Suarez Pena, on his thesis, to classify based on quality, the results having a prediction of 83% in classification, and Mean Absolute Error (MAE) of 14,61% (Suarez Pena, 2019,100), this would be a big tool not only for coffee tasters but growers and purchasers as well as people who really enjoy drinking quality coffee.

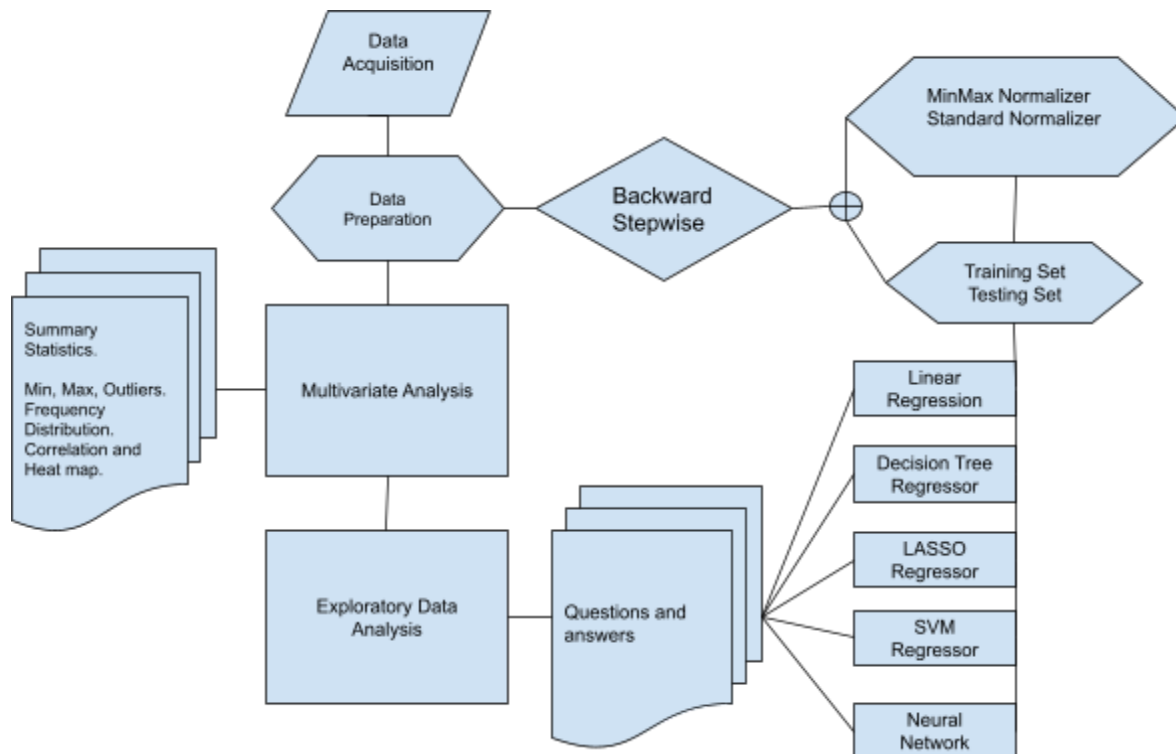
‘Professional investors favour two dominant schools of thought on investing which are Fundamental Analysis and Technical Analysis, and Machine learning techniques are one of the

Technical Analysis, (Siew et al., 2012,2), and some of these algorithms are the ones that I will be using for the project, using examples and getting help from some of the papers published in the scientific community (Sreehari et al., 2018,1) where the author uses Multiple Linear Regression to predict climate, another very interesting article where they use regression tree to predict the Indonesian stock price during the Covid-19 era (Hindrayani, et al.,2020,1), as well as a comparative analysis on linear regression and Support Vector regression (SVR)(Kavitha S, et al.,2016,1) where they analyze a time series data in order to have better prediction and accuracy on their data. Which is the most accurate algorithm to predict the future price of the OIC_prices? The need to choose a different algorithm varies according to the needs of each investigation (Gil Serna, 2012, 82), however the final decision, in this case, will be made once the results of the analysis have concluded.

The project is very important for the student as it opens new fields of thinking in the machine learning and Data Science world, and encourages him to do his own research about topics that the student has never seen or taken and is because of research that new things are discovered.

Overall Methodology

Diagram of an overall methodology



After acquiring the data and preparing it, will be used to extract a summary of Statistics and do an Exploratory Data Analysis in order to answer possible questions that might arise, then the data will be separated into Training Set and Testing Set, and Algorithms like Linear Regression, Decision tree Regression, Lasso Regressor, SVM Regressor, and Neural Network will be used to answer the questions that were formulated in the abstract and to see how our regressors are behaving

When data needs to be normalized, it will be normalized via MinMax Normalizer and Standard Normalizer before applying the algorithms previously mentioned above, however, some of the algorithms will be applied without normalization.

Data Acquisition

The source of the dataset, can be downloaded from the website of the Federación Nacional de Cafeteros de Colombia (National Federation of Coffee Growers of Colombia) here:

<https://federaciondecafeteros.org/app/uploads/2020/01/Precios-%C3%A1rea-y-producci%C3%B3n-de-caf%C3%A9.xlsx>

Even if it contains a variety of sheets, please use the sheet called: **6. Precio OIC Mensual**

It will look like this:

	Precios indicativos OIC por grupos - Promedio Mensual												
	Centavos de dólar por libra												
	Fuente: ICO												
		Suaves colombianos (arábigo)			Otros suaves (arábigo)			Naturales del Brasil (arábigo)			Robustas		
Mes	Precio del indicador compuesto OIC	Nueva York	Europa	Promedio ponderado	Nueva York	Europa	Promedio ponderado	Nueva York	Europa	Promedio ponderado	Nueva York	Europa	Promedio ponderado
Jan-00	82.15	130.12	124.36	130.13	109.17	116.82	111.11	97.67	103.10	97.68	53.62	52.41	53.18
Feb-00	76.15	124.72	118.67	124.73	101.17	110.19	103.44	91.51	96.58	91.51	49.41	47.97	48.85
Mar-00	73.49	119.51	115.78	119.51	98.26	108.13	100.73	89.93	94.78	89.93	47.26	44.73	46.25
Apr-00	69.53	112.67	109.12	112.67	92.41	101.51	94.61	86.46	90.70	86.46	45.21	43.31	44.45
May-00	69.22	110.31	107.85	110.31	91.76	100.99	94.17	87.23	91.01	87.23	45.19	43.01	44.32
Jun-00	64.56	100.30	98.57	100.30	84.10	92.94	86.44	78.32	83.34	78.32	43.72	41.12	42.68

This data contains 4 sub-divisions of Coffee types:

Name in Spanish

Suaves Colombianos (Arábigo)

Otros Suaves (Arábigo)

Naturales de Brazil (Arabigo)

Robustas

Name in English

Colombian Mild (Arabicas)

Other Mild (Arabicas)

Brazilian (Arabicas)

Robustas

There are 14 Columns, the names have been translated or changed as per the following table.

Subdivision Coffee Type	Column Original name	Column New name
	Mes	Date
	Precio del indicador compuesto OIC	OIC_price
Suaves Colombianos (Arábigos)	Nueva York	Colombia_ny
	Europa	Colombia_europe
	Promedio ponderado	Colombia_average
Otros suaves (Arábigo)	Nueva York	Other_ny
	Europa	Other_europe
	Promedio ponderado	Other_average
Naturales de Brazil (Arabigo)	Nueva York	Brazil_ny
	Europa	Brazil_europe
	Promedio ponderado	Brazil_average
Robustas	Nueva York	Robustas_ny
	Europa	Robustas_europe
	Promedio ponderado	Robustas_average

Columns Metadata

Date: Column expressing the date monthly beginning January of 2000, all prices will have a reference for this date.

OIC_price: Is the average price of the International Coffee Organization for the month and year shown, measured in US cents/lb

Colombia_ny: Are the average price of Colombian Mild Arabicas for the month and year shown and is expressed in US cents/lb, in the US market

Colombia_europe: Is the average price of Colombian Mild Arabicas for the month and year shown and is expressed in US cents/lb, in Germany and France

Colombia_average: Is the weighted average Colombian Mild Arabicas Composite Indicator Price, as per "Section 4 "of the Indicator Prices SC-106/21 for the month and year shown and is expressed in US cents/lb

Other_ny: Is the average price of Other Mild Arabicas for the month and year shown and is expressed in US cents/lb, in the US market

Other_europe: Is the average price of Other Mild Arabicas for the month and year shown and is expressed in US cents/lb, in Germany and France

Other_average: Is the average price of Other Mild Arabicas Composite Indicator Price, as per "Section 4 "of the Indicator Prices SC-106/21 for the month and year shown and is expressed in US cents/lb

Brazil_ny: Is the average price of Brazilian Naturals for the month and year shown and is expressed in US cents/lb, in the US market

Brazil_europe: Is the average price of Brazilian Naturals for the month and year shown and is expressed in US cents/lb, in Germany and France

Brazil_average: Is the average price of Brazilian Naturals Composite Indicator Price, as per "Section 4 "of the Indicator Prices SC-106/21 for the month and year shown and is expressed in US cents/lb

Robustas_ny: Is the average price of Robustas for the month and year shown and is expressed in US cents/lb, in the US market

Robustas_europe: Is the average price of Robustas for the month and year shown and is expressed in US cents/lb, in Germany and France

Robustas_average: Is the average price of Robustas Composite Indicator Price, as per "Section 4 "of the Indicator Prices SC-106/21 for the month and year shown and is expressed in US cents/lb

Multivariate Analysis

Summary Statistics

There are 272 rows

The data does not have NA's or empty cells

Measures of central tendency and measures of dispersion table:

	count	mean	std	min	25%	50%	75%	max
OIC_price	272	113.633237	43.687941	41.17	88.5475	113.155682	133.130252	231.24
Colombia_ny	272	153.333888	62.437782	58.92	112.94	144.413636	182.577237	319.63375
Colombia_europe	272	148.409523	59.732402	57.72	111.6975	141.123636	178.760455	311.45
Colombia_average	272	151.222932	61.156478	58.1	112.67	143.529552	179.0225	312.95
Other_ny	272	145.099616	58.41441	51.95	108.72	141.896818	169.232857	303.59
Other_europe	272	143.098234	55.916915	55.76	110.295	138.104348	165.942045	297.22
Other_average	272	143.96633	56.927377	54.28	109.7125	140.704773	166.686126	300.12
Brazil_ny	272	118.365112	49.732689	37.67	94.405	111.98	132.726023	271.39
Brazil_europe	272	123.408718	51.170812	38.71	96.056883	117.983409	143.199599	273.43
Brazil_average	272	121.959193	50.984818	38.63	95.605714	116.833333	140.72888	273.4
Robustas_ny	272	79.670588	28.448193	21.25	57.895	84.680554	103.530147	126.3
Robustas_europe	272	74.456376	26.5673	22.79	54.765	78.150682	97.329432	121.3
Robustas_average	272	75.376692	26.767165	22.81	55.3475	79.203636	98.367841	121.98

Note that Colombian_average maximum is almost 3 times the price of the Robustas_average which is predominantly from Vietnam, the reason is that “Robustas has a high caffeine content (2% to 4%), so the flavor is not as pure as Arabica” (Roldan Perez et al., 2009,32), “quality of the Robusta produced is uneven because of processing technology, drying equipment and post-harvest technological problems. These cause the coffee beans to have a high humidity level, and not meet the required standard of color, quality, and so on. This is the reason that Vietnam’s coffee price is lower than the world price.” (Roldan Perez et al., 2009,32).

The 3rd Quantil (75%) of Robustas_average is below the 1st Quantil (25%) of Colombian_average and Other_average, and almost the same for the 1st Quantil (25%) of Brazil_average.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 272 entries, 0 to 271
Data columns (total 14 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Date                  272 non-null   object
1   OIC_price             272 non-null   object
2   Colombia_ny          272 non-null   object
3   Colombia_europe      272 non-null   object
4   Colombia_average     272 non-null   object
5   Other_ny             272 non-null   object
6   Other_europe         272 non-null   object
7   Other_average        272 non-null   object
8   Brazil_ny            272 non-null   object
9   Brazil_europe        272 non-null   object
10  Brazil_average       272 non-null   object
11  Robustas_ny          272 non-null   object
12  Robustas_europe      272 non-null   object
13  Robustas_average     272 non-null   object
dtypes: object(14)
memory usage: 29.9+ KB
```

There are a total of 14 Columns, each with 272 rows, and the type of data per column is the type Object that is like a String type, which will have to be converted to float type and time series for the column Date

Checking for duplicates on each column [duplicated index]:

Colombia_europe [20 - 40] In the years 2001-09 and 2003-05, it was exactly the same price coffee.

Brazil_ny[75 - 89] In the years 2006-04 and 2007-06, it was exactly the same price coffee.

Other_ny [158 - 159] In the years 2013-03 and 2013-04, it was exactly the same price as the coffee

Other_europe [29 - 41] In the years 2002-06 and 2003-06, it was exactly the same price as the coffee

Robustas_europe [118 - 119 - 130 - 183] On years 2010-11 and 2020-04, it was exactly the same price of the coffee

Robustas_ny [35 - 39] On years 2002-12 and 2003-04, it was exactly the same price of the coffee

Min, Max, and Outliers

There are no outliers in the Robustas columns, but the other columns do have outliers

Column	Max Outlier	Min Outlier	# of Outliers
OIC_price	231.24	200	13
Colombia_ny	319.63	288.43	16
Colombia_europe	311.45	283.74	9
Colombia_average	312.95	279.55	19
Other_ny	303.59	262.94	19
Other_europe	297.22	250.75	19
Other_average	300.12	255.9	19
Brazil_ny	271.39	201.6	25
Brazil_europe	273.43	216.46	23
Brazil_average	273.4	214.8	24

Boxplot or candle sticks

Creating a boxplot for the columns, which can be seen the outliers graphically, we can appreciate that the variety of coffee Robustas, doesn't have outliers, but the rest of the varieties have outliers



The median of OIC_price is basically where the lower quartile Q1 of all “Colombian” columns start as well as the “Other” columns

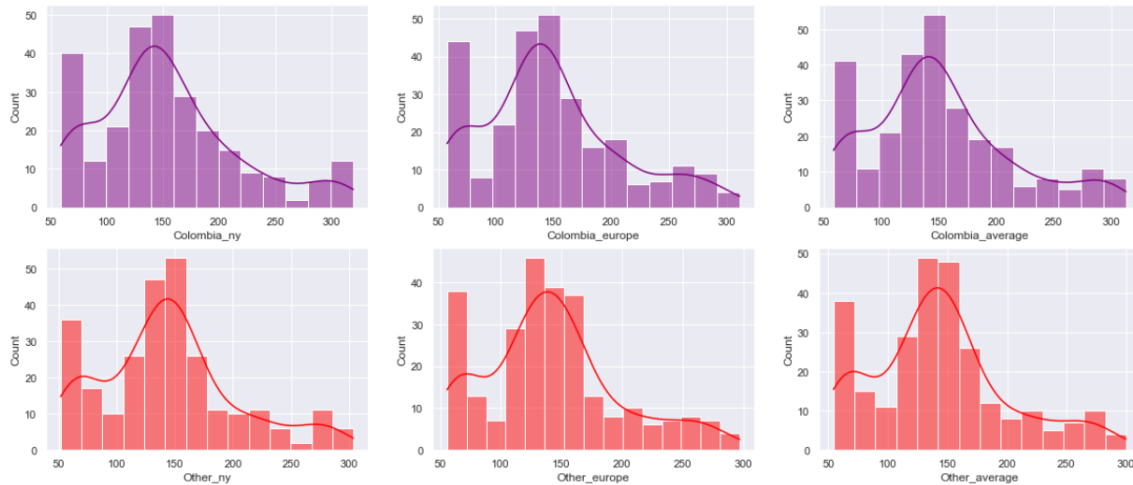
The median of “Robustas” columns is smaller than the lower quartile Q1 of OIC_price column

The upper quartile or Q3 of “Robustas” is smaller than the lower quartile Q1 of all the columns with the exception of OIC_price and “Robustas_ny”

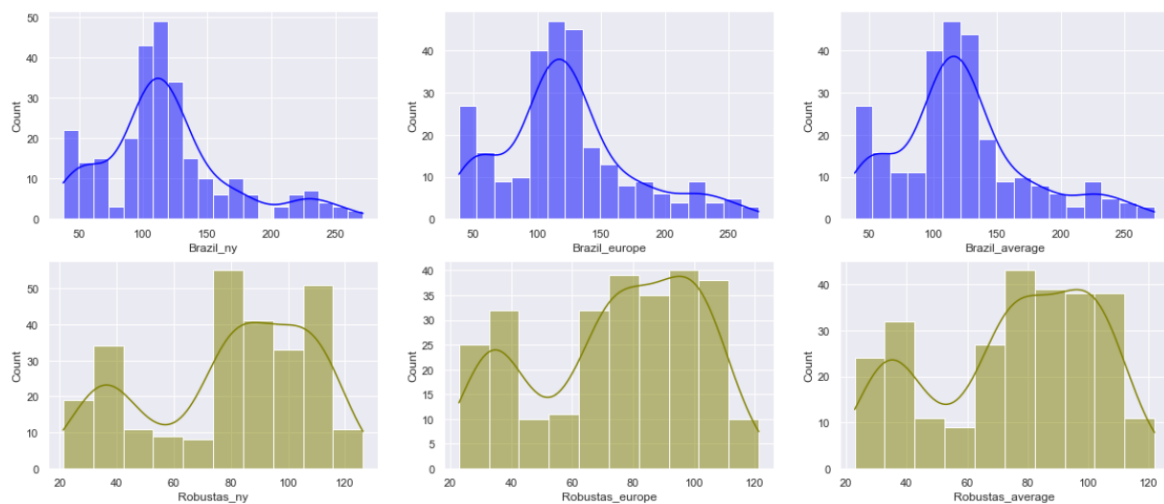
Brazil_ny has a small IQR, while all “Colombia” columns have a big IQR

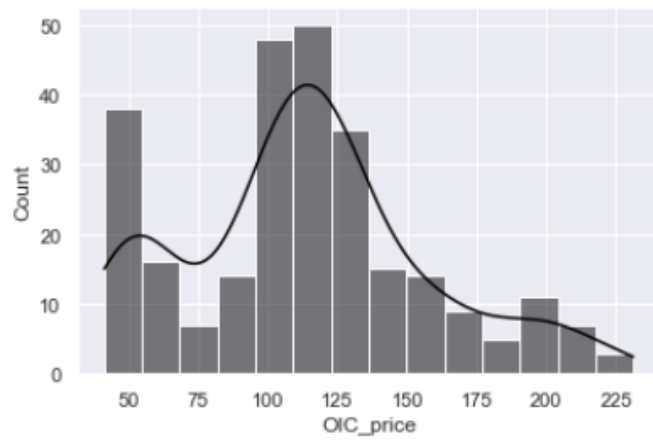
Frequency Distribution

Creating a histogram with each average variable:



All columns follow almost the same distribution pattern, however, Robustas_average is quite different from the others, and the data is not that “normally distributed”. Please note that Robustas type coffee follows a different distribution that looks like a bimodal distribution, it has two local maxima points that are notable in the graph.



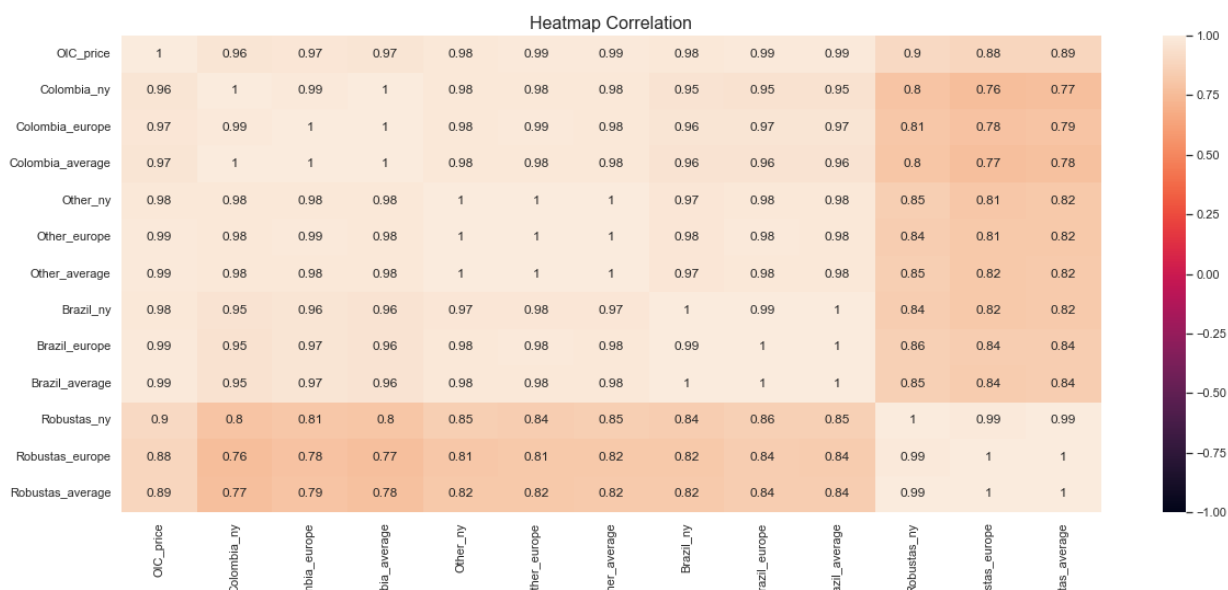


The variable OIC_price, here in color black, follows almost the same distribution of all the other columns, with a slight peak at around US \$55 dollars.

Correlation and Heatmap

Creating a correlation matrix between all the columns, can be seen that there is a high correlation between all the averages, not that much with Robustas_average, but there is still a correlation, the lowest correlation is between Robustas_average and Colombia_ny with a value of 0.76, and with our target column which is OIC_price, the lowest correlation is Robustas_europe with 0.88

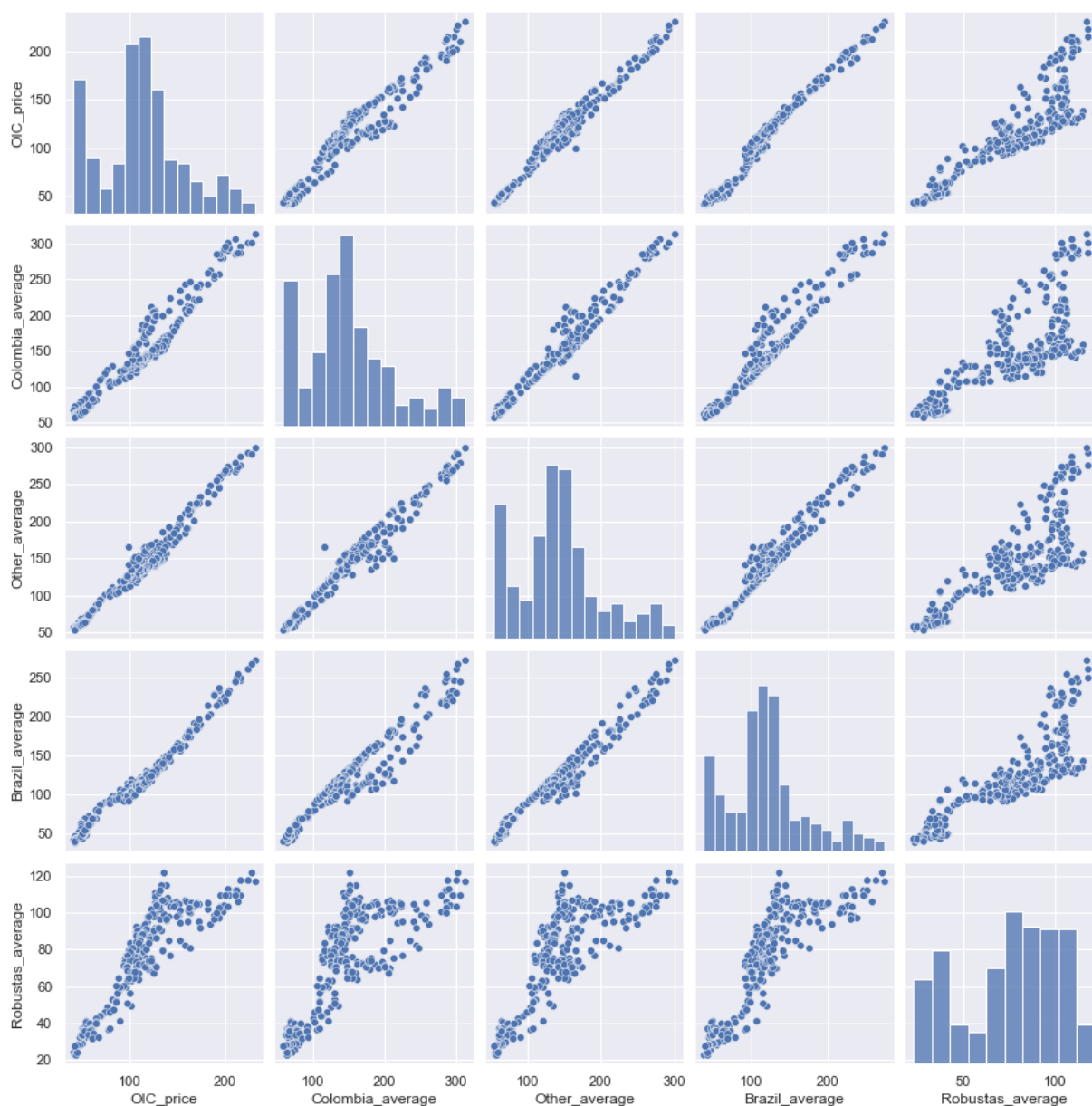
Overall, all columns have a high correlation between all of them, and it can be seen as well that the average columns have a correlation of 1 with the same group of coffee that they are averaging.

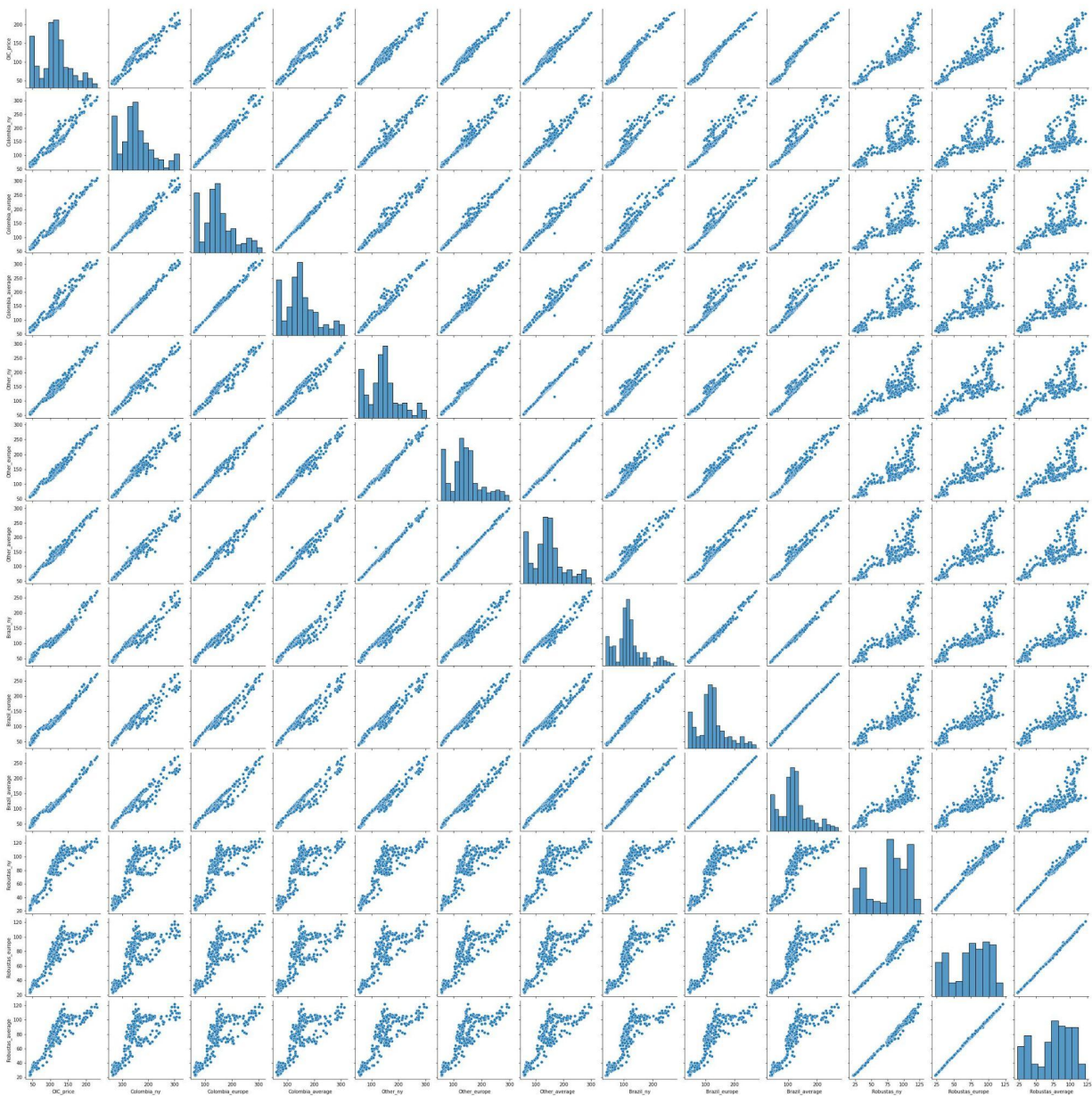


Scatterplot Matrix

The scatterplot between all average columns and OIC_price confirms the correlations seen above on the matrix.

There is a linear relationship between the variables and the target, which is confirmed by the scatterplot.





There is a linear relationship between almost all columns, but this can be seen better in a heat map.

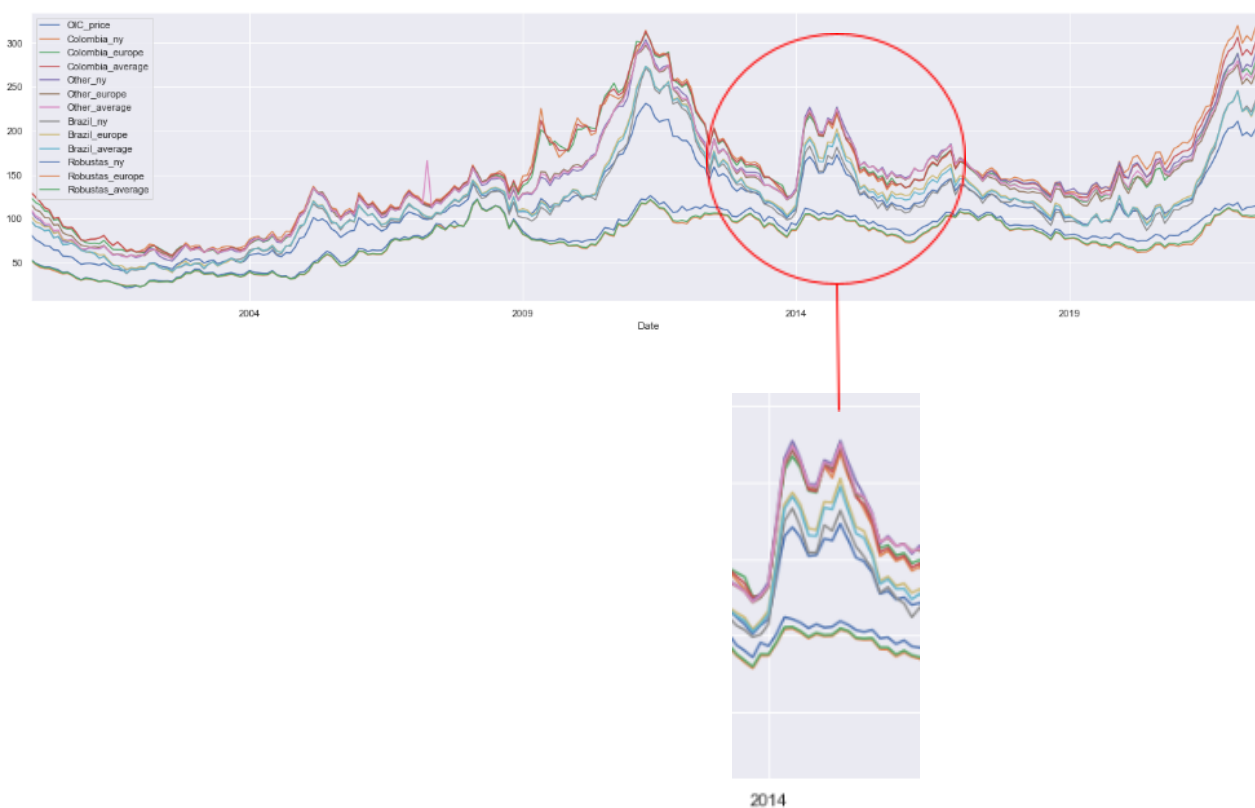
Exploratory Data Analysis

Coffee averages price distribution



The date column is on a monthly basis for a period of 10 years and behaves as a queue, where it has a front and rear, end every time a new month is added to the end of the queue, the month on the front is withdrawn from the queue.

On the Graph distribution between the averages over time can be seen that there some coffees reached up to \$300 dollars twice during the decade and had lots of peaks, while the robustas had a more flat-like behavior.

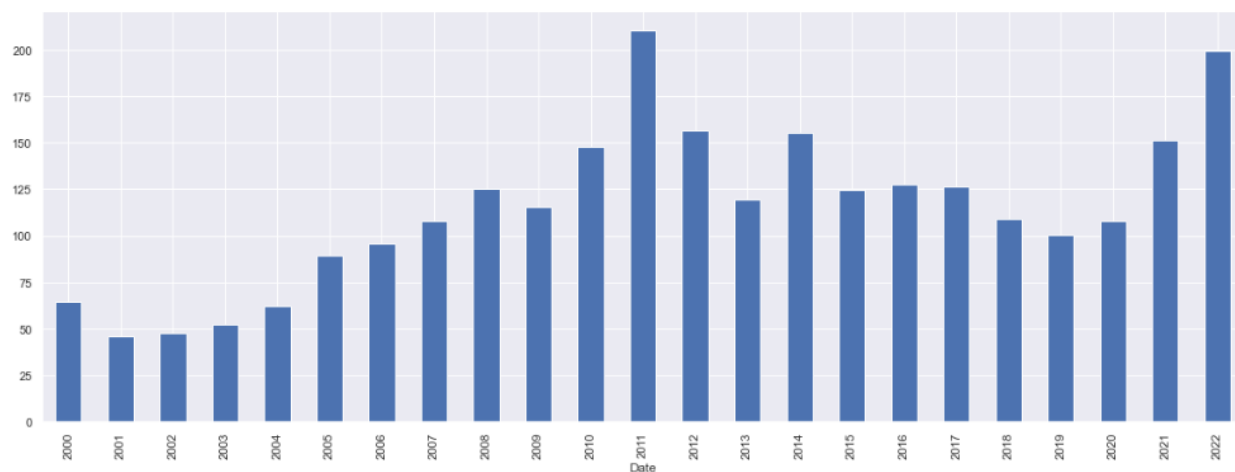


Note, that “the daily price increased by over 50% between 30 January and 10 March, as the ongoing drought in Brazil and uncertainty over the 2014/15 crop put upward pressure on prices” (ICO.ORG, 2014), this is particularly important due that January 2014 was one of the hottest months in “Brazil, which produces nearly 40% of the world’s coffee” (Wile, 2014), and lots of the crops were lost on this year

Average price per year

Date	OIC_price	Colombia_ny	Colombia_europe	Colombia_average	Other_ny	Other_europe	Other_average	Brazil_ny	Brazil_europe	Brazil_average	Robustas_ny	Robustas_europe	Robustas_average
2000	64.25	102.60	99.80	102.60	85.09	92.89	87.08	79.86	83.67	79.86	42.12	40.36	41.41
2001	45.59	72.21	68.24	72.05	61.94	63.14	62.28	50.52	52.42	50.70	27.30	27.49	27.54
2002	47.76	65.27	64.78	64.90	60.44	62.35	61.55	45.10	45.92	45.23	30.84	29.78	30.03
2003	51.90	67.31	64.34	65.33	64.09	64.30	64.20	50.82	50.16	50.31	38.39	36.50	36.94
2004	62.15	83.85	79.49	81.44	80.15	80.64	80.47	68.18	69.11	68.97	37.28	35.66	35.98
2005	89.34	117.00	114.67	115.73	114.29	114.83	114.83	101.33	102.49	102.29	53.38	49.86	50.51
2006	95.75	117.92	115.70	116.80	113.95	114.80	114.40	102.88	104.19	103.92	70.28	66.98	67.56
2007	107.68	126.74	124.70	125.57	123.16	123.81	127.83	110.69	112.06	111.79	88.26	86.30	86.37
2008	125.47	146.08	144.27	145.37	139.63	141.99	141.21	124.47	129.48	128.35	107.66	106.32	106.56
2009	115.67	180.87	174.58	177.43	141.65	145.48	143.84	111.39	116.55	115.33	77.16	74.02	74.58
2010	148.16	224.62	227.08	226.33	195.44	197.62	196.97	146.68	156.92	154.66	85.07	78.46	79.55
2011	210.39	283.82	283.67	283.84	273.20	269.55	271.07	243.67	248.72	247.62	115.99	107.91	109.21
2012	156.36	203.95	200.53	202.15	187.59	185.76	186.53	171.37	176.13	175.03	110.58	101.30	102.76
2013	119.51	148.25	147.53	147.87	141.08	138.42	139.53	117.95	123.56	122.23	100.50	92.95	94.16
2014	155.26	198.09	198.16	197.95	202.85	199.08	200.39	161.30	175.29	171.59	105.60	99.47	100.43
2015	124.67	149.88	154.02	151.80	160.53	159.54	159.94	123.11	135.72	132.45	94.20	86.84	88.05
2016	127.38	155.58	155.37	155.38	164.63	163.49	163.88	124.18	142.72	137.86	94.28	87.47	88.63
2017	126.68	154.07	150.41	152.37	152.41	149.50	150.73	126.55	133.78	131.91	104.09	100.28	100.95
2018	109.04	139.59	133.26	136.70	137.40	129.10	132.73	109.62	115.10	113.65	88.34	84.03	84.80
2019	100.52	137.07	129.19	133.60	137.46	125.52	130.66	100.07	101.99	101.53	80.06	72.15	73.56
2020	107.94	166.28	146.10	157.67	156.81	146.77	150.72	102.46	107.86	106.42	78.20	66.68	68.75
2021	151.29	228.42	206.53	219.05	209.88	201.42	204.62	158.23	163.01	161.70	99.81	87.74	89.87
2022	199.43	309.18	272.31	293.69	277.86	260.35	266.66	228.77	225.65	226.49	114.73	103.73	105.49

Plotting the average price per year as a distribution graph, shows the Average Maximum Price of OIC has been US \$210.38 in the year 2011, while the Average Minimum Price of IC has been US \$ 45.59 in the year 2001.

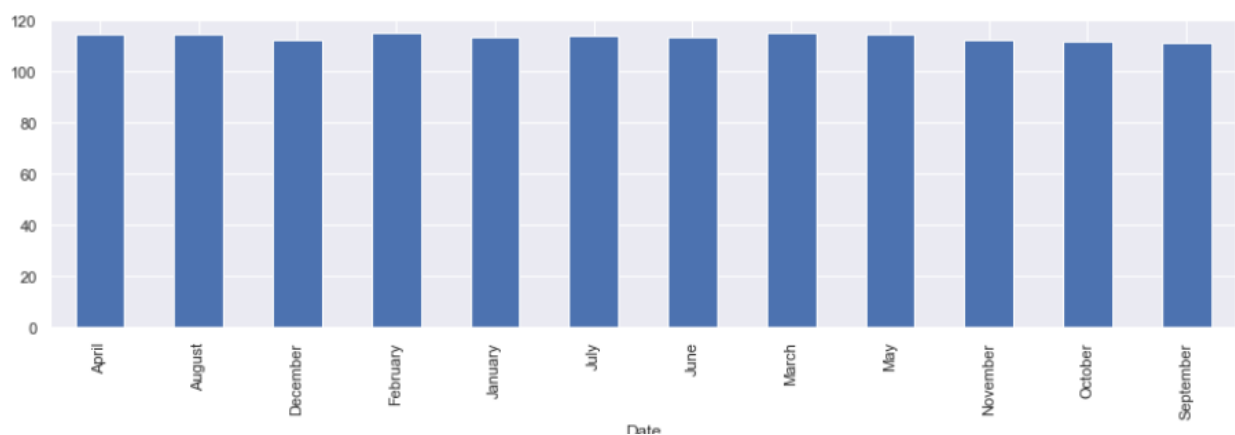


The months of February and March, are when the coffee has the highest prices, however, there is not a significant increase in price, only 3%

Minimum Month price: 111.48

Maximum Month price: 115.20

The graph shows the average price per month for OIC_price



Features Selection and Backward Pairwise Relations

As there are 14 columns in our data set, in order to build a proper model to do regression, there will be a limit of $SL = 0.05$ and obtain the p-values for each of the columns, please note that the independent column is OIC_price, and there won't be an analysis for this column, and the same will be done with the column Date.

In order to obtain an equation that satisfies the model of multiple linear regression

$$\hat{Y} = b_0 + b_1X_1 + b_2X_2 + \dots + b_pX_p,$$

I'll obtain the p-value, using a backward stepwise regression, and if the p-values for the columns are $> SL$, then it will be discarded.

OLS Regression Results						
=====						
Dep. Variable:	OIC_price	R-squared:	0.999			
Model:	OLS	Adj. R-squared:	0.999			
Method:	Least Squares	F-statistic:	3.291e+04			
Date:	Wed, 26 Oct 2022	Prob (F-statistic):	0.00			
Time:	15:56:37	Log-Likelihood:	-415.90			
No. Observations:	272	AIC:	857.8			
Df Residuals:	259	BIC:	904.7			
Df Model:	12					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	0.3823	0.277	1.378	0.169	-0.164	0.929
Colombia_ny	0.3603	0.049	7.366	0.000	0.264	0.457
Colombia_europe	0.4448	0.042	10.672	0.000	0.363	0.527
Colombia_average	-0.6751	0.088	-7.703	0.000	-0.848	-0.502
Other_ny	0.0438	0.021	2.090	0.038	0.003	0.085
Other_europe	0.1799	0.030	6.090	0.000	0.122	0.238
Other_average	0.0339	0.022	1.526	0.128	-0.010	0.078
Brazil_ny	-0.1526	0.037	-4.093	0.000	-0.226	-0.079
Brazil_europe	-0.7977	0.077	-10.403	0.000	-0.949	-0.647
Brazil_average	1.2232	0.107	11.406	0.000	1.012	1.434
Robustas_ny	0.3961	0.060	6.596	0.000	0.278	0.514
Robustas_europe	2.0278	0.255	7.959	0.000	1.526	2.530
Robustas_average	-2.0975	0.308	-6.821	0.000	-2.703	-1.492
=====						
Omnibus:	93.960	Durbin-Watson:	0.725			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	801.467			
Skew:	-1.124	Prob(JB):	9.20e-175			
Kurtosis:	11.103	Cond. No.	2.77e+03			

There are two columns with a high p-value, but only one will be removed in this step, in this case, the column with the constant value, which has a p-value of 0.169

```

=====
                        OLS Regression Results
=====
Dep. Variable:          OIC_price      R-squared (uncentered):          1.000
Model:                  OLS           Adj. R-squared (uncentered):        1.000
Method:                 Least Squares  F-statistic:                     2.556e+05
Date:                   Wed, 26 Oct 2022  Prob (F-statistic):              0.00
Time:                   15:56:37       Log-Likelihood:                  -416.89
No. Observations:      272           AIC:                             857.8
Df Residuals:          260           BIC:                             901.1
Df Model:              12
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Colombia_ny	0.3665	0.049	7.512	0.000	0.270	0.463
Colombia_europe	0.4508	0.042	10.856	0.000	0.369	0.533
Colombia_average	-0.6899	0.087	-7.919	0.000	-0.861	-0.518
Other_ny	0.0366	0.020	1.802	0.073	-0.003	0.077
Other_europe	0.1953	0.027	7.126	0.000	0.141	0.249
Other_average	0.0349	0.022	1.568	0.118	-0.009	0.079
Brazil_ny	-0.1293	0.033	-3.885	0.000	-0.195	-0.064
Brazil_europe	-0.7743	0.075	-10.337	0.000	-0.922	-0.627
Brazil_average	1.1698	0.100	11.680	0.000	0.973	1.367
Robustas_ny	0.3887	0.060	6.487	0.000	0.271	0.507
Robustas_europe	1.9771	0.253	7.828	0.000	1.480	2.474
Robustas_average	-2.0351	0.305	-6.679	0.000	-2.635	-1.435

```

=====
Omnibus:                80.667      Durbin-Watson:                0.711
Prob(Omnibus):          0.000      Jarque-Bera (JB):             638.622
Skew:                   -0.940      Prob(JB):                     2.11e-139
Kurtosis:               10.267      Cond. No.                     2.72e+03
=====

```

Then after removing the constant column, there are more columns again with different value, and once again, I'll remove the one with the highest p-value, in this case, is column number 6 called Other_average, with a p-value of 0.118

```

=====
                        OLS Regression Results
=====
Dep. Variable:          OIC_price      R-squared (uncentered):          1.000
Model:                  OLS           Adj. R-squared (uncentered):        1.000
Method:                 Least Squares  F-statistic:                     2.773e+05
Date:                   Wed, 26 Oct 2022  Prob (F-statistic):           0.00
Time:                   15:56:38       Log-Likelihood:                  -418.17
No. Observations:      272           AIC:                             858.3
Df Residuals:          261           BIC:                             898.0
Df Model:              11
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
Colombia_ny	0.3649	0.049	7.462	0.000	0.269	0.461
Colombia_europe	0.4502	0.042	10.813	0.000	0.368	0.532
Colombia_average	-0.6882	0.087	-7.879	0.000	-0.860	-0.516
Other_ny	0.0506	0.018	2.764	0.006	0.015	0.087
Other_europe	0.2169	0.024	9.141	0.000	0.170	0.264
Brazil_ny	-0.1331	0.033	-3.999	0.000	-0.199	-0.068
Brazil_europe	-0.7909	0.074	-10.635	0.000	-0.937	-0.644
Brazil_average	1.1895	0.100	11.940	0.000	0.993	1.386
Robustas_ny	0.3915	0.060	6.519	0.000	0.273	0.510
Robustas_europe	1.9955	0.253	7.888	0.000	1.497	2.494
Robustas_average	-2.0558	0.305	-6.734	0.000	-2.657	-1.455

```

=====
Omnibus:                82.149    Durbin-Watson:              0.703
Prob(Omnibus):          0.000    Jarque-Bera (JB):          675.352
Skew:                   -0.950    Prob(JB):                  2.23e-147
Kurtosis:               10.482    Cond. No.:                 2.57e+03
=====

```

Now is the turn to remove the column `Other_ny` as it has a p-value = 0.06 and is above my limit of 0.05

The model is completed, keeping all the columns with the exemption of Columns: `Other_average` and `Other_ny`.

The coefficients b in the equation can be seen in the column `coef`, and the p-values can be seen in the column `p>|t|` and they all tend to zero, without being zero themselves.

```

=====
                        OLS Regression Results
=====
Dep. Variable:          OIC_price      R-squared (uncentered):          1.000
Model:                  OLS            Adj. R-squared (uncentered):          1.000
Method:                 Least Squares   F-statistic:                    2.773e+05
Date:                  Wed, 26 Oct 2022  Prob (F-statistic):              0.00
Time:                  15:56:38         Log-Likelihood:                 -418.17
No. Observations:      272             AIC:                           858.3
Df Residuals:          261             BIC:                           898.0
Df Model:              11
Covariance Type:       nonrobust
=====
                        coef      std err          t      P>|t|      [0.025      0.975]
-----
Colombia_ny            0.3649      0.049       7.462     0.000      0.269      0.461
Colombia_europe        0.4502      0.042     10.813     0.000      0.368      0.532
Colombia_average      -0.6882      0.087     -7.879     0.000     -0.860     -0.516
Other_ny               0.0506      0.018      2.764     0.006      0.015      0.087
Other_europe           0.2169      0.024      9.141     0.000      0.170      0.264
Brazil_ny              -0.1331      0.033     -3.999     0.000     -0.199     -0.068
Brazil_europe          -0.7909      0.074    -10.635     0.000     -0.937     -0.644
Brazil_average         1.1895      0.100     11.940     0.000      0.993      1.386
Robustas_ny            0.3915      0.060      6.519     0.000      0.273      0.510
Robustas_europe        1.9955      0.253      7.888     0.000      1.497      2.494
Robustas_average       -2.0558      0.305     -6.734     0.000     -2.657     -1.455
=====
Omnibus:               82.149    Durbin-Watson:              0.703
Prob(Omnibus):         0.000    Jarque-Bera (JB):           675.352
Skew:                  -0.950    Prob(JB):                   2.23e-147
Kurtosis:              10.482    Cond. No.                   2.57e+03
=====

```

The model:

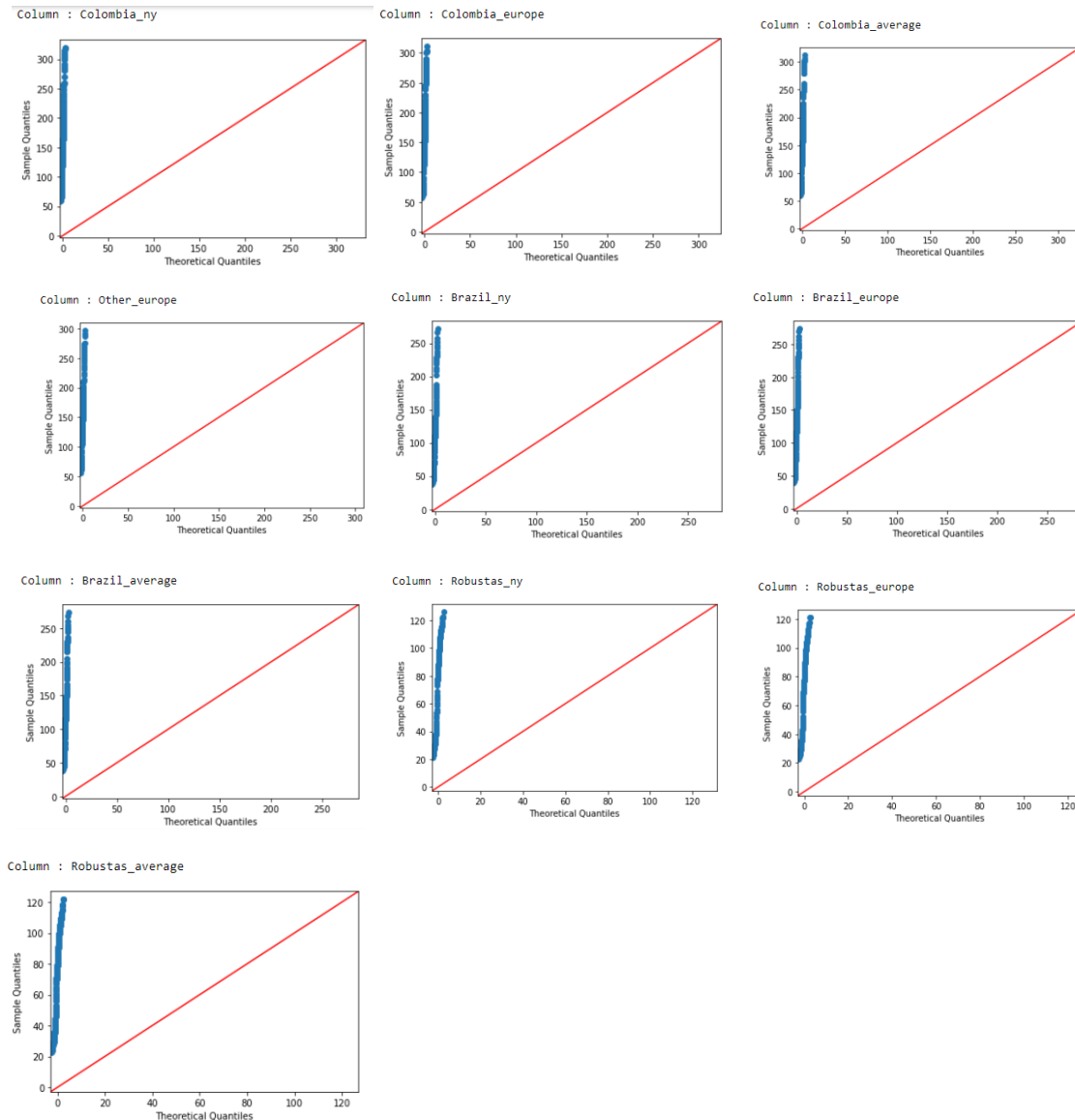
$$\begin{aligned}
 \text{Price_OIC} = & (0.3649 * \text{Colombia_ny}) + (0.4502 * \text{Colombia_europe}) - (0.6882 * \text{Colombia_average}) \\
 & + (0.0506 * \text{Other_ny}) + (0.2169 * \text{Other_europe}) - (0.1331 * \text{BrazilNY}) - (0.7909 * \text{Brazil_europe}) \\
 & + (1.1895 * \text{Brazil_average}) + (0.3915 * \text{Robustas_ny}) + (1.9955 * \text{Robustas_europe}) \\
 & - (2.0558 * \text{Robustas_average})
 \end{aligned}$$

Normalization

This work will be done without Normalization and with Normalization, and at the end compare all the errors and values in a data frame, this is done for academic purposes and as a learning tool.

To normalize the data, I am going to create a data frame without the ['Date'] column, named **test**, then I'll select the **X** which contains the columns of the model, and **y** which contains the column with the independent variable "Price_OIC".

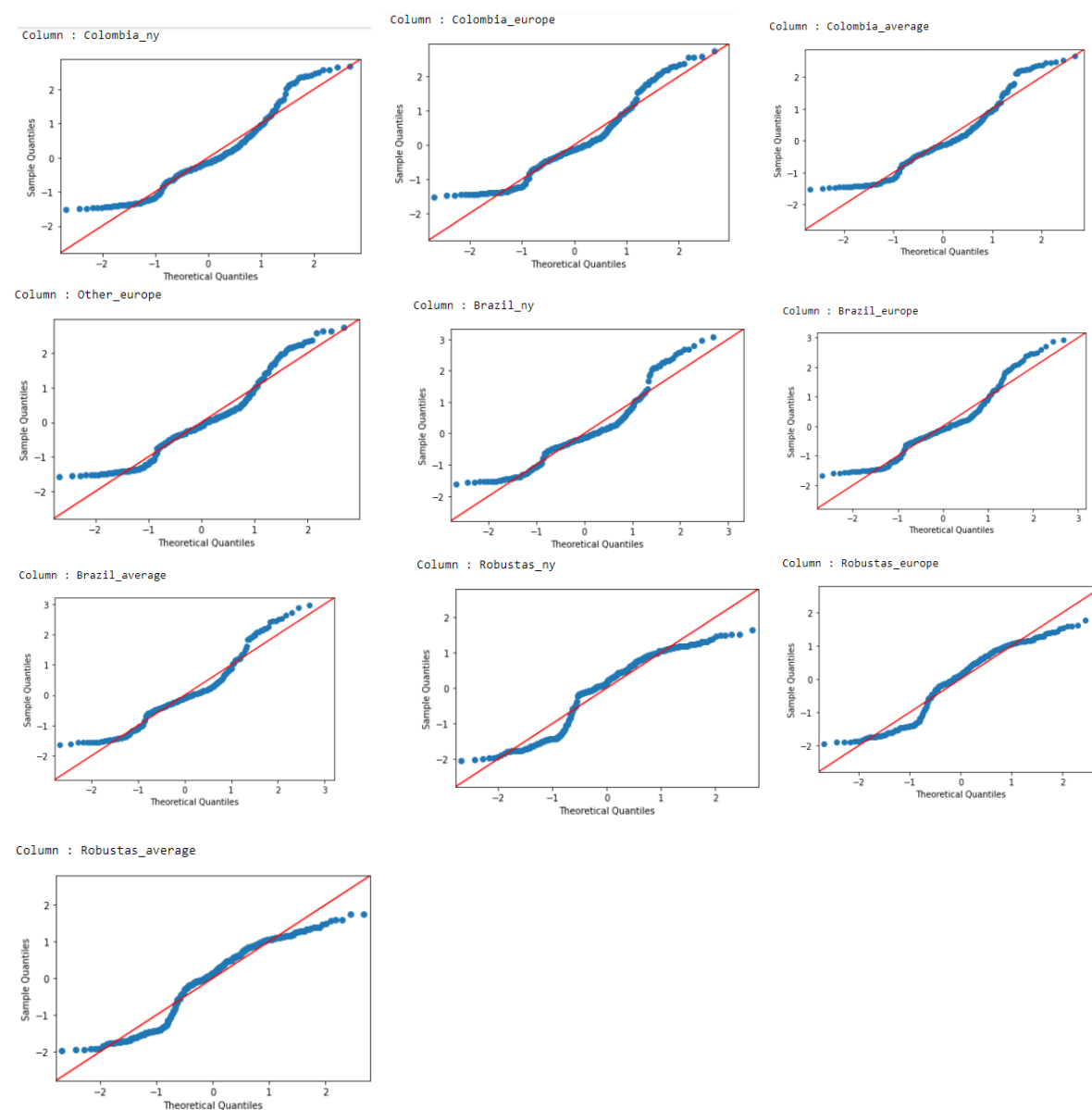
To confirm that normality has to be done, I'll use a Q-Q plot where can be seen that the scatterplot doesn't follow the 45-degree line and needs to be normalized.



The function **StandardScaler()** will take care of the normalization:

```
X = ['Colombia_ny', 'Colombia_europe', 'Colombia_average', 'Other_europe', 'Brazil_ny',
      'Brazil_europe', 'Brazil_average', 'Robustas_ny', 'Robustas_europe', 'Robustas_average']
y = ['Price_OIC']
```

After normalizing, the same function to draw a Q-Q plot is applied to the columns and can be seen that now it follows normality.



Screenshot of **X** normalized, not including all the columns as it won't fit in the screenshot

	Colombia_ny	Colombia_europe	Colombia_average	Other_europe	Brazil_ny	Brazil_europe	Brazil_average	Robustas_ny	Robustas_europe
0	-0.372478	-0.403363	-0.345537	-0.470818	-0.416894	-0.397612	-0.477082	-0.917408	-0.831361
1	-0.459123	-0.498797	-0.433998	-0.589605	-0.540985	-0.525264	-0.598322	-1.065669	-0.998792
2	-0.542720	-0.547269	-0.519510	-0.626513	-0.572813	-0.560505	-0.629368	-1.141385	-1.120971
3	-0.652471	-0.658971	-0.631560	-0.745121	-0.642715	-0.640385	-0.697553	-1.213578	-1.174519
4	-0.690338	-0.680272	-0.670221	-0.754438	-0.627203	-0.634316	-0.682423	-1.214283	-1.185832

Screenshot of **y** Normalized, not including all the values as it won't fit in the screenshot

```
array([[ -0.72196744],
       [ -0.85955826],
       [ -0.92055686],
       [ -1.01136681],
       [ -1.01847567],
       [ -1.12533788],
       [ -1.13611582],
       [ -1.28517255],
       [ -1.29159346],
       [ -1.3124614 ],
       [ -1.40923361],
       [ -1.49889697],
       [ -1.47779971],
       [ -1.47321335],
       [ -1.49316402],
       [ -1.5209115 ],
       [ -1.47344266],
       [ -1.53856899],
```


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