\*4709words in total, **3635** without the Abstract, Appendices, and references  
GitHub repository link: <https://github.com/ZdenkoCCT/CA2Git>

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Sirloin Steak price analysis in the USA and Ireland from 1997-to 2021

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# Abstract

The agricultural sector is characterized by low operational efficiency, a high level of uncertainty because of weather and environmental conditions, and a volatile balance between food supply and demand (Osinga et al., 2022). Data science can help improve all these factors by use of data analysis and machine learning models. Together with use of automation processes, drones and AI, sustainable production model can be become a reality probably in the short future.

When

# Introduction

The agricultural sector is characterized by low operational efficiency, a high level of uncertainty because of weather and environmental conditions, and a volatile balance between food supply and demand (Osinga et al., 2022). European Union is trying to promote a sustainable agricultural system by combining several social, economic, and environmental approaches (European Commission - European Commission, 2021). Several EU initiatives are trying to find better business models and secure investments for farmers that will increase productivity, improve skills, and provide sustainable high-quality food (European Commission - European Commission, 2021). Cockburn (2020) argues that although large amounts of dairy data are becoming available, a lack of data integration makes it difficult to analyze the data. In their research, where they analyzed peer-reviewed research about machine learning in the dairy sector, findings were that tested algorithms did not perform to that extent where they could be used in the practice. The conclusion states that the main reason for this is the lack of data integration and availability of public data. Osinga et al. (2022) also mentioned that data analysis has not been widely applied in the agricultural sector because of lack of human resources and expertise, non-reliable infrastructure, and a lack of data standardization and governance.

# Analysis

In our research, we will compare Sirloin steak price change in the USA in Ireland in the last 25 years. We will also conduct sentiment analysis from tweets containing the words ‘beef production cost’ that relates to manufacturing, and we will also review sentiments from the consumer side, analyzing tweets containing the words ‘steak price’. Our initial hypothesis will state that Sirloin steak prices history in Ireland is related to Sirloin steak prices history in the USA. Project timeline is created to break down tasks into periods (Appendix X.)

## Sirloin steak price change in the USA in Ireland over the last 25 years

In the initial search, we searched for datasets from Ireland and other countries related to the beef production. Central Statistics Office (www.cso.ie) was our first choice to find the data. 10+ datasets were related to beef production (beef exports, average price, meat supply balance, etc.). Decision was made to focus our research on how steak prices changed over the years (Datasets downloaded from: <https://data.cso.ie/table/CPM12>, <…/CPM04>, […/CPM08](https://data.cso.ie/table/CPM08) ). The next step was to find related data from a different country. The first database that we investigated was the Eurostat database, but we were not able to find completely matching data. The search was expanded to worldwide data and after reviewing datasets from the UK, Argentina, and the USA where we found matching data (downloaded from: <https://data.bls.gov/pdq> ).

##### Initial Data Analysis

Komorowski et al. (2016) describe EDA as a step where the data is visualized and manipulated without any assumptions.   
We start EDA by importing relevant libraries and uploading three Irish datasets into the Jupiter notebook using the pandas. Anthony (2015) says that the benefit of using panda lies in easy data representation via *DataFrames* and data series, easy filtering, and easy code writing. Visual inspection of the first Irish dataset shows that this dataset contains 8 variables and 3953 observations with monthly prices for different products. By using the *‘data set.describe()*’ function we can see the minimum and maximum values for the month column (‘TLIST(M1)’) to check the start and the end date of the data – which are January 1997 -November 2001. We repeat the same process with the second and third Irish datasets.  
The second dataset contains 8 variables and 10527 observations with monthly prices for different products from December 2001 till December 2012.   
The third dataset contains 8 variables and 9348 observations with monthly prices for different products from December 2012 till February 2022. As the second and third datasets contain a duplicate value for December 2011, we will remove that record from the third dataset.   
After validating that the duplicated record is removed, we need to see how many observations are related to ‘steaks’. We do this by creating *def function* in Python. In the next step, the function will keep only observations containing the string ‘steak’ and in the last step, the function will print those values for all three datasets. Outputs (In [12]) shows that all three datasets have only one steak type in common – Sirloin steak. Now we are ready to merge all three datasets into one, restructure the dataset and keep only the data related to Sirloin steak. We used *for loop* function that will iterate through all three datasets with the following steps:

* Rename columns ('Consumer Item':'SteakType','TLIST(M1)':'Daystamp') to work with more meaningful column names.
* Keep only observations that contain string ‘Sirloin’
* Use *pivot.table* function to transform observations into columns and assign them values from the original ‘Values’ column
* Reset indexing and add the Index column name
* Append new data from each dataset into one list using *list.append* function

Once all observations are appended to the list, we *use pandas.concat* function to create a new DataFrame. Using df.info() function we can check the Data Frame features. Our new dataset has 302 observations, two columns, and no empty values. Next, we will transform the integer type column into a DateTime column type that is crucial when dealing with the time-series data analysis. Kirchgssner (2014) describes time series s a set of quantitative observations arranged in chronological order.   
We will also create new ‘Year’ and ‘Month’ columns that will be used to group and visualize data using plots.   
The final data cleaning step is to remove the last two observations from the Irish dataset that are for January and February 2022, to have year start end data only (from January 1997- to December 2021).  
Using the *df. describe function* we will get Pandas to calculate descriptive statistics values.

Text

Description automatically generated with medium confidence

Figure 1 Irish Sirloin steak prices column description

The minimum value found is 7.994, and the maximum observed value is 16.982. The average steak price over 25 years was 13.360 Euro, and the standard deviation is 2.605. Percentiles or quartiles tell us where our data exist in the dataset. We can say that 25% of data values are higher than 15.471, and less than 25% of those values are lower than 12.175. Grouping the data by year, we can see that the highest average price was recorded in 2013 and the lowest average price was in 1998.

Kirk (2012, pp.13-14) reasons that data visualization is more successful than data set exploration because human visual functions are faster and more efficient than human cognitive processes. First, we will visualize the data using a Line plot that will show us prices over years.

Chart, line chart, scatter chart

Description automatically generated

Figure 2. Line plot IRL

The plot shows that steak price was lowest in 1997-1999 and the highest price was recorded in 2013. Over 25 years price went through 3 major cycles of increase/decrease with the latest tendency being price decrease. It would be interesting to investigate other social/economic variables to understand what was driving these price changes.

The next visualization that we will use is a boxplot that will help us identify outliers. Mozaffari et al. (2021) state that a boxplot is an easy to compute and read outlier detection tool that uses the entire sample to determine the cut-off values.

Chart, waterfall chart

Description automatically generated

Figure 3 Boxplot IRL

The next step is to replace outliers with their yearly median values.   
We will also plot Poisson distribution to see how many times the event is likely to occur over some time (Hu, 2008).  
To find out are variables correlated we will use a correlation matrix to see correlation values and a pair plot to visualize correlations.

Chart, treemap chart

Description automatically generated

Figure 4 Correlation Matrix IRL

Chart

Description automatically generated

Figure 5 Pair plot IRL

Matrix and the pair plot show that there is a strong positive correlation between the price and the year variables and a weak positive correlation between the price and the month variable.

Same as for Irish dataset, we will import the USA dataset and use the *dataset.head(*) function to review first 20 observations. Dataset has 6 columns, but we are interested only in 3 columns that contain data for steak price, year, and a month. The first 9 rows in the dataset contain table information and we can discard them from the model. We re-import the dataset again, but now without the first 9 rows.   
We remove the ‘M’ character from the ‘Period’ column, and then merge the ‘Period’ column with the ‘Year’ column to get an integer type column with month/year values. By using *df.drop()* function, we remove 3 columns from the dataset that we won’t need anymore. Column ‘Year’ is renamed to ‘Daystamp’ to match the Irish dataset column name.   
The next step is to check for blank values (there are none) and change the integer type column ‘Day stamp’ into a daytime type of column. Also, we add back ‘Year’ and ‘Month’ columns. The USA steak prices are shown in pounds, we multiply price values by 2.2 to match values in kilograms. Last step before we visualize data is to remove unmatching month/year data from the USA dataset. As the Irish dataset holds data from 1997 -to 2021, we remove values that are less than December 1996 or greater than January 2022 from the USA dataset. This will leave us with two matching datasets – they have the same number of columns and rows. To visualize USA data, we repeat the steps that we did with the Irish dataset :

Chart, line chart, scatter chart

Description automatically generated

Figure 6 USA line plot

The line plot shows that over the 25 years, the Sirloin steak price was almost constantly growing in the USA, with price spikes around 2004, 20015, and 2021. The lowest mean price was recorded in 1998 and the highest in 2021.   
We continue data visualization by plotting boxplots, checking, and replacing the outlier’s values.

Chart, waterfall chart

Description automatically generated

Figure 7.USA boxplot  
  
Finally, we plot the correlation matrix and pair plot to check is there a correlation between the variables.

Chart, treemap chart

Description automatically generated

Figure 8 USA Correlation Matrix

Chart, histogram

Description automatically generated

Figure 9 USA pair plot

*Matrix show that there is a strong positive correlation between the steak price and the year variables (93%) and almost no correlation between price and the month*.

##### Inferential statistics

Inferential statistics utilizes probabilistic techniques to analyze sample information from a certain population to improve our knowledge about that population (Asadoorian and Kantarelis, 2009). We used the following statistical techniques to review and compare data:

* + - 1. Linear Regression

Linear regression is based on linear correlation and the assumption that a change in one variable will result in a proportional change in another variable (Bazdaric et al., 2021). The time feature creates time dependence and enables values to be predicted from the time that they occurred. We will create an index ‘Time’ column that will be used as an independent variable and the ‘price’ column will be our dependent variable. The fitted linear regression model will be plotted together with the existing time series values to show us the model trend

Chart, scatter chart

Description automatically generated

Figure 10 IRL linear regression model

* + - 1. Lag feature

Lag operators are useful in time series analysis as they can show autocorrelation within the values with previous copies of themselves. This can identify patterns within the time series and help determine the seasonality of the data (Matt Dancho, 2017).  
We will use *data.shift()* function to create a new column (‘Lag’) with price values shifted for one place down and predict and plot the model:

Chart

Description automatically generated

Figure 11. IRL lag feature model

* + - 1. Mood’s Median Test (Appendix 1.)

This test tests do the medians of two or more groups differ We calculate the overall median that is used to define how many values are above and how many are below the median.

Table

Description automatically generated

Figure 12 Mood’s Median Test

In **Appendix 1**. we state our null and alternate hypotheses, define rejection criteria, and calculate the Test Statistics value. Calculation shows that we can support our null hypothesis and conclude that the Medians are the same for the differences in monthly price changes for USA and IRL data.

* + - 1. Kruskal-Wallis Test (Appendix 2.)

The Kruskal-Wallis H test (KWt) is a nonparametric statistical procedure frequently used to compare several populations (Vargha, Delaney, and Vargha, 1998). In this test we will observe are the steak prices means equal for samples in the last 3 observed years in the USA. We will filter the USA dataset and keep only values for the last three years, sort them by price and add ranks in the way that that highest value gets ranked 1. Then, we will sum ranks for every year.

Table

Description automatically generated

Figure 13 Kruskal-Wallis Test

In Appendix 2. we state our hypotheses, calculate the Test Statistics H value and conclude that we canreject ourNull Hypothesis (H0) and we can say that medians are not the same in 3 selected years and at least one of them is different.

* + - 1. Mann-Whitney U Test (Appendix 3.)

Nachar (2008) states that the Mann‐Whitney U test can be used to answer the concerning the difference between his groups. The test can be also used when we are dealing when measured variables are of an ordinal type and not very precise. In our test, we will test the Null Hypothesis that the mean prices are greater in the USA than in Ireland. First, we merge USA and Ireland datasets and add a column with a country code for each observation. Next, we add ranks to all observations where the smallest value has rank 1.

Table

Description automatically generated

Figure 14. Mann- Whitney test

Then we perform the Shapiro-Wilk test and plot a histogram of the data distribution to confirm that data is not normally distributed, and that the Mann-Whitney U test is appropriate. In Appendix 3. We state our hypothesis, calculate the Z value, and conclude that as Z = -0.766 and it is greater than -1.96 and is less than 1.96. We can accept Null Hypothesis H0.

* + - 1. Spearman’s r Test

The Spearman rank correlation coefficient evaluates the correlation between two independent variables (Sedgwick, 2014). The test returns values from -1 to 1 where +1 is a perfect positive correlation and -1 is a perfect negative correlation. We will calculate the correlation between mean prices in the USA and Irish datasets. Using Python, we calculate that coefficient id 0.792 meaning that there is a strong correlation between the means of the two datasets. (Calculation is also done manually in Appendix 4.

##### Machine learning

We will use three machine learning models to predict steak prices in the future. We will use ARIMA, SARIMAX, and LSTM models.

##### ARIMA

ARIMA or Autoregressive Integrated Moving Average is a machine learning model that forecasts a value in a response Time Series which is a linear combination of its related past values, past Errors, and current and past values of alternative Time Series (Jain and Mallick, 2017).   
To start building the model, we use the seasonal decompose function to check for trend and seasonality in the Irish dataset. The trend is the direction of the time series. Seasonality is a periodic behavior.

Timeline

Description automatically generated with medium confidence

Figure 15. Decomposed data

We can see that we have a growing trend and frequent seasonality with a high residue.   
Using the Augmented Dickey-Fuller test we can determine if our data is stationary by calculating the p-value. If the p-value is less than 0.05, we can say that our data does not have a unit root and is stationary – it doesn’t have time dependency.

Text, letter

Description automatically generated

Figure 16. adfuller test

The p-value is 0.2, is greater than 0.05, and is not stationary. To transform to stationary data, we can use a rolling mean feature that will calculate the average for a window of the data.   
To find out which ARIMA model is best fitted we grid search ARIMA parameters by using a function that will loop through possible combinations of p, s, and q values by calculating the Mean Square Error. Function showed that the best ARIMA model is (8,0,2) with train/test split 90/10 where Mean Square Error is 0.324. Running this model, we get pretty accurate predictions.

##### SARIMAX

SARIMAX is an extension to ARIMA, and it is used on data that have seasonal cycles. We will use SARIMAX in combination with Auto ARIMA. Auto ARIMA can automatically select which model is best to use. The best-suggested model for IRL data is SARIMAX (2,1,3). When we run and plot the model, we can see that the predicted models fit with the actual results.

##### LSTM

LSTM – Long Short-Term Memory is a recurring neural network model that is fit to use with the time series. In this case, we couldn’t find the correct fit that would create accurate predictions. The prediction was always shown as a flat line.

###### Results Ireland

ARIMA Model:

Table

Description automatically generated

Figure 17ARIMA model results

We can see that AIC is 448, this is an acceptable value because AIC estimates the relative amount of information lost by a given model: the less information a model loses, the higher the quality of that model.  
And BIC value is 462, this is also a good signal of our model, because similarly to the AIC, among various alternative models, the model to be preferred is the one with the minimum BIC value.   
HQ is an alternative to the Akaike information criterion (AIC) and Bayesian information criterion (BIC). It’s 454 in the ARIMA model. It’s approximating AIC and BIC.

Chart, line chart

Description automatically generated

Figure 18ARIMA model IRL plot

We can see the predicted values fit with the true values, the mean loss of the ARIMA model is very low and we can use the ARIMA model to predict the future’s values.

SARIMAX model

Graphical user interface, table

Description automatically generated with medium confidence

Figure 19 SARIMAS model IRL results

The AIC is 426, it’s lower than the AIC of the ARIMA model, also BIC and HQIC lower than ARIMA’s values so this model is better than ARIMA.

Chart, line chart

Description automatically generated

Figure 20. SARIMAX model IRL plot

The predicted value of the SARIMAX model is more accurate than the ARIMA model.

Chart, line chart

Description automatically generated

Figure 21 SARIMAX model prediction

LSTM model: Train loss and validation loss:  
 

Chart, line chart

Description automatically generated

Figure 22. LSTM model plot

The LSTM model predicts results like a linear straight, LSTM is not suitable for our dataset.

Compare ARIMA vs SARIMA:

|  |  |  |
| --- | --- | --- |
|  | ARIMA | SARIMA |
| AIC | 448 | 426 |
| BIC | 462 | 456 |
| HQIC | 454 | 438 |

###### Results USA

ARIMA model

Table

Description automatically generated

Figure 23 ARIMA model results in USA

We can see AIC is 406, and the BIC value is 432, this is also a good signal of our model, because similarly to the AIC, among various alternative models, the model to be preferred is the one with the minimum BIC value.   
HQIC is 417 in ARIMA model. It’s approximate AIC and BIC and lower than the ARIMA model for the IRL dataset. It means this model is more suitable for this dataset than the IRL dataset.

SARIMAX model

Graphical user interface, table

Description automatically generated

Figure 24 SARIMAX model results USA

The AIC, BIC, and HQIC are higher than the ARIMA model, we can see in the IRL dataset SARIMAX model is better than the ARIMA model but in this dataset, the ARIMA model is better than SARIMAX.

**LSTM**

Chart, line chart, scatter chart

Description automatically generated

Figure 25 LSTM model USA

The LSTM is still not good for this dataset.

## Sentiment Analysis

This analysis aims to find out what Twitter users think about beef products. We will check sentiment from both, the consumer’s, and producer’s sides. To get twitter data, we will use *snscrape.modules.twitter* scraper (social network services scraper). The original plan was to use the official Twitter API, but complications with registration, elevated access, and restrictions on data gathering, turned us to find a different data gathering method.   
\*As at this stage we reached a 3300-word limit, we will focus here only on sentiment analysis results, while the steps will be commented in the Jupyter notebook.

**Producer’s sentiment analysis:**Scraper returned 1342 tweets related to the query: ‘beef production cost’. When we processed data using Natural Language Toolkit, removed stop words, removed special characters, and used *TextBlob* to find sentiment for each tweet, results showed that 675 tweets were positive, and 305 tweets were negative (362 neutral values).

Chart, bar chart

Description automatically generated

Figure 26 Sentiment Analysis Producers

**Consumers sentiment analysis:**Scraper returned max (5000) tweets related to query: ‘steak price’. Following the same process as in the first analysis, results showed that 2682 tweets were positive, and 1265 tweets were negative (1062 neutral values).

Chart, bar chart

Description automatically generated

Figure 27 Sentiment Analysis Consumers

## Dashboard

Interactive dashboard can be accessed by opening CMD shell from the folder where the dashboard is, then typing command: ‘python Dashboard.py’ and pasting the returned URL (http://127.0.0.1:8080/) into the browser.

Graphical user interface, text, application, email

Description automatically generated

Figure 28 Open CMD command line

Text

Description automatically generated

Figure 29 Run CMD command

Graphical user interface, chart, histogram

Description automatically generated

Figure 30 open URL n browser

# Conclusion

##### Compare datasets

Plotting line plots with lines from both datasets we can visually compare how prices were changing over the years.

Chart, line chart

Description automatically generated

Figure 31 Comparing prices from USA and IRL in line plot

We can see that prices in both countries had similar trends up to 2014 from when the prices in the USA are increasing.

Chart, line chart

Description automatically generated

Figure 32 Comparing monthly price differences

Correlation matrixes between price differences and monthly prices show us that there is a 75% correlation between UA and Irish prices, but no correlation between the price differences.

Chart, application

Description automatically generated with medium confidence

Figure 33 Correlation Matrix of the price differences

Chart

Description automatically generated

Figure 34 Correlation Matrix USA/IRL data

This tells us that although price changes are corralled, monthly price changes in the USA and in the Ireland were following different patterns.   
Our initial Null Hypothesis can be upheld as we can see that prices in both countries are correlated.  
Price increases in Ireland in 2002 and in the USA in the 2014 were probably result of some unusual effect. Quick internet search shows that Irish beef market was impacted by Foot and Mouth Outbreak disease. In the USA in 2014 extreme hot weather and draught caused price spike in agricultural sector. Future research would involve getting more relevant data (yearly beef production, beef export/import, currency prices, etc.) to build more complex model that can make better prediction.

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# Appendices

### Appendix 1.Mood’s Median Test

Null Hypothesis H0: The medians of the populations all are equal

Alternative Hypothesis H1: The medians of the population are not all equal

Known values:

Overall Median =0.02829999999999977 (Jupyter notebook )  
Critical value of χ2 (0.05, 1) = 3.841

Observed values (Jupyter notebook)

|  |  |  |  |
| --- | --- | --- | --- |
| Observed | USA | IRL | Totals |
| > median | 151 | 148 | 299 |
| <= median | 148 | 151 | 299 |
| Totals | 299 | 299 | 598 |

Expected values = (Column total \* Row Total) / N

|  |  |  |  |
| --- | --- | --- | --- |
| Observed | USA | IRL | Totals |
| > median | 149.5 | 149.5 | 299 |
| <= median | 149.5 | 149.5 | 299 |
| Totals | 299 | 299 |  |

(Column total \* Row Total) / N

All Values = 299\*299/588=149.

Critical value of χ2 (0.05, 1) = **3.841**  
Calculated **=0.194**

Since 0.194 is less than 3.841 , we accept the Null Hypothesis. We can conclude that the Medians are the same for the differences in monthly price changes for USA and IRL data.

### Appendix 2**.** Kruskal-Wallis Test

Null Hypothesis H0: the medians (mean on ranks) are equal across the samples

Alternative Hypothesis H1: at least one median is different

Known values:

Critical value of χ2 (0.05, 2) = 5.99  
N=36  
k=3  
Ri=97,211,358  
ni=12,12,12

Observed values (Jupyter notebook)

|  |  |  |  |
| --- | --- | --- | --- |
| Observed | 2019 | 2020 | 2021 |
| Sum of Ranks | 97 | 211 | 358 |

Calculate test statistics H:

H=12N(N+1)∑ki=1R2ini−3(N+1)H=12N(N+1)∑i=1kRi2ni−3(N+1)=

H=\*[ +] – 3(18-1)=

\*[ +] – 3(18-1)=

\*[ + – 51)=

0.009\*15123.499=**136.111**

As **H=136.111** is greater than **χ2(0.05,2)=5.99** we will **reject** ourNull Hypothesis (H0) and we can say that medians are **not the same** in 3 selected years and at least one of them is different.

### Appendix 3. *Mann-Whitney U test*

Null Hypothesis H0: USA mean prices are greater in the USA.  
Alternative Hypothesis H1: The mean prices are the same or greater in IRL  
Known values:α = 0.05  
Results: If z is less than -1.96, or greater than 1.96, reject the null hypothesis.

|  |  |  |
| --- | --- | --- |
| Observed | IRL | USA |
| Sum of Ranks | 598 | 677 |
| Population | 25 | 25 |

U = -∑= - 598= -598 =**352**

U’ = -∑= - 677= -677 =**273**

U = 352 U’ = 273 MIN(U ; U’) = 273

Calculate Z:

Z= = = = -0.766

Results: Z = -0.766 and it is greater than -1.96 and is less than 1.96. We can accept Null Hypothesis H0

### Appendix 4. *Spearman’s r Test*

Use values from the Jupyter notebook to calculate squared difference values



The formula for Spearman’s r is:

*p*= =

### Appendix X **–** Project Timeline

Project Start: Saturday 23rd April:

* Review Project Requirements
* Review individual tasks
* Create a project timeline

Week ending Sunday 1st May:

* Initial literature review
* Twitter API review
* Sentiment analysis task review
* Sentiment analysis task – analysis in Python

Week ending Sunday 8th May:

* Review Agriculture related data sources
* Select suitable data analytics topic from available data
* Clean data

Week ending Sunday 15th May:

* Review Machine Learning models and task
* Create Machine learning models
* Review Statistics tasks
* Calculate Statistics tasks
* Review Literature

Week ending Sunday 22nd May:

* Dashboard
* Complete Report
* Review code and report
* Complete and upload the assignment