Predicting Certain Commodities Related to our Bovine Friends

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1 Abstract

We examine the potential of predicting future prices of commodities with a case study– the prices of common bovine commodities over time. We use time-series methods to help predict future prices. These include looking for seasonality, applying Vector Auto-Regression and VARMAX ARMA methods to forecast prices across commodities, and the Prophet method developed by Meta. We used Ordinary Least Squares (OLS) to get a simple benchmark used in measuring the effectiveness of the Vector Auto-Regression, Prophet, and ARMA models. We found that the ARMA and Prophet models were much more accurate at predicting future prices, resulting in significantly lower Mean Squared Errors than returned by the OLS model, with the ARMA model performing the best of all. From the VAR and Impulse Response Function, we also found some results indicating that the price of certain commodities could forecast others.

2 Introduction and Background

Predicting the price of commodities and stocks is difficult, yet many professions necessitate such forecasting. We aim to use time series models to determine if there are patterns that can aid in price prediction. We look at a few aspects of prices, including seasonality and dependence upon other commodities.

Previous studies have found that there are links between certain commodities or stocks. One study found the price of gold is useful in forecasting oil prices[5], and another found that a sudden rise in the price of Facebook stock could forecast a rise in the price of Amazon stock prices[1]. Such studies used time series methods to find links between the commodity prices or the stocks, respectively.

We aim to answer questions relating to predicting future prices, such as: How can we use time series methods to better predict future prices of commodities? Do these methods perform better than simpler methods? How can we use the price of related commodities to help in the forecasting?

As a case study, we examine prices related to bovine products, including beef, corn, hay, and milk. Farmers and ranchers need to attempt to predict prices when they plan to buy and sell their products. Theoretically, since these commodities are related (cows in the US eat mostly corn and hay products[2]), it is possible that we could use them in combination to build a more accurate time series model. Additionally, these commodities may have a seasonal component, since crops grow seasonally and the other commodities may sell for different prices depending on the time of year.

3 Data

All data sets for this project came from the Federal Reserve Bank of St. Louis[3], a reliable source for clean data. For our project, we included data sets for the prices of milk, hay, beef and corn. The data sets included values for the first day of each month for years between 1947 and 2022.

The data sets did not run over the same time period, but since they were from the same source, they had the same format in the date column, so it was simple to merge the sets together on the date column. We dropped dates that were not included in all four of the data sets. After cleaning, the data set we used included 317 data points, with data from every month from July 1995 - November 2021. It should be noted that the data has some limitations. A significant limitation is that the units vary from each other greatly (i.e. milk is in dollars per gallon while corn is in dollars per metric ton.)

The data was not previously adjusted for seasonality, so we decided to investigate its seasonal component ourselves.

When examining the seasonal components of each product there are several different behaviors. There is a large change in price for hay and a smaller difference in price for corn. The seasonal component of corn and hay can be explained by the growing seasons. For example, the usual harvest season for corn is around August. Around that time the price for corn has a sudden decrease as farmers are harvesting their crops and supply dramatically increases. The seasonal components of milk and beef have very little change. The price of milk varies by only a 7 cents and beef varies by only 4 cents. This makes sense, because a cow can be milked and slaughtered at any time of the year, but crops only grow in certain periods.

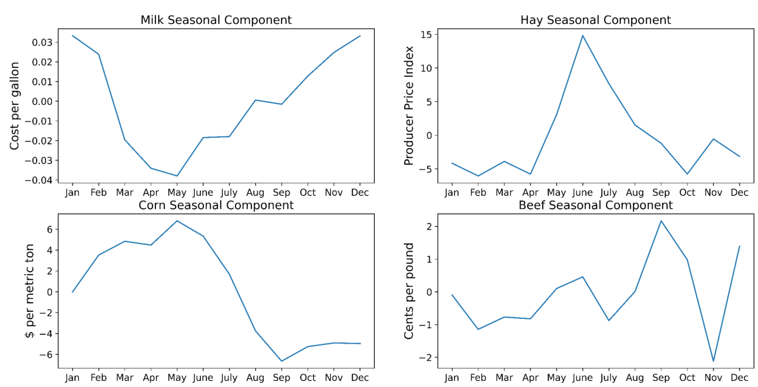


Figure 1: Seasonal components of Milk, Hay, Corn, and Beef prices

4 Methods Used

We tried several different time-series methods to attempt to forecast future commodity prices.

4.1 Ordinary Least Squares

We decided to use Ordinary Least Squares (OLS) as a baseline in evaluating how well our other models did at forecasting future prices. We picked 2016 as the division between our training and test sets. For each instance of OLS that we used, we only trained it on its own data, then compared it to the test set to gauge how well our linear model predicted the actual data beyond 2016. We then calculated the Mean Squared Error (MSE) of each model to quantify the accuracy.

After running this model we realized that although OLS is efficient at capturing the general trend of the data, it should not be used to predict any future values. Thus, we decided that we would not use it as a benchmark in assessing the accuracy of our subsequent models, and instead we would use it to understand the trend of the training set.

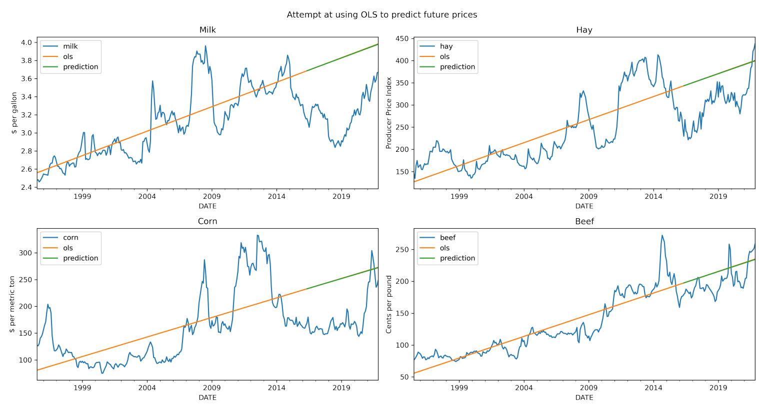


Figure 2: Results from OLS

4.2 Vector Auto-Regression with Impulse Response Function

To examine the dynamic relationship among the variables, we looked at links between corn and hay as well as between beef and milk by estimating a VAR model using Python's statsmodels library. A time-series can be said to Granger-cause another time series if it can be used to provide information about the time-series at a significant level [6]. Granger causality is not true causality. The intuition is simply that a variable X Granger-causes Y if a regression including lagged values of both X and Y has better predictive power than a regression including only lagged values of Y.

We plotted the Impulse Response Function to get a visual of what happens when the prices of certain commodities receive a "shock" or drastic change in the input. The plots outline the response of a variable given the change in another.

We took the log differences of the data to make the series stationary, then used the Akaike Information Criterion (AIC) to determine the optimal number of lags. We can examine this information by examining the t-statistics, using a standard statistical significance level of 5 percent. Notably, hay did not seem useful in forecasting the price of corn (t-stat of 0.140), but corn can be said to Granger-cause the price of hay (t-stat = 2.742). We also found that beef Granger-causes milk with 3 lags (t-stat of -2.311), but milk does not Granger-cause beef.

An impulse is a type of stimulus (often called a "shock") to the price of a commodity; that is, the price of corn suddenly shoots up. The Impulse Response Function (IRF) shows the reaction of the time-series system over time due to the shock. These graphs give a visualization of how a shock to one price (e.g., corn) can affect the future price of other commodities.

Our IRF graphs show 4 relationships, including the effect of the commodity on itself (e.g., hay on hay) and the effect of the commodities on the other (hay on corn). In our impulse response functions, as can be seen from that of corn on hay (bottom-left), an increase in the price of corn results in an increase in the price of hay, whereas in the top-right graph, there is little effect (i.e., hay has little effect on corn.)

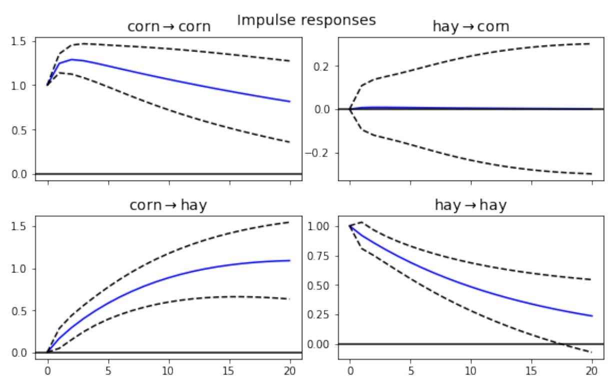


Figure 3: Impulse Response Function results from VAR with corn and hay. Plotted with 95% confidence interval.

Similarly, in the following chart, the top right graph shows that a shock in beef price may also result in a similar price rise in milk.

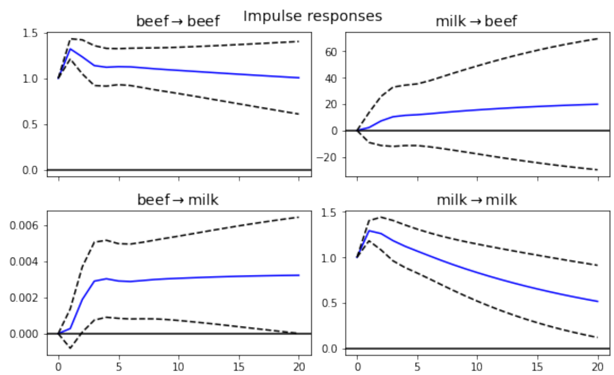


Figure 4: Impulse Response Function results from VAR with beef and milk. Plotted with 95% confidence interval.

4.3 Prophet Method

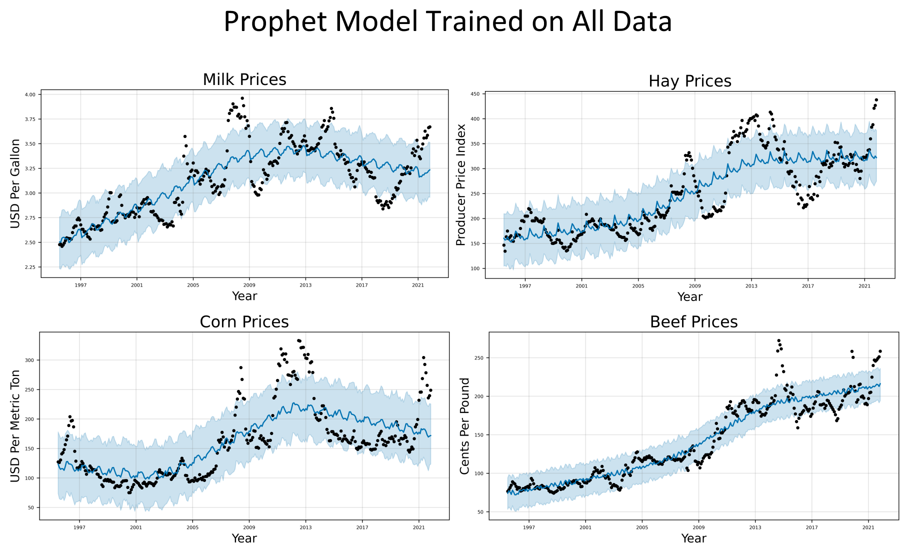
As our additional forecasting method, we fit a Prophet model, created by the Core Data Science Team at Meta [4]. This model decomposes time series as

$$y(t) = g(t) + s(t) + h(t) + (t)$$

where $y(t)$ is the price, $g(t)$ is the general trend, $s(t)$ is the seasonal trend, $h(t)$ is the holiday trend, and $e(t)$ is the error. The trend component of this model is piece-wise linear, the seasonal component is trained on a Fourier series. In this use, the season component is cyclical and repeats every year.

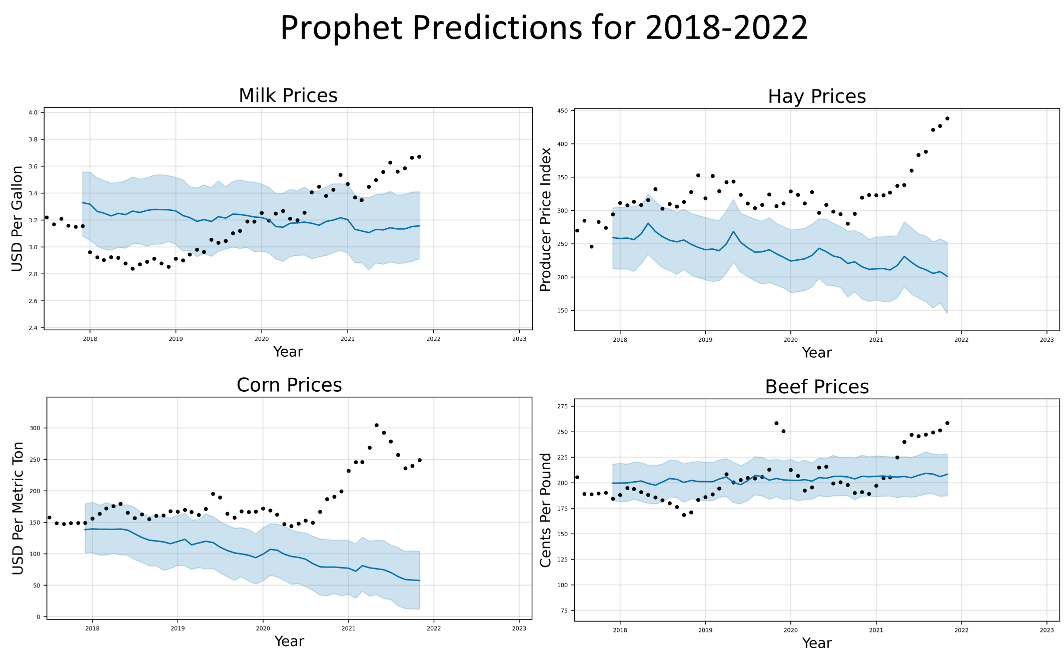
This model was picked due to the cyclical nature of our data. The trend component is good for capturing the business cycle and gradual changes in the market. Yearly cycles are a good fit for the seasonal trend.

Below, we can see the Prophet model fit on all the available data, along with the model's corresponding MSE. Black dots are data points, the blue line is the model's predictions, and the shaded blue region is the model's confidence interval.



	Milk	Hay	Corn	Beef
MSE	0.0477	1775.1	1692.0	274.1

Below, we divide the data into training and testing sets, with 1997-2017 being used to train the model, and 2018-2022 being used to test. The black dots are data points and the blue line is the prediction.



	Milk	Hay	Corn	Beef
MSE	0.0914	10485	10590	511.90

4.4 VARMAX Method

We attempted to fit the data to an Autoregressive–Moving-Average (ARMA) model using the VARMAX method in Python's statsmodels package. We began by trying to predict the price of each commodity up to 2023-11-01 (two years in advance), using the default parameters and no trend. The model seemed to capture the previous pattern of the data pretty well, and it resulted in an AIC of 6,357.

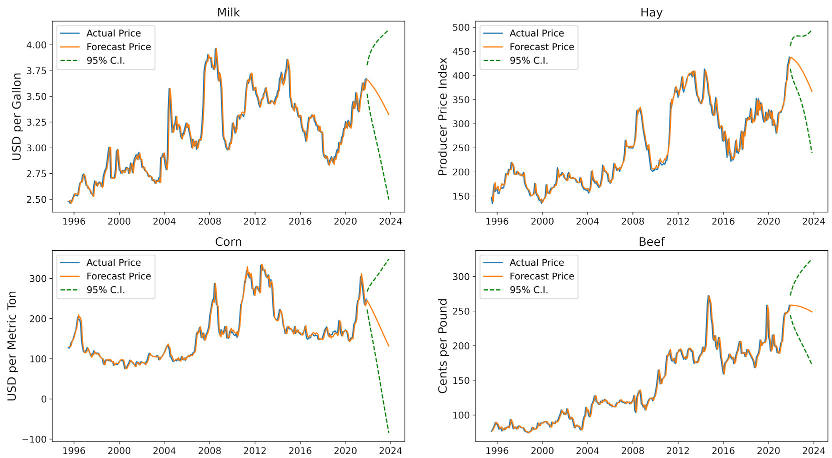


Figure 5: VARMAX method

Although we were fairly pleased with this model's performance, we wanted to see how well our model could predict some of the later observations in our data set. We ran our model again, but this time trained it on prices up to 2016-04-01 (the first 250 observations), and used it to predict the prices up to 2021-05-01, which was the last observation in our data set. We then compared our model's predicted prices to the actual prices in order to see how closely the model matched the data set's pattern. We found that, upon initial examination, the model performed quite well for prices of milk and hay, and slightly poorer for corn and beef.

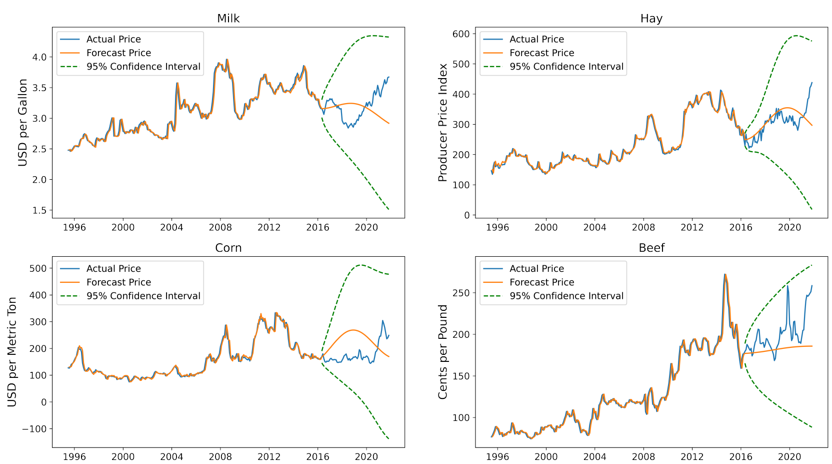


Figure 6: VARMAX method compared to the test set

This model resulted in an AIC of 4,890. In order to generalize the model's efficiency and to lend to more accurate model comparison, we calculated the MSE for each feature. The comparison of each model's MSE's are shown below in the Results and Analysis section.

This multivariate ARMA model seemed to be performing well, suggesting that the four commodities were useful in predicting each other's prices. We decided to check if including a subset of these commodities in our model would yield better models with a lower MSE. After including various different combinations of the commodities in our model we found that, on average, these models performed worse than the full model that included all four commodities. There were a few models that were similar in accuracy to the full model, with little variance in their MSE's and the way they fit the data, but most of them were significantly worse.

5 Results and Analysis

	Milk $/Gal	Hay PPI	Corn $/metric ton	Beef cents/pound
OLS	.4457	5680	6529	525.4
Prophet	.0914	10485	10590	511.9
VARMAX	.03	194.95	193.36	60.24

Figure 7: Mean Squared Error of the models used

As noted above, the OLS model was effective at providing a quick generalized view of the trend of the data, but failed to capture many of the nuances, making its prediction of future values less than desirable. The ARMA model was quite effective at not deviating too far from the observed data, resulting in the best MSE's for each commodity. At times it appeared that it did not follow the trend as well as OLS, but it was very effective at capturing some of the seasonal components that it had learned from the training set. The ARMA model also performed much better when all four of the commodities were used in the training process, rather than a subset of them. The fact that the model's performance decreased as we decreased the amount of time series used in the training process led us to conclude that each of the commodities were quite useful in predicting one another.

The Prophet method performed quite well, capturing some of the small changes in the data due to seasonality while also capturing the general trend. However, the ARMA model still outperformed the Prophet model, following the trend and nuances of the data more effectively, resulting in lower MSE's for each of the commodities.

In addition to the ARMA and Prophet models, we found there are other time-series methods that can be somewhat effective in predicting future prices. The t-statistics from the VAR model as well as the IRF plots indicated that hay has little effect on the future price of corn, whereas corn has an effect on the price of hay. Similarly, beef can forecast milk, but not vice versa. This may indicate that for example, a spike in the price of corn may indicate a spike in the price of hay some time in the future, which would be helpful when buying/selling commodities.

6 Ethical Considerations

While these methods were somewhat successful at predicting future prices of commodities, these predictions in no way guarantee an accurate forecast of prices. They should be used with caution when attempting to make decisions on buying/selling commodities. It should be noted that if a company with a large market share used our analysis to price their commodities, they could have significant power in the future prices, potentially harming smaller companies.

7 Conclusion

From the results above, we found that using the ARMA and Prophet models will be most effective in forecasting the data for several years, with the ARMA model giving the most accurate predictions. OLS appeared to capture the general trend, but it would be inappropriate to use it when forecasting. When shocks may be forecast in the future, the results from the impulse response model indicate that some of the commodities may be used to predict subsequent related shocks, while others cannot. Overall, combining the results from these different models will enable one to most accurately predict the prices of milk, hay, corn, and beef in the future.

References

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[6] Wikipedia. *Granger Causality*. 2022. URL: https://en.wikipedia.org/wiki/Granger_causality.