THE IMPACTS OF SUPPLY CHAIN VOLATILITY ON PRICE ELASTICITY

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Abstract

The world economy has never been more connected, or more vulnerable. If there is anything that we have learned from the last 2 plus years, it's that disruptions to our global supply chains are the new normal. The goal of this research is to first, give insight into the baseline change in price elasticity for inelastic commodities, and secondly lay a framework for how to forecast volatile supply chains.

Food commodities are the very bedrock of our economy, in this analysis commodities were examined to understand the baseline increase in price elasticity as a result of increased supply chain volatility. Data was collected from the United States Department of Agriculture, and the Organization for Economic Co-operation and Development on price and supply to the United States economy for wheat and beef. This data cleaned, then modeled using Meta's prophet package to demonstrate how recent improvements in algorithms can improve accuracy of forecasting in volatile supply chains. Price elasticity is then used as lens to quantify how the increased volatility has impacted price.

The key findings from this study show that despite major shifts in the supply chain behavior Meta's prophet can predict with a high degree of accuracy. A Median Absolute Percent Error (MDAPE) of less than 3 percent is achieved over the total training period of the model, in supply chain conditions where the inelastic commodity wheat has exhibited a trend towards becoming elastic. This accuracy is compared with that of beef which achieves a 3.9 percent MDAPE over the training period and does not show any trend towards becoming elastic.

The implications for this research are a clear improvement in the ability of algorithms to improve supply chain management in dynamic and stable environments, as well as indicating a potential shift in wheat pricing behavior. Future research could build on this analysis by applying

the methods highlighted here to other industries to better optimize their product blend, and supply chain management practices. Governments could utilize this research as an aid to craft better subsidy policies as indicators point towards a need for policy adjustment.

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CHAPTER 1: INTRODUCTION

Background

COVID-19 disrupted the economy in a way that has never been seen before. Overnight supply chains, employment, and prices were all called into question. In the face of such uncertainty business leaders have few options. Businesses are forced to look at their supply chains and prices in new ways. An important way to do this is through price elasticity. When price is inelastic it means that demand is unlikely to change when price increases. When price is elastic, demand changes as a function of price. Current research has failed to identify the relationships between price and demand in dynamic environments like that of a pandemic. The goal of this paper is to fill that gap, by analyzing existing data on the commodities beef and wheat. Wheat which has been subjected to its own global catastrophe, the Ukrainian-Russian war, which escalated in February of 2022, and beef which has seen no significant disruption outside of macroeconomic trends induced by COVID-19.

Objectives

The significance of this can be conceptualized of in two ways. Firstly, to the people studying macroeconomic effects, this analysis should yield an understanding of the baseline price elasticity effects of a volatile supply chain induced by the pandemic. Secondly, this paper aims to outline a methodology to forecast supply chains and price elasticity in stable and dynamic business environments. This will allow the readers to reduce waste and improve costs. This should not only reduce any disruptions to the economy in the future but facilitate the migration to a more sustainable and equitable world through improved supply chain and price management.

Limitations

The limitations to this analysis are centered on the computing power of the device in which it is being conducted on, the ability of the model to deal with large ranges of data in the same population, and the industry in which the data is gathered. Data is of varying quality in different industries, if the correct level of granularity is not available then the model will not perform as expected. Additionally, there are varying levels of accuracy amongst different industries as well, this is an even greater risk because this data may be modeled easily, however the results are of no value because the data acquisition systems are inaccurate. There are also limitations on what the model can accomplish, algorithms have progressed significantly in recent years, however large variations in values from a day-to-day basis can mislead the tools available. Additionally, commodities may not be representative of other industries, and methodologies will need to be changed to fit the needs of each business case.

Inspiration

There are many challenges facing the world today. Climate change, inequality in numerous areas, and unsustainable practices in almost every industry. Luckily, data science can help with all these issues. By leveraging the power of computing, we can increase the performance of systems already established, while migrating to a more sustainable, equitable future. With an aging population in most of the developed world, and no replacements arriving, the shortfall in labor will have to be replaced. This shortfall must be replaced with efficiency, and the quickest way to do this is by leveraging computers. These wonderful devices are already ingrained into our lives in so many ways. Let us utilize them to solve problems that seem insurmountable, let us utilize them with data science to improve the world, and our future.

Organization of the Paper

This paper contains an introduction where the goal, benefits, limitations, and structure of the research are outlined. Then a review of the relevant literature on this topic, a section centered on the methodology of the analysis, and a review of the results. Followed by a conclusion with a summary of the work and the findings. A bibliography is included at the end, along with an appendix containing all relevant facts and figures not included in the analysis.

CHAPTER 2: LITERATURE REVIEW

Introduction

To understand this new and developing topic it is important to review the relevant literature pertaining to the two subtopics, dynamic supply chain forecasting and price elasticity, as well as review the nature of agricultural commodities in the economy. The review will start with an in-depth analysis of the relevant literature, and how it pertains to agricultural commodity subsidization, as this will have direct effects on the dynamic nature of both the supply chain, and the corresponding pricing behavior. This is crucial because without a basic understanding of the products we are using for this analysis, there is no basis for assessment when it comes to model performance.

Next the review will move to the study of supply chain forecasting. This topic is vast enough for an entire analysis. Therefore, for the purpose of this review we will be focusing on a specific component of supply chain forecasting, that is supply and demand forecasting in dynamic supply chains. Thus, we will examine the larger trends of supply chains, events that can induce supply chain dynamism and volatility, the characteristics of a dynamic supply chain, a review of the forecasting methods that have been employed in this field already. This will be followed with a careful discussion about the gaps and potential shortcomings in the existing research.

Then a review of price elasticity is necessary, once again this is a vast topic, so the discussion is centered on price elasticity in dynamic environments. A review of business approaches, and modeling techniques will be explored centering on energy companies, and gaps in this research will be discussed and analyzed. This analysis aims to draw conclusions on the greater trends in this field and understand the approaches that have been taken previously

Subsidies and Commodities

Commodities are the bedrock of our economy. They cover everything from water to copper and are used in every sector of the global economy. For this review, the focus is on how subsidies effect the commodity pricing, and their supply chain management.

Subsidies work on the price side by their nature, as they are monies granted to a specific entity by the government or public body to keep prices low or competitive. When the goal is to keep prices low, that makes a product insulated to supply and demand fluctuations. There are many different reasons for government to do this, primarily as a national security concern. If a country is reliant on another for goods or food or any other commodity for that matter, they are extremely vulnerable. In fact, had the United Kingdom listened to Winston Churchill during the start of World War II it is likely that Nazi Germany would have never risen to the heights that it did. Churchill suggest a naval blockage of the shipping routes between Germany and Scandinavia to cut off Germany's supply of iron ore (Shirer, 1990). Therefore, governments are incentivized to insulate their domestic markets from manipulation by foreign powers. Subsides are the key method for doing this.

In directly then, subsidies work on the supply chain by inducing a market condition where demand is always in excess of supply. While subsidy policy can be used in a variety of ways, to increase output, reduce pollution, improve profits, and increase consumer surplus it is recommended not to set to high a subsidy rate to achieve the optimal benefit to society (Zhang et al., 2020). From two things can be concluded, firstly that subsidies are necessary, and critical to national security, and secondly there is an optimum where subsidies are doing just enough that it benefits the entire country.

Critical commodities that are subsidized by the government are not insulated to global catastrophes. For some time, a era of prosperity was present on the global stage where commodities like food and oil were subsidized in such a way that narrowed the gap between the wealthiest and poorest nations. However, global supply chain catastrophes like COVID-19 and the war in Ukraine created such disruption that the subsidies were not able to insulate the economies from the supply and price fluctuations. These two global events have shifted trade, production and consumption behaviors on a fundamental level and shifted the needs for subsidization, in such a way that prices may not recover for years (Gill, n.d.). To summarize, heavily subsidized commodities like food and oil are not insulated from global supply chain catastrophes.

Supply Chain Volatility

Supply chains are integrated into our everyday lives. Conceptually speaking a supply chain is a string of events that is initiated with demand and ends with a completed transaction between an individual and a business. In each part of our world supply chains are becoming more dynamic according to (Yu et al., 2019), and for numerous reasons. Consider the geopolitical atmosphere today, as recent as 2018 the Trump administration was in a tariff war with China, creating instability in the global supply chain. Climate change has created less predictable and more severe weather phenomena, and in 2020 the world was rocked with a global pandemic. Effectively shutting down the global supply chain for weeks at a time, and at different times when infections were widespread. These would be considered events that are out of our control. However, it is not just global events, consumers and businesses are also driving this increased volatility. Each business focuses on getting their products to market faster and businesses with an established customer base have the infrastructure to market faster than they can produce. Therefore, increasing demand faster than they can solicit materials. Consequently, this creates an environment of increased uncertainty (Syntetos et al., 2016).

As a result, businesses have looked for ways to improve their response to these conditions. Two terms have been used with increasing frequency. Supply chain resilience (SCR) which aims to improve a company's ability to adapt to dynamic conditions, as well as supply chain disruption orientation (SCDO) which aims to learn from previous experiences with dynamic supply chains and improve the response as a result (Yu et al., 2019). Businesses know that improved performance in these two areas is key to financial success. In a previous disruption a company lost close to 14 percent of its market share because of its inability to deal with the corresponding supply chain change (Mithun Ali et al., 2021). Additionally, a meta-analysis of supply chain approaches found that companies that did not integrate SCR or SCDO methodologies into their existing business practices had on average 33 to 40 percent lower stock returns than those that did (Mithun Ali et al., 2021).

The research is clear that dynamic supply chains are becoming more prevalent, and that companies that fail to adjust suffer as a result. Now let us investigate the research on the methods implemented to improve the response to supply chain volatility. Despite the wide adoption of enterprise resource planning tools (ERPs) like SAP the most common forecasting tool is still the spreadsheet (Weller & Crone, 2012). Coincidentally the mean average percent error (MAPE) found in these forecasts for a one-to-three-month interval was around 40 percent (Weller & Crone, 2012). These forecasts therefore are unlikely to bring any real business value. The supply chain team would be better suited to look at historical data and use that instead. Fortunately, there are better tools like Python that can be used. With these tools time series models like the autoregressive integrated moving average (ARIMA), artificial neural networks (ANN), and regression models can be employed. In a meta-analysis of supply chain forecasting it was found that ANN was used most frequently (30), Regression analysis (27) second, and time-series forecasting (13) third (Seyedan & Mafakheri, 2020). Each of these methods have positives and negatives, and the research fails to describe in detail the parameters of the supply chain in which they were modeled on. The performance of the three different types of models above were all improved through utilization of some sort of clustering or unsupervised classification algorithm to identify the segments that were about to be modeled. The ANN mentioned in the meta-analysis used a genetic algorithm-based cost function, and clearly outperformed linear regression regarding MAPE (Seyedan & Mafakheri, 2020). However, there is no mention of the performance relative to the ARIMA model. Therefore, it would be best to have a side-by-side comparison of the two models themselves to determine which performed better. In an idealized situation the ANN and ARIMA would be tested on different supply chains with varying levels of volatility and compared, this is an opportunity for further research. The ARIMA model does have short comings of its own. It fails to predict accurately when volatility is high and struggles with forecasting seasonality. To summarize, the research is clear ANN, regression, and time-series models all have short comings, and struggle with different aspects of modeling dynamic supply chains.

Price Elasticity

The ability to forecast demand is critical to forecasting price elasticity as it relates to this analysis. However, establishing price elasticity can be done independently from forecasting demand, it makes sense then to start the review of the literature by reviewing the approach to establishing baseline price elasticity. To start, businesses need to understand how to set their prices. It is estimated that around 30 percent of businesses are making price decisions sub optimally, which means that there is a lot of money being left on the table (Sun et al., 2021). The interesting part is that businesses appear to have a strong grasp on the theory but not the implementation. This results in a lot of money being spent to understand price elasticity if they don’t reside on the upper or lower end (Sun et al., 2021). In short, unless the price elasticity is obvious to the business, the business owners do not understand it. Building business understanding is one of the goals of this paper.

Secondly, businesses need to understand whether they are dealing with a homogenous or heterogenous marketplace, and whether that has an impact on consumers preference for price. The thought process is that if consumers are sensitive to price in some markets and not sensitive to price in others than the business should adjust accordingly in terms of marketing and supply. If businesses failed to do this, it would lead to inefficient pricing structures and reduced profits. On this topic, the research is clear, in general it is safe to model most markets as homogenous. Heterogeneous markets exist however there appears to be little improvement when using a model that allows for heterogeneous differentiation regarding price elasticity (Weber & Steiner, 2021). This seems to go against intuition, the study referenced focuses on retail businesses, and it would be advantageous to have a wider spread study on this topic crossing multiple industries. This could be an opportunity for further research.

Another component to the price elasticity analysis is whether consumers respond to incentives or not. An incentive would be defined as a sale or rebate for a specific product. The research indicates that the impact of incentives has the lowest value for high dynamic prices, average for moderately dynamic prices, and highest value for static prices (Pandey et al., 2022).

The would seem to indicate that the likelihood of a consumer to respond to incentives is not linked to their sensitivity to price, but rather the frequency in which the price is changed. Therefore, reinforcing the value of price elasticity analysis and demand planning in a dynamic environment. If the supply chain shifts and businesses shift prices as a result only to have inventories rise unexpectedly, they are unlikely to be successful with incentives to reduce inventory.

Having fully explored the business components to price elasticity analysis, the research can now be reviewed on the modeling methods and results after determining price elasticity. First when analyzing price elasticity on a more general note, the research indicates that price elasticity is best determined through a use of decision trees, and logit decision trees (Arevalillo, 2021). After utilization of these models an analysis was carried out comparing prices that had not been analyzed and those that had to determine the results. It was found that the group that had price elasticity analyzed, and price optimized had tighter distribution of revenue, and more realistic revenue predictions than the non-optimized group. This study would indicate that this analysis does work in improving revenues and reducing uncertainty, however it only discusses one modeling technique. That of decision trees and random forests. There is opportunity for comparison using other classification algorithms to better determine which is the most effective methodology.

Now reviewing the research about price elasticity in a dynamic supply chain, the research discussed smart energy systems that allow for bidirectional communication about consumption and demand. Through this an algorithm is developed to support demand-side dynamic pricing for utility companies to encourage end users to participate in their demand response programs (Ruan et al., 2022). In short, this asked the consumers to give the energy companies better insights into their energy consumption behaviors through their smart devices. What this allows companies to do is better forecast energy consumption by their customers and ensure that they are always selling at the optimal price point for their consumers while reducing waste. The analysis is clear that feedback from the consumers and buy in to the demand response program resulted in clear picture of the supply chain and resulted in a decrease in the peak-average-ratio of energy consumption without any price risk. This is contradictory to what we discussed earlier. The difference here is that the consumer is aware of the price fluctuation and therefore not negatively impacting purchasing behavior.

Having reviewed price elasticity from a general standpoint, the discussion can move to commodities specifically. In general, commodities can be elastic or inelastic, depending on the consumer behavior. The focus of this analysis however is on beef and wheat, two food commodities. These two commodities are considered inelastic, meaning they are stable in price fluctuations and insulated to the changes in supply and demand (MasterClass, 2022). This is by design from a subsidy standpoint, in addition to be classified as a necessity. Therefore it can be concluded that in normal supply chain conditions the two commodities analyzed, exhibit inelastic behaviors.

In conclusion, we reviewed the research on supply chains and price elasticity and found that supply chains are becoming more unpredictable, and to achieve optimal price points businesses can assume that markets are homogenous even though they are not. Then we discussed the research on industry trends indicated that methodologies like SCR and SCDO are key to financial success when managing supply chains and through these the groundwork is placed for price elasticity analysis. After we reviewed the most innovative modeling techniques for forecasting supply chains and concluded that not one model choice stood out. It appears that price elasticity has a preferred model, however there is minimal research and development on the topic of dynamic demand and therefore requires more research. While the research is clear, it is not conclusive on the research question proposed above. There is no concrete evidence contrasting dynamic supply chain model techniques and their resulting effect on prediction of price elasticity.

CHAPTER 3: METHODOLOGY

Introduction

This chapter can be thought of as five separate parts and will be discussed as such. The methodology centers on the commodity wheat. While there are two commodities used in this analysis for comparison purposes, wheat and beef are treated in the same way. If there is a difference between the two it will be explicitly mentioned. The first part will review the methodology behind data selection. This will cover the thought process behind why the data was selected, why the data range of the data selected, and what makes the data a good candidate for the research. The second part will review the methodology for the data cleaning. The third part will review how the forecasting model was built, what methods were used, the parameters that were included or excluded. The fourth part will discuss how we judge the performance of the model, the definitions of the different model metrics considered, and the benefits and drawbacks to each one. Then the last part will discuss how the price elasticity component was developed. Then this section will conclude with a summary what was discussed.

Data Selection

Selecting the proper data is critical for the research. As a reminder, the goal of this analysis is to not only explore supply chain volatility and the pass-through effects on price elasticity but serve as a guide for future research into different topics. It was with this in mind that commodity data was selected. It has several characteristics that make it a good candidate. First, it is easily accessible and widely available which is critical for reproduction of this analysis. All data for this analysis was taken from the Organization for Economic Co-operation and Development (OCED), and the United States Department of Agriculture, specifically the Economic Research Service arm of the USDA.

Second, the data is available on a month level granularity, and over many years encompassing the various macro-economic cycles. This is critical because it introduces cycles of volatility that for different economic conditions, meaning volatility may appear with different pass-through characteristics during economic recessions and expansions. Data was collected from 2016 to 2022, this data range was collected because it contains the COVID-19 pandemic, the current labor force conditions, and the conflict between Russia and Ukraine. A larger date range was considered, however the business trends of "just-in-time" (JIT) shipping and receiving, the change to the labor force, and the recent global disruptions are key drivers to supply chain volatility and may not have been as significant in the years prior to 2016.

Thirdly, commodity data is inelastic this component of the data is critical because demand is unlikely to fluctuate from any change in price. While this may seem like a reason to disqualify commodity data from an analysis like this it is a key reason to choose commodity data. When demand is insulated from price, supply chain volatility has a direct pass-through effect. Therefore, conditions of brand loyalty and economic conditions are unlikely to have an overweighted effect on the price as they would on other products. Furthermore, commodities being inelastic allow the analysis to get a distilled view into what affects supply chain volatility has on price. In other words, it allows us to determine to cost of supply chain volatility in the current supply chain ecosystem.

Fourth, commodities are sold on the world stage, and distributed everywhere in the world. Therefore, it is reasonable to consider this to be one of the largest and best managed supply chains in the world as the incentive structure is one that works to minimized costs globally. Therefore, the analysis aims to examine one of the largest, and best performing supply chain networks to understand the impact volatility has on price. Fourth, commodity price data is widely available, and easily accessible. Data for this analysis was taken from the United States Department of Agriculture (USDA), from their Economic Research Service branch.

Data Cleaning

Commodity data is available in numerous different data source types. For this analysis, the data was downloaded from the OCED website for the years of 2016 to 2022 in csv files. From there it was stored and loaded into Python using pandas. Each file was read and appended into a pandas dataframe with all the columns. A sample of the raw dataset is below in table 1.

Table 1

A view of the raw dataset

WasdeNu	ReportDate	ReportTitle	Attribute	ReliabilityProject	Commodity	Region	MarketYear	ProjEstFlag	AnnualQuarterFlag	Value	Unit	ReleaseDate	ReleaseTi	ForecastYear	ForecastMonth
549	Jan-16	Mexico Sugar Supply and Use and	Beginning Stocks		Sugar	Mexico	2014/15	Est.	Annual	831	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Mexico Sugar Supply and Use and	Domestic		Sugar	Mexico	2014/15	Est.	Annual	4691	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Mexico Sugar Supply and Use and	Ending Stocks		Sugar	Mexico	2014/15	Est.	Annual	811	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Mexico Sugar Supply and Use and	Exports		Sugar	Mexico	2014/15	Est.	Annual	1442	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Mexico Sugar Supply and Use and	Imports		Sugar	Mexico	2014/15	Est.	Annual	128	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Mexico Sugar Supply and Use and	Production		Sugar	Mexico	2014/15	Est.	Annual	5985	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Mexico Sugar Supply and Use and	Beginning Stocks		Sugar	Mexico	2015/16	Proj.	Annual	811	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Mexico Sugar Supply and Use and	Domestic		Sugar	Mexico	2015/16	Proj.	Annual	4725	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Mexico Sugar Supply and Use and	Ending Stocks		Sugar	Mexico	2015/16	Proj.	Annual	1081	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Mexico Sugar Supply and Use and	Exports		Sugar	Mexico	2015/16	Proj.	Annual	1150	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Mexico Sugar Supply and Use and	Imports		Sugar	Mexico	2015/16	Proj.	Annual	90	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Mexico Sugar Supply and Use and	Production		Sugar	Mexico	2015/16	Proj.	Annual	6056	1000 Metric Tons, Actual Weight	1/12/2016	00:00.0	2016	1
549	Jan-16	Reliability of January Projections	Domestic Use	above_final	Coarse Grain	Foreign			Annual	10	Years	1/12/2016	00:00.0	2016	1
549	Jan-16	Reliability of January Projections	Domestic Use	average	Coarse Grain	Foreign			Annual	7.2	Million Metric Tons	1/12/2016	00:00.0	2016	1

This data presented a few challenges for modeling. Firstly, it contained numerous global regions, commodity types and attributes. Region was filtered to equal United States, as this is the supply chain that will be focused on. This was picked because the United States is one of the largest consumers of wheat in the world (5th largest consumer globally), and the price data was reliable and easily found (Shahbandeh, n.d.). Commodity type was filtered to equal wheat because of the recent escalation in the conflict between Russia and Ukraine, which has strained the wheat supply chain globally. The analysis could be conducted on any of the other commodities in the dataset as well, however they are likely to represent the global baseline. The attribute variable was not filtered at all and was eliminated from the dataset. As seen above, there are numerous attributes for each commodity, to list some Beginning Stocks, Domestic, Export, Import, Ending Stocks, Domestic Use, and others. The reason it was eliminated and not filtered was because this analysis is looking at the whole system. What the use case of the commodity does not matter because it is so inelastic. Therefore, a key assumption to this analysis is that the people responsible for managing the supply chain are attempting to optimize the supply chain for the region selected. To be clear then the assumption is that the United States is optimizing the supply chain for the benefit of their consumers and that the export quantity is the quantity that is beneficial to the United States economy, and their domestic demands have already been met. The columns WasdeNum, ReportDate, ReportTitle, ReliabilityProjection, MarketYear, ProjEstFlag, AnnualQuarterFlag, and ReleaseTime were all eliminated because they contained data that was not required for the analysis.

Once the data was loaded and filtered and excess columns were eliminated the Unit column needed to homogenize. See the table below for counts of the different unit labels.

Table 2

A table displaying the counts, and percent of population for the different units of wheat

Unit	Counts	Percent
Million Metric Tons	3876	44%
Million Bushels	2673	30%
Percent	640	7%
Years	640	7%
Million Acres	486	5%
$/bu	282	3%
Bushels	243	3%

Units of Years, $/bu, and Percent were eliminated because there was not a conversion with reasonable reliability that could be found. Million Metric Tons was selected as the unit of choice for modeling because it was consistent the price data, and the conversion between million metric tons, and million bushels was consistent and straightforward. Million Acres was also converted to maintain a homogenous unit set.

ReleaseDate was included in the initial dataset however eliminated afterwards. ReleaseDate was designated as the date upon which the commodity was released to the market. However, in this data set all quantities were released to the market at the same time. For this analysis, the month value was taken from the ForecastMonth column, the year value from the ForecastYear column, and the day was a randomly selected number between 1 and 28. The goal of this induce random variation into the daily component of the supply chain, as a consistent release date amongst the data may train the model in a manner inconsistent with actual commodity markets. It is more likely that commodities are released when the market needs them throughout the month, than releasing on a specific day of the month.

Forecasting Model Development

Supply chain volatility is difficult to model. One of the key reasons is that volatility is inconsistent in how it presents in data. There are cyclical components to supply chains that present as seasonality, and this seasonality may be consistent from one year to another, but different over the course of the 6-year data sample. For the wheat commodity data specifically, the cyclical nature is apparent in both the June pricing component, and of course the harvesting season. While the actual price elasticity component will be explored in the next part, the prophet model can be used to model predicted price as well if desired. Fall is typically the time when wheat is harvested, however growing cycles may vary amongst geolocations. Shipment times and shipment type also play a factor in how the supply to a market changes. However, there is no way in this analysis to factor in the type of shipment (i.e., water, air, or truck). All these components induce a degree of noise into our data, that the model must account for.

Wheat itself as a product has inherent difficulties as well. The degree of moisture in the product itself is another component to consider. When wheat is transported, it is dried beforehand. Moisture levels can fluctuate 10 percent or more since the preferred unit is weight for this analysis, it is likely to expect some level of variation in moisture amongst the sample. It is possible to have 100 pounds of wheat from two different shipments produce different quantities of a good as a result (consider flour), and therefore the impact to the demand may fluctuate as a result. All these components must be considered when modeling this supply chain.

Beef on the other hand does have its own cyclical nature, however this can be controlled by restricting when cattle give birth or when cattle are slaughtered. It is true that farmers do have preferences as to when beef is harvested, however, to maintain a constant supply to the market beef is distributed evenly from different geolocations to minimize this fluctuation in the supply chain, and therefore does not have as drastic a cyclical nature as wheat, which is obviously dependent on the weather and growing seasons.

It is for this reason that the prophet package originally developed by Meta was selected for modeling. Prophet has a few key features that allow it to be reliable and robust in modeling supply chains like this, and others that are highly dynamic. Firstly, prophet can have seasonality parameters. These are values modulated by the partial Fourier sum, this parameter is essentially there to help the model judge how quickly seasonality can change in the model. The higher the Fourier sum the quicker the model will adjust to seasonal changes in the data (Prophet, 2022)). There are seasonality parameters for daily, monthly, yearly, and quarterly frequencies.

Seasonality parameters were input for monthly and yearly frequencies, and not for the quarterly or daily components. The daily seasonality parameter was not used because the daily variation in the model is at random, and therefore does not have any seasonality. The quarterly seasonality was not used because the quarterly seasonality is too similar to the monthly, and therefore do not want the model to be overfit to the quarterly and monthly fluctuations in the data. Values for the Fourier sum are included in the results section of the paper.

Secondly, prophet also has a built method for cross validation. The cross-validation component of the model is unique in that it allows us to use cutoff points in our data. What this means is that we specify a performance horizon, in this case 365 days, and we train the data on 2 times that horizon, and we make predictions for half of our prediction interval or around 182 days. This function gives us the ability to train and assess our model performance on what would be the equivalent of 4.5 forecasts. There is 6 years of data, and 2 years of initial training, 1 year prediction then increasing prediction intervals by 182 days each increment. This allows us to investigate the performance of our model with a high degree of accuracy and compare the actuals and the predictions over many different intervals. The many different intervals allow us to understand which economic trends our model excels at predicting and which trends it may struggle with.

Thirdly, in addition to the cross-validation component of prophet, a hyperparameter optimization loop was developed and implemented in the code. The hyperparameter modeling approach was a grid search methodology for the parameters. The parameters that are tuned are for this model are:

- Changepoint_prior scale – Responsible for the flexibility of the trend. Essentially how much the trend changes at the trend changepoints. Too small and the trend will underfit, and too large and the trend will overfit.
- Seasonality_prior_scale – Responsible for the flexibility of the seasonality. A large value allows for the model to fit large fluctuations in seasonality. A small value shrinks the magnitude of the seasonality.
- Changepoint_range – Responsible for setting the proportion of the history in which the trend is allowed to change. It keeps the model from changing too much as it reaches the end of the data. It is designed as protection to recency bias.

These hyperparameters optimized using the cross-validation function, and the grid search methodology will give us the best possible forecasting model for our data.

Prophet was chosen over other time series modeling tools like neuralprophet and the ARIMA model. Firstly, prophet has been shown to perform better in the long term than neuralprophet, and while the dynamic nature of the supply chains may suggest this as a better option, for the purpose of this analysis prophet was selected because of its ability to be accurate over the long term and therefore guide the analysis to insights about pricing strategy. The difference in performance in the short term not well represented in research yet, and therefore prophet was given the edge. Secondly, prophet was selected over the ARIMA model because of the seasonality components, which are critical to modeling this type of data as explained above. Additionally, the built-in nature of a cross-validation function, model metrics function, and seasonality graph, all give the user greater insights to the performance of the model, and thus aide in developing a more accurate model.

Model Metrics

There are numerous methods for assessing the performance of a forecasting model, however there are four that were considered for assessing the performance of this model. They are Mean Absolute Error (MAE), Mean Average Percent Error (MAPE), Median Absolute Percent Error (MDAPE), and Symmetric Mean Absolute Percent Error (SMAPE). Each of these metrics have benefits and drawbacks. Therefore, each will be explored and discussed and at the end a selection will be made.

Mean Absolute Error, and Mean Absolute Percentage Error are quite similar, it is the average of the error for a specific period. The difference between MAE and MAPE is that the MAE does not always give us an understanding of the context of the size of the error. This is critical for this analysis because two different commodities and therefore two different forecasting models will be compared. It is with this in mind that MAE was disqualified from being the metric that was used to judge the performance of the model. MAPE was also disqualified from being the model metric of choice for this model, the reason being is that prophet has a unique behavior in which it calculates error over different horizons and improves as the model is introduced to more data. This will become clear in the results section if it is not already, it is this component that could make MAPE misleading when using prophet on this specific data, as the average error rate at the beginning or end of the training process could skew the overall error rate.

Symmetric Mean Absolute Percent Error unfortunately is subject to the same issue as MAPE. SMAPE does do a better job of showing the difference between predictions and forecasts when there are negative values present. This however does nothing to its reliance on the mean for the calculation, and SMAPE can be difficult to understand because the bounds are between 0 and 200 percent (Lewinson, 2020).

Median Absolute Percent Error is therefore the selected metric by which the model will be judged. This does not mean that the model has been trained by ignoring the other model metrics, only that MDAPE is the gold standard for this analysis. Due to the nature of training, and the hyperparameters of the prophet model, it is critical to understand the median error of our model. When comparing two different models, the magnitude error values must be nullified so our metrics are easy to compare side by side. These two components are the principle reasons for selecting MDAPE as the metric of choice for this model.

Price Elasticity

In comparison to the forecasting model, the price elasticity assessment is far easier. Price elasticity is defined in figure 1 as the:

Figure 1

Equation showing how price elasticity is calculated, it is the same for demand and supply

$$E = \frac{\%\Delta Demand}{\%\Delta Price}$$

Therefore, the price elasticity component is a simple calculation of the how the price for the month changed in comparison to the demand for the month. For this analysis, we do not have price changes within a specific month. Thus, the price elasticity will be calculated in an month to month frequency. It should be noted that if the absolute value of E in this case is greater than 1 a product is considered elastic, and if it is less than 1 a product is considered inelastic.

Although commodities are inherently inelastic, the goal is to determine whether supply chain volatility can cause some change in price elasticity in inelastic products. Therefore, establishing a baseline for the rest of the economy. The logic is that if a product that is inelastic starts showing signs of elasticity the rest of the economy will follow suit to a greater degree.

Summary

To summarize, this section covered the rationales behind selecting commodity data as the candidate for this research, in the context of the goal. The logic in data cleaning was reviewed along with assumptions of the supply chain. The model development process was reviewed and the features that made prophet a strong candidate for modeling this type of supply chain. Then concluded with a review of basic price elasticity calculations and how they would be interpreted in context of the goal of the research.

CHAPTER 4: FINDINGS AND RESULTS

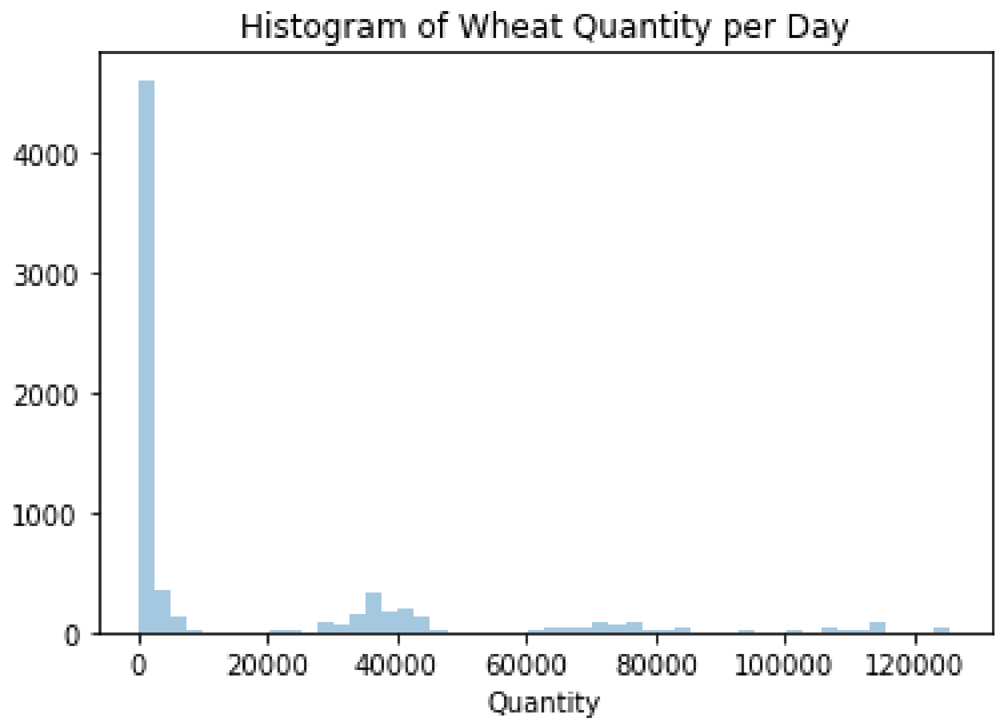
Having comprehensively discussed the methodology behind the data, model development process, and the overarching context of the analysis the discussion moves on to results. First, it is important to state that there are two commodities that we have investigated wheat and beef. Commodities inherently are inelastic; this is by design as they are heavily subsidized. If a commodity were to show characteristics of being elastic, it would indicate on an overall shift in price for the economy. This shift would likely be driven by the dynamic nature of the supply chain (i.e., the supply side or lack thereof) as demand is known to stay relatively constant, and therefore is the reason for our interest. The results section of this analysis will first review the decisions related to the level of granularity for the date level data. Then review the process for hyperparameter tuning, discuss how the model was able to interpret seasonality on default settings, then review the model prediction results. It is important to note here that the model results for both commodities while different do indicate similar trends. Where there are specific differences, they will be highlighted. If not explicitly mentioned the visualizations for the commodity not reviewed in the paper can be found in the appendix. The results section will conclude by discussing the price elasticity results for the two commodities and summarize all the results discussed.

Date Level Granularity

The granularity of time was not predetermined for this analysis. In fact, random noise was induced into the daily level of granularity to show how the model would perform when there was no seasonality present on a daily level. Figure 2 below shows a histogram of the quantity of wheat received on a daily level.

Figure 2

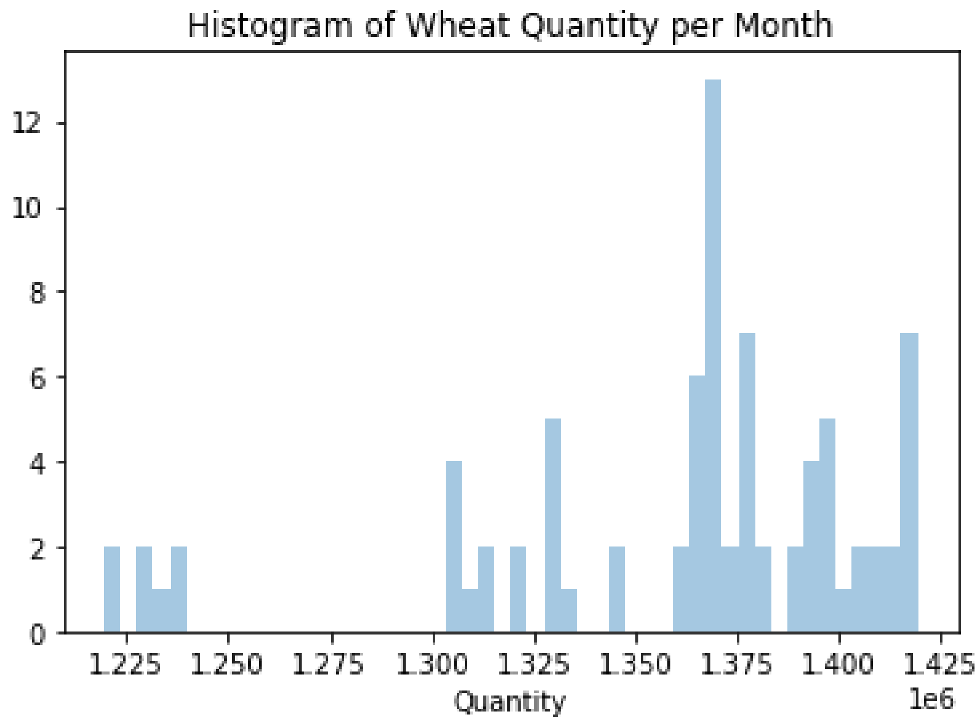
Histogram of Wheat Quantity by Day



Histograms do not consider the date value, and therefore the behavior shown in Figure 2 is not a result of noise introduced. We see the range of values span from 0 to 120,000 with no clear distribution. This range of values proved to be problematic for modeling purposes with an average median average percent error (MDAPE) in values well over 240 percent for optimal hyperparameters, a table showing the average model metrics by hyperparameter settings is included in the appendix. Therefore, data had to be aggregated to a monthly basis. Figure 3 shows the results of the aggregation on the raw data below.

Figure 3

Histogram of Wheat Quantity by Month



As shown in Figure 3, the quantity received now spans a range of 1.225e6 to 1.425e6. While the data shows a slight skew left it does not have a clear distribution. This reduced range allowed the model to predict more accurately. A reduction in MDAPE from well over 240 percent for the daily values, to 2.7 percent for the monthly values for ideal hyperparameters. A table showing the average model metrics by hyperparameter is included in the appendix.

Hyperparameter Tuning

As described in the methodology section, a grid search hyperparameter tuning methodology was employed to optimize the performance of the model. Varying the changepoint_range hyperparameter did not have an impact on the performance of the model, and therefore the discussion of this parameter will be excluded. However, this does not mean that the parameter should not be included in future hyperparameter optimization loops as there is strong reason to believe that data without consistent seasonal nature (which will be explored later) may benefit from this optimization. The values for the hyperparameters in the grid are shown below in Table 3.

Table 3

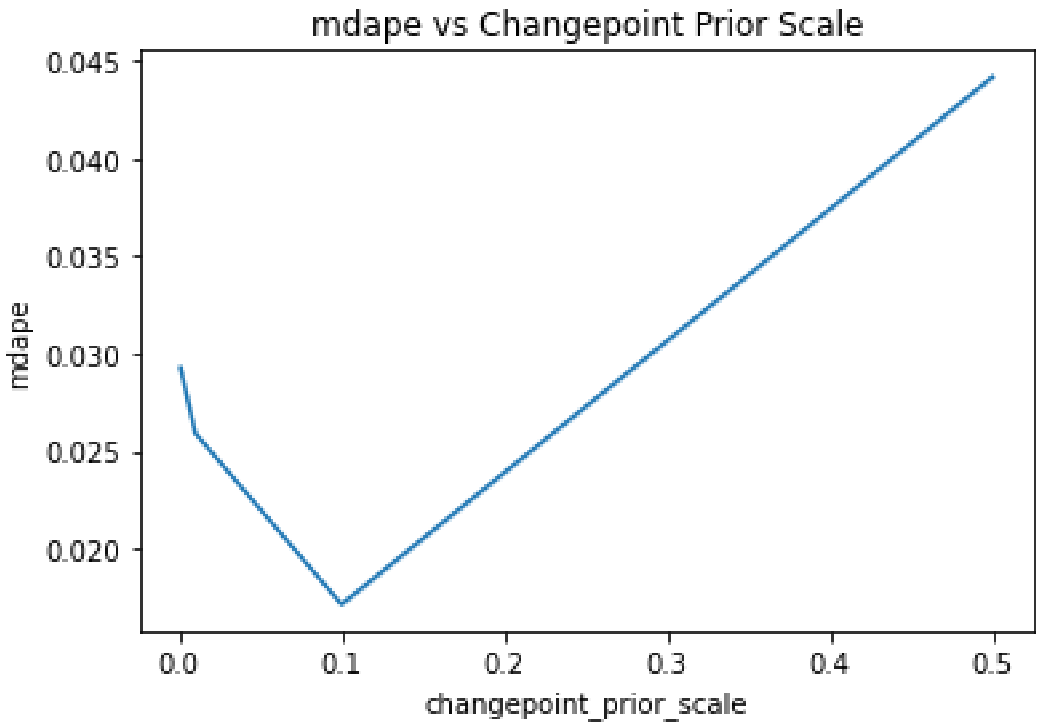
Table displaying the parameters used for tuning the model

CPS	0.001	0.01	0.1	0.5
SPS	0.01	0.1	1	10

Where CPS refers to the hyperparameter changepoint_prior_scale and SPS refers to the hyperparameter seasonality_prior_scale. Both parameters affect how the model changes in response to the data it is presented. With CPS focusing on how the model adjusts to data overall, and SPS focusing on how the model adjusts to seasonality-based changes. These values where put into the model, and then trained on the same data, using a cross-validation methodology. Then the overall result of the model metrics was saved and evaluated. Below in figure 4 the performance of CPS vs MDAPE is shown.

Figure 4

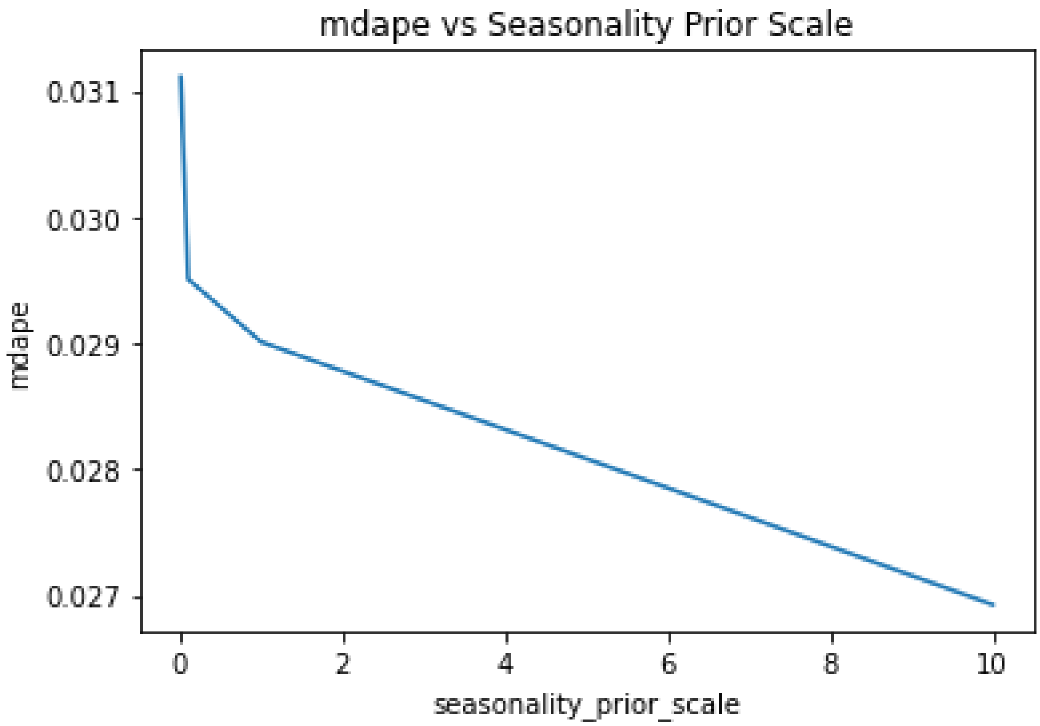
Median Absolute Percent Error vs Changepoint Prior Scale



It is clear that the value of 0.1 achieves a minimum MDAPE. Therefore, this parameter was selected for the final model. The graph showing the SPS vs MDAPE is shown below in figure 5.

Figure 5

Median Absolute Percent Error vs Seasonality Prior Scale

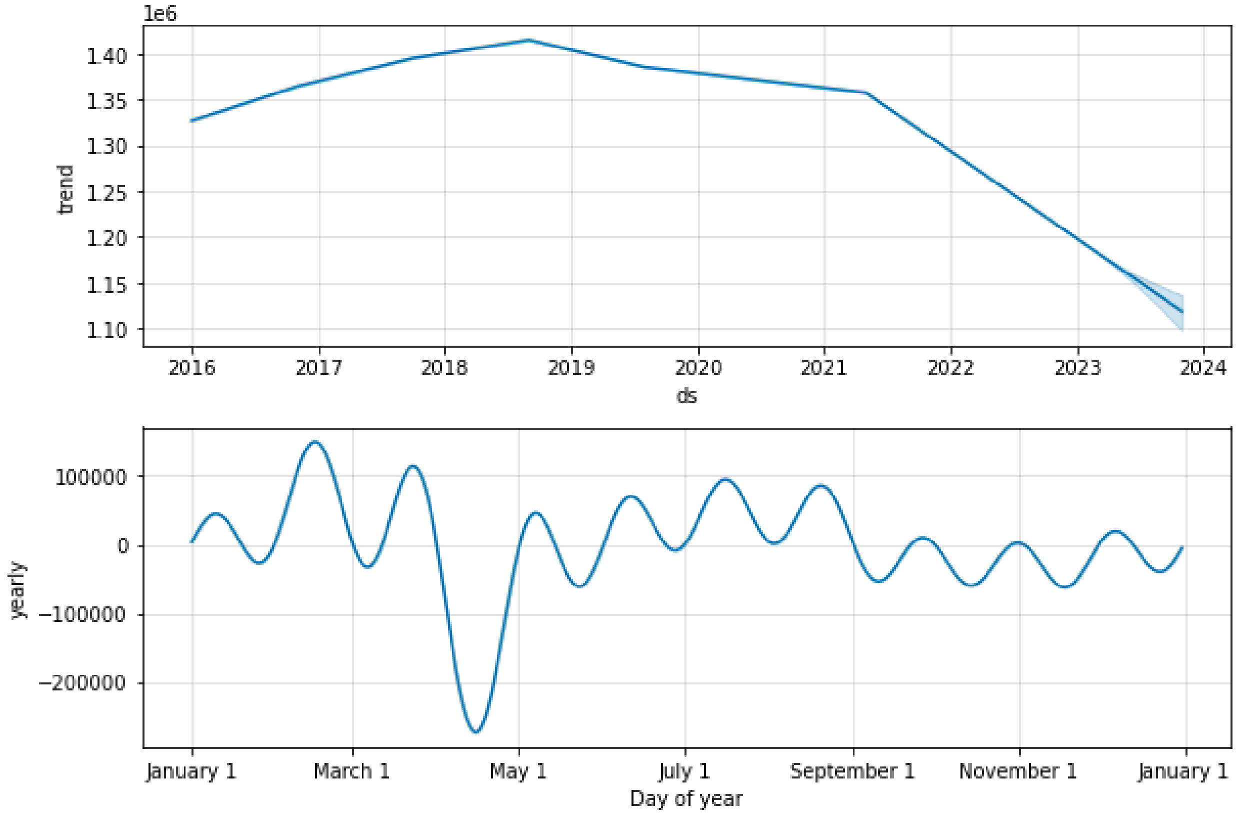


It is clear that the value of 10 for SPS achieves the lowest MDAPE. Therefore, this parameter was chosen for that hyperparameter.

Seasonality is another component that has the option to be tuned. However, varying these parameters did not show any increase in prediction accuracy. Therefore, default settings for the model were left in place. Prophet does have a default graph indicating the seasonality of the data and the macro trends shown in the data, and these are shown in Figure 6 below.

Figure 6

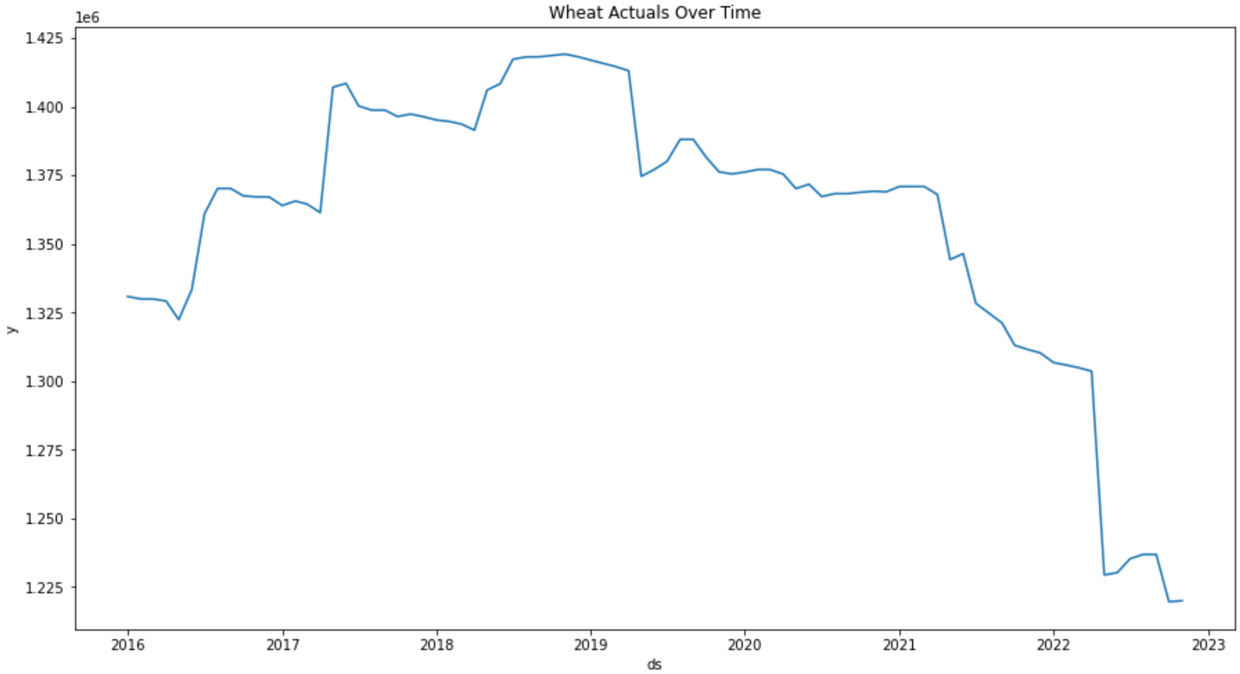
Seasonality profile, top is the yearly seasonality, bottom is the monthly seasonality



First let's discuss the top graph in Figure 6. This is the trend of the data over time, and it displays a confidence interval out through 2023. What we can see is that the demand for wheat is decreasing over time in our data and is predicted to continue to decrease. This is a macro trend for our model, and if we were to visualize our raw data over time shown in Figure 7 below, it would mirror this trend.

Figure 7

Line graph of Wheat Actuals from 2016 to 2022



Therefore, the model is picking up on a macroeconomic trend in its seasonality component. This reduction in the overall supply of wheat is obvious in the data. This is no doubt a result of the conflict in Ukraine (one of the largest exporters of wheat in the world), and evidence of one of the many ways volatilities can be induced into critical supply chains. For context purposes, Russian hostilities escalated in Ukraine as of late February of 2022, and the impact to the supply chain is felt almost immediately (*Timeline: The Events Leading up to Russia's Invasion of Ukraine | Reuters*, 2022).

The other component of seasonality found by the model is on a monthly frequency. When looking at the bottom graph of figure 6, we can see that the supply of wheat decreases dramatically each May. This makes sense because of the cyclical nature of the growing cycle of crops like wheat, and as stated in the methodology section, June is when the prices are set for wheat. There could be numerous reasons that this cycle is present inventories are low, and therefore the price is inflated as a result. However, what is more likely is that this is the start of the planting and growing season, and the resources allocated to the supply chain have been repurposed to preparation activities. Therefore, the supply chain is vulnerable to a fluctuation at this time.

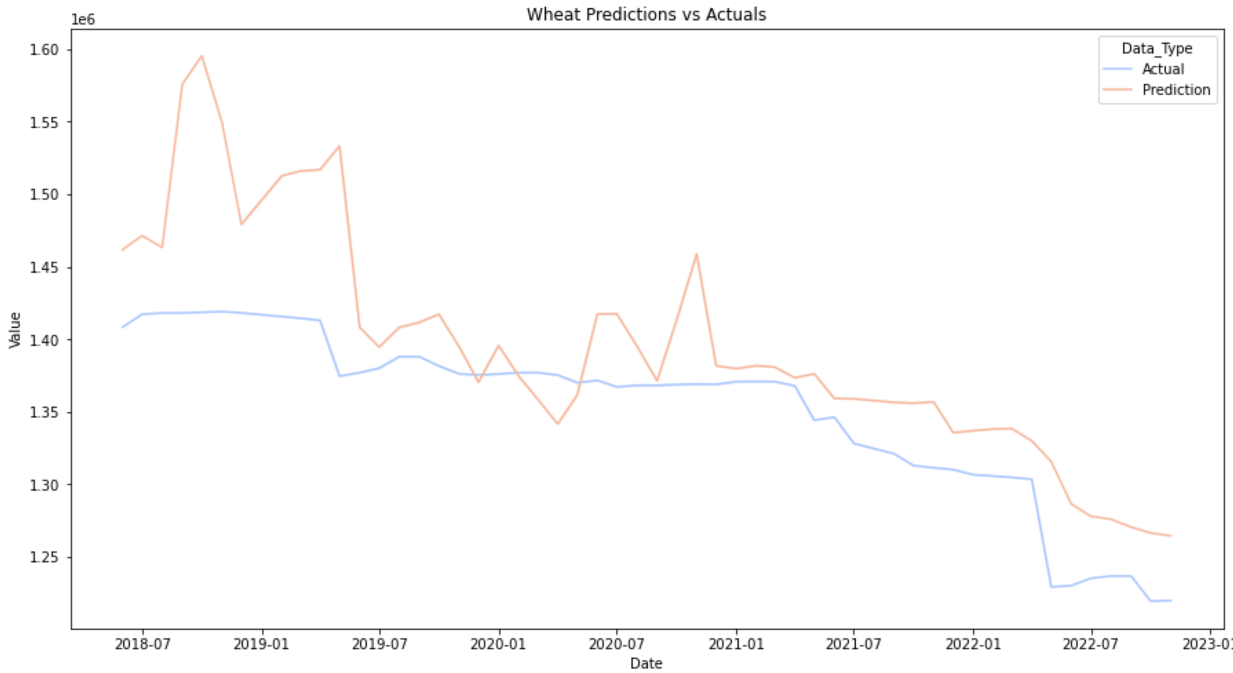
When reviewing figure 6 its critical to understand that the two graphs are characteristics of the data and interact with each other simultaneously during the training of the model. Thus, we must interpret them as such. A macro trend of the data is the increase of overall supply of wheat until just before 2019, then a gradual decrease until 2021, where then the rate of decline increases. While the cyclical nature of the monthly seasonality stays constant year over year, the magnitude of the change is relative to the year over year change. This component is critical to understanding the behavior of the model.

Model Prediction Results

Having discussed the data, the hyperparameters, and the seasonality components of the model the discussion can move to the performance of the model. The graph of the actuals versus the predictions is below in figure 8.

Figure 8

Wheat actuals (blue) model predictions (orange)



The predictions are in orange, and the actuals in blue. It's important to understand that the model is trained on 730 days (2 years) of data first, and therefore has no predictions for these values. Then as a part of the process the model is consistently retraining on segments of 182 days and predicting out on 365 days. Figure 8 shows that the model does not perform well on the first prediction segment. If we reference figure 7, which shows the full raw dataset this makes sense, because the model has been trained on data that how shown a clear pattern, only for that pattern to be broken in the next prediction cycle. An annotated version of figure 7 is shown in figure 9 below.

Figure 9

Annotated indicating the data the model was trained on, and first prediction period

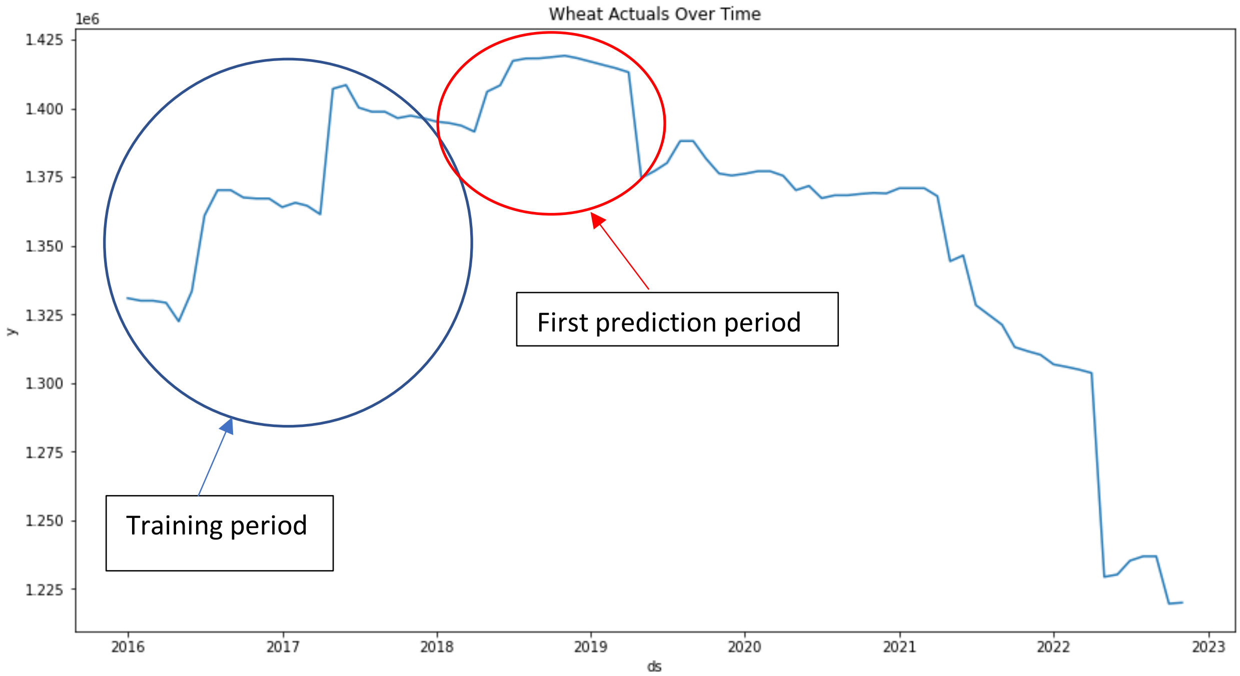
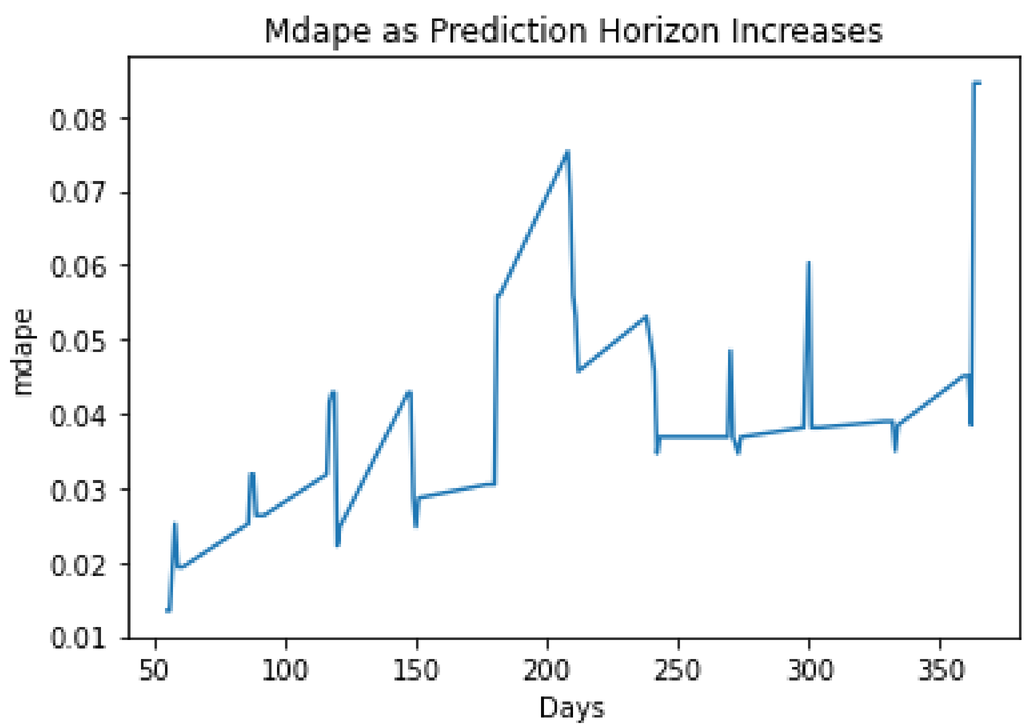


Figure 9 further illustrates the difference between the training period of the model and the first prediction period. The training period was characterized by an increase of .5e6 followed by a slow decrease (shown in the monthly seasonality profile) then another .5e6 increase. The first training period indicates a much smaller increase, at a slower rate followed by flat supply instead of a decrease. The graph shows that the model expects this and starts to correct after looking at an additional 182 days of data. It is clear that the behavior indicated in the first two years of data is prevalent throughout the prediction process but is slowly smoothed. A greater value for the parameter of CPS may have improved the performance of the model over the first intervals, however it is likely that this would lead to overfitting, and this is reflected in the higher MDAPE values for the model with higher CPS parameters.

While model looks to perform well overall, what we are interested in is how well it predicts the immediate future. Once again, the purpose of this analysis is to set the standard for predicting dynamic supply chains, and if the model fails to predict over the short term, then it is not of use to us to responded changes in the supply chain quickly. Figure 10 shown below indicates the MDAPE as a function of prediction horizon.

Figure 10

Median Absolute Percent Error as prediction horizon changes



This is where the model excels. On prediction intervals around 50 days the MDAPE is less than 2 percent. As a result of supply chain volatility, the wheat model performs worse than the beef over the total interval (MDAPE for beef on the total interval is 1.5 percent), but almost as accurate in the initial 50-day horizon. The same chart for beef is included in the appendix. While we can see the seasonal fluctuations of the data do force our model to perform worse evident by the increase in MDAPE on a monthly, and semi-annual basis, the model shows strong capability to adjust shortly after. This gives us confidence that the correct parameter has been selected by our hyperparameter tuning process for SPS. Although as time increases, the prediction accuracy decreases, the model still maintains a reasonable accuracy close to a year out. This gives confidence to the performance of the model and the CPS parameters selected, a decrease in accuracy tells us that the model is not fitting to the changes in the data too quickly, and therefore is not overfit on this parameter either. Additionally, the model has validity predicting values in the short and long term, therefore meeting the criteria to predict volatile supply chains.

Price Elasticity

With confidence in our ability to predict the changes in supply chains secure, investigation into price elasticity as a function of supply chain volatility can begin. For this discussion we will look at two different commodities, beef, and wheat. Both of which have been predicted using the same model, and the same methodologies. First, let us review that price elasticity is simply the absolute value of the percent change in supply or demand over the percent change in price. Or shown by the equation below in figure 11.

Figure 11

Equation for calculating price elasticity of both supply and demand

$$E = \frac{\%\Delta Demand}{\%\Delta Price}$$

Commodities are historically inelastic meaning that they have values less than 1. What this means is that changes in demand are less than changes in price. If price elasticity were to be greater than 1 that would indicate that changes in demand are greater than changes in price and prices could be adjusted. Figure 12 below shows the price changes of wheat over time.

Figure 12

Line graph showing the change in the price month to month of Wheat from 2016 to 2022

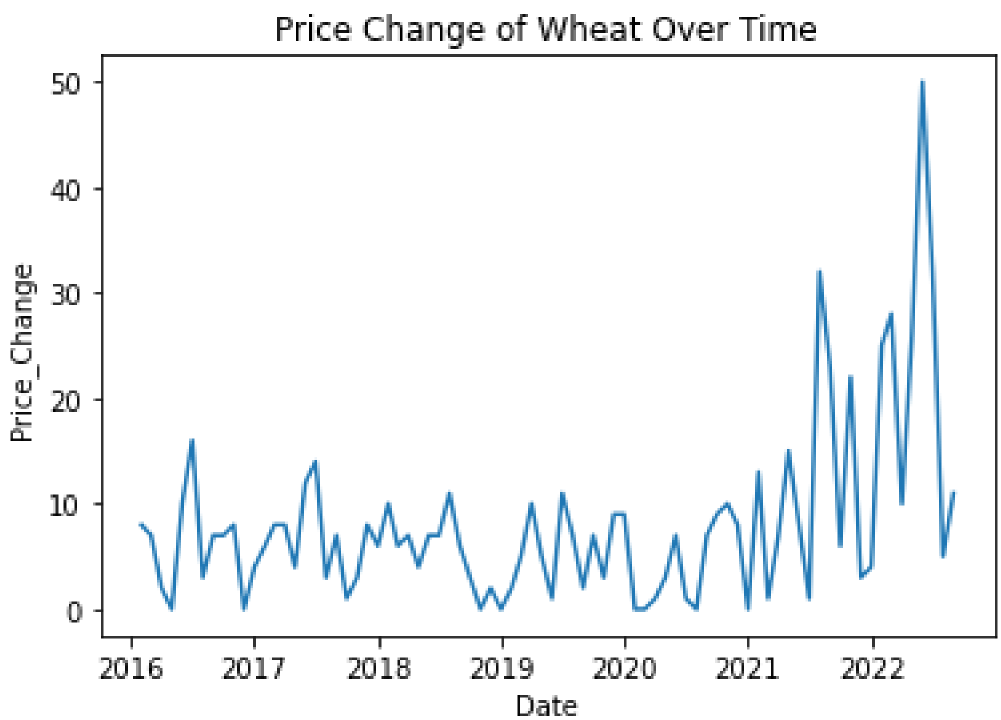
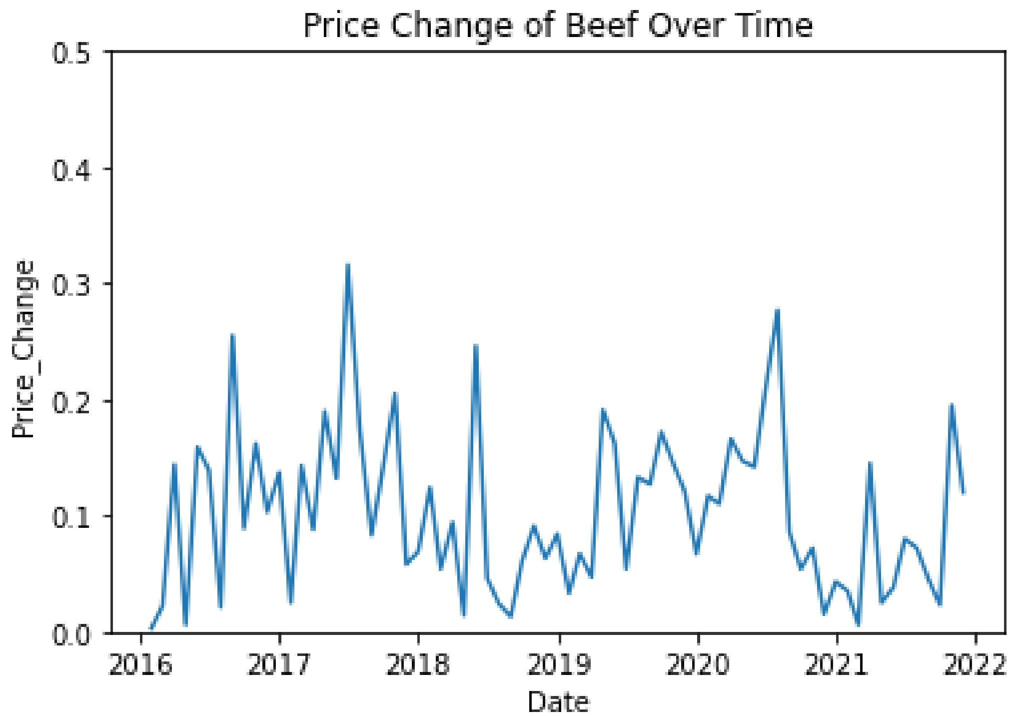


Figure 12 shows a variable pricing behavior, while the pricing change variable is in percent and therefore can be a bit misleading, in instances where supply chain volatility is present, like around the Ukrainian conflict (February 2022), it's clear that it has induced strain on the supply chain, and therefore affected price. If we then compare this to figure 13, which shows the price change of beef over the same time period.

Figure 13

Line graph showing the change in price from month to month of Beef from 2016 to 2022



In normal markets, beef is clearly more volatile than wheat. However, in recent years when supply chain volatility has become more prevalent, beef has stayed relatively similar, and wheat has become far more volatile. Thus, increasing the need for improved supply chain management as to realize understand the price increases of the commodity as a result of volatility. Figures 14 and 15 below show the difference in price elasticity amongst the commodities.

Figure 14

Price elasticity of Beef month to month, outliers result from small price changes

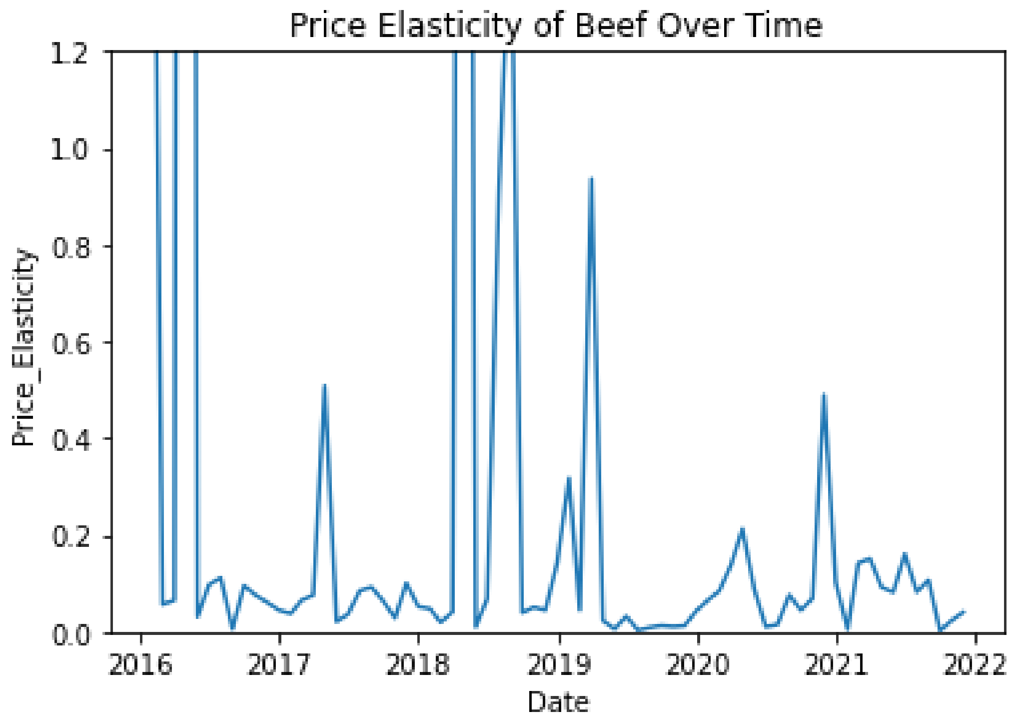
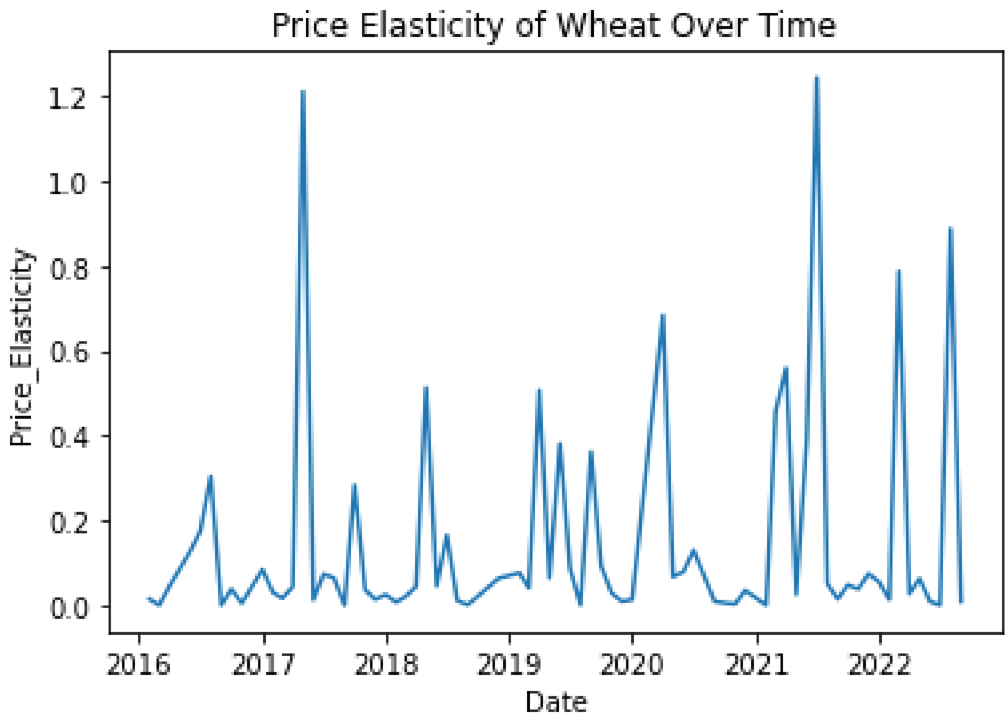


Figure 15

Price elasticity of Wheat month to month



While the price elasticity of beef has a few intervals where it jumps, we know from figure 13 that these intervals have incredibly small price changes (one case a change of .006 dollars). Therefore, these are not representative of the actual supply trends of the commodity. In contrast to wheat, which from figure 12 indicates abnormal changes in price, and has real world context to support these changes. Considering this, we see that supply chain volatility has pushed the overall price elasticity upwards. Although there are still the same number of peaks over 2 year periods, the magnitude of the peaks has increased substantially with 3 of the 4 peaks breaking .6 for a price elasticity over that interval, where over the 6 years prior there were only 2 intervals breaking the .6 price elasticity barrier.

Outcomes in Context of Analysis

Thus far we have examined the data, discussed hyperparameter tuning, how seasonality affects the performance of the model, and how volatility has been impacting price, and price elasticity. The goal of this analysis was twofold, first to determine a method to predicting supply chains with dynamism present, second to contrast how inelastic supply chains react when dynamism is induced. The methodology selected is supported by the results, supply chains with dynamism can be predicted with accuracy in the short term and long term, and through these predictions we can gain insights into pricing strategies using a historical price elasticity analysis.

CHAPTER 5: RECOMMENDATIONS AND CONCLUSIONS

A reason for this analysis was to understand the impact that recent global catastrophes have had on our critical commodities. It is clear from this analysis that wheat has transitioned from being inelastic to exhibiting behaviors of elasticity over certain periods. This would indicate that there is need for policy adjustment. Further research should be conducted on all critical commodities for the sake of national security. This analysis, and analysis of commodities in general, can give insights into the baseline macroeconomic status of the US economy. If a highly subsidized commodity is displaying elastic pricing behavior while also exhibiting a dynamic supply chain condition. It is likely that supply chain volatility could have an even greater effect on other sectors of the economy.

The other reason for this analysis was to lay the groundwork for future analysis, as well as establishing a methodology for assessing supply chain dynamism, volatility, and suggesting a methodology for predicting it accurately. This analysis succeeded in doing so, prophet displayed the ability to adjust for seasonality and changing trends on the monthly period.

There are however other opportunities for exploration related to price elasticity and supply chain volatility. Firstly, an expansion on this analysis centering on goods that are considered luxury goods and comparing them with their normal counter parts. The central question here would be how the price elasticities of the products are different, and what characteristics differentiate them inside the market segment. There are numerous opportunities here for exploration, as well as application of various supervised and unsupervised learning methods. The same modeling technique used in this analysis could be used to predict prices in the future, and from that predict price elasticity of the different products.

Secondly, there is opportunity for expansion on this analysis. Repeating this analysis with the new and somewhat improved package from Meta. This package is called neuralprophet, and leverages many of the same components used in this analysis with the added benefit of the algorithm being built with a neural network. This option was considered, however the research on this package indicates that there is only increased performance in the short term over the package used in this analysis, and that over the long-term prophet outperforms neuralprophet (*Neuralprophet · PyPI*, n.d.). An analysis comparing the two modeling techniques using the same hyperparameter optimization methods would be of value.

In conclusion, this analysis aimed to lay the groundwork for predicting volatile supply chains and understand how they effected price elasticity. The relevant research on this topic was reviewed, best practices for modeling were considered, and it was decided that the Meta prophet model was to be used. After an in-depth explanation of the methodologies behind data development, hyperparameter tuning, and model development, the prophet model was built and yielded a median absolute percent error of less than 3 percent over the entire period. Once the model assessment was concluded, it was found that supply chain volatility can increase the price elasticity of a highly subsidized product, and consequently through prediction of the dynamic supply chain, prediction of the price can be attained using the modeling methodology described. The analysis then considered the relevant expansions on this topic, and suggested future topics for further investigation related to price elasticity, and volatile supply chain prediction. The hope is that this analysis gives confidence to other data scientists in industry and shows a path forward for supply chain and price management. Using algorithms like the one discussed can dramatically reduce waste, decrease costs, and maintain profitability when global catastrophes like the conflict in Ukraine and COVID-19 disrupt the global economy. Adoption of these techniques are not only a strong option as evidence by this analysis but highlight an opportunity to do better as a society. With greater clarity on supply chains critical sources of food, or medical supplies should not delay, and underprivileged communities need not be gouged on prices. Proper management of price and supply chains is one of the biggest steps towards a more sustainable and equitable future.

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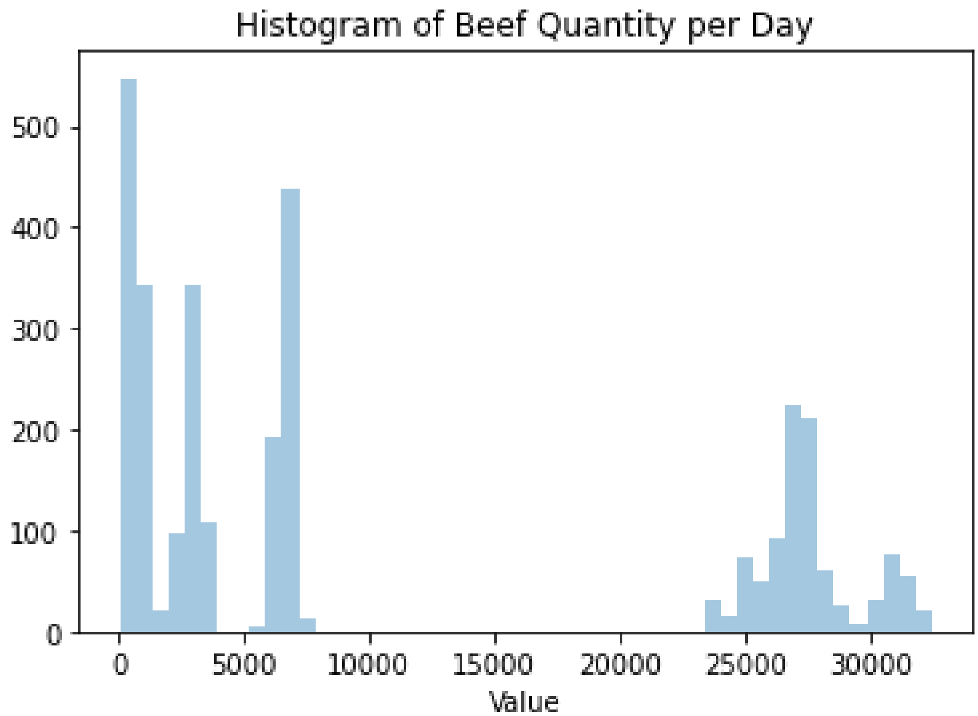
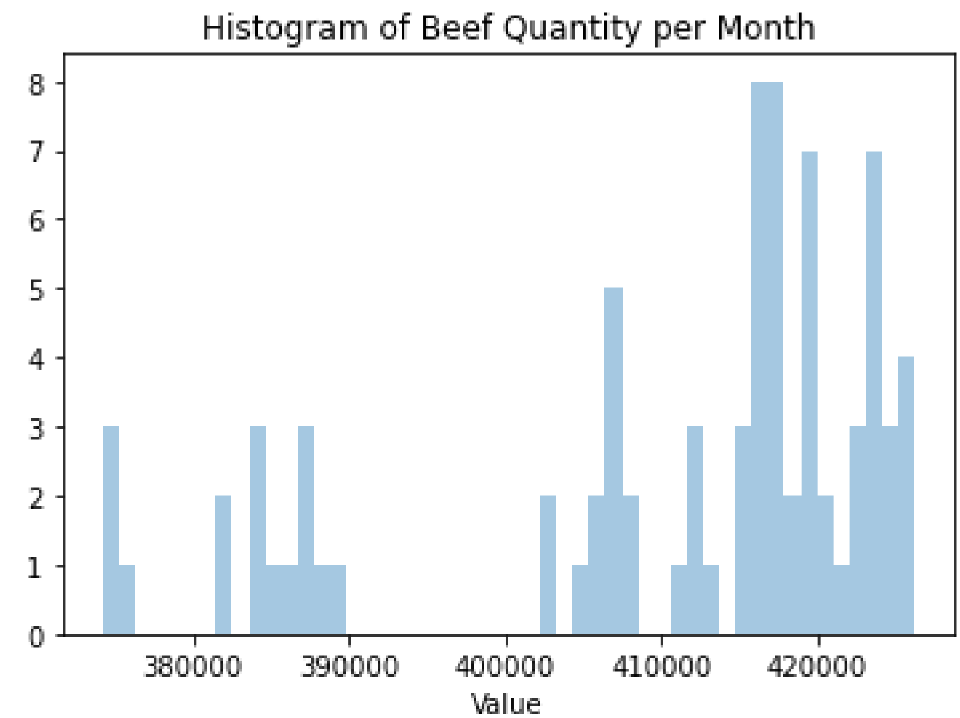
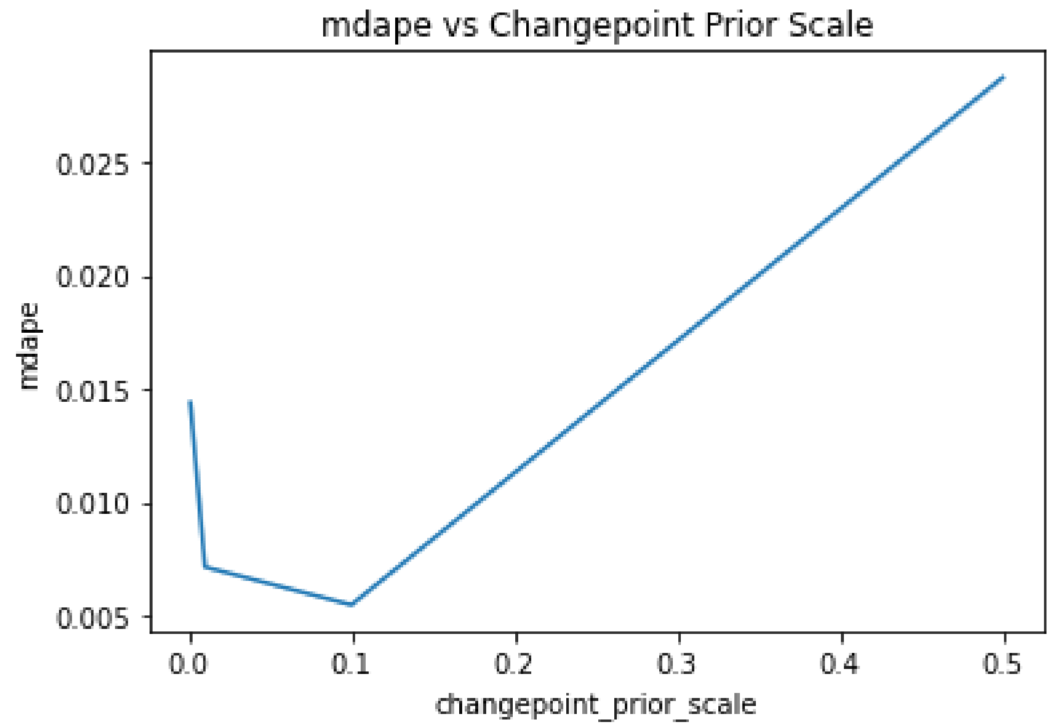
APPENDICIES

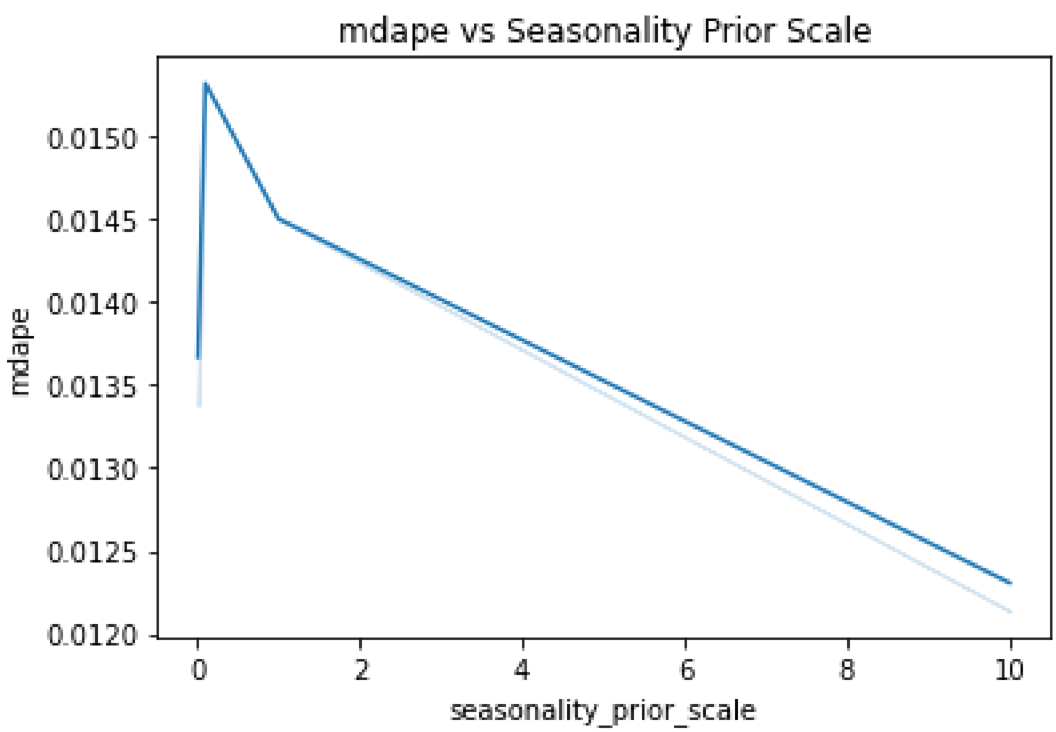
Appendix A: Beef



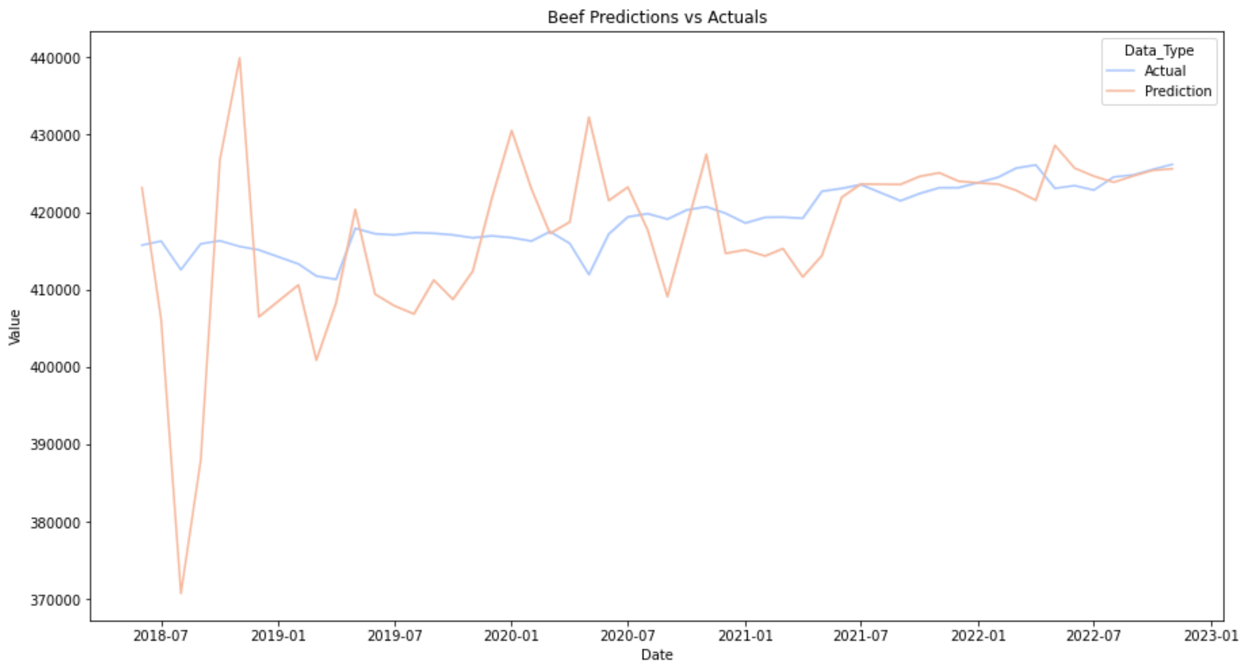


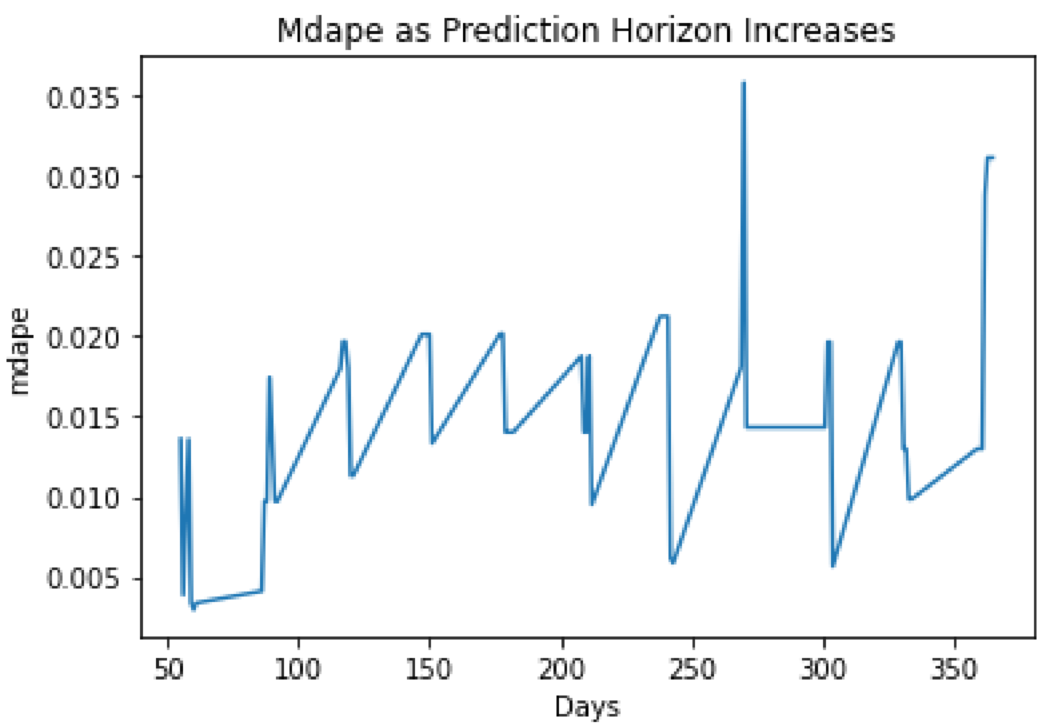


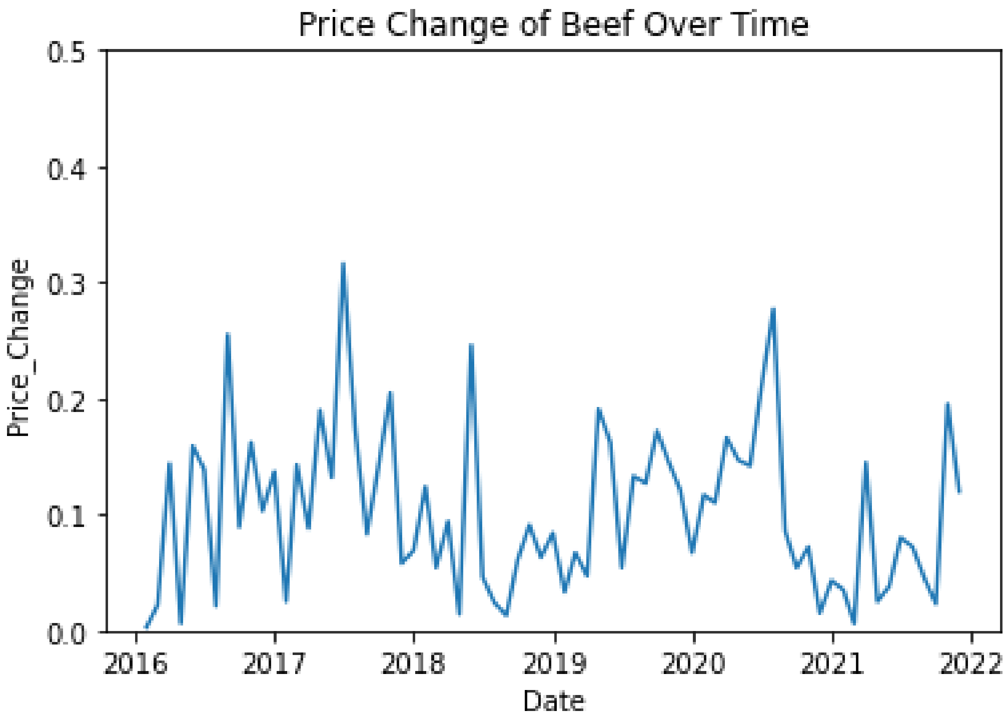
mdape vs Changepoint Prior Scale
mdape
0.025
0.020
0.015
0.010
0.005
0.0
0.1
0.2
0.3
0.4
0.5
changepoint_prior_scale



mdape vs Seasonality Prior Scale
mdape
0.0150
0.0145
0.0140
0.0135
0.0130
0.0125
0.0120
0
2
4
6
8
10
seasonality_prior_scale


Beef Predictions vs Actuals
Data_Type
Actual
Prediction
440000
430000
420000
410000
400000
390000
380000
370000
Value
2018-07
2019-01
2019-07
2020-01
2020-07
2021-01
2021-07
2022-01
2022-07
2023-01
Date


Mdape as Prediction Horizon Increases
0.035
0.030
0.025
0.020
0.015
0.010
0.005
mdape
50
100
150
200
250
300
350
Days



Price Change of Beef Over Time
0.5
0.4
0.3
0.2
0.1
0.0
Price_Change
2016
2017
2018
2019
2020
2021
2022
Date

Appendix B: Code

The code for this capstone can be found at this link:
https://github.com/rotationalphysics495/Capstone