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Shaina S. Bullock, David W. Bullock,
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Short-Term Factors Influencing Corn Export Basis Values in the Pre- and Post-COVID Periods: A Comparison of Econometric and Machine Learning Approaches

Shaina S. Bullock, David W. Bullock, and William W. Wilson*

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*Shaina S. Bullock is an M.S. graduate from the Department of Agribusiness and Applied Economics at North Dakota State University and is currently employed as a Senior Economist and Research Analyst at Bozic, LLC; David W. Bullock is a Research Associate Professor and William W. Wilson is a University Distinguished Professor and CHS Endowed Professor in Trading and Risk in the Department of Agribusiness and Applied Economics at North Dakota State University.

Short-Term Factors Influencing Corn Export Basis Values in the Pre- and Post-COVID Periods: A Comparison of Econometric and Machine Learning Approaches

Rapid technological improvements in data digitization and computing power have paved the way for more advanced quantitative techniques in market analysis, particularly in the area of machine learning. This study utilized two traditional econometric and four machine learning techniques for a side-by-side comparison of their effectiveness in short-term forecasting of international corn basis in the five major global export markets. The models were developed under two different forecasting regimes representing a structural break brought on by the COVID-19 pandemic and related concurrent events with the latter regime characterized by a significant increase in volatility. Machine learning offered considerable improvement in out-of-sample forecast performance measurements when compared to econometric methods, particularly in the latter, more volatile forecasting regime. An analysis of the feature selection and variable rankings indicated substantial diversity of selection across the modeling techniques; however, some common observations were derived from the results.

Keywords: corn basis, export markets, forecasting, machine learning

Introduction

Rapid technological improvements in the digitization of data and increased computing power have paved the way for more advanced quantitative techniques in data analysis and predictive analytics. Among these advancements are tools under the broad category of artificial intelligence (AI) and, in particular, machine learning (ML) which offer many benefits over traditional econometric and statistical techniques. Some of these benefits include advancements related to automation, intelligence, and precision (Newlands et al. 2019). The benefits from machine learning tools provide tremendous opportunity for improvements in risk management, competitive trading strategies, and market efficiency to name a few; however, these tools remain largely underutilized in today's agricultural markets.

The utility of understanding and creating accurate predictions of the basis is widely recognized by marketers, traders, analysts, and competitive firms. By the nature of the its definition, basis forecasts can be combined with futures prices to project future cash prices for commodities (Dhuyvetter and Kastens 1998). Rather than attempting to predict cash prices directly, it is more conducive to focus efforts on deriving cash price predictions using the prevailing futures market price and forecasted basis values (Manfredo and Sanders 2006). Basis forecasts are also critical for evaluating hedging opportunities in both the futures and option markets. In a foundational paper, Working (1953) discussed the importance of hedging in facilitating buying and selling decisions and risk management.

Intense competition is observed both domestically and internationally within various commodity markets. The nature of this competition involves differences in agricultural production processes, port locations, ocean shipping patterns and cost differentials, seasonal secondary railcar and barge markets, exchange rates, and numerous other factors (Bullock, Wilson and Lakkakula 2020). The effects of such competition are manifested as basis values, ultimately leading to market participants competing based on these basis values. Accurately predicting and interpreting basis behavior is vital to formulating trading strategies and understanding competition. In order for countries and traders to remain competitive in the commodity markets, a thorough understanding of basis along with precise short- and long-term basis predictions is necessary.

The purpose of this study is to examine two primary questions. First, do cutting-edge ML tools outperform traditional econometric methods in the short-term (one week ahead) forecasting of corn basis for the five major international markets: (1) the U.S. Pacific Northwest (PNW) which includes ports tributary to the Seattle, Tacoma, and Portland areas; (2) the U.S. Gulf (USG) which includes ports tributary to the New Orleans and Houston areas; (3) Argentina which includes the port of Rosario; (4) Brazil which includes the port of Paranagua; and (5) Ukraine which includes the ports of Odesa and Mykolaiv. The forecasting accuracy of these tools was compared to a set of traditional econometric forecasting methods using a standard set of forecast performance metrics. Second, is their consistency among the ML tools in terms of the selection and ranking of explanatory variables (i.e., feature selection) and what key themes can be learned from these variable rankings.

A traditional time series and an econometric approach (vector autoregression and stepwise regression) were compared with four machine learning techniques (partial least squares regression, elastic net regression, generalized regression neural networks, and random forests) using a set of forecast performance metrics. This study also aimed to determine the critical factors influencing international corn export basis using feature selection and variable importance scores provided by the various modeling techniques. For the regression-based methods (stepwise, partial least squares, and elastic net regression), the standardized coefficients were used to rank variable importance. For the neural net and random forest models, perturbation methods were used to provide variable importance rankings. The pre- and post-COVID periods were analyzed separately to examine how performance ranking and feature selection changed with the increased volatility in the latter period.

The results of this study will provide valuable insights to those engaged in the international and domestic corn markets. First, many major agribusiness firms are currently evaluating and analyzing the potential for using AI and ML tools in both short-term and long-term forecasting to make better operational and risk management decisions (Meyer 2018; Archer Daniels Midland, Bunge, Cargill, and Louis Dreyfus 2018). Many of these decisions relate to spot basis pricing at major export locations, where moving corn from the origin elevators to the port typically operates on a one- to two-week cycle. The results of this study should provide useful information in evaluating these forecasting methodologies and some of the explanatory factors that drive short-term basis movements.

Second, the results of this study contribute the body of academic literature evaluating the relative advantages versus shortcomings of AI / ML versus traditional econometric tools (Storm et al. 2020). ML tools, in general, do not depend upon the need for "well-behaved" functional relationships in the data. Therefore, they can better pick up patterns and relationships in the data that are nonlinear, discontinuous, quasi-categorical, and/or exhibit threshold behaviors. Another potential advantage of ML tools is the use of global "tuning parameters" that generally are optimized using out-of-sample data properties such as n-fold cross-validation. The ML use of tuning and testing datasets for model development can greatly enhance the out-of-sample predictability of the models while reducing the effects of “overfitting” the models to the data.

However, most ML tools also tend to trade statistical rigor in exchange for predictive accuracy. Many of these tools use mathematical metrics and perturbations in place of the sample statistics that are used in econometrics to evaluate and rank explanatory variables. This often creates a “black box” problem in that while the model predicts very well, there is little understanding of the dynamics behind the model. This potentially makes these models more susceptible to “Black Swans” and other extreme behaviors in the data which can sometimes be ameliorated with a good understanding of the variable mechanics behind the model. This lack of statistical rigor and the inability to place structure on ML models generally makes them almost completely useless for economic hypothesis testing. However, the feature selection and data reduction abilities of ML tools can be very useful in exploratory data analysis (EDA) where a “Big Data” dataset can be reduced to a smaller dataset that can be better subjected to rigorous statistical testing. Another potential drawback of ML models is the lack of utility in facilitating time series modeling, generally rendering ML models to cross-sectional and panel datasets. However, over the past decade, there has been substantial development in new ML tools for time series forecasting (Sezer et al. 2020).

The organization of this paper is as follows. The next section provides a review of previous studies related to crop basis forecasting and machine learning. This includes a comprehensive review of the existing literature as it relates to time series, fundamental, and nontraditional methods of basis forecasting. The section concludes with a discussion of ML applications in related disciplines, including general applications, and prediction of transportation rates, credit defaults, and commodity market prices and related indicators.

This is followed by a section that discusses the data selection and aggregation processes, along with the theory and conceptual framework for each of the models developed in the study. A description of each collected variable and its source is provided for the corn export basis, logistical factors, ocean freight rates, WASDE projections, and other explanatory variables. The additional steps to prepare the data, including the split of pre- and post-COVID observations, division of tuning and testing subsets, and the time series characteristics of the basis series are also provided. Next, a discussion of the theoretical background behind each forecasting method used in the study (naive forecast, VAR, stepwise regression, partial least squares regression, elastic net regression, generalized regression neural network, and random forests) is presented. Further, the theoretical background behind the forecast quality and comparison metrics is also discussed.

This is followed by a discussion detailing the forecasting performance, feature selection, and variable importance ranking results for each of the forecasting methods. First, the time series characteristics of the export basis series are presented including the results of stationarity, unit root, and cointegration tests; determination of the optimal lag order for VAR; and Granger causality analysis for both the pre- and post-COVID time periods. This is followed by subsections containing the parameter tuning (where applicable), model estimation, forecast performance, and feature selection results for each forecast technique and export basis series (PNW, USG, Argentina, Brazil, and Ukraine) subdivided by the pre- and post-COVID periods.

The final section summarizes the key takeaways and insights from the previous study results. This is followed by a discussion of the various limitations of the study along with opportunities for further research in the areas of basis forecasting and machine learning.

Background and Previous Studies

There have been few previous studies that have examined the application of machine learning (ML) tools to basis forecasting, particularly at export locations. Many of the previous studies into basis forecasting have examined the use of traditional time series methods (Taylor, Dhuyvetter, and Kastens 2006; Manfredo and Sanders 2006; Sanders and Manfredo 2006; Hatchett, Brorsen, and Anderson 2010; Onel and Karali 2014; Bullock, Wilson, and Lakkakula 2020), fundamental / econometric methods (Taylor and Tomek 1984; Parcell 2000; Zhang and Houston 2005; Welch, Mkrtchyan, and Power 2009; Wilson and Dahl 2011; Bekkerman, Brester and Taylor 2016; Hart and Olson 2017), or a combination of time series and fundamental / econometric methods (Jiang and Hayenga 1997). There were also applications of nontraditional approaches such as event methods (Lara-Chavez and Alexander 2006) and stochastic optimization (Skadberg et al. 2015).

An exception was Bullock and Wilson (2020), who used partial least squares regression (PLS-R) to conduct an exploratory analysis of the explanatory factors impacting the marketing year average soybean basis at the PNW and USG export markets. While sometimes considered a traditional econometric tool, PLS-R does also meet the definition of a ML tool in that it can incorporate both tuning and testing phases for parameter (i.e., number of extracted factor variables) and feature (i.e., retained explanatory variables via VIP scores) selection. Also, PLS-R relies upon out-of-sample data properties (i.e., cross-validation with jackknife leave-one-out sampling, PRESS statistic) for optimization of parameters.

Another exception was a master's thesis by Carlson (2021), who used seasonal analog, time-series, regression, and recurrent multi-layer neural network approaches to compare the out-of-sample forecasting performance with regards to the weekly PNW export basis for soybeans. The models were designed to create multi-step forward weekly forecasts, in which a range of forecast periods were tested for each model and variable.

The basis has several important roles in commodity markets. For market participants these include 1) facilitating making hedging decisions, versus storage of forward cash contracts; 2) deriving predictions of forward prices simply as the current forward futures price plus the predicted basis; and 3) being used in bidding competition among exporters for sales to importers (buyers) which are commonly made of forward basis contracts.

Basis is defined as the difference between the cash price of a physical commodity and a relevant futures contract price. The fundamental theory of basis was developed through a series of foundational papers by Working (1948; 1949; 1953a; 1953b; 1962), who defined the basis and its relationship to prices, futures markets, and storage, along with its temporal characteristics and benefits to intermediary and end-user hedging. These concepts were further refined by the later work of Tomek and Gray (1970) who argued that futures markets, through the basis, provide a stabilizing influence upon commodity markets where storage is a primary concern.

The definition of basis depends on the location of the commodity and its cash price (Kolb and Overdahl 2006). Thus, there are several types of basis to consider. Par basis, or the basis at par markets near the delivery location, is assumed to be close to zero. There is no assumed premium or discount from the futures price due to its local availability, so the additional storage and transportation costs to obtain the grain often factored into the basis in other regions are irrelevant at the delivery market. Origin basis, or the basis of a storable commodity originating from a specific country or elevator, does not converge to zero due to the need for further transportation costs. The most relevant basis for a farmer is the basis at the local elevator (Leibold and Hofstrand 2022). If local supply exceeds local demand, additional transportation costs may be necessary to ship a commodity to processors or export markets.

Away from the par delivery market, the basis is also referenced and used in transactions for domestic users and export buyers. The destination basis for a domestic user, such as a feed lot or an ethanol plant, reflects the profit or loss situation of the user and what they can afford to spend. Export basis, or the basis occurring at the point of leaving the United States or another country, is driven by the value of the users of the export port, along with exchange rates, growing seasons, or economic conditions of other countries.

Relatively few papers have explored export basis influences and forecasting, particularly in the case of international export basis levels. An exception is Tilley and Campbell (1988) who examined the influences of fundamental factors, including the early 1980's Russian Grain Embargo, upon the U.S. Gulf hard red winter wheat basis. Another exception is a paper by Bullock and Wilson (2020) that examined the effects of logistics, export competition, and supply / demand variables upon the market year average level and seasonality of the PNW soybean basis.

Crop Basis Forecasting

Traditional approaches to basis forecasting in the agricultural economics literature can basically be divided into three broad categories. First, there are studies that rely exclusively upon time series methods for forecasting the basis. For storable commodities, basis is generally observed to be highly seasonal (Sorensen 2002; Hevia, Petrella, and Sola 2018). This characteristic, by itself, lends support to using time series methods to forecast basis.

Second, there are studies that use fundamental / econometric methods to forecast basis. For a storable commodity, it is well established that aggregate supply and inventory demand functions are critical factors in determining both spot and futures prices (Turnovsky 1983). Additionally, the role of transportation and logistics costs in commodity price determination, including the basis, is also well established (Roehner 1996). These well-established precepts facilitate the use of fundamental / econometric modeling in forecasting the basis.

Third, there are studies that utilize a combination of time series and/or fundamental modeling or other methods that don't fit neatly into either category. These include the utilization of event methodologies such as differences-in-differences to examine the impact of specific events upon basis. Also, stochastic optimization and Monte Carlo simulation have been used to examine the role of basis in optimal decision-making.

Time Series Methods

Numerous recent studies have analyzed the basis for corn, soybean, wheat, and other storable commodities using time series modeling techniques. Seamon, Kahl and Curtis (2001) examined cotton basis for seasonal and locational differences across several regions in the U.S. Using a nonparametric Friedman test, significant differences in cotton basis across regions were found to vary with transportation costs. Additionally, they found a pronounced seasonal basis pattern in regions predominately serving domestic textile mills that weakened in westerly regions serving the export market.

Taylor, Dhuyvetter and Kastens (2006) compared basis forecasting methods for wheat, soybeans, corn, and milo in Kansas. A simple historical one-year average model tended to be optimal in most scenarios over longer-term averages, except for a five-year average model being optimal for wheat basis at harvest. For post-harvest basis forecasts, naive forecasts in which current basis levels are predicted to equal future basis levels generally produced the best results.

Using Granger causality tests, Manfredo and Sanders (2006) examined causal relationships among export and origin basis values at different U.S. corn market locations using week basis data from 1996 to 2005. The locations examined in included export terminals at Toledo and the U.S. Gulf, river terminals located on the Illinois River and at Omaha, and interior locations in Illinois, Iowa, and at Denver. Their results indicated that Toledo and U.S. Gulf export terminal basis, along with Illinois River terminal basis, were key in determining basis information for the other river terminal and interior locations.

Several time series methods were compared by Sanders and Manfredo (2006) when analyzing Central Illinois soybean, soybean meal, and soybean oil data from 1975-2004. Basis forecasts were generated using exponential smoothing techniques, autoregressive moving average (ARMA) models, and vector autoregression (VAR) models, and compared with five-year average, previous year, and no change methods. However, their results indicate that the improvement gained by using the time series approaches is relatively small compared to simple a five-year average basis.

Hatchett, Brorsen and Anderson (2010) also examined the duration for moving average forecasts that yield the greatest accuracy in basis forecasting for soft and hard wheat, corn, and soybean basis in Oklahoma and Kansas. Results indicated that the use of moving average forecasts worked best when there are no structural changes in the market. However, in cases where there is a structural change, such as the construction of a new ethanol plant permanently affecting corn markets, the use of the previous year's basis was more optimal.

Semi-parametric and nonparametric time series techniques have also been used in basis forecasting studies. A semi-parametric, generalized additive model was tested by Onel and Karali (2014) using weekly futures and soybean prices data from 1988-2013 in North Carolina markets. This type of model allowed for more simplicity over traditional parametric time series models, while also accounting for nonlinearities in local prices and basis values. Their results indicated the semi-parametric approach yielded greater accuracy over the traditional parametric approach to basis forecasting.

Bullock, Wilson, and Lakkakula (2020) investigated the short-term dynamics of U.S. and Brazil basis markets using various time series methods. Weekly basis data from 2004-2019 from 31 U.S. origins and the Pacific Northwest and U.S. Gulf export locations, along with the Santos export market in Brazil, were used to analyze seasonality, mean level homogeneity, and information flows across markets. Box-Jenkins autoregressive moving average models with a seasonal component (SARIMA) were developed for the monthly observations at each location. Information flows among basis markets, before and after the announcement of tariffs in the U.S.-China trade dispute, were determined using Granger causality tests. Agglomerative hierarchal clustering (AHC) was used to identify seasonal analogs at each location.

The seasonal analog analysis identified three to eight unique seasonal analogs at each location. Also, many locations typically had at least one single-year outlier analog that corresponded to logistical issues. Additional results yielded evidence that seasonal patterns vary year-to-year at each location, and the time series analysis showed the U.S.-China trade dispute had significant impacts upon the Brazilian basis, while similar impacts were not observed at the U.S. locations. Lastly, the Granger causality tests showed a dampening effect on intermarket information flows after the announcement of tariffs.

Fundamental / Econometric Methods

Taylor and Tomek (1984) developed a simple econometric model to forecast corn basis at the Batavia, New York origin market. They found three variables of interest that were significant in explaining the basis: U.S. corn production, the New York feed surplus or deficit, and the CBOT corn futures open interest. Their results suggested that this type of model could be useful in making hedging decisions, however, the difficulty in projecting the explanatory variables for use in the model limited its usefulness.

Tilley and Campbell (1988) used a fundamental regression model to evaluate U.S. Gulf hard red winter (HRW) wheat basis performance for the period following the implementation of the Russian Grain Embargo in the early 1980’s. Their partial adjustment regression model included export commitments, a grain embargo indicator variable, a measure of market liquidity on the KCBT wheat futures (all contract months) and indicator variables for the futures contract delivery months. Their primary conclusion was that the Gulf HRW basis adequately reflected fundamental changes in the market. They also found that the imposition of the grain embargo had a significant negative effect upon the basis.

The impacts of the Loan Deficiency Payment (LDP) program in Missouri on corn and soybean basis were analyzed by Parcell (2000) using an econometric model. Daily corn and soybean data from 1993-1999 for multiple Missouri locations was included for estimation. Lagged basis, futures liquidity, and days to expiration were used as explanatory variables along with contract and location dummies. Results showed there were no significant impacts of the LDP on corn and soybean basis for that period, and that factors affecting the basis varied with time throughout the marketing year.

Zhang and Houston (2005) developed an econometric model to investigate the effects of soybean production in South America and futures volatility on the basis. Their results showed significant negative effects of both variables on the par market basis for the Chicago Board of Trade soybean contract.

Welch, Mkrtchyan and Power (2009) examined corn basis in the Texas Triangle. An econometric model was compared to a baseline three-year moving average basis model using monthly corn basis data from the Texas Triangle for the years 1997 through 2008. A transport cost indicator was used to capture impacts of oil price increases, and other explanatory variables included lagged basis, ending stocks, and several seasonal dummy variables. Their results suggested that the fundamental econometric model outperformed the three-year moving average model in forecasting basis.

Wilson and Dahl (2011) analyzed the interrelationships of basis and shipping costs in the wake of more volatility and less predictability in basis relationships using data from 2004-2009 for soybeans and 2004-2010 for corn at various U.S. origins. Results from the econometric model showed that volatility in basis values increased over time. Variables such as shipping costs, ocean rate spreads between the U.S. Gulf and PNW, outstanding export sales, shipping industry concentration, rail performance, futures prices, futures and destination spreads, and stocks to storage capacity ratios were significant to explaining variability in origin basis values at the tested locations.

Bekkerman, Brester and Taylor (2016) analyzed hard wheat basis patterns across 215 grain-handling facilities in the upper Midwest to test the forecasting capabilities of several basis models. Using fixed effects panel regression, they found long-run relationships existed between grain-handling facility cash bids and futures prices that were historically consistent. Thus, it was concluded that the fixed effect from the model was capturing historical spatial and temporal relationships existing within the wheat basis market.

Corn, soybean, and wheat basis patterns in four major domestic production areas were examined by Hart and Olson (2017) using daily data from 2003-2016. Export basis, indicators of ethanol and livestock production, the S&P index, diesel costs, secondary rail shuttle values, ocean shipping costs from the U.S. Gulf to Japan, and other indicators for months, winter, drought, and hurricanes were used in a regression model to estimate local basis values. Results indicated a significantly negative impact of ocean shipping costs and shuttle premiums on the local basis values.

<u>Other Methods</u>

Jiang and Hayenga (1997) did a forecast comparison using a simple three-year moving seasonal average (by month) as the base model for several corn and soybean markets across the U.S. Additional models included the base model supplemented with current fundamental information, a fundamental forecast model using projections of the explanatory variables, a seasonal ARIMA model, two state-space models (2-crop and 7-market), two artificial neural network (ANN) models (NFD and SCG algorithms), and a composite of the forecasting models. The models were compared using four different forecast metrics (RMSE, MAE, Theil U1 and U2). In general, they found that the base model supplemented with current fundamentals along with the seasonal ARIMA performed the best across the two commodities and time horizons. The more structural econometric and state-space models tended to perform better in the shorter time periods (1 to 4 months ahead). The ANN-NFD model performed well for corn in the 1 to 12 months ahead time horizon.

Lara-Chavez and Alexander (2006) studied the impacts of Hurricane Katrina on the basis for corn, soybean, and wheat. They used a parametric constant mean return procedure and a nonparametric rank test procedure developed by Corrado (1989) in an event study to determine any significant impacts. Results showed few abnormal returns on the futures and basis markets during this time; however, the wheat futures market was more largely affected than the corn and soybean markets. They conclude that logistics were generally most affected by Hurricane Katrina as opposed to the supply and demand for these commodities.

Skadberg et al. (2015) used the several variables from the Tilley and Campbell (1988) study along with shipping costs to examine spatial arbitrage opportunities in the U.S. soybean market. Additionally, export basis at the U.S. Gulf and Pacific Northwest and origin basis from several interior locations were included. Rail tariff rates, fuel service charges, and secondary rail market values were also included to represent shipping costs. A spatial stochastic optimization model was developed using copula distributions to determine likely spatial arbitrage opportunities. Results indicated that origins in the Upper Midwest significantly depended on the Pacific Northwest destination market and that arbitrage payoffs vary by region.

Applications of Machine Learning

Though the literature of machine learning applications in basis forecasting is sparse, there are many studies utilizing and assessing the effectiveness of machine learning applications in related agricultural areas and other markets. Machine learning is a branch of artificial intelligence and computer science that encompasses algorithms that attempt to imitate the way that humans learn. This is done using an iterative process of tuning and testing the model to gradually improve its accuracy. While sometimes used in conjunction with the term “deep learning”, it must be noted that there are nuanced differences between the two. Deep learning is a subset of machine learning and is generally confined to neural networks that utilize labeled datasets to inform the algorithm.

General Applications

Machine learning applications have been recently explored in several areas relating to agriculture. Biffis and Chavez (2017) employed machine learning techniques to study maize production in Mozambique by mining satellite data and identifying optimal weather indices. Local weather variability was challenging to estimate due to feedback effects and non-stationarity in climate systems. Recursive partitioning, a nonparametric regression approach, was used to create classification and regression trees to separate response parameters by similar response values. Tree partitioning allowed for nonlinear interactions which cannot be captured by traditional linear regression models. The resulting optimal weather indices provided useful characterizations of local weather variability to inform crop loss risk management strategies.

Newlands et al. (2019) used machine learning techniques to model crop yields under uncertain weather conditions by modifying generalized linear models. Screening regression (SR) and principal component analysis screening regression (PCASR) models were used to select predictors with the highest correlation to crop yield. These methods used dimension reduction and addressed multicollinearity among the explanatory variables. Random forest (RF) and gradient boosting (GB) methods were used to aggregate the regression trees and address variance and bias problems. The machine learning models were compared to more conventional models, and results indicated that the deep learning approaches offered the highest predictive accuracy.

Chen, Rehman and Vo (2021) used unsupervised machine learning techniques to study log returns and conditional volatility in commodities trading. K-means clustering and hierarchal clustering, in conjunction with the manifold methods of multidimensional scaling (MDS) and t-distributed stochastic neighbor embedding (t-SNE), were used to reduce high-dimension objects down to three dimensions. Their results indicated that volatility-based clustering was effective in identifying periods of market distress, including the 2008-09 global financial crisis and the COVID-19 pandemic.

Ghaffarian et al. (2022) created a mapping study to identify publications and other works on the use of machine learning methods in farm risk management. Results showed a significant increase in the use of machine learning methods, including deep learning and neutral networks, for farm risk management in recent years. Production risk and damage assessment were the most frequently addressed risk types. Additionally, the need for machine learning methods for different risk types and more advanced machine learning methods were identified as research gaps and recommended for future studies.

Default Prediction and Supply Chain Management

Bracke et al. (2019) developed an approach to address the “black box” problem that arises with the use of machine learning applications. The approach was implemented to a real-world ML mortgage default prediction model using the Quantitative Input Influence (QII) method developed by Datta, Sen and Zick (2016). QII examines model inputs and outputs only, as opposed to the internal workings of the model. The influence of the features was measured by intervening on inputs and estimating their average marginal contributions over all possible combinations. Clustering techniques were used to group explanations for different areas within the input space, as there were significant differences among the various groups of loans. The authors proposed this analytical framework as a method to address interpretability issues in real-world financial applications.

Baryannis, Dani and Antoniou (2019) examined applications of machine learning in supply chain risk management from an interpretability standpoint. A less interpretable support vector machine (SVM) was compared to a more interpretable decision tree machine learning algorithm to quantify the trade-off between prediction performance and model interpretability. Results showed a 5% decrease in prediction performance and a 37% average precision decrease from the SVM model to the decision tree model.

Freight and Logistics

Han et al. (2014) presented an improved support vector machine (SVM) model for forecasting the dry bulk freight index (BDI), which is a valuable tool for shipping industry operators and investors in managing market trends and avoiding price risks. The BDI is influenced by various factors, particularly random incidents in the dry bulk market, making BDI forecasting challenging. To mitigate the impact of these random incidents, the paper used wavelet transforms to remove noise from the BDI data series. The proposed combined model of wavelet transforms and SVM was tested using weekly data from 2005 to 2012, where model parameters were optimized using a genetic algorithm and the final model was confirmed via SVM training. The paper compared the forecasting results of the proposed method with three other forecasting methods and found that the proposed method had higher accuracy, making it more useful for short-term BDI forecasting.

Eslami et al. (2017) created a hybrid tanker freight rate (TFR) prediction model using an artificial neural network (ANN) and an adaptive genetic algorithm (AGA) to address the needs of stakeholders in the oil industry that rely on short-term predictions. The AGA adaptively searches the network parameters, such as input delay size, while the ANN iteratively improves the prediction network by accounting for parsimonious variables (crude oil price, fleet productivity, and bunker price) and time-lag effects. The study compared its proposed hybrid model performance to two traditional approaches (regression and moving average) and existing ANN studies. The hybrid model results showed significantly improved root mean squared error (RMSE) values when compared to the regression and moving average approaches. The hybrid model also offered slight improvements over the results of existing ANN studies.

Yang and Mehmed (2019) utilized artificial intelligence techniques and forward freight agreement (FFA) information to improve the accuracy of freight rate forecasts in a highly volatile shipping market. The paper used two dynamic ANN models, a non-linear autoregressive dynamic network (NARNET) model and a non-linear autoregressive with external input (NARXNET) utilizing FFA data, to compare forecast performance at various intervals between 1 and 6 months. The authors used the mean squared error (MSE) to compare the accuracy of the two models, based on the historical Baltic Panamax Index and Baltic forward assessment data. Results showed that the NARXNET performance was superior to NARNET in all the forecast horizons, highlighting the significance of FFA information in improving the accuracy of freight rate forecasts.

Commodity Market Prediction

An early example of artificial neural network techniques in price forecasting comes from Kohzadi et al. (1996), who compared the performance of a feed-forward neural network price forecasting model to an ARIMA model on monthly live cattle and wheat prices from 1950-1990. Results showed that the neural network models had reduced mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) when compared to the ARIMA model.

Zou et al. (2007) compared the predictive accuracy of three models in forecasting the price of wheat in the Chinese market: an autoregressive integrated moving average (ARIMA) model, an artificial neural network (ANN), and a linear combination of the two forecasts. Several evaluation criteria (MSE, MAE, MAPE, and RMSE) were used to compare the performance of the models. The findings suggested that the combined model was better than the separate ARIMA and ANN models from an error evaluation perspective, but the ANN model was overall more effective at capturing significant turning points and profit criteria.

Chiroma et al. (2016) presented a thorough review of research on the use of computational intelligence algorithms for forecasting crude oil prices, including an analysis of published studies and their limitations. The nonlinear, non-stationary, and volatile nature of crude oil prices produce challenges when using conventional modeling methods that rely on linearity. Although these conventional methods still have value, the authors found that there is a rapidly growing interest in wavelet analysis, neural networks, SVM, genetic algorithms, and hybrid intelligence systems for crude oil price forecasting among researchers.

Ouyang, Wei and Wu (2019) used a long- and short-term time series network (LSTNet) to predict global agricultural commodity futures prices. Due to the mix of long- and short-term information available in futures data along with linear and nonlinear structures, the LSTNet approach was compared to the baseline methods of using ARIMA and VAR. The results, based on performance evaluation measures, showed that the LSTNet model performed better than the baseline methods in most periods.

Gopinath et al. (2021) used supervised machine learning (ML) and neural networks to examine the trade patterns of seven significantly traded agricultural commodities. The ML model trained on data up until 2010, while the neural network trained on data up until 2014. The results showed that, relative to traditional time-series modeling approaches, the ML models were highly effective in forecasting trading patterns both in the short-term and long-term. The supervised ML techniques were most useful in quantifying key economic factors underlying trade flows, while the neural networks offered a better fit for long-term forecasting.

Padilla, Garcia, and Molina (2021) used information fusion and data mining techniques to improve time series forecasting in local agricultural markets in Ecuador. Transactional data were used to form associated rules between products sold in different local markets. A time series model was constructed using a machine learning formulation enhanced with multivariate predictions based on the association rules. Results showed an improvement in prediction accuracy, indicating the use of knowledge about significant dependencies among the variables is a viable technique for improving forecasting models and neural networks.

Drachal and Pawłowski (2021) provided a review of genetic algorithm applications in commodity price forecasting, with a focus on energy, metals, and agricultural products. The authors noted that genetic algorithms are well-suited for commodity forecasting due to their ability to handle non-stationary data without assuming a specific statistical distribution and have seen a growing interest in recent years. They also noted researchers' interest in hybrid genetic algorithms, which combine genetic algorithms with other econometric methods to improve their effectiveness. The advantages and disadvantages of these methods are discussed, along with possibilities for improvements and future applications.

Carlson (2021) used naive, seasonal analog, time-series, regression, deep learning, and recurrent deep learning approaches to compare the out-of-sample forecasting performances of PNW soybean basis forecasting models and the rail secondary car market values. The models were designed to create multi-step forward weekly forecasts, in which a range of forecast periods were tested for each model and variable. Results highlighted the superior performance of the recurrent neural networks across all performance quality metrics. The seasonal average model was shown to be consistent with previous literature in its ability to capture common seasonality but was unable to adjust to current information and structural market changes. The ANN model had the next best performance, followed by the ARIMA and linear exponential smoothing (LES) models, which also outperformed the naive model. The recurrent deep learning approaches yielded consistently low errors with respect to the various forecasting horizons, unlike the remaining models which had greater out-of-sample errors as the forecast horizons increased.

Data and Methodology

Data Sources and Aggregation

The forecasted variables in this study are the weekly (1/7/2015 to 5/25/2022) average basis values (U.S. cents per bushel) for five of the major export locations (by volume) in the international corn market. They include the U.S. Gulf, U.S. Pacific Northwest (PNW), Argentina (Rosario), Brazil (Paranagua), and Ukraine (Odesa). Additional details on the basis data series are provided in Table 1 in Appendix A. The sources for the basis data series were Eikon (Refinitiv 2022), AgriCensus (Fastmarkets 2023), and ProphetX (Data Transmission Network 2023). The basis values were also calculated based upon free-on-board (FOB) cash export prices, meaning the seller of the grain was responsible for delivering the goods to the port and loading them onto the vessel, while the buyer was responsible for shipping costs, insurance, and other transportation charges. These cash prices were converted into U.S. cents per bushel and subtracted from the Chicago nearby corn futures price to arrive at the basis value.

Where a single week was missing from a data series, linear interpolation was used to fill in the missing value. For missing values of two or more consecutive weeks, the NIPALS (Wold 1974) procedure was used to fill in the missing values. The procedure was applied to both the forecasted and explanatory data series.

Figure 1 (in Appendix B) shows a weekly time series plot of the five export basis time series for the time period between January 2015 to the end of May 2022 which includes the first 3 months of the ongoing Russia - Ukraine conflict. An examination of the plot provides strong visual evidence of a significant structural shift in terms of the market volatility that begins approximately around July 2020, which is about 3 months following the full onset of the COVID-19 pandemic. For simplicity, the data preceding the break (January 2015 through June 2020) will be referred to as the “pre-COVID” period while the data following the break (July 2020 through May 2022) will be referred to as the “post-COVID” period. Note that this designation refers more to the progressive, cumulative effects following the beginning of the COVID-19 pandemic in March 2020 rather than trying to ascribe a beginning of the pandemic itself.

This abrupt shift in basis behavior was confirmed by applying a two-sample, one-tail F-test to the variances in the two periods. For all five series, the F-tests confirm a statistically significant increase in variance in the latter period at the 99% confidence level. Additionally, the application of one-tailed t-tests confirmed increases in the mean basis levels for three of the five series. This structural shift pre-dates the major U.S. election cycle and the beginning of the Russia-Ukraine conflict, thus it is likely attributable to market and supply chain disruptions brought on by the earlier onset of the COVID-19 pandemic. The pandemic began in March 2020, but the full impacts upon the markets were likely not realized until months later. Besides the COVID-19 pandemic, the volatility of the latter period can also be explained by concurrent increases in crude oil prices and ocean shipping rates; a rebound in global demand following the sharp decline at the onset of COVID; increased logistical congestion at most ocean ports; increases in rail dwell times, fuel surcharges, demurrage and other rail costs; and acute labor shortages particularly with regards to rail.

Therefore, the weekly data series were split into the pre- and post-COVID time periods, using the noted July 2020 structural breakpoint for dividing the data. Within each time epoch (pre- and post-COVID), a random sampling without replacement procedure was used to divide the time observations into tuning (80% of observations) and testing (20% of observations) subdivisions. The random sampling procedure was used to assure complete time coverage across each time period for the forecast evaluation and eliminate any further time frame bias from the forecasting results.

The data analysis approach of this study is exploratory which plays to one of the primary advantages of "Big Data" approaches such as machine learning. Therefore, a large set of variables was included in the explanatory data set. These variables fit into the broad categories of transportations costs (including ocean freight) and other logistical factors, USDA WASDE projections of major exports and imports by major participating nations, cash and futures prices (including ethanol and time spreads), historical export volumes, and foreign exchange rates.

Table 2 (Appendix A) lists the key U.S. domestic transportation costs and other logistical factors. Many of these variables were also considered in the Bullock and Wilson (2020) study of factors influencing the PNW soybean basis. The 'daily car value' (*DCV*) represents the quoted market value for railcars in the secondary market. Shippers initially order a set number of trains (railcars) in the primary market using a market instrument such as a Certificate of Transportation (COT). If the shipper later finds out that they don't need the railcars, they can resell them into the secondary market. Likewise, if a shipper needs additional railcars, they can buy them through the secondary market. Therefore, the DCV is a measure of the current supply and demand for railcars and can be quite volatile – particularly to the upside when the supply of available railcars is very tight relative to demand.

Likewise, the *Velocity* variable represents the average number of round-trips that a BNSF shuttle train (110 cars) can make in a single month. Since shippers of grain generally order a set number of shuttle trains per month in the primary market, the actual volume of grain that can be moved in a month is essentially equal to the unit train volume multiplied by the velocity (number of trips). This variable is an essential indicator of the rail system performance since bottlenecks and adverse weather delays can impact this value negatively while ideal shipping conditions would impact it positively. Therefore, like DCV, the Velocity variable is a good indicator of the state of the rail logistical system for moving grain.

The rail fuel surcharge (*FSC*) is add-on fee to the rail tariff that is charged in times of high fuel costs incurred by the railroad. It is typically a schedule of rates per railcar per mile that is tied to a benchmark fuel price such as the U.S. Department of Energy's on-high ultra-low sulfur diesel (ULSD) price. This can be a critical cost factor for rail shippers – particularly in times of high energy prices and has a major impact upon rail shipping costs.

The rail delivery volumes to ports on the Mississippi River system (*RailMS*) and Pacific Ocean (*RailPAC*) are used as measures of relative logistical activity tributary to the USG and the PNW respectively. The St. Louis barge spot rate (*Barge_STL*) is included to represent a proxy for the Mississippi River system shipping costs to the USG since a significant share of USG grain exports arrive by barge on the Mississippi River system and St. Louis is considered a major bellwether location on the river system. Likewise, the weekly number of grain vessels in port for loading at the USG (*Ship_USG*) and PNW (*Ship_PNW*) are used as proxies for relative loadout activity and demand at each port location. The volume of grain exports at each port (*Insp_USG* and *Insp_PNW*) are also used as relative barometers of logistical activity (and demand) at each port along with overall projected demand (*ExpCommit*) for U.S. ports.

Table 3 (Appendix A) lists the ocean shipping rates (U.S. $ per metric ton, Panamax bulk carrier) for the key routes included in the explanatory data set. These variables represent a major component of the grain shipping costs from each of the given export ports to the major international corn buyers (China, Indonesia, the European Union, the Middle East, Japan, South Korea, and Vietnam). Since basis is part of the FOB value at the export port and is the primary adjustable factor for the exporter, the ocean rate is of primary consideration when making basis adjustments to maintain international competitiveness.

Table 4 (Appendix A) lists the USDA World Agriculture Supply and Demand Outlook (WASDE) projections used in the explanatory dataset. Unlike the preceding explanatory variables, the WASDE report is released monthly and typically around the second Friday of the month. For each weekly observation, the WASDE data is synchronized to the most recent report release *at or preceding* the weekly date. So each WASDE variable represents the most current forecast as of the weekly date in the database. Also, the WASDE export and import values are adjusted to reflect the annual increase or decrease in the raw value (in million metric tons).

Table 5 (Appendix A) lists the other variables included in the explanatory dataset. The Brazilian domestic corn price (*BrazilPrice*) was included as a proxy for domestic demand within South America. Ethanol refining is a major domestic use of corn that competes with exports in the U.S. and in South America. The U.S. ethanol price (*EthanolPrice*) was included in this study to capture this particular impact upon domestic demand which would impact export basis as well. Bullock and Wilson (2020) used nearby futures prices and futures spreads in their analysis of soybean export basis. The nearby futures price (*Fut_Nearby*) is a base for calculating FOB export as well as domestic prices while the nearby spreads (*Fut_Sprd1* and *Fut_Sprd2*) are indicators of nearby versus deferred demand at the par delivery market (Chicago). A strong inverse (negative spread) would indicate strong nearby demand versus deferred and a strong carry (positive spread) would indicate strong deferred demand versus nearby. A strong nearby domestic demand would compete with export demand which is hypothesized to drive up the export basis in order to competitive source grain for that market.

The historical export volumes for each country (*Exp_USA*, *Exp_Arg*, *Exp_Brazil*, and *Exp_Ukr*) are reported monthly and like the WASDE variables, were synchronized to the weekly dates using the most recent reported value. These can be considered as reflective of the relative historical export activity from each of the major exporting nations and is more of a momentum rather than a projection indicator of export activity. Exchange rates can also have a major impact upon export competitiveness and thus, the export basis levels. Therefore, five highly relevant exchange rates / indices (*DEXBZUS, DEXCHUS, DEXJPUS, DEXUSEU,* and *DTWEXBGS*) were included in the dataset.

Additionally, a set of monthly dummy variables was added to the dataset to reflect seasonal impacts upon basis levels. These variables were calculated such that if the observation occurs in the month signified by the dummy variable, it is equal to 1; otherwise, it is equal to 0. Monthly dummies were created for each month (*Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov,* and *Dec*) and included in the explanatory variable set.

Dividing Data into Tuning and Testing Samples

The out-of-sample performance of each of the forecasting methods is the key area of interest for the study. The creation of tuning (estimation) and testing (validation) samples for the study allows the opportunity to obtain the out-of-sample performance results of interest. All the models are first tuned and fitted using the tuning subsamples of data. Then, the fitted models are applied to the observations contained in testing subsample of data, and the resulting out-of-sample results and residuals are calculated for comparison.

Figure 2 (Appendix B) illustrates the division of the dataset into the tuning and testing subsets for both the pre- and post-COVID periods. After aggregating all the variables and splitting the observations into the pre- and post-COVID periods, the dataset was split into tuning and testing subsets for the creation of the models. A random sample without replacement composing 80% of the observations in each of the pre- and post-COVID periods was drawn for the tuning subset with the remaining 20% of the observations assigned to the testing subset. The eighty-twenty split was chosen due to its common use in similar studies (Carlson 2021). The pre-COVID tuning dataset contained 228 observations, and the pre-COVID testing dataset contains 57 observations. The post-COVID tuning and testing datasets contained 80 and 20 observations, respectively.

The forecast horizon for the models estimated in this study is one week ahead using a cross-sectional approach to facilitate the random sampling for the tuning and testing datasets. This was primarily a result of the data limitations (only 100 observations to work with in post-COVID period) and the goal of testing the overall effectiveness of each forecasting model across the entire time horizons for both the pre- and post-COVID time windows. There was concern, particularly with the post-COVID dataset, that dividing the testing and tuning by time periods would introduce some time bias to the results — particularly with the run-up and onset of the Russian invasion of Ukraine at the latter part of the data series. The time series characteristics of the data (discussed in detail in a later section) also strongly indicated a significant one-week lag structure in not only the dependent variables but also in the explanatory dataset. This makes some intuitive sense since it typically takes one to two weeks (on average) for a corn shipment to reach its export location from the origin. Also, since it is typical of most forecast errors to increase with the time horizon, the one-week forecast is also useful to examine because if a model does not perform well in the one-week horizon, it is not likely to perform any better in more distant time horizons.

Forecasting Methods and Comparison Metrics

The forecasting methods chosen for evaluation in this study were based upon the goal of comparing a time series and a fundamental econometric approach with a set of machine learning approaches to compare short-term forecasting performance and also to compare how the fundamental econometric and machine learning approaches weigh and implement the explanatory variables (sometimes referred to as *feature selection*). Therefore, a major criterion in choosing the machine learning modeling approaches was that they also provided (in addition to forecasts) some interpretable information regarding how the explanatory variables factor into the forecasting.

Before the tuning, estimation, and forecast evaluations were conducted, an examination of the time series characteristics of the dependent and explanatory variables was conducted using classical time series methods. One of the weaknesses of many of the machine learning tools is that they are not amenable to deriving the time series structure of the data with a few exceptions such as the *tslearn* package for the Python computing language by Tavenard et al. (2020).[1] Therefore, in working with time series data with machine learning, it is always a good idea to examine the time series characteristics using classical time series methods. In this study, the stationarity and cointegration aspects of the dependent variables were examined using the Augmented Dickey-Fuller (Dickey and Fuller 1979), KPSS (Kwiatkowski et al. 1992), and Johansen (1991) tests which were applied separately to both the pre- and post-COVID datasets. In addition, a Granger causality analysis (Granger 1969) was conducted on the dependent variable series separately in pre- and post-COVID periods to examine any changes in causality between the two periods.

For the time series forecasts, a *vector autoregression* model (Quenouille 1957; Sims 1980) (VAR) was estimated using the current and lagged values of the export basis variables. The optimal lag length was determined by application of the information criterion (Akaike 1974; Schwarz 1978; Hannan and Quinn 1979). The models were estimated by application of OLS regression individually to each basis series using only the observations in the tuning datasets. The *XLStats* (Addinsoft 2023) statistical analysis add-in to the *Excel* (Microsoft 2022) spreadsheet software program was used to estimate the OLS equations and apply the forecasts to the testing dataset.

For the fundamental econometric forecasts, the explanatory variable set was determined individually for each basis series by application of *stepwise regression* (Efroymson 1960) (STR) to observations in the tuning dataset. Bidirectional elimination was used with a step-in alpha (using t-statistic on coefficient) of 0.05 and using 0.10 for the step-out value. The estimation and forecast analysis was conducted using the XLStats software. The retained explanatory variables were ranked using the absolute value of their standardized coefficients.

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[1] Also see the book by Lazzeri (2021) and the survey article by Lim and Zohren (2021) for discussions regarding use of Recurrent Neural Networks (RNN) and common neural network encoder and decoder designs that can be used for time series forecasting.

The first machine learning technique evaluated was *partial least squares regression* (Wold 1966) (PLS-R) which is similar to principle components regression but has the advantage of using information in both the dependent and independent variable sets in extracting the component variables. Additionally, PLS-R is one of the few machine learning techniques that can be applied to multiple dependent variables simultaneously. It was developed as a technique to handle issues of overidentification and multicollinearity in regression analysis. This technique was recently applied to the analysis of explanatory variables for determining the marketing year average soybean basis for the U.S. Gulf and PNW (Bullock and Wilson 2020).

One of the primary tuning parameters for the PLS-R model is the number of latent component variables to retain. This was determined by maximal grid search with the quality statistic (Q^2) as the primary metric. Once the number of component variables was determined, the number of explanatory variables to retain in the model was determined by retaining those variables whose variable importance in projection (VIP) statistic (Wold, Sjostrom, and Eriksson 1993) was 0.8 or greater. Tuning, estimation, and forecast evaluation was conducted using the XLStats software package which uses the NIPALS algorithm first proposed by Wold (1974). The ranking of explanatory variables was provided by the absolute value of the standardized coefficients.

The second machine learning technique evaluated was *elastic net regression* (Zou and Hastie 2005) (ENR). This technique combines the L1 regularization of lasso regression (Tibshirani 1996) with the L2 regularization of ridge regression (Hoerl and Kennard 1970). The mixing and regularization (tuning) parameters were optimized by individual application of the coordinate descent algorithm (Friedman, Hastie, and Tibshirani 2010) with 5-fold cross-validation to achieve minimization of the following loss function:

$$L(\boldsymbol{\beta}) = \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|^2 + \lambda \sum_{j=1}^{p} \left[(1-\alpha)\beta_j^2 + \alpha|\beta_j|\right], \quad (1)$$

where **y** is the dependent variable vector, **X** is the matrix of explanatory variables, **β** is the regression coefficient vector, *p* is the number of explanatory variables, α is the mixing parameter (between 0 and 1) and λ is the regularization parameter. Like PLS-R, ENR is a technique that can handle overidentification and multicollinearity issues. Because ENR includes L1 regularization, feature reduction is accomplished as the penalty function effectively drives the coefficients of some variables to zero. The remaining variables retained were ranked based upon the absolute value of their standardized coefficient values. The XLStats implementation of ENR was used for tuning, estimation, and forecast evaluation in this study.

The third machine learning technique evaluated was the *generalized regression neural network* (Specht 1991) (GRNN). The GRNN is a simple and efficient neural network model often used to approximate non-linear functions and time-series with a high degree of accuracy. It is a feedforward neural network that uses smoothing parameters and distance calculations to weight the independent variable observations in the calculation of the predicted output. The main advantage of using the GRNN relative to other linear regression techniques are its ability to model extremely complex relationships, and it provides a mapping from one set of sample points to another.

The structure of the GRNN network involves four layers: an input layer, a pattern layer, a summation layer, and an output layer. Figure 3 (Appendix B) shows the general structure of the GRNN with two independent input variables and three training cases (Specht 1991; Masters 1995). The input layer contains nodes for each variable contained in the independent variable vector. The input layer is simultaneously fed into each of the training cases, where each neuron in the pattern layer represents one training case. In the pattern layer, each neuron computes its distance from the input case, where closer training cases tend to contribute more significantly to the value of the output than distant cases. The distance function is calculated with the use of smoothing factors for each input.

This study used the *NeuralTools* (Palisade Software 2023) software for training (tuning) and forecast evaluation of the export basis series. The algorithm used by NeuralTools closely follows that proposed by Specht (1991) which uses the conjugate gradient descent (CGD) algorithm to reduce the number of iterations needed to reach the minimum mean squared error over different sets of smoothing factors. The explanatory variable ranking was calculated by measuring the sensitivity of the output to changes in the independent variables. For a given explanatory variable, the analysis steps through the range from its minimum to maximum training values and measures changes within the output for every training case. Each explanatory variable is assigned a relative variable impact score percentage, in which the sum of all scores add to 100%. A higher percent indicates that the output of the trained GRNN is highly affected by changes in the given explanatory variable. Likewise, a lower percent indicates the variable has a less significant impact on the model output. Variables with low impact scores may be eliminated during the training process to favor those with more relevance to accurate predictions.

The fourth and final machine learning technique evaluated in this study was the *random forest regression* model (Breiman 2001) (RFR). The implementation used in this study close follows the original procedure proposed by Breiman, in which a random perturbation of binary regression trees are used to aggregate a collection of predictors. Rather than the generation of one uniquely optimal tree, the result is instead a more efficient combination of several predictions. The random forest process creates decision trees using a recursive algorithm to split the data based on the most significant features until a stopping criterion is met, such as reaching a minimum sample size in a leaf. At each iteration, the observations are divided into two subpopulations, or “nodes.” The iterative process continues for each node, until it is no longer possible to separate the observations. The terminal nodes are known as “leaves” of the tree.

Dividing of the dataset into nodes is based upon the Classification and Regression Trees (CART) process, first introduced by Breiman et al. (1984), is used to obtain the best splits at each node according to the m_{try} selected variables. CART is a binary splitting algorithm used to divide the observations into 2 classes at each node based on a quality measure, which minimizes the maximum of the variances of the dependent variable between the 2 child nodes. The variance of each node can be expressed by the following equation:

$$\sum_{X_i \in t}\left(Y_i - \bar{Y}(t)\right)^2, \qquad (2)$$

where X_i are the independent variable observations based upon the split in X at node t, Y_i is the corresponding value of the dependent variable associated with observation i, and $\bar{Y}(t)$ is the average of the outputs associated with node t. The splitting process continues until one of several possible stopping criteria is met. The predictions of the *n* generated trees $(g_1, \ldots, g_n)$ are then aggregated by taking the average of the *n* individual predictions to arrive at a final prediction.

The primary tuning parameters for the RFR model implemented in this study are the number of trees generated (*n*) and the number of explanatory variables selected randomly without replacement to build each tree (m_{try}) which is a subset of the total number of explanatory variables. In this study, a grid search was used to select first the number of trees (*n*) and then the number of explanatory variables (m_{try}) that minimize the "out-of-bag" (OOB) mean squared error. The XLStats software was used for the tuning, estimation, and forecast evaluation for the RFR models.

The ranking of the explanatory variables in the RFR model uses a variable impact analysis where the primary metric is the mean increase (across all trees) in the OOB mean squared error when the independent variable is not included in the initial m_{try} sample of variables used to build the tree. The larger the MSE, the more important the independent variable. Negative values would indicate variables that actually decrease the forecasting accuracy of the model.

In addition to the six model methodologies mentioned above, a simple *naive* forecasting model (NAIVE) was constructed as a baseline for evaluating the informative content of the forecasting models. The model forecast was generated by taking the previous week's basis value and projecting it as the forecast value for the following week. In other words, the naive forecast utilized the following forecast equation:

$$\hat{y}_{t+1} = y_t, \tag{3}$$

where $\hat{y}_{t+1}$ is the forecasted basis in period *t+1* and y_t is the basis value in the previous period.

All of the models were tuned and estimated using the tuning datasets for both the pre- and post-COVID time periods. Since the forecasts are all one week forward, a one-period lag of the explanatory variables was incorporated to reflect the information available one week prior to the forecast period. Lag length tests using the 3 information criteria all indicated that the one-week lag was optimal not only for the dependent variables (basis) but also for the explanatory variables. Therefore, no lags beyond one week were used in the explanatory dataset. For monthly variables (WASDE forecasts and historical export volumes), the most recent released value as of the lagged date were used. Once the models were tuned and estimated, sample forecasts were generated using the testing datasets for each period.

Forecasting performance was evaluated using a combination of four commonly used forecast performance metrics. The first metric was the *root mean squared error* (RMSE) which is essentially the population standard deviation of all of the forecast errors. Generally, the lower the RMSE, the better the forecasting performance. However, the RMSE is scale dependent so caution must be taken when using it as a metric for comparing forecasts of variables that are measured in different units or have different mean levels. In some cases, the ratio of the RMSE to the mean can be used as a standardized volatility metric for comparisons; however, for variables that can have both positive and negative values (such as basis), this ratio cannot be used. For comparing alternative forecast methods across the same dependent variable (as in this study), the RMSE can be used to assess forecast performance.

The second metric was the *mean absolute error* (MAE) which is the average of the absolute difference between the forecast value and the actual value, or essentially the absolute value of the forecast error. While similar to the RMSE since it is scale dependent, the MAE is less susceptible to extreme (or outlier) forecast error values when compared to the RMSE.

The third metric was the *out-of-sample R-squared* statistic (R^2_{OS}) which is essentially the square of the Pearson correlation coefficient between the forecasted and actual values in the testing set. As with the regular R^2, this metric ranges from 0 to 1 and measures the percentage of variability in the forecasted values that is explained by the forecast model. Since this measure is independent of scale, it can be used to compare forecast performance across variables that are measured with different scales.

The fourth metric was the *Theil U-statistic of the 2nd kind* (U2) which is essentially the ratio of the RMSE's of the evaluated forecast model over the naive forecast model. Therefore, the U2 evaluates how much better or worse the forecast model performs when compared to a simple naive (no information) forecast. A Theil U2 statistic value of greater than one would indicate that the forecast model was performing more poorly than the naive model and thus, adding little to no forecasting value. A Theil U2 statistic value that is less than one would indicate a forecasting model that performs better than the naive model and thus, adds forecasting value. This value is greater as the ratio falls closer to zero. As a scale-dependent measure (ratio), the Theil U2 statistic can be used to compare forecasting performance across variables with differences in measurement and scale.

Forecasting Results and Feature Selection

Time Series Characteristics

Application of the Augmented Dickey-Fuller (ADF) test to the five basis series indicated that 3 out of the 5 were non-stationary in the pre-COVID period and four out of five were non-stationary in the post-COVID period. Similar mixed results arose with the application of the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test. After first-differencing of the series, all were confirmed stationary using both the ADF and KPSS. Therefore, the series were considered integrated at the order of one or I(1). The calculation of the autocorrelation (ACF) and partial autocorrelation (PACF) functions on the differenced basis series generally indicated, with the exception of the PNW and Ukraine series in the pre-COVID period, that the series followed a white noise process [ARIMA (0,1,0)]. For both exceptions, the results strongly indicated an ARIMA (1,1,1) process.

Application of vector autoregression lag-order selection using the information criterion (AIC, BIC, and HQIC) all indicated on optimal order of lags at one week in the pre- and post-COVID periods. Application of the Johansen trace tests for cointegration indicated that the pre-COVID series had at most four cointegrating equations and the post-COVID had at most one cointegrating equation. Therefore, a procedure proposed by Toda and Yamamoto (1995) was used to test Granger causality between the series for the pre- and post-COVID time periods. The results are summarized in Table 6 (Appendix A) and Figures 4 and 5 (Appendix B).

The pre-COVID causality results indicated a significant and unidirectional causal flow from the USG to the PNW during this period. This is likely due to a variety of factors such as the larger relative size of the USG (in corn export volume), the fact that USG ships to a wider range of international markets, and the USG market prices and shipments/sales are more transparent to the marketplace. It should also be noted that both markets are highly integrated both internally (by interior market logistics) and externally (due to ocean freight differentials) which strengthens the relationship between these markets during this more stable period.

Additionally, Argentina basis levels have a causal effect on the U.S. Gulf. There are also signs of bi-directional causality among U.S. Gulf and Ukraine basis levels, and a weak causal effect of Ukraine on both Brazil and Argentina basis levels. These were likely due to Argentina and Ukraine being the two major competitors to the U.S. in the global marketplace and the U.S. basis having to react in order to maintain some competitiveness. This same effect was noticed for soybeans in the Bullock and Wilson (2020) study.

The post-COVID causality results revealed significantly different causal relationships among the five markets. Notably, Ukraine was exogenous to the system in the post-COVID period and had a direct impact upon both the USG and Brazil. This was most likely due to a combination of factors including the rapid growth of Ukraine exports in 2020 which were record large and also a reduced export capacity out of Ukraine along with increased logistical costs at the end of this period due to the prelude and onset of the Russian invasion. These factors crowded out the international competition influences and caused the Ukrainian market to take on a life of its own.

Another notable change from the pre- to post-COVID period was the separation of the PNW from the USG with direct causal flows running from Argentina and Brazil to the PNW. This was likely the result of increased ocean shipping rates and the related differential which made the PNW more attractive relative to the USG for a greater share of the global marketplace. The increased shipping rates were primarily driven by higher energy prices as the market rebounded from the initial COVID pandemic effects.

In addition to the time series tests discussed in the previous sections, additional information criterion tests performed on the explanatory variables indicated an optimal lag length of one week in explaining the dependent export basis variables. Therefore, it was decided to evaluate the forecasting potential of the explanatory variables for the one-week forward period in this study since this is strongly indicated by the time series results. Note that this does not rule out the possibility that good longer-term forecasting models cannot be developed; however, if a model does not perform well in the one-week duration, then there is little likelihood that it will perform well in the longer weekly durations.

The length of the post-COVID time series window (100 weeks) was also not amenable to implementing a traditional time series forecasting evaluation process. Also, one of the goals of this study was to evaluate feature selection and ranking, and forecast performance across the entire range of each time window rather than introducing some bias into the results due to selection of testing window. To facilitate a randomized sampling for both windows, the data were converted into a cross-sectional series by taking the weekly lag of each explanatory variable along with one-week lags on the dependent variables for the explanatory dataset.

Therefore, the dataset would represent the state of information available to market participants one week prior to the forecast period.

U.S. Pacific Northwest (PNW)

The forecast performance of the alternative models for the PNW basis in the pre-COVID period is contained in Table 7 (Appendix A). The neural net (GRNN) model had the most desirable performance for the pre-COVID PNW basis forecasts with the highest R_{OS}^2, lowest MAE, lowest RMSE, and lowest Theil U2. Notably, each modeling technique showed at least some improvement over the R_{OS}^2 and RMSE of the naive forecast. The elastic net (ENR) and random forest (RFR) models saw the next greatest improvements beyond the dominating performance of the neural net. In summary, three of the ML models (GRNN, RFR, ENR) outperformed both the traditional VAR and STR models across all of the forecasting metrics. Only the partial least squares regression (PLS-R) showed slightly worse performance when compared to the traditional models.

Table 8 (Appendix A) lists the feature selection and independent variable ranking (top 10 variables) across the five selective modeling techniques (STR, PLS-R, ENR, GRNN, and RFR).[2] For the three linear modeling techniques (STR, PLS-R, ENR) the sign of the coefficient value is also provided. For the GRNN and RFR models, the directional sign of each variable is not available and can vary conditionally based upon the node (GRNN) or tree branch (RFR) where the variable resides.

The lagged USG basis ($Basis\_USG_{t-1}$) featured highly in all five models which is reflective of the Granger causality results for the pre-COVID period. While the rail fuel surcharge (FSC_{t-1}) figured highly in the three linear models, it is interesting that the optimal GRNN forecast model placed domestic railroad performance ($Velocity_{t-1}$) and secondary railcar market values (DCV_{t-1}) as more prominent measures of rail costs. Also, of interest is that the GRNN model does not place a high emphasis upon the lagged PNW basis value ($Basis\_PNW_{t-1}$) as is the case with the other models. Instead, it ranks WASDE projections of Ukrainian exports ($D\_EXP\_UKR_{t-1}$) as the most important variable. Featuring highly was the weekly volume of barge shipments of corn on the Mississippi River system ($BargeMS_{t-1}$) and the Japanese yen to U.S. dollar exchange rate ($DEXJPUS_{t-1}$). Also, of interest is the consistency of the top 3 ranking and variable coefficient signs across the three linear models while the nonlinear and discontinuous ML models (GRNN and RF) have completely different rankings — an indication that some nonlinear and threshold behavior may be at play in predicting PNW basis during this period.

For the post-COVID period, the PNW forecast performance metrics are in Table 9 (Appendix A). In the post-COVID period, the ENR model had the highest rank across all four of the metrics. The post-COVID forecast metrics across all models were generally poorer than those of the pre-COVID period, which can most likely be explained by fewer observations and much greater volatility in that time period. The PLS-R and STR models performed worse relative to the

[2] For brevity, the actual estimated model parameters are not included in this manuscript but can be obtained from the corresponding author (David W. Bullock) upon request.

naive forecast, while the VAR, GRNN, and ENR models saw only minor improvements relative to the naive model. Like the pre-COVID period, three of the ML models (ENR, GRNN, and RFR) had overall better performance in the post-COVID period than the traditional VAR and STR models.

Feature selection and variable ranking for the post-COVID period is contained in Table 10 (Appendix A). The lagged PNW basis (*Basis_PNW*$_{t-1}$) was the overall most significant feature selected by the five post-COVID models. Notably, the lagged USG basis (*Basis_USG*$_{t-1}$) was not among the top post-COVID features, despite being the top feature selected by the pre-COVID models. The GRNN selected Mississippi River rail deliveries (*RailMS*$_{t-1}$) as its most impactful feature and was the only model to select this variable in the top 10 rankings. Rail velocity (*FSC*$_{t-1}$) was also highly represented in the selected features. The Brazilian Real to USD (*DEXBZUS*$_{t-1}$) and USD to Euro (*DEXUSEU*$_{t-1}$) exchange rates, nearby futures price spread (*Fut_Sprd1*$_{t-1}$), and PNW export inspections (*Insp_PNW*$_{t-1}$) were also highly selected for among the five post-COVID models. Also notable is the lack of consistency in variable ranking across all five of the forecasting techniques. As with the pre-COVID period, the biggest divergence is seen in the GRNN model.

U.S. Gulf (USG)

The pre-COVID model performance results for the U.S. Gulf basis are presented in Table 11 (Appendix A). The RFR model had the most desirable performance with the highest R_{OS}^2, lowest RMSE, and lowest Theil U2. The GRNN model had a slightly more desirable MAE statistic compared to the RFR model — an indication that the RFR model performance may be more influenced by extreme values. Notably, the STR and PLS-R models performed worse overall than the naive forecast as indicated by the Theil U2 statistics. As with the PNW, three of the ML models (ENR, GRNN, and RFR) outperformed the other models (VAR, STR, and PLS-R) by a significant margin.

Feature selection and variable rankings for the pre-COVID period are shown in Table 12 (Appendix A). The lagged USG basis (*Basis_USG*$_{t-1}$) was the overall most significant feature selected by four of the five models. The lagged Ukraine (*Basis_Ukr*$_{t-1}$), PNW (*Basis_PNW*$_{t-1}$), and Argentina (*Basis_Arg*$_{t-1}$) basis values were the next top features selected. The GRNN model selected the secondary railcar value (*DCV*$_{t-1}$) as its third most impactful feature and was the only model to select this variable in the top 10 rankings. U.S. corn export commitments (*ExpCommit*$_{t-1}$), Mississippi River barge volume (*BargeMS*$_{t-1}$), and Japanese Yen to USG exchange rates (*DEXJPUS*$_{t-1}$) were also highly selected for among the five models.

The performance metrics of the basis forecasting models for the post-COVID U.S. Gulf market are compared in Table 13 (Appendix A). In the post-COVID period, the RFR model showed the most optimal performance across all four forecasting metrics. The post-COVID performance results were also considerably lower overall than those of the pre-COVID period, which if reflective of the fewer observations and much greater volatility in the latter time period. The ENR and GRNN models also showed considerable improvements over the naive forecast with Theil U2 statistics that were even lower than those for the pre-COVID period. Overall, all of the forecasting models had lower Theil U2 statistics in the post-COVID period.

The top 10 ranking of the explanatory variables for the post-COVID period is shown in Table 14 (Appendix A). Like the pre-COVID period, the lagged USG basis (*Basis_USG*$_{t-1}$) was the overall most significant feature selected by the five post-COVID models. The lagged Ukraine basis (*Basis_Ukr*$_{t-1}$) also had the second largest overall impact. However, the remaining features with the highest post-COVID impact were largely different than those seen in the pre-COVID period. The change in monthly USA corn exports (*Exp_USA*), September (*Sep*) and March (*Mar*) seasonal indicators, lagged Brazil basis values (*Basis_Brazil*$_{t-1}$), and PNW export inspections (*Insp_PNW*$_{t-1}$) were also highly selected for among the five post-COVID models.

Argentina (Rosario)

The performance metrics of the basis forecasting models for the pre-COVID Argentina market are compared in Table 15 (Appendix A). The RFR model had the most desirable performance with the highest R^2_{OS}, lowest MAE, lowest RMSE, and lowest Theil U2 statistic. The ENR and VAR models had MAE and R^2_{OS} statistics tying those of the RFR, respectively, and offered only slight improvements over the naive forecast in terms of the Theil U2. The VAR had the most favorable performance of the traditional econometric techniques. The STR, PLS-R, and GRNN procedures all had Theil U2's of greater than one indicating that they provided no value relative the naive forecast. Unlike the results for the PNW and USG basis models, the ML techniques added margin value when compared to the traditional econometric approaches and the naive model.

Table 16 (Appendix A) shows the feature selection and variable ranking for the pre-COVID models. The lagged Argentina basis (*Basis_Arg*$_{t-1}$) was the overall most significant feature selected by the five models. Brazil corn prices (*BrazilPrice*$_{t-1}$) and lagged Brazil basis values (*Basis_Brazil*$_{t-1}$) had the next largest impacts on the pre-COVID model results. Notably, the GRNN model selected the lagged USG basis (*Basis_USG*$_{t-1}$) and USG export inspection (*Insp_USG*$_{t-1}$) variables as most significant, where the PLS-R model was the only other technique with USG variables in its top 10 features. Lagged Ukraine basis (*Basis_Ukr*$_{t-1}$), projected Chinese imports (*D_IMP_PRC*$_{t-1}$), and November seasonal indicators (*Nov*) were also frequently selected among the five models.

The performance metrics of the basis forecasting models for the post-COVID Argentina market are compared in Table 17 (Appendix A). In the post-COVID period, the RFR model again showed the most optimal performance for all metrics. The post-COVID performance results overall were substantially more favorable than the pre-COVID performance results, particularly for the ML models (PLS-R, ENR, GRNN, and RFR). Notably, the PLS-R model had better metrics when compared to the ENR and GRNN models. All of the models offered at least some improvement over the naive forecast in this scenario as evidenced by all of the Theil U2's below 1.0 in value.

The feature selection and variable ranking for the post-COVID period is shown in Table 18 (Appendix A). Like the pre-COVID period, the lagged Argentina basis (*Basis_Arg*$_{t-1}$) was the overall most significant feature. Lagged Ukraine basis values (*Basis_Ukr*$_{t-1}$) and projected Chinese imports (*D_IMP_PRC*$_{t-1}$) were also some of the top features selected across the models. However, unlike the pre-COVID models, the nearby futures price spreads (*Fut_Sprd1*$_{t-1}$) was highly significant in the post-COVID results and was the top variable selected by the GRNN model. April (*Apr*) and June (*Jun*) seasonal indicators, along with PNW export inspections ($Insp\_PNW_{t-1}$), were also frequently selected among the five post-COVID models.

Brazil (Paranagua)

The performance metrics of the basis forecasting models for the pre-COVID Brazil market are compared in Table 19 (Appendix A). The RFR model had the best performance with the highest R^2_{OS}, lowest RMSE, and lowest Theil U2 statistics. The naive forecast, however, had the lowest MAE of all the pre-COVID models. The ENR, VAR, and STR models also had Theil U2 statistics slightly below 1.0 which indicates slightly better performance compared to the naive forecast. The VAR had the most favorable performance out of the traditional econometric techniques, while the RFR model greatly outperformed the ENR and GRNN models. The GRNN and PLS-R models both performed worse relative to the naive forecast as indicated by Theil U2's exceeding 1.3 in value.

The feature selection and variable ranking for the pre-COVID period is summarized in Table 20 (Appendix A). The lagged Brazil basis ($Basis\_Brazil_{t-1}$) was the overall most significant feature selected by the five models. Japanese Yen to USG exchange rates ($DEXJPUS_{t-1}$) and Brazil corn prices ($BrazilPrice_{t-1}$) were the next most highly selected for features among the five models. The GRNN model selected nearby futures contract prices (Fut_Nearby_{t-1}) as the variable with the most significant impact on its results. Lagged Argentina ($Basis\_Arg_{t-1}$) and Ukraine ($Basis\_Ukr_{t-1}$) basis values, along with the monthly change in Ukraine exports (*Exp_Ukr*), were also significant within the most selected pre-COVID features.

Table 21 (Appendix A) shows the basis forecasting performance metrics for the post-COVID period for the Brazil market. The GRNN model had the optimal performance across all four forecast metrics. As with Argentina, the post-COVID results showed substantial improvement relative to the pre-COVID performance results. The RFR, ENR, and STR models also had considerably better performance relative to the naive forecast as evidenced by Theil U2's of 0.75 or below. Notably, the GRNN results for the post-COVID Brazil model had the most favorable Theil U2 improvement (relative to pre-COVID) of all models in the study. Three of the ML approaches (GRNN, ENR, and RFR) clearly had much better forecasting performance when compared to the traditional VAR and STR models. PLS-R had the worst forecasting performance across both time horizons.

The post-COVID feature selection and variable ranking for Brazil basis is summarized in Table 22 (Appendix A). The lagged Ukraine basis ($Basis\_Ukr_{t-1}$) was overall most significant to the post-COVID model, while the lagged Brazil basis ($Basis\_Brazil_{t-1}$) was the second most selected feature. Like the pre-COVID period, lagged Argentina basis values ($Basis\_Arg_{t-1}$) were also highly selected across models. The nearby futures price spread (Fut_Sprd1_{t-1}), PNW export inspections ($Insp\_PNW_{t-1}$), lagged U.S. Gulf ($Basis\_USG_{t-1}$) basis values, and projected world exports ($D\_EXP\_WRLD_{t-1}$) were also widely selected overall in the post-COVID period but did not rank highly in the pre-COVID listing.

Ukraine (Odesa and Mykolaiv)

The performance metrics of the basis forecasting models for the pre-COVID Ukraine market are compared in Table 23 (Appendix A). The naive forecasting model had the best forecasting performance for the pre-COVID period with the highest R_{OS}^2, lowest MAE, and lowest RMSE. Each modeling approach produced worse forecasts relative to the naive forecast as evidenced by all of the Theil U2's having values of 1.0 or greater. The VAR, STR, and ENR models had only slightly worse performance while the other models (PLS-R, GRNN, and RFR) clearly had very poor forecasting performance. Notably, the Ukraine forecasting models were significantly less accurate than those of the other four basis markets in the pre-COVID period as evidenced by the significantly higher RMSE's for all models.

Feature selection and variable ranking for the pre-COVID Ukraine models is presented in Table 24 (Appendix A). The lagged Ukraine basis ($Basis\_Ukr_{t-1}$) was the overall most significant feature selected by the five models, and the lagged USG basis ($Basis\_USG_{t-1}$) has the second largest impact overall. The GRNN selected secondary railcar value (DCV_{t-1}) as its third most important feature and was the only model to select this variable in the top 10 rankings. Brazilian Real to USD ($DEXBZUS_{t-1}$) and Japanese Yen to USD ($DEXJPUS_{t-1}$) exchange rates, lagged Argentina ($Basis\_Arg_{t-1}$) and Brazil ($Basis\_Brazil_{t-1}$) basis values, and Mississippi River barge volume ($BargeMS_{t-1}$) were also widely selected among the pre-COVID models.

The performance metrics of the basis forecasting models for the post-COVID Ukraine market are compared in Table 25 (Appendix A). Like the pre-COVID period, the naive forecasting model clearly had the most desirable performance among the post-COVID forecasting models for the Ukraine basis. The naive outperformed all other models in each of the forecast quality comparison metrics. The VAR and ENR models performed slightly worse relative to the naive forecast, while the PLS-R and GRNN models were significantly less accurate overall. Like the pre-COVID period, the naive and VAR methods outperformed the ML techniques in the post-COVID period. The Ukraine basis models continued to have the least favorable performance of all the post-COVID models in the study as evidenced by much higher RMSE's.

Table 26 (Appendix A) summarizes the feature selection and variable ranking for the post-COVID Ukraine models. The Japanese Yen to USD exchange rate ($DEXJPUS_{t-1}$) was the overall most significant feature across the five post-COVID models. Like the pre-COVID period, lagged Ukraine ($Basis\_Ukr_{t-1}$), U.S. Gulf ($Basis\_USG_{t-1}$), and Argentina ($Basis\_Arg_{t-1}$) basis values were also among the top features selected in the post-COVID period. The March indicator variable (*Mar*), PNW export inspections ($Insp\_PNW_{t-1}$), and average St. Louis barge quotes ($Barge\_STL_{t-1}$) also saw significance in the post-COVID period but were not as widely selected in the pre-COVID period.

Summary and Conclusions

For the global corn market, the basis at the major export locations has become more volatile over time as has been the case with many of the global commodity markets. Deriving short-term basis forecasts based upon current market information is critical for many of the participants in the corn supply chain, both domestically and internationally. With the increase in volatility, there has been a noticeable breakdown in the effectiveness of traditional forecasting tools including time series and econometric forecasting. Part of this breakdown can be attributed to the nonlinearities, discontinuities, and threshold behavior that this volatility has introduced into the market dynamics. A developing class of forecasting tools, called machine learning, are designed to handle these complications more effectively and have the potential to enhance the accuracy of forecasting in these volatile markets.

The purpose of this study is to examine two primary questions. First, do cutting-edge ML tools outperform traditional econometric methods in the short-term (one week ahead) forecasting of corn basis for the five major international markets. Second, is there consistency among the ML tools in terms of the selection and ranking of explanatory variables (i.e., feature selection) and what key themes can be learned from these variable rankings.

A graphical examination of the basis data over this time period showed a major structural break occurring around the beginning of July 2020 with a significant upward shift in volatility and basis mean level (for three of the five series). Therefore, the data was divided into two time windows: a pre-COVID period (prior to July 2020) and a post-COVID period (July 2020 and afterwards). The forecasting performance and feature selection was evaluated separately over these two different time windows. The key observations from this analysis are summarized below.

Feature Selection and Variable Ranking

The underlying factors that most significantly influenced short-term basis levels, along with the various intermarket influences on export basis at the five export markets were another key area of interest within the study. Additionally, the shift to more volatile basis levels in the post-July 2020 period brought new questions as to which factors had the greatest influence on basis after the onset of the COVID-19 pandemic and whether the driving short-term forces affecting pre-COVID basis levels are different from those of the post-COVID period.

The transition from the pre- to post-COVID period saw some changes to intermarket patterns of influence among the five markets based upon an analysis of Granger causality. Firstly, the U.S. Gulf and PNW markets have a strong connection in both periods. The PNW has less influence on the Gulf in the post-COVID period, however, when compared to the pre-COVID period. The Ukrainian market variables seem to have greater overall influence in the pre-COVID period, while they are noticeably less influential in the post-COVID period for the PNW, Gulf, and Argentina models. Ukraine maintains a strong influence on Brazil throughout the pre- and post-COVID periods. Lastly, there is a strong connection between Argentina and Brazil basis levels in both periods, but Argentina has a much weaker influence on Brazil in the post-COVID period.

The explanatory variables with the greatest influences on U.S. export basis levels (PNW and USG) also saw some differences between the pre- and post-COVID periods. For PNW, the top variables in the pre- and post-COVID periods (one lag of the USG basis and PNW basis, respectively) were also reflective of the Granger causality results. The U.S. Gulf had a lower overall influence on PNW values in the post-COVID period when compared to its causal importance in the pre-COVID period. Logistics variables were important influences on PNW basis levels in both periods. The rail fuel surcharge was highly important in the pre-COVID period, while railroad performance (velocity) became more important in the post-COVID period.

The WASDE projection forecasts were more important in the pre-COVID period, as opposed to current market factors (exchange rates with key exporter and importer, logistics and port activity) which were more important in the post-COVID period. The GRNN neural network model, which performed best out of the pre-COVID period PNW models, placed less emphasis on time-series (lagged) variables compared to the other methods. The GRNN ranks Ukraine export competition and barge competition from the Gulf as the top factors in the PNW pre-COVID period, where the elastic net puts more emphasis on time series behavior, export activity, and Gulf connections in the post-COVID period.

The U.S. Gulf models consistently placed greater significance on time series variables and basis competition (levels at other ports) in both periods compared to PNW, particularly in the pre-COVID period. Feature selection in both periods indicates the importance of Ukraine competition on U.S. Gulf basis levels. The pre-COVID period Gulf forecasts had greater influences from Argentina and PNW, while the post-COVID period saw a greater emphasis on competition from Brazil. Overall, the Gulf seems to be more driven by market competition in both periods compared to PNW and the other markets. Unlike the Gulf, PNW was greatly impacted by railroad performance (velocity) in the post-COVID period, indicating the Gulf was somewhat less susceptible to supply chain issues compared to PNW basis levels in the post-COVID period.

The explanatory variables with the greatest influences on the international basis markets (Argentina, Brazil, and Ukraine) also varied in comparison with the U.S. markets. The South American basis markets seem to be influenced more by ethanol prices, exchange rates, and Ocean freight rates than the other markets. The WASDE forecasts for China imports was an important feature in both periods for the Argentina models. Argentina was most influenced by Brazil in the pre-COVID period and Ukraine in the post-COVID period. Ukraine was also an important feature for Brazil in both periods, though more particularly in the post-COVID period. The Ukraine models had poor overall performance, but the U.S.-Japan exchange rate seems to have some importance in the models of both periods.

In summary, the selected features of the models seemed to vary widely depending on the time period and the employed methodology. The GRNN models tended to have the most deviation in feature selection from the other techniques, but also generally remained among the top performing methodologies in each market and time period. The U.S. basis markets were influenced by a mix of logistical and international factors, with the Gulf in particular being driven most by market competition. The PNW appeared to be most susceptible to supply chain factors in the post-COVID period. The international models generally had worse performance relative to the U.S. models, which is likely a result of the explanatory variable set consisting mostly of U.S.-based measures.

Forecast Performance

A key question of the study is whether the modeling techniques based in machine learning (partial least squares regression, elastic net regression, GRNN neural nets, and random forests) offered one-week ahead basis forecasts of either comparable or superior accuracy than those of the traditional econometric techniques (naïve forecast, vector autoregression, and stepwise regression). Particularly in the case of the post-COVID period, it was hypothesized that the machine learning models would have advantages in handling both the increased volatility in basis levels and the limitation of fewer observations within the data to use for model tuning and testing.

For the U.S. PNW and Gulf markets, the performance of the machine learning models dominated that of the traditional econometric models in both periods. The GRNN and elastic net had the greatest success among the PNW models, while the random forest technique performed the best of the USG models. The random forest also dominated both periods in the Argentina model results but saw considerably more success in the post-COVID period as opposed to overall poor results across the board in the pre-COVID period. Similarly, the random forest had the most favorable results of the pre-COVID period Brazil models, but the stepwise and VAR methods performed better than the elastic net and GRNN. Post-COVID period Brazil also saw the dominance of the three machine learning techniques, showing substantial improvement over the pre-COVID period.

The machine learning models were generally superior in forecasting the PNW, USG, Argentina, and Brazil basis forecasts in both the pre- and post-COVID periods. The machine learning models in the post-COVID period saw substantial improvements over the econometric methods, offering evidence that the machine learning techniques were better able to forecast with the increased volatility of basis levels and decreased number of observations after the markets began to be affected by the onset of the COVID-19 pandemic around July of 2020. Further, it appears as though no single machine learning method dominated the performance of the others. Rather, the best machine learning technique varies depending on the market and the time period (pre- vs. post-COVID). Overall, the random forest was most frequently the best performing model of its competitors, but all the machine learning techniques tended to outperform the traditional econometric approaches for the U.S. and South American markets in both periods.

In contrast, none of the econometric and machine learning methods could improve upon the naïve forecast for Ukraine in either period. Aside from the naïve forecasts, the VAR models appear to perform the best for forecasting Ukraine basis in both periods. The lack of performance from each of the more complex forecasting techniques (stepwise regression, partial least squares regression, elastic net regression, GRNN neural nets, and random forest) also indicates a lack of reliable market data from Ukraine. The Ukraine basis data used by the study came from two separately reported sources, likely contributing to poor model performance. Additionally, the models for the South American markets (Argentina and Brazil) saw considerably higher RMSE values when compared to the U.S. markets (PNW and USG) in both time periods. This can most likely be attributed to the greater proportion of U.S.-based measures in the variable set versus the international markets.

In summary, the machine learning models outperform the econometric models in every case besides Ukraine, where the lack of reliable data contributed to poor model performance beyond the naive forecast. Particularly, the machine learning methods offer more substantial improvements in the post-COVID period. Overall, the post-COVID period data is difficult to accurately forecast using the traditional econometric methods (vector autoregression and stepwise regression). The machine learning methods appear to have the greatest value in the post-COVID PNW, USG, Argentina, and Brazil cases over the other forecasting methods studied.

Implications for Market Participants

The results of this study clearly indicate that there was a significant increase in international corn basis risk beginning with a strong structural break in July 2020 as the markets began to rebound from the adverse impacts brought on by the beginning of the COVID19 pandemic in March 2020. This had significant implications for global commodity traders among which were increases in difficulty of price reporting by the various international price reporting agencies. For example, in recent months, forward quotations for Ukrainian export basis were shortened to two months while most international trades are typically for 4 to 6 months forward. This forces traders to absorb greater risk than they would otherwise. Since the basis has become more volatile and less predictable, the escalation in risk would affect basis contracts, as well as in flat priced contracts that are hedged in futures. Since the Ukraine basis is more risky and less predictable, it likely implies traders would need to infer a greater risk premium in trades from that market area.

In this environment of increasing basis risk, it is important to have better prediction methods and strategies that can support core trading functions including logistics and price risk management. The results from this study indicated that machine learning tools provided significant value in the short-term frequency of basis forecasting and trading. While feature selection and explanatory variable ranking varied widely across the various machine learning tools, it is important to note that in most of the cases examined, the machine learning tools outperformed the naive and traditional econometric tools by a wide margin as indicated by the Theil U2 statistic of forecast quality.

Finally, in most cases the results suggest that inter-port area rivalry is important. Hence, understanding the features impacting basis in competing markets is important to predicting basis in other markets.

Study Limitations and Avenues for Future Research

The econometric and machine learning methods did not improve upon the naïve forecast for Ukraine. This is most likely due to the limitations on the availability of explanatory variables from the Ukrainian interior price and logistics markets. In general, the study results point to the need for better availability of regularly reported market data for the Ukraine interior corn markets.

Another limitation related to the data is the lack, in general, of explanatory variables outside of the U.S. domestic market. Much of this data likely exists; however, this data is generally less accessible and, in some cases, less transparent when compared to the U.S. market. We used explanatory variables from the U.S. primarily due to accessibility and also because it matched the time frequency and period covered in this study. Where international data of the right frequency and period was available from our data sources (i.e., Brazilian domestic corn price), it was included in this study. However, a broader effort to include more internal market variables from the Argentinian, Brazilian, and Ukrainian markets would likely improve the forecasting results; particularly for those international markets.

Another potential limitation of this study was the conversion of the time series data into cross-sectional for the purposes of forecasting and forecast evaluation. This was primarily a limitation imposed by the data and the software used. Also, a secondary consideration was the objective of evaluating the forecasting performance and feature selection across the entirety of the pre- and post-COVID time periods without introducing a time window bias. Traditional time series forecasting applications would divide the dataset into tuning and testing datasets by setting a time window (typically using the traditional 80/20 percentage split). With only 100 observations in the post-COVID dataset, this would have limited the testing dataset to 20 weeks from January through May 2022, a period dominated by the run-up and beginning of the Russian invasion of Ukraine. This would likely have added a substantial time window bias to the results.

Also, the software utilized in this study (XLStats and NeuralTools) are Excel spreadsheet add-ins which do not include recursive forecasting features that are amenable to generating time series forecast evaluation. This is not a limitation to other forecasting tools that include procedural coding such as Stata, R, and Python.

This study offers evidence that the machine learning forecasting methods (elastic net, GRNN, and random forests) perform more favorably than the traditional econometric methods (VAR, stepwise regression, and PLS-R) when creating one-week basis forecasts with out-of-sample testing data. This result was more pronounced in the post-COVID period with more observed volatility in corn export basis levels. These results promote avenues for future research in the post-COVID world, either using more comprehensive international basis data or more observations for basis and/or price levels of similar commodities and markets. This study only utilizes data through May 2022 and earlier, and thus the number of post-COVID observations continues to grow over time and will likely offer further improvements in forecasting the post-COVID basis levels.

Machine learning applications are constantly being discovered and improved upon. The elastic net, GRNN, and random forests methodologies employed in this study are only a few possibilities in the list of possible viable methods for forecasting in the basis markets. Further, each method showed favorable results across the various corn basis markets and pre- and post-COVID periods, with no clear favorite that dominated among the three. These insights promote further research into which circumstances are most ideal to apply the various machine learning forecasting techniques under. Overall, the machine learning techniques show great promise for pre- and post-COVID corn export basis forecasting, most significantly seen in their superior ability to handle volatility in the post-COVID basis markets.

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Appendix A: Tables

Table 1. International Corn Export Basis Variables Included in Dependent Variables

Variable	Description	Source(s)	Notes
Basis_PNW	Corn FOB basis for PNW (¢/b)	*Eik*on: USDA Daily Market Rates Corn (BU) YC Portland (2YC-PNW); DTN: Nearby corn futures (@C@C)	Basis calculated by multiplying the price by 100c/b and subtracting the nearby futures price.
Basis_USG	Corn FOB basis for U.S. Gulf (¢/b)	*Eikon*: Corn FOB US Gulf Continuation 1 (C-US2YNOLAF)	---
Basis_Arg	Corn FOB basis for Argentina (¢/b)	*Eikon*: J.J. Hinrichsen Yellow Corn Argentina FOB Position 1 (C-FOBARG-P1); *ProphetX*: Nearby corn futures (@C@C)	Prices quoted in $ per MT. Basis calculated by multiplying price by (56/2204.6) to convert to c/b, then subtracting the nearby futures price.
Basis_Brazil	Corn FOB basis for Brazil (¢/b)	*Eikon*: Yellow Corn Paranagua Brazil FOB Ask 1 (C-FOBPNG-A1); *ProphetX*: Nearby corn futures (@C@C)	Prices quoted in $ per MT. Basis calculated by multiplying price by (56/2204.6) to convert to c/b, then subtracting the nearby futures price.
Basis_Ukr	Corn FOB basis for Ukraine (¢/b)	*Eikon*: FOB UKR (QMAZ-FOBUA-P1), *ProphetX*: Nearby Futures (@C@C); *AgriCensus*: Corn FOB Ukraine Handy Premium $/bushel	The data from January 2015 – August 2018 are sourced from *Eikon* data which is no longer reported. The data from September 2018 onward are sourced from *AgriCensus*, which only began reporting data in 2018.

Table 2. Key U.S. Transportation Costs and Logistical Factors Included in Explanatory Variables

Variable	Description	Source(s)	Notes
DCV	Secondary railcar values ($/car)	*TradeWest Brokerage Company* daily market reports (private subscription)	—
Velocity	BNSF Shuttle trips per month from any origin to PNW	*TradeWest Brokerage Company* daily market reports (private subscription)	—
FSC	Railroad Fuel Surcharge Weighted Average ($/ mile/car)	*ProphetX*: Railroad Fuel Surcharge Weighted Average (GTR_RFSCWTDAVG)	—
RailPAC	Rail Deliveries to Port - Pacific	*ProphetX*: Rail Deliveries to Port - Pacific (GTR_RDPPAC)	---
RailMS	Rail Deliveries to Port - Mississippi River	*ProphetX*: Rail Deliveries to Port - Mississippi River (GTR_RDPMIR)	---
Barge_STL	Weekly Average Barge Spot Rate Survey Quotes ($/ton)	*USDA Grain Transportation Report* Datasets: Figure 8 Table 9 (GTRFigure8Table9.xlsx),	Located at https://www.ams.usda.gov/services/transportation-analysis/gtr-datasets.
Ship_USG	Weekly number of loaded grain vessels: Gulf	*USDA Grain Transportation Report* Datasets: Table 17 (GTRTable17.xlsx), Gulf_In_Port	Located at https://www.ams.usda.gov/services/transportation-analysis/gtr-datasets
Ship_PNW	Weekly number of loaded grain vessels: PNW	USDA Grain Transportation Report Datasets: Table 17	Located at https://www.ams.usda.gov/services/transportation-analysis/gtr-datasets.
BargeMS	Barge Corn Tons Mississippi Total Weekly Volume (tons)	*ProphetX*: Barge Corn Tons Mississippi Total Weekly Volume (GTR_BCMSWVL)	Located at https://www.ams.usda.gov/services/transportation-analysis/gtr-datasets.
Insp_USG	Weekly Inspections of grain for export – USG (million bushels)	*USDA Grain Transportation Report* Datasets: Table 16 Figure 14 Figure 15	Variable is a sum of the variables Mississippi_Gulf_Corn + Texas_Gulf_Corn.
Insp_PNW	Weekly Inspections of grain for export – PNW (million bushels)	*USDA Grain Transportation Report* Datasets: Table 16 Figure 14 Figure 15	Located at https://www.ams.usda.gov/services/transportation-analysis/gtr-datasets.
ExpCommit	Corn Export Commitments (million bushels)	*ProphetX*: Total Commitments Current Year Corn Total (GTR_CTOTCCYTOT)	---

Table 3. Ocean Shipping Rates Included in Explanatory Variables

Variable	Description	Source(s)
USG_CHN	Ocean rates: USG to China ($/MT)	*Eikon*
USG_IND	Ocean rates: USG to Indonesia ($/MT)	*Eikon*
USG_EU	Ocean rates: USG to the European Union ($/MT)	*Eikon*
USG_ME	Ocean rates: USG to the Middle East ($/MT)	*Eikon*
USG_JPN	Ocean rates: USG to Japan ($/MT)	*Eikon*
USG_SK	Ocean rates: USG to South Korea ($/MT)	*Eikon*
PNW_CHN	Ocean rates: PNW to China ($/MT)	*Eikon*
PNW_IND	Ocean rates: PNW to Indonesia ($/MT)	*Eikon*
PNW_JPN	Ocean rates: PNW to Japan ($/MT)	*Eikon*
PNW_SK	Ocean rates: PNW to South Korea ($/MT)	*Eikon*
ARG_CHN	Ocean rates: Argentina to China ($/MT)	*Eikon*
ARG_IND	Ocean rates: Argentina to Indonesia ($/MT)	*Eikon*
ARG_EU	Ocean rates: Argentina to the European Union ($/MT)	*Eikon*
ARG_ME	Ocean rates: Argentina to the Middle East ($/MT)	*Eikon*
ARG_JPN	Ocean rates: Argentina to Japan ($/MT)	*Eikon*
ARG_SK	Ocean rates: Argentina to South Korea ($/MT)	*Eikon*
BRZ_CHN	Ocean rates: Brazil to China ($/MT)	*Eikon*
BRZ_IND	Ocean rates: Brazil to Indonesia ($/MT)	*Eikon*
BRZ_EU	Ocean rates: Brazil to the European Union ($/MT)	*Eikon*
BRZ_JPN	Ocean rates: Brazil to Japan ($/MT)	*Eikon*
BRZ_SK	Ocean rates: Brazil to South Korea ($/MT)	*Eikon*
UKR_CHN	Ocean rates: Ukraine to China ($/MT)	*Eikon*
UKR_IND	Ocean rates: Ukraine to Indonesia ($/MT)	*Eikon*
UKR_EU	Ocean rates: Ukraine to the European Union ($/MT)	*Eikon*
UKR_ME	Ocean rates: Ukraine to the Middle East ($/MT)	*Eikon*
UKR_JPN	Ocean rates: Ukraine to Japan ($/MT)	*Eikon*
UKR_SK	Ocean rates: Ukraine to South Korea ($/MT)	*Eikon*
UKR_VNM	Ocean rates: Ukraine to Vietnam ($/MT)	*Eikon*

Table 4. USDA WASDE Export and Import Projections Included in Explanatory Variables

Variable	Description	Source(s)	Notes
D_EXP_WRLD	Year-on-year Change in Projected Corn Exports – World (million MT)	*USDA WASDE* report database	https://www.usda.gov/oce/commodity-markets/wasde/historical-wasde-report-data
D_EXP_US	Year-on-year Change in Projected Exports – USA (million MT)	*USDA WASDE* report database	https://www.usda.gov/oce/commodity-markets/wasde/historical-wasde-report-data
D_EXP_BRZ	Year-on-year Change in Projected Exports – Brazil (million MT)	*USDA WASDE* report database	https://www.usda.gov/oce/commodity-markets/wasde/historical-wasde-report-data
D_EXP_ARG	Year-on-year Change in Projected Exports – Argentina (million MT)	*USDA WASDE* report database	https://www.usda.gov/oce/commodity-markets/wasde/historical-wasde-report-data
D_EXP_UKR	Year-on-year Change in Projected Exports – Ukraine (million MT)	*USDA WASDE* report database	https://www.usda.gov/oce/commodity-markets/wasde/historical-wasde-report-data
D_IMP_PRC	Year-on-year Change in Projected Imports – China (million MT)	*USDA WASDE* report database	https://www.usda.gov/oce/commodity-markets/wasde/historical-wasde-report-data
D_IMP_JAP	Year-on-year Change in Projected Imports – Japan (million MT)	*USDA WASDE* report database	https://www.usda.gov/oce/commodity-markets/wasde/historical-wasde-report-data
D_IMP_EU	Year-on-year Change in Projected Imports – EU (million MT)	*USDA WASDE* report database	https://www.usda.gov/oce/commodity-markets/wasde/historical-wasde-report-data

Table 5. Other Explanatory Variables and Sources

Variable	Description	Source(s)	Notes
BrazilPrice	Brazilian Corn Price ($ per 60kg bag)	*ProphetX*: CEPEA/ESALQ Corn (60 kg) Price Index (US Dollar) (cpCORN_USD.X)	---
EthanolPrice	Ethanol Price ($ per gallon)	*ProphetX*: ETHANOL NATIONAL RACK Spot (AC$Y)	---
Fut_Nearby	Nearby Corn Futures (¢/bushel)	*ProphetX*: Nearby Corn Futures (@C@C)	---
Fut_Sprd1	Futures Price Spread to next expiring contract (¢/bushel)	*ProphetX*: Nearby Corn Futures Spread	Spread calculated as @C@C2 minus @C@C.
Fut_Sprd2	Futures Price Spread from next two expiring contracts (¢/bushel)	*ProphetX*: 2nd Nearby Corn Futures Spread	Spread calculated as @C@C3 minus @C@C2.
Exp_USA	USA – Monthly change in corn exports (MT)	*AgriCensus* Export Dashboard	Data are reported monthly. Lagged values used in the study refer to the previous month rather than the previous week.
Exp_Arg	Argentina – Monthly change in corn exports (MT)	*AgriCensus* Export Dashboard	Data are reported monthly. Lagged values used in the study refer to the previous month rather than the previous week.
Exp_Brazil	Brazil – Monthly change in corn exports (MT)	*AgriCensus* Export Dashboard	Data are reported monthly. Lagged values used in the study refer to the previous month rather than the previous week.
Exp_Ukr	Ukraine – Monthly change in corn exports (MT)	*AgriCensus* Export Dashboard	Data are reported monthly. Lagged values used in the study refer to the previous month rather than the previous week.
DEXBZUS	Brazilian Reals to USD exchange rate	Federal Reserve Bank of St. Louis - FRED Online Database.	Located at https://fred.stlouisfed.org/
DEXCHUS	Chinese Yuan to USD exchange rate	Federal Reserve Bank of St. Louis - FRED Online Database.	Located at https://fred.stlouisfed.org/
DEXJPUS	Japanese Yen to USD exchange rate	Federal Reserve Bank of St. Louis - FRED Online Database.	Located at https://fred.stlouisfed.org/
DEXUSEU	USD to Euro exchange rate	Federal Reserve Bank of St. Louis - FRED Online Database.	Located at https://fred.stlouisfed.org/
DTWEXBGS	Nominal Broad USD Index	Federal Reserve Bank of St. Louis - FRED Online Database.	Located at https://fred.stlouisfed.org/

Table 6. Granger Causality Test Results Using Toda-Yamamoto (1995) Procedure[a]

Pre-COVID					
Dependent Variables	**Independent Variables**				
	Pacific NW	**US Gulf**	**Argentina**	**Brazil**	**Ukraine**
PNW	-	14.78***	1.93	1.20	0.13
US Gulf	0.00	-	17.13***	1.69	4.50**
Argentina	0.27	0.66	-	0.65	3.39*
Brazil	0.07	0.36	0.21	-	2.78*
Ukraine	0.20	3.85*	0.03	0.21	-
Post-COVID					
Dependent Variables	**Independent Variables**				
	Pacific NW	**US Gulf**	**Argentina**	**Brazil**	**Ukraine**
PNW	-	2.39	3.50*	3.58*	0.08
US Gulf	0.39	-	0.05	0.02	5.15**
Argentina	4.28**	0.99	-	0.01	1.97
Brazil	0.60	2.61	7.81***	-	28.85***
Ukraine	0.16	2.63	1.52	1.49	-

Significance: *$p \leq 0.1$ | **$p \leq 0.05$ | ***$p \leq 0.01$

[a]Values are distributed chi-squared with one degree of freedom (i.e., Wald coefficient exclusion tests) with the null hypothesis of no causal link between the series.

Table 7. Pre-COVID Performance Metrics for PNW Basis Forecasts

Measure	Naive	VAR	STR	PLS-R	ENR	GRNN	RFR
R^2_{OS}	0.851	0.863	0.879	0.861	0.886	0.902*	0.890
MAE	4.486	4.576	4.403	4.988	4.456	3.953*	4.267
RMSE	6.114	5.850	5.513	5.906	5.346	4.952*	5.263
Theil U2	1.000	0.957	0.902	0.966	0.874	0.810*	0.861

*Optimal result

Table 8. Pre-COVID Feature Selection and Variable Ranking for PNW Basis Forecasts[a]

Rank	STR	PLS-R	ENR	GRNN	RFR
1	(+) Basis_PNW$_{t-1}$	(+) Basis_PNW$_{t-1}$	(+) Basis_PNW$_{t-1}$	D_EXP_UKR$_{t-1}$	Basis_PNW$_{t-1}$
2	(+) Basis_USG$_{t-1}$	(+) Basis_USG$_{t-1}$	(+) Basis_USG$_{t-1}$	BargeMS$_{t-1}$	Basis_Arg$_{t-1}$
3	(+) FSC$_{t-1}$	(+) FSC$_{t-1}$	(+) FSC$_{t-1}$	DEXJPUS$_{t-1}$	D_EXP_BRZ$_{t-1}$
4	(+) D_IMP_JAP$_{t-1}$	(-) D_EXP_BRZ$_{t-1}$	(+) D_IMP_JAP$_{t-1}$	Basis_USG$_{t-1}$	Basis_USG$_{t-1}$
5	(-) Barge_STL$_{t-1}$	(+) Exp_USA$_{t-1}$	(+) Exp_USA	EthanolPrice$_{t-1}$	Fut_Sprd1$_{t-1}$
6	(+) BrazilPrice $_{t-1}$	(-) Fut_Sprd1$_{t-1}$	(-) D_EXP_BRZ$_{t-1}$	Basis_Arg$_{t-1}$	Fut_Sprd2$_{t-1}$
7	(-) RailMS$_{t-1}$	(+) DEXBZUS$_{t-1}$	(+) DEXBZUS$_{t-1}$	Velocity$_{t-1}$	DEXJPUS$_{t-1}$
8	---	(-) D_EXP_WRLD$_{t-1}$	(-) RailPAC$_{t-1}$	DCV$_{t-1}$	DTWEXBGS$_{t-1}$
9	---	(+) Basis_Arg$_{t-1}$	(+) Basis_Arg$_{t-1}$	DEXBZUS$_{t-1}$	Insp_USG$_{t-1}$
10	---	(-) D_IMP_EU$_{t-1}$	(-) Oct	DEXCHUS$_{t-1}$	D_EXP_US$_{t-1}$

[a]Signs of variable are in parentheses (note: GRNN and RF do not provide signs).

Table 9. Post-COVID Performance Metrics for PNW Basis Forecasts

Measure	Naive	VAR	STR	PLS-R	ENR	GRNN	RFR
R^2_{OS}	0.605	0.613	0.556	0.414	0.731*	0.617	0.615
MAE	15.463	16.618	16.117	21.652	14.662*	14.980	14.968
RMSE	26.199	25.928	27.762	31.908	21.607*	25.812	25.857
Theil U2	1.000	0.990	1.060	1.218	0.825*	0.985	0.987

*Optimal result

Table 10. Post-COVID Feature Selection and Variable Ranking for PNW Basis Forecasts[a]

Rank	STR	PLS-R	ENR	GRNN	RFR
1	(+) $Basis\_PNW_{t-1}$	(+) $Basis\_PNW_{t-1}$	(+) $Basis\_PNW_{t-1}$	$RailMS_{t-1}$	$Basis\_PNW_{t-1}$
2	(-) $Velocity_{t-1}$	(-) $DEXUSEU_{t-1}$	(+) $ExpCommit_{t-1}$	$Basis\_PNW_{t-1}$	$DEXCHUS_{t-1}$
3	---	(-) $D\_IMP\_PRC_{t-1}$	(+) $Basis\_USG_{t-1}$	$Velocity_{t-1}$	DCV_{t-1}
4	---	(+) $DTWEXBGS_{t-1}$	(-) $Velocity_{t-1}$	$DEXBZUS_{t-1}$	$BrazilPrice_{t-1}$
5	---	(+) $DEXBZUS_{t-1}$	(+) Fut_Sprd1_{t-1}	$Insp\_PNW_{t-1}$	$DEXBZUS_{t-1}$
6	---	(-) $D\_EXP\_WRLD_{t-1}$	(+) $Insp\_PNW_{t-1}$	$D\_EXP\_BRZ_{t-1}$	Fut_Sprd1_{t-1}
7	---	(+) $DEXJPUS_{t-1}$	(-) $DEXUSEU_{t-1}$	$RailPAC_{t-1}$	$DEXJPUS_{t-1}$
8	---	(+) $D\_IMP\_EU_{t-1}$	(+) $D\_EXP\_BRZ_{t-1}$	Nov	Fut_Nearby_{t-1}
9	---	(-) $Basis\_Ukr_{t-1}$	(-) $DEXBZUS_{t-1}$	Fut_Sprd1_{t-1}	FSC_{t-1}
10	---	(+) FSC_{t-1}	(+) $BrazilPrice_{t-1}$	$BargeMS_{t-1}$	Exp_Arg

[a]Signs of variable are in parentheses (note: GRNN and RF do not provide signs).

Table 11. Pre-COVID Performance Metrics for USG Basis Forecasts

Measure	Naive	VAR	STR	PLS-R	ENR	GRNN	RFR
R^2_{OS}	0.852	0.868	0.848	0.775	0.871	0.873	0.888*
MAE	3.877	3.905	4.357	5.429	4.082	3.635*	3.775
RMSE	5.643	5.329	5.724	6.959	5.266	5.222	4.911*
Theil U2	1.000	0.944	1.014	1.233	0.933	0.925	0.870*

*Optimal result

Table 12. Pre-COVID Feature Selection and Variable Ranking for USG Basis Forecasts[a]

Rank	STR	PLS-R	ENR	GRNN	RFR
1	(+) $Basis\_USG_{t-1}$	(+) $Basis\_USG_{t-1}$	(+) $Basis\_USG_{t-1}$	$Basis\_PNW_{t-1}$	$Basis\_USG_{t-1}$
2	(+) $Basis\_Ukr_{t-1}$	(+) $Basis\_Ukr_{t-1}$	(+) $Basis\_Ukr_{t-1}$	$DEXJPUS_{t-1}$	$Basis\_Arg_{t-1}$
3	(-) $BargeMS_{t-1}$	(-) $D\_EXP\_WRLD_{t-1}$	(+) $Basis\_Arg_{t-1}$	DCV_{t-1}	$Basis\_PNW_{t-1}$
4	(+) Fut_Nearby_{t-1}	(+) $Basis\_Arg_{t-1}$	(+) $Barge\_STL_{t-1}$	$EthanolPrice_{t-1}$	$ExpCommit_{t-1}$
5	(-) Sep	(+) $Basis\_PNW_{t-1}$	(-) $BargeMS_{t-1}$	$ExpCommit_{t-1}$	$BrazilPrice_{t-1}$
6	(-) $D\_IMP\_PRC_{t-1}$	(-) $D\_IMP\_PRC_{t-1}$	(+) $Basis\_PNW_{t-1}$	$Ship\_PNW_{t-1}$	Exp_Ukr_{t-1}
7	(-) $RailPAC_{t-1}$	(+) Fut_Nearby_{t-1}	(-) $D\_EXP\_WRLD_{t-1}$	$Basis\_Ukr_{t-1}$	$D\_EXP\_BRZ_{t-1}$
8	(-) $DEXJPUS_{t-1}$	(+) $ExpCommit_{t-1}$	(+) $Ship\_USG_{t-1}$	$BrazilPrice_{t-1}$	$Basis\_Ukr_{t-1}$
9	---	(-) $Insp\_USG_{t-1}$	(-) Fut_Sprd1_{t-1}	$D\_IMP\_PRC_{t-1}$	$DEXJPUS_{t-1}$
10	---	(-) $BargeMS_{t-1}$	(-) $D\_IMP\_PRC_{t-1}$	Aug	$Basis\_Brazil_{t-1}$

[a]Signs of variable are in parentheses (note: GRNN and RF do not provide signs).

Table 13. Post-COVID Performance Metrics for USG Basis Forecasts

Measure	Naive	VAR	STR	PLS-R	ENR	GRNN	RFR
R^2_{OS}	0.259	0.353	0.419	0.340	0.619	0.519	0.632*
MAE	15.200	14.917	15.073	19.791	14.467	13.630	11.977*
RMSE	26.000	24.282	23.020	24.537	18.646	20.939	18.324*
Theil U2	1.000	0.934	0.885	0.944	0.717	0.805	0.705*

*Optimal result

Table 14. Post-COVID Feature Selection and Variable Ranking for USG Basis Forecasts[a]

Rank	STR	PLS-R	ENR	GRNN	RFR
1	(+) $Basis\_USG_{t-1}$	(+) $Basis\_USG_{t-1}$	(+) $Basis\_USG_{t-1}$	$Basis\_Ukr_{t-1}$	$Basis\_USG_{t-1}$
2	(+) Sep	(-) $Insp\_PNW_{t-1}$	(+) Sep	Mar	$Basis\_Brazil_{t-1}$
3	(-) Exp_USA	(+) $Basis\_Brazil_{t-1}$	(-) Exp_USA	Apr	BRZ_JPN_{t-1}
4	(+) Mar	(-) $BargeMS_{t-1}$	(+) $Basis\_Ukr_{t-1}$	$Ship\_USG_{t-1}$	Exp_USA
5	---	(+) $Basis\_Arg_{t-1}$	(+) $BrazilPrice_{t-1}$	$RailPAC_{t-1}$	$Basis\_Ukr_{t-1}$
6	---	(-) $ExpCommit_{t-1}$	(-) $Insp\_PNW_{t-1}$	Dec	FSC_{t-1}
7	---	(+) $Basis\_Ukr_{t-1}$	(+) $Basis\_PNW_{t-1}$	$Barge\_STL_{t-1}$	Fut_Nearby_{t-1}
8	---	(+) Fut_Sprd1_{t-1}	(-) Aug	$Basis\_PNW_{t-1}$	$Barge\_STL_{t-1}$
9	---	(+) $Barge\_STL_{t-1}$	(+) Oct	$DEXBZUS_{t-1}$	$ExpCommit_{t-1}$
10	---	(-) Exp_USA	(-) Jun	$Velocity_{t-1}$	$BargeMS_{t-1}$

[a]Signs of variable are in parentheses (note: GRNN and RF do not provide signs).

Table 15. Pre-COVID Performance Metrics for Argentina Basis Forecasts

Measure	Naive	VAR	STR	PLS-R	ENR	GRNN	RFR
R^2_{OS}	0.782	0.803*	0.770	0.706	0.793	0.737	0.803*
MAE	9.855	9.378	9.846	11.820	9.368*	10.037	9.368*
RMSE	12.795	12.168	13.118	14.847	12.452	14.047	12.161*
Theil U2	1.000	0.951	1.025	1.160	0.973	1.098	0.950*

*Optimal result

Table 16. Pre-COVID Feature Selection and Variable Ranking for Argentina Basis Forecasts[a]

Rank	STR	PLS-R	ENR	GRNN	RFR
1	(+) $Basis\_Arg_{t-1}$	(+) $Basis\_Arg_{t-1}$	(+) $Basis\_Arg_{t-1}$	$Basis\_USG_{t-1}$	$Basis\_Arg_{t-1}$
2	(+) $BrazilPrice_{t-1}$	(+) $Basis\_Brazil_{t-1}$	(+) $BrazilPrice_{t-1}$	$Insp\_USG_{t-1}$	$Basis\_Brazil_{t-1}$
3	(+) Nov	(+) $Basis\_USG_{t-1}$	(+) $Basis\_Ukr_{t-1}$	PNW_JPN_{t-1}	$BrazilPrice_{t-1}$
4	(+) $Basis\_Ukr_{t-1}$	(+) $BrazilPrice_{t-1}$	(+) $Basis\_Brazil_{t-1}$	PNW_SK_{t-1}	$Barge\_STL_{t-1}$
5	(-) $D\_IMP\_PRC_{t-1}$	(-) $D\_IMP\_PRC_{t-1}$	(-) $D\_IMP\_PRC_{t-1}$	$D\_EXP\_BRZ_{t-1}$	$Ship\_PNW_{t-1}$
6	---	(+) $Basis\_Ukr_{t-1}$	(+) Nov	$BrazilPrice_{t-1}$	Fut_Nearby_{t-1}
7	---	(-) $D\_EXP\_BRZ_{t-1}$	(+) Exp_Ukr	PNW_IND_{t-1}	$ExpCommit_{t-1}$
8	---	(-) $D\_IMP\_EU_{t-1}$	(-) Oct	Exp_USA	$D\_EXP\_WRLD_{t-1}$
9	---	(-) $DEXBZUS_{t-1}$	(-) $Ship\_PNW_{t-1}$	$D\_IMP\_JAP_{t-1}$	Exp_Ukr
10	---	(+) $RailPAC_{t-1}$	(+) $Velocity_{t-1}$	$D\_EXP\_UKR_{t-1}$	$D\_EXP\_UKR_{t-1}$

[a]Signs of variable are in parentheses (note: GRNN and RF do not provide signs).

Table 17. Post-COVID Performance Metrics for Argentina Basis Forecasts

Measure	Naive	VAR	STR	PLS-R	ENR	GRNN	RFR
R^2_{OS}	0.689	0.702	0.724	0.865	0.777	0.759	0.868*
MAE	21.966	22.390	21.701	17.386	19.507	19.873	17.245*
RMSE	36.946	36.176	34.814	24.306	31.261	32.514	24.091*
Theil U2	1.000	0.979	0.942	0.658	0.846	0.880	0.652*

*Optimal result

Table 18. Post-COVID Feature Selection and Variable Ranking for Argentina Basis Forecasts[a]

Rank	STR	PLS-R	ENR	GRNN	RFR
1	(+) $Basis\_Arg_{t-1}$	(+) $Basis\_Arg_{t-1}$	(+) $Basis\_Arg_{t-1}$	Fut_Sprd1_{t-1}	$Basis\_Arg_{t-1}$
2	(-) Apr	(+) $Basis\_USG_{t-1}$	(-) Apr	Fut_Sprd2_{t-1}	$ExpCommit_{t-1}$
3	(-) Jun	(+) $Basis\_Brazil_{t-1}$	(+) Fut_Sprd1_{t-1}	$Basis\_Ukr_{t-1}$	$Basis\_Ukr_{t-1}$
4	(-) $D\_IMP\_PRC_{t-1}$	(-) $Insp\_PNW_{t-1}$	(-) $D\_IMP\_PRC_{t-1}$	$Velocity_{t-1}$	Fut_Sprd1_{t-1}
5	---	(+) Fut_Sprd1_{t-1}	(-) Jun	$DEXUSEU_{t-1}$	$EthanolPrice_{t-1}$
6	---	(-) $BargeMS_{t-1}$	(-) $Insp\_PNW_{t-1}$	Dec	PNW_JPN_{t-1}
7	---	(-) $ExpCommit_{t-1}$	(-) ARG_EU_{t-1}	Aug	UKR_VNM_{t-1}
8	---	(+) $Basis\_Ukr_{t-1}$	(-) BRZ_EU_{t-1}	$Barge\_STL_{t-1}$	Fut_Nearby_{t-1}
9	---	(+) Fut_Sprd2_{t-1}	---	$Ship\_PNW_{t-1}$	$DEXUSEU_{t-1}$
10	---	(-) Jun	---	Exp_Ukr	$Insp\_PNW_{t-1}$

[a]Signs of variable are in parentheses (note: GRNN and RF do not provide signs).

Table 19. Pre-COVID Performance Metrics for Brazil Basis Forecasts

Measure	Naive	VAR	STR	PLS-R	ENR	GRNN	RFR
R^2_{OS}	0.918	0.925	0.925	0.847	0.921	0.848	0.935*
MAE	4.783*	5.152	5.313	8.562	5.395	6.168	4.808
RMSE	7.868	7.537	7.552	10.781	7.759	10.752	7.029*
Theil U2	1.000	0.958	0.960	1.370	0.986	1.367	0.893*

*Optimal result

Table 20. Pre-COVID Feature Selection and Variable Ranking for Brazil Basis Forecasts[a]

Rank	STR	PLS-R	ENR	GRNN	RFR
1	(+) $Basis\_Brazil_{t-1}$	(+) $Basis\_Brazil_{t-1}$	(+) $Basis\_Brazil_{t-1}$	Fut_Nearby_{t-1}	$Basis\_Brazil_{t-1}$
2	(-) $DEXJPUS_{t-1}$	(+) $Basis\_Arg_{t-1}$	(-) $DEXJPUS_{t-1}$	$BrazilPrice_{t-1}$	$DEXJPUS_{t-1}$
3	(+) $Basis\_Ukr_{t-1}$	(+) $BrazilPrice_{t-1}$	(+) $BrazilPrice_{t-1}$	$D\_EXP\_US_{t-1}$	$Basis\_Arg_{t-1}$
4	(-) $Ship\_PNW_{t-1}$	(-) Fut_Nearby_{t-1}	(-) Fut_Nearby_{t-1}	$RailMS_{t-1}$	$BrazilPrice_{t-1}$
5	(+) Exp_Ukr	(-) $DEXJPUS_{t-1}$	(+) Nov	$DEXUSEU_{t-1}$	FSC_{t-1}
6	(-) $D\_IMP\_PRC_{t-1}$	(-) $ExpCommit_{t-1}$	(+) $Basis\_Arg_{t-1}$	Exp_Ukr	$Basis\_Ukr_{t-1}$
7	---	(+) $Basis\_Ukr_{t-1}$	(-) $D\_EXP\_BRZ_{t-1}$	$BargeMS_{t-1}$	$EthanolPrice_{t-1}$
8	---	(+) $RailPAC_{t-1}$	(+) Dec	$D\_IMP\_JAP_{t-1}$	$D\_EXP\_WRLD_{t-1}$
9	---	(-) $D\_IMP\_EU_{t-1}$	(+) $DEXUSEU_{t-1}$	$Ship\_USG_{t-1}$	$DEXUSEU_{t-1}$
10	---	(-) $D\_EXP\_BRZ_{t-1}$	(+) $Basis\_Ukr_{t-1}$	$Ship\_PNW_{t-1}$	$Basis\_PNW_{t-1}$

[a]Signs of variable are in parentheses (note: GRNN and RF do not provide signs).

Table 21. Post-COVID Performance Metrics for Brazil Basis Forecasts

Measure	Naive	VAR	STR	PLS-R	ENR	GRNN	RFR
R^2_{OS}	0.398	0.430	0.679	0.316	0.702	0.840*	0.692
MAE	24.470	29.396	22.336	33.250	22.275	15.041*	22.490
RMSE	40.934	39.836	29.885	43.644	28.807	21.112*	29.293
Theil U2	1.000	0.973	0.730	1.066	0.704	0.516*	0.716

*Optimal result

Table 22. Post-COVID Feature Selection and Variable Ranking for Brazil Basis Forecasts[a]

Rank	Stepwise	PLS-R	Elastic Net	GRNN	Random Forest
1	(+) Basis_Ukr_{t-1}	(+) Basis_USG_{t-1}	(+) $\text{Basis\_Brazil}_{t-1}$	Basis_Ukr_{t-1}	$\text{Basis\_Brazil}_{t-1}$
2	(+) Fut_Sprd1_{t-1}	(-) Insp_PNW_{t-1}	(+) Basis_Ukr_{t-1}	D_EXP_BRZ_{t-1}	Basis_Ukr_{t-1}
3	(+) $\text{Basis\_Brazil}_{t-1}$	(+) Basis_Arg_{t-1}	(+) Fut_Sprd1_{t-1}	Fut_Sprd1_{t-1}	Fut_Sprd2_{t-1}
4	(-) D_EXP_WRLD_{t-1}	(+) $\text{Basis\_Brazil}_{t-1}$	(-) Insp_PNW_{t-1}	Insp_PNW_{t-1}	Insp_PNW_{t-1}
5	(+) BrazilPrice_{t-1}	(-) BargeMS_{t-1}	(+) Basis_Arg_{t-1}	Jul	UKR_IND_{t-1}
6	(-) Barge_STL_{t-1}	(-) ExpCommit_{t-1}	(-) D_EXP_WRLD_{t-1}	Sep	$\text{EthanolPrice}_{t-1}$
7	---	(+) Basis_Ukr_{t-1}	(+) Sep	Basis_Arg_{t-1}	Fut_Sprd1_{t-1}
8	---	(+) Fut_Sprd1_{t-1}	(+) Basis_USG_{t-1}	Velocity_{t-1}	Basis_USG_{t-1}
9	---	(+) Barge_STL_{t-1}	(+) Nov	Aug	Ship_PNW_{t-1}
10	---	(+) Fut_Sprd2_{t-1}	(+) Mar	Ship_PNW_{t-1}	Basis_Arg_{t-1}

[a]Signs of variable are in parentheses (note: GRNN and RF do not provide signs).

Table 23. Pre-COVID Performance Metrics for Ukraine Basis Forecasts

Measure	Naive	VAR	STR	PLS-R	ENR	GRNN	RFR
R^2_{OS}	0.840*	0.822	0.832	0.787	0.813	0.649	0.798
MAE	9.022*	9.426	9.162	10.605	9.737	11.190	9.836
RMSE	11.519*	12.163	11.825	13.325	12.482	17.097	12.963
Theil U2	1.000*	1.056	1.027	1.157	1.084	1.484	1.125

*Optimal result

Table 24. Pre-COVID Feature Selection and Variable Ranking for Ukraine Basis Forecasts[a]

Rank	STR	PLS-R	ENR	GRNN	RFR
1	(+) Basis_Ukr$_{t-1}$	(+) Basis_Ukr$_{t-1}$	(+) Basis_Ukr$_{t-1}$	DCV$_{t-1}$	Basis_Ukr$_{t-1}$
2	(-) DEXJPUS$_{t-1}$	(+) Basis_USG$_{t-1}$	(+) DEXBZUS$_{t-1}$	Insp_USG$_{t-1}$	Basis_USG$_{t-1}$
3	(-) D_IMP_JAP$_{t-1}$	(+) BargeMS$_{t-1}$	(+) Basis_Brazil$_{t-1}$	Ship_USG$_{t-1}$	DEXBZUS$_{t-1}$
4	(-) Sep	(+) ExpCommit$_{t-1}$	(+) DEXUSEU$_{t-1}$	Fut_Sprd1$_{t-1}$	Basis_Arg$_{t-1}$
5	(-) Oct	(-) D_EXP_WRLD$_{t-1}$	(+) Basis_Arg$_{t-1}$	Ship_PNW$_{t-1}$	DEXJPUS$_{t-1}$
6	(+) Apr	(-) Fut_Nearby$_{t-1}$	(+) BargeMS$_{t-1}$	Fut_Sprd2$_{t-1}$	Barge_STL$_{t-1}$
7	---	(+) Insp_PNW$_{t-1}$	(+) ExpCommit$_{t-1}$	Basis_Ukr$_{t-1}$	Fut_Sprd1$_{t-1}$
8	---	(+) Basis_Brazil$_{t-1}$	(+) Basis_USG$_{t-1}$	Fut_Nearby$_{t-1}$	Insp_PNW$_{t-1}$
9	---	(+) D_EXP_BRZ$_{t-1}$	(-) DEXJPUS$_{t-1}$	Insp_PNW$_{t-1}$	DTWEXBGS$_{t-1}$
10	---	(+) Basis_Arg$_{t-1}$	(-) Sep	BargeMS$_{t-1}$	D_IMP_JAP$_{t-1}$

[a]Signs of variable are in parentheses (note: GRNN and RF do not provide signs).

Table 25. Post-COVID Performance Metrics – Ukraine Basis Forecasts

Measure	Naive	VAR	STR	PLS-R	ENR	GRNN	RFR
R^2_{OS}	0.802*	0.750	0.678	0.261	0.740	0.638	0.715
MAE	14.425*	18.721	20.633	31.066	17.173	19.463	19.494
RMSE	20.692*	23.266	26.415	40.026	23.725	28.008	24.839
Theil U2	1.000*	1.124	1.277	1.934	1.147	1.354	1.200

*Optimal result

Table 26. Post-COVID Feature Selection and Variable Ranking for Ukraine Basis Forecasts[a]

Rank	STR	PLS-R	ENR	GRNN	RFR
1	(-) $DEXJPUS_{t-1}$	(+) $Basis\_Ukr_{t-1}$	(-) $DEXJPUS_{t-1}$	Mar	Fut_Nearby_{t-1}
2	(+) $D\_EXP\_ARG_{t-1}$	(-) $Basis\_PNW_{t-1}$	(+) $Basis\_Ukr_{t-1}$	$Basis\_Arg_{t-1}$	$DEXJPUS_{t-1}$
3	(+) $Basis\_Ukr_{t-1}$	(-) $Insp\_PNW_{t-1}$	(-) $D\_EXP\_US_{t-1}$	Apr	$Basis\_Ukr_{t-1}$
4	(+) Mar	(-) $DEXJPUS_{t-1}$	(+) Mar	$Basis\_USG_{t-1}$	$Basis\_Arg_{t-1}$
5	(+) $Basis\_USG_{t-1}$	(-) Exp_Arg	(-) Exp_Brazil	$Velocity_{t-1}$	$Barge\_STL_{t-1}$
6	---	(+) $DEXBZUS_{t-1}$	(+) $Basis\_USG_{t-1}$	Fut_Sprd1_{t-1}	$Insp\_PNW_{t-1}$
7	---	(+) $DEXUSEU_{t-1}$	(-) $DEXCHUS_{t-1}$	$Barge\_STL_{t-1}$	$RailPAC_{t-1}$
8	---	(-) $ExpCommit_{t-1}$	(-) $BargeMS_{t-1}$	$RailMS_{t-1}$	$Basis\_USG_{t-1}$
9	---	(+) $Basis\_Brazil_{t-1}$	(+) Exp_USA	$Ship\_PNW_{t-1}$	$EthanolPrice_{t-1}$
10	---	(+) $Ship\_USG_{t-1}$	(-) $Ship\_PNW_{t-1}$	$RailPAC_{t-1}$	$D\_IMP\_PRC_{t-1}$

[a]Signs of variable are in parentheses (note: GRNN and RF do not provide signs).

Appendix B: Figures

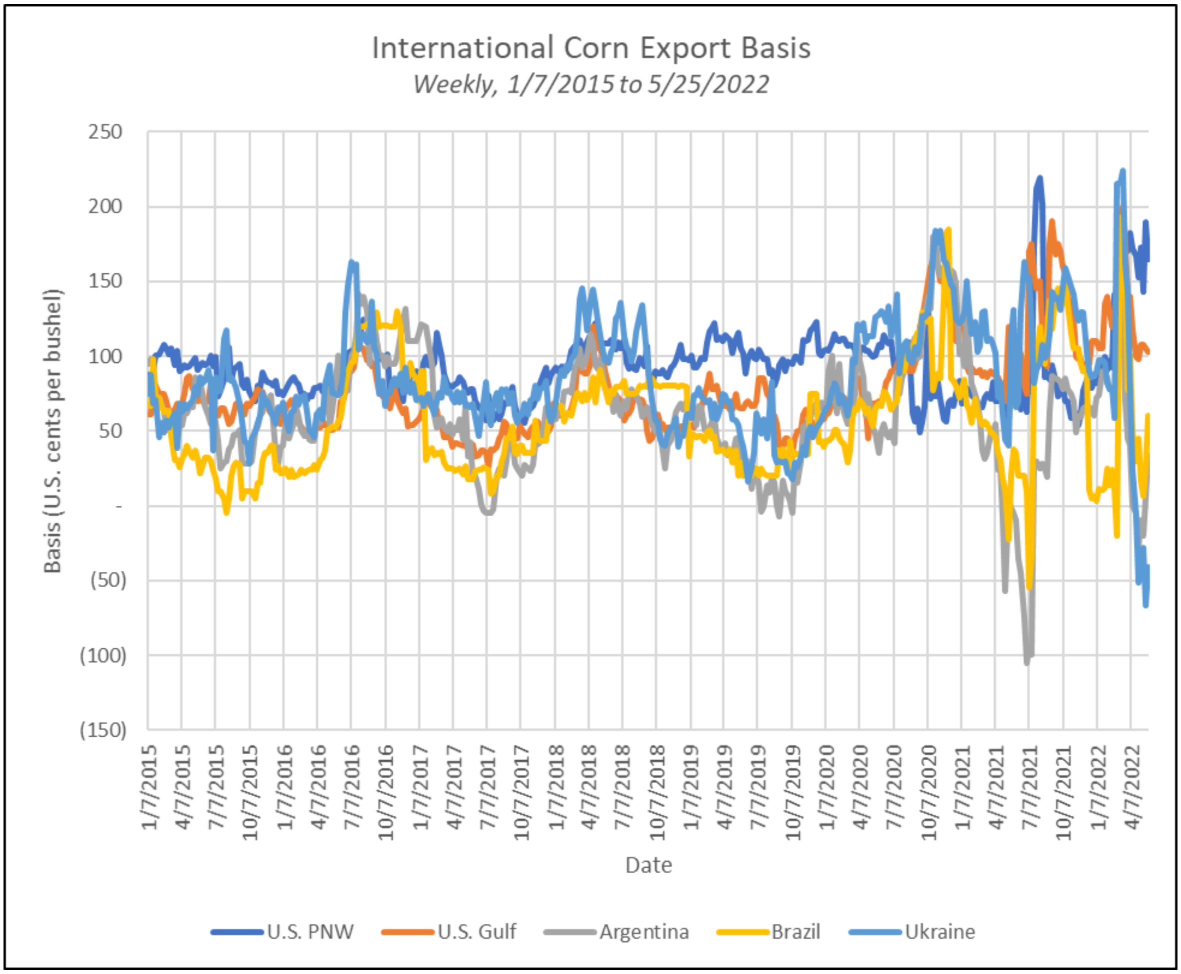

Figure 1. Weekly time series plot of international corn basis series from 1/7/2015 to 5/25/2022 (Source: Refinitiv *Eikon* and Fastmarkets *AgriCensus*).

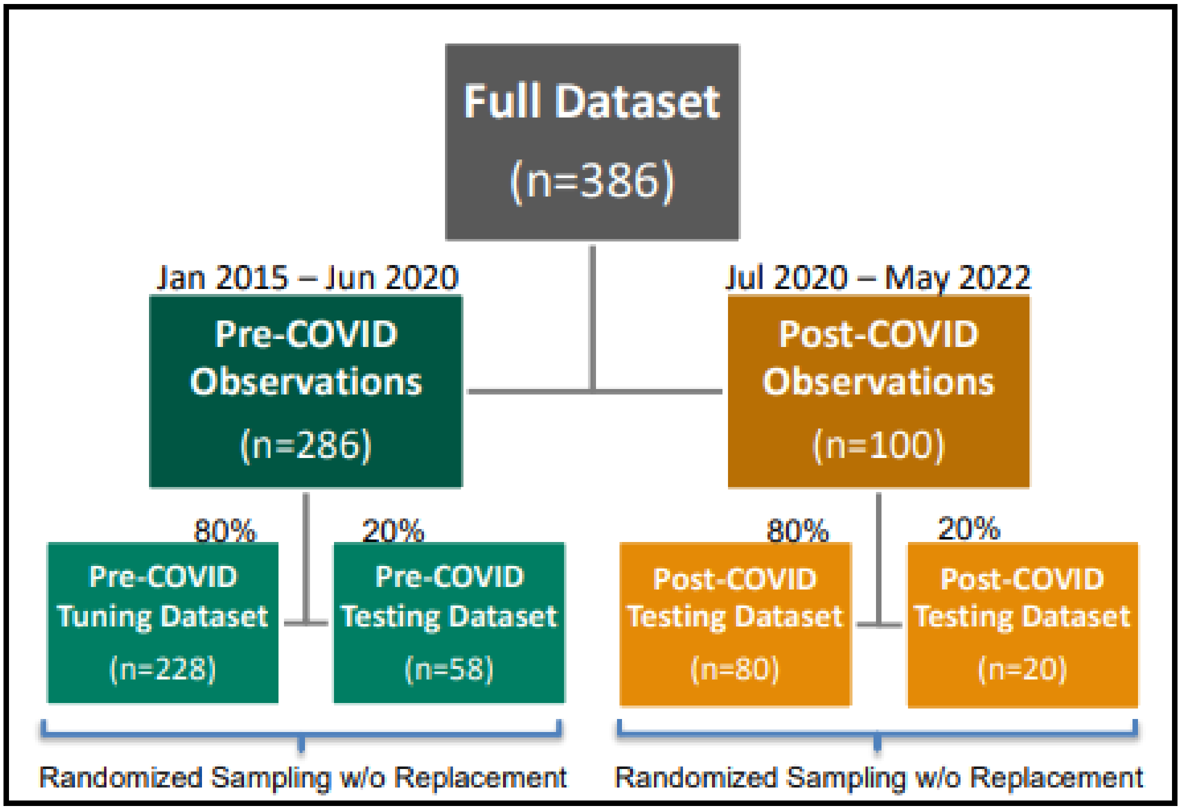

Figure 2. Illustration of the division of the dataset into tuning and testing subsets.

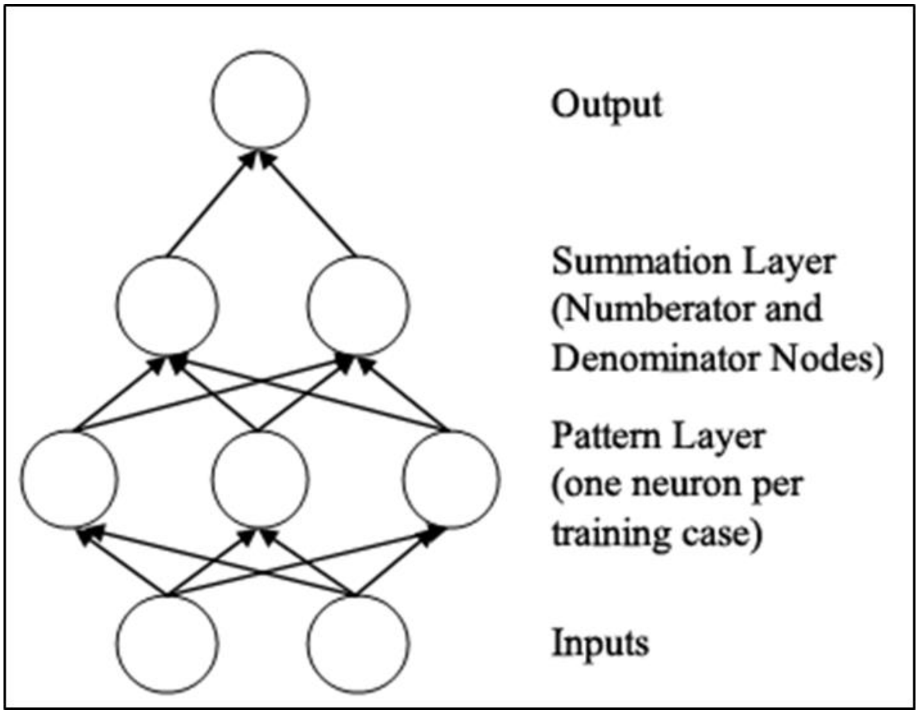

Figure 3. Diagram of the layers of a GRNN (Masters 1995).

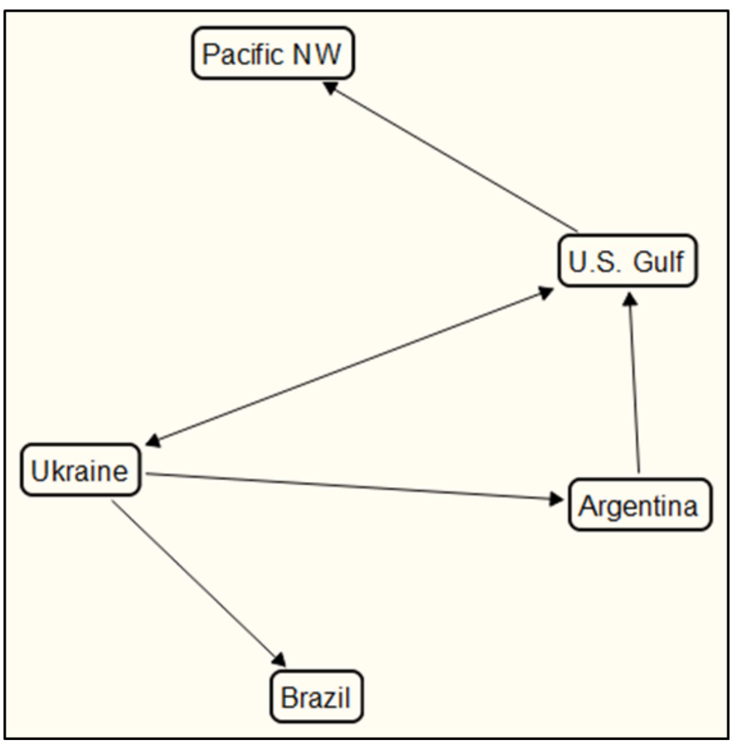

Figure 4. Causal flow diagram for basis series in pre-COVID period.

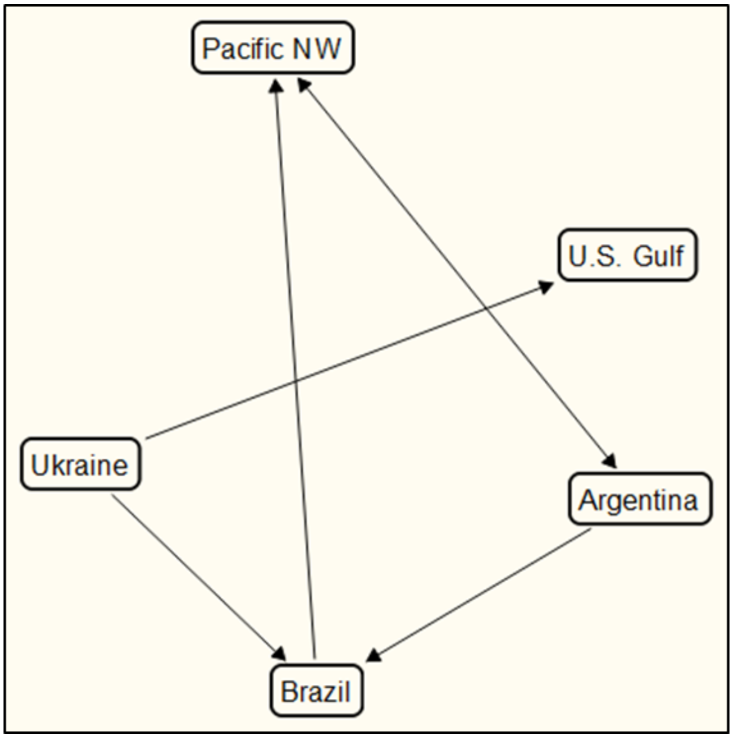

Figure 5. Causal flow diagram for basis series in post-COVID period.