# The Changing Import/Export Dynamic Between the U.S. and China

Hannah Goldstein, Nicolas Renaud, Brendan Hennessey, Jarrett Rennie

**Abstract -**

Imports and Exports between the world's two largest economies and global superpowers are a critical indicator of not only trade relations between the two nations, but also hold implications for global economic well-being. Our investigation of two time series, one of imports to the U.S. from China, and other exports. IT covers a range of important political and economic events from 1985 to the present day, several of which are visible as changes in the graph's appearance like the 2009 recession and China's entrance into the WTO. We discovered annual seasonality in both series, pointing to a late fall maximum. Statistical analysis pointed to non-linear structure, and we were able to develop a neural network model for imports as well as a bagged model for exports that satisfy our accuracy checks. Still, questions remain about the predictive power of this model given the very new nature of tariffs enacted by both countries' since 2018. If anything, these forecast models can be used as a reference for what could have been, should the bilateral relationship deteriorate in the face of tariffs.

**Index Terms -** economics, trade relations, imports/exports, ETS, ARIMA, neural network

# 1 Introduction/Motivation

There has been a flurry of regulatory activity between the United States and China over the past 20-30 years. As tensions have grown worse recently, the economies of the two countries are more likely than ever to be negatively impacted. Through the various tariffs, threats of tariffs, and other political strong-arming, the most likely place where the impact would manifest is in the imports/exports between the U.S. and China. Ultimately, we hypothesize that the trade dynamic between the U.S. and China has shifted significantly in recent years.

In the sections below, we'll explore the tenability of this hypothesis. We'll first briefly touch on the source of the dataset, its frequency, and any peculiarities. Then, with the 35 years of import/export data collected, we'll conduct an exploratory data analysis (EDA) to better

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understand each time series. In this EDA, we'll examine the trend and seasonality of imports and exports over the entire time period, as well as discern any other patterns that can be deduced from the graphs. We'll also compare the data to known historical events in this initial analysis.

After conducting an EDA, we'll dive deeper into each time series. We'll use various decomposition methods to break down imports and exports on a more granular level. Next we'll perform various tests on each series, checking for things such as linearity and stationarity. The results of the decomposition and tests will inform the modeling, and any transformations necessary prior to fitting.

With EDA and the deep dive complete, we'll attempt to fit various linear and nonlinear models to each time series. Here, we'll leverage modeling techniques such as ETS (where the smoothing parameter could inform us about the anomaly of the most recent time periods), ARIMA, neural networks, and bagging. With the various types of models, and their respective results, we'll be able to discern whether or not it's possible to fit an accurate model for simulating (train) and forecasting (test) imports and exports.

## 2 The Data Set

Both the "imports" [1] and "exports" [2] data sets used to conduct this analysis originated from the U.S. Bureau of Economic Analysis and U.S. Census Bureau. The data sets were retrieved and downloaded from the Federal Reserve Bank of St. Louis (FRED), a group that conducts various types of global economic research.

Both data sets are time series, capturing monthly imports/exports in millions of U.S. dollars. They each span from January 1985 to September 2019. There are no missing observations or major outliers in either time series.

Given each data set is captured at the macro level, representing the entire U.S., the information is not inherently sensitive. This data is publicly available and published/cited in numerous places. If we were instead looking at a given company's imports/exports, then one could conclude that the data contains sensitive and/or confidential information.

Additionally, because the frequency of each time series is monthly, and over thirty years of data is captured, it is safe to conclude that the volume is sufficient for the purpose of this analysis.

## 3 Exploratory Data Analysis

Let's first explore ordinary time plots of the imports and exports time series themselves. These two series, along with a trend line for each, may be examined in Figure 1 below.
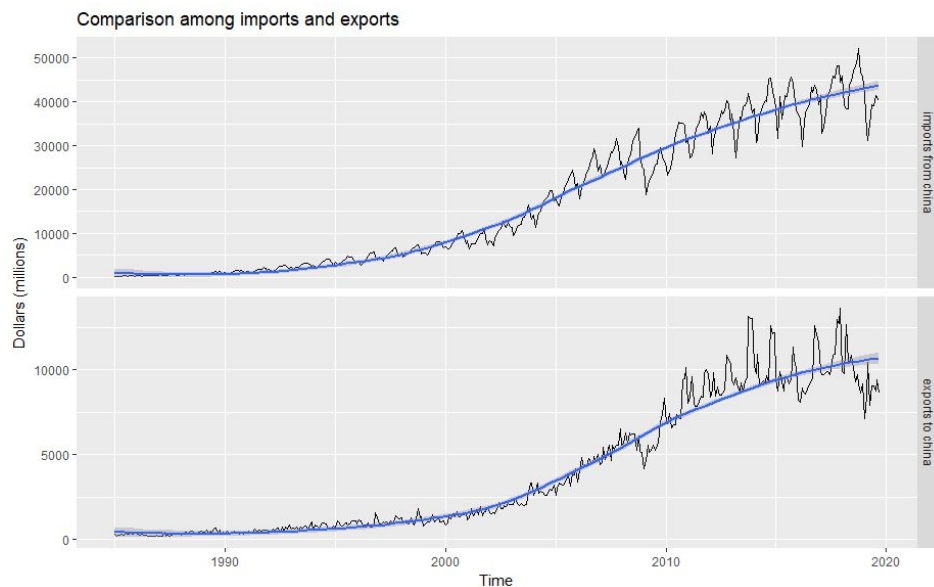


Figure 1 - Plotting the Imports and Exports Time Series

Each series appears to have strong trend and some (nonzero) seasonality. From the year 2001 onward, each series get's especially interesting where it appears that U.S. business with China grew exponentially. To better understand this uptick, the Council on Foreign Relations' timeline of U.S. Relations with China [3] was referenced. From the timeline, it appears that in 2001, China officially joined the World Trade Organization, which is a perfect explanation for the massive growth.

It was important to confirm that the catalyst could be attributed to something specific, rather than being unexplainable. If unexplainable, a concern would be that perhaps the method for measuring imports/exports changed around this timeframe, which would make it difficult to properly compare values before/after 2001.

Along with the 2001 event, several other significant trade relations events (2009 recession, 2018-2019 increased tariff activity) were pulled out of the Council on Foreign Relations' timeline. These events are in fact visible in the time plots, and thus are called out in Figure 2 below to add some additional color to the variances.
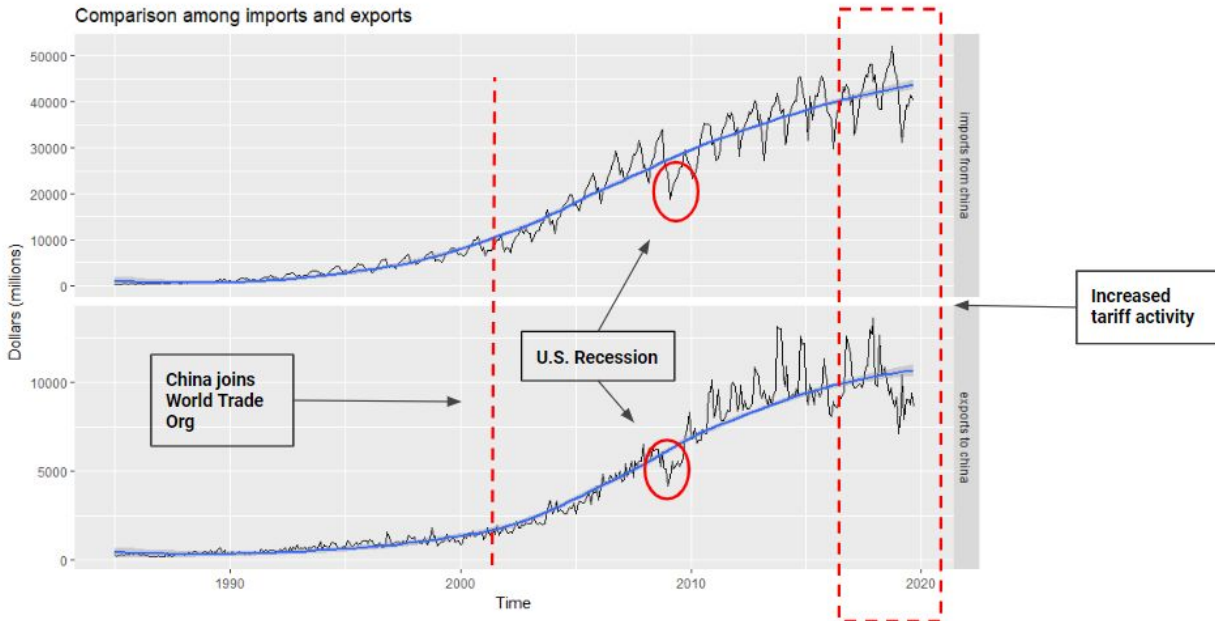
Figure 2 - Imports and Exports with Significant Trade Relations Events

Next, we'll dive deeper into the trend and seasonality of each time series. In order to quantify the relative strength of the trend and seasonality, we calculate the F(T) and F(S) coefficients. The coefficients were determined using a classical additive decomposition. The values may be examined in Table 1 below.

| | Imports | Exports |
|---|---|---|
| $F_T$ | 0.9884271 | 0.9816865 |
| $F_S$ | 0.5088625 | 0.2667869 |

Table 1 - Trend Strength and Seasonality Strength of Imports and Exports

Both series have trend strength very close to one, indicating a strong trend. The seasonality is less strong in both, but higher for the imports series. This means that both series have seasonality, but it's more recognizable in the imports series. To further study the trends and seasonalities, Polarmaps (Figure 3 and 4) and Lag Plots (Figure 5 and 6) were produced below. Through these other graphical means, we should be able to perceive any other trend/seasonality intricacies.
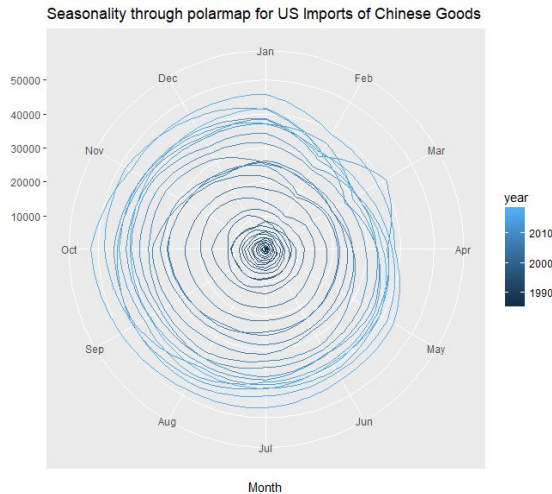
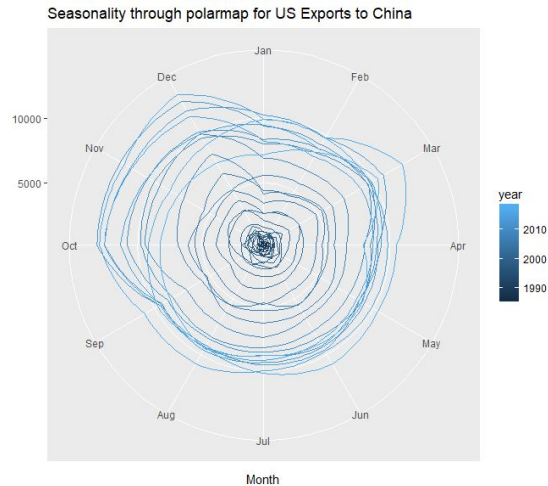Figure 3 - Polarmap of U.S. Imports of Chinese Goods



Figure 4 - Polarmap of U.S. Exports to China

If we examine both the imports' and exports' Polarmaps (Figures 3 and 4), we can see a clear trend from the fact that the circles (generally) grow larger as time goes on. In the imports' Polarmap, the peak tends to happen around October, where the dip happens somewhere in the February-March months. Generally Q3 and Q4 have larger values, where Q1 and Q2 are lower. This relationship by nature is seasonal, but not perfectly clear cut, which supports the lower seasonality strength. In the exports' Polarmap, peaks happen in October-December, where dips occur in January and February. Generally here, Q4 has the largest values, Q2 and Q3 have moderate values, and Q1 has the lowest values. This explains why the seasonality strength is a much smaller value for this series, as it's much less straightforward. Let's see if the Lag plots of each series can tell us more.
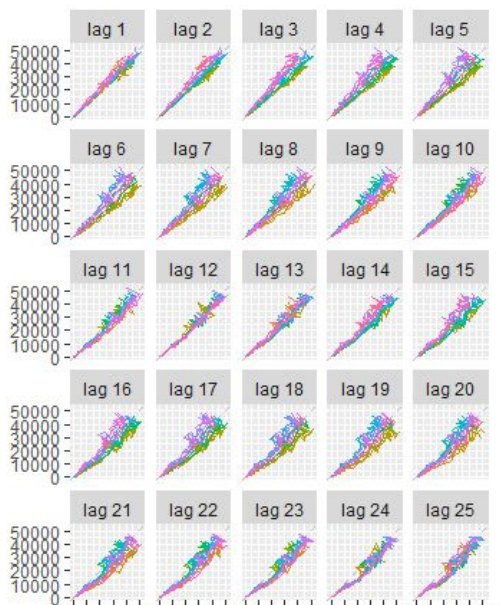


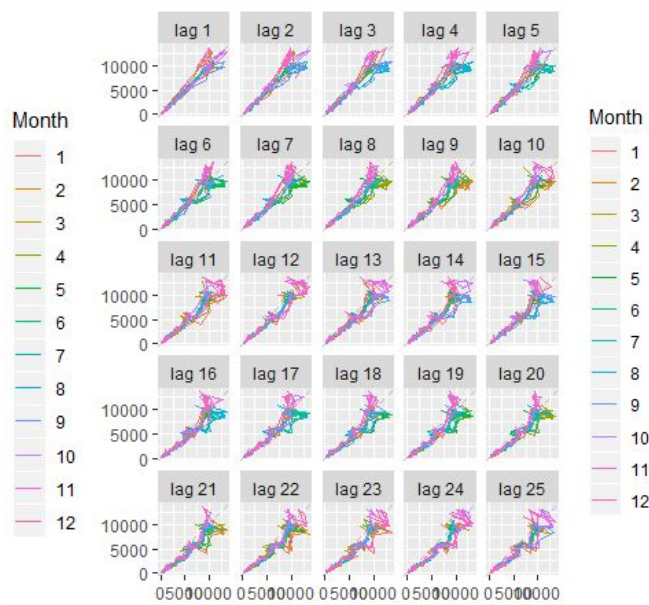Figure 5 - Lag Plots for Imports.



Figure 6 - Lag plots for Exports

The lag plots for imports and exports (Figure 5 and 6) both display a clustering on the diagonal at Lag 12. This is consistent with the time plot investigation (Figure 1) of the data which indicated a general yearly cyclicality. Other than Lag 12, no other lags offer insights that are different than those gleaned from the other graphical methods employed above.

With a solid grasp on each series' trend and seasonality, let's look at their entropies.

```
SampEn(imp.ts)

## [1] 0.1134533

SampEn(exp.ts)

## [1] 0.1184296
```

Figure 7 - Entropy of Each Time Series

It's first clear that imports and exports have similar entropy. Given the low entropy values, we know that there's limited randomness to the data, and that each data point has some relationship with previous data points.

Finally, we'll apply decomposition methods to set the stage for modeling. Given the 2001 spikes in both series we saw in Figures 1 and 2, we know that multiplicative decomposition must be used. We cannot use additive because the seasonality magnitude/trend variations change with the average level of the series. In Figure 8 (imports) and Figure 9 (exports) below, these decompositions are shown.
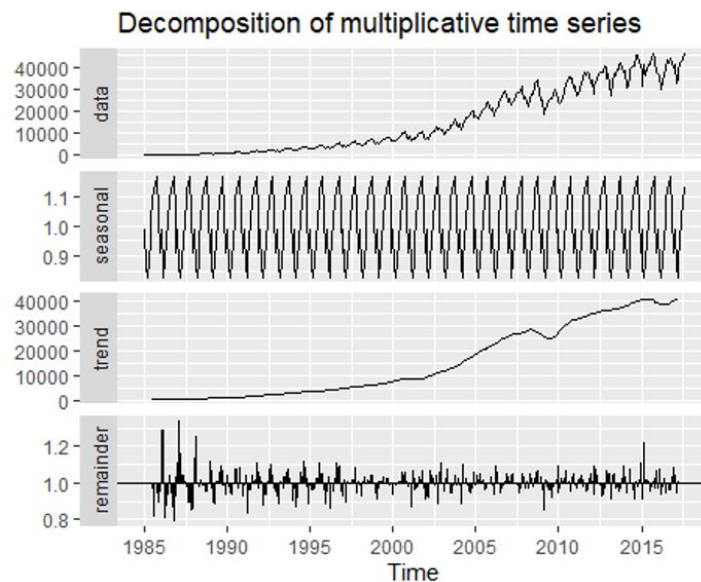


Figure 8 - Multiplicative Decomposition of Imports

```
autoplot(decomp.exp.mult)
```

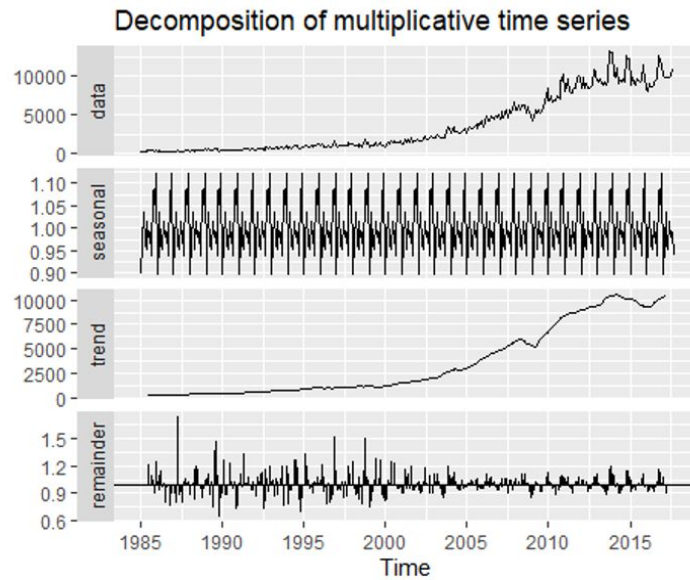### Decomposition of multiplicative time series

Figure 9 - Multiplicative Decomposition of Exports

In both decompositions, we can see that the random components have slightly larger variances prior to 2001, which is expected due to the event called out above. An interesting take-away from each decomposition is that although some seasonality is present, it is not much larger than the random component. This means that it's really the trend driving the most significant change over the time period examined. We'll see how this affects modeling in section 5 below.

## 4 Theory and Methods

Our analysis consisted of initial data formatting using Microsoft Excel. Following this, we utilized R software analysis and associated packages to conduct all further testing and visualization.

The first step was to conduct the previously displayed descriptive exploration of the two time series, using graphical methods such as polar plots and lag plots. Through this the core features of the set become clearer, which then informs the modelling process. Critically, it allows us to have a logical basis for determining if our forecast model makes sense in reality given the behavior of the underlying data. In our case, we know we have a non-stationary increasing trend, with annual seasonality and likely non-linear nature. Even still, we wanted to test linear methods first to see if they may actually perform well for this case study. As such, we plugged

the model into the corresponding functions to produce the best ETS and best SARIMA models possible. Following this, we also conducted non-linearity testing and model-building using neural networks and bagging. Lastly, we reviewed all the available accuracy metrics across all models to choose the best ones and draw conclusions.

# 5 Modeling

ETS

We began by trying to fit the best ETS model to our data. For both imports and exports, an ETS (M,Ad,M) was presented as the best ETS model. This is using multiplicative error, additive trend and multiplicative seasonality. Interpreting this model did not move very far; the Ljung-Box test showed evidence that the residuals for both datasets were dependent. This means that the models are not recommended to move forward with.

| data | method | model | lambda | sigma**2 | subset | mape | mase | residuals |
|------|--------|-------|--------|----------|--------|------|------|-----------|
| import | ets | M,Ad,M | N/A | 0.0763 | train | 5.494712 | 0.3703234 | dependent |
| | | | | | test | 7.537235 | 1.763118 | |
| export | ets | M,Ad,M | N/A | 0.1551 | train | 10.37534 | 0.5103051 | dependent |
| | | | | | test | 15.89129 | 2.8818206 | |

SARIMA

SARIMA was the next model that was run with our data. Knowing that the data was seasonal led us to using the SARIMA instead of ARIMA. The first SARIMA model for import data has two auto regressive terms, one differencing term, one moving average term, two seasonal auto regressive terms, one seasonal differencing term, no seasonal moving average terms, a seasonality of twelve and does not include a transformation.The second model for imports includes the same terms but includes a transformation. In the figure below, the models with better training and testing data are highlighted but the residuals were found to be dependent, with very small Ljung-Box p-values.

| data | method | model | lambda | sigma**2 | significant parameters | subset | mape | mase | residuals |
|------|--------|-------|--------|----------|------------------------|--------|------|------|-----------|
| import | sarima | ARIMA(2,1,1)(2,1,0)[12] | N/A | 1180427 | YES | train | 5.356059 | 0.3627931 | dependent |
| | | | | | | test | 6.900162 | 1.6583602 | |
| import | sarima | ARIMA(2,1,1)(2,1,0)[12] | 0.1637399 | 0.07768 | YES | train | 4.977908 | 0.3433272 | dependent |
| | | | | | | test | 7.287937 | 1.7651253 | |
| export | sarima | ARIMA(2,1,1)(0,1,1)[12] | N/A | 119334 | YES | train | 11.35756 | 0.4513094 | independent |
| | | | | | | test | 19.70742 | 3.5138966 | |
| export | sarima | ARIMA(2,1,1)(2,0,0)[12] with drift | 0.220129 | 0.4778 | YES | train | 10.81068 | 0.4775985 | independent |
| | | | | | | test | 22.87962 | 4.1109044 | |

The first SARIMA model for export data has two auto regressive terms, one differencing term, one moving average term, two seasonal auto regressive terms, no seasonal differencing terms, no seasonal moving average terms, a seasonality of twelve and does not include a transformation.The second model for imports includes the same terms but includes a

transformation and drift. Above the highlighted training and testing accuracy figures are highlighted to show that overall the model without the transformation performs better. The export models' residuals also proved to be independent. As discussed before though, we predict that our model will be nonlinear and therefore will perform nonlinear tests.

Nonlinear Modeling

The nonlinear tests make it clear that this data should not be modeled by a linear model and that some nonlinear model should instead be used for both the import and export time series.  We looked at neural network models with and without a Box Cox transformation, as well as, bagged models with and without a Box Cox transformation for both the import and export data.

| data | method | model | lambda | sigma**2 | subset | mape | mase |
|------|--------|-------|--------|----------|--------|------|------|
| import | neural | NNAR(4,1,3)[12] | N/A | 1618448 | train | 7.23142 | 0.4292306 |
| | | | | | test | 8.17489 | 2.02708 |
| import | neural | NNAR(1,1,2)[12] | 0.1637399 | 0.1308 | train | 6.597035 | 0.5082465 |
| | | | | | test | 8.48026 | 2.0782421 |
| export | neural | NNAR(1,1,2)[12] | N/A | 195589 | train | 12.53733 | 0.5520151 |
| | | | | | test | 19.45795 | 3.5122214 |
| export | neural | NNAR(2,1,2)[12] | 0.220129 | 0.5041 | train | 11.04153 | 0.5366247 |
| | | | | | test | 16.06305 | 2.9532921 |

In the above figure are the results of the neural network models for import and export data.  The first neural network model for import data does not include a Box Cox transformation, recalls 4 ordinary lags, 1 seasonal lag, uses 3 hidden nodes, and has seasonality of order 12.  The second neural network model for import data does include a Box Cox transformation, recalls 1 ordinary lag, 1 seasonal lag, uses 2 hidden nodes, and has seasonality of order 12.  Because these two models use different data, one has been transformed using Box Cox, the best way to compare the two is using mean absolute scaled error (mase) in order to avoid the the problem mean absolute percentage error (mape) has with favoring underestimation as well as the ambiguity of percentages.  Between these 2 models the non transformed model performs better in terms of mase.

The first neural network model for export data does not include a Box Cox transformation, recalls 1 ordinary lag, 1 seasonal lag, uses 2 hidden nodes, and has seasonality of order 12.  The second neural network model for export data does include a Box Cox transformation, recalls 2 ordinary lags, 1 seasonal lags, uses 2 hidden nodes, and has seasonality of order 12.  Again the best way to compare these 2 models is using mase; however, in the case of exports the transformed model performs better.

| data | method | lambda | subset | mape | mase |
|------|--------|--------|--------|------|------|
| import | bagged | N/A | train | 5.215448 | 0.3438924 |
| | | | test | 8.673755 | 2.0504201 |
| import | bagged | 0.1637399 | train | 60220.0962 | 22417.894 |
| | | | test | 147209.9 | 62004.77 |
| export | bagged | N/A | train | 9.4366 | 0.4757732 |
| | | | test | 15.04068 | 2.7782196 |
| export | bagged | 0.220129 | train | 13916.27189 | 3543.666 |
| | | | test | 35757.59 | 10691.656 |

In the above figure are the results of the bagged models on imports and exports with and without a Box Cox transformation applied.  Out of the transformed and non transformed bagged models for the import data the non transformed model performs better.  This pattern continues for the export data where again the non transformed model outperforms the transformed model.

Overall, the best performing nonlinear model for import data we found to be the non transformed neural network model.  The best performing nonlinear model for export data we found to be the non transformed bagged model.  Both of the these models may not perform as well as some of the SARIMA and ETS models however it would not make sense to model a nonlinear time series using one of those linear methods.

Rolling Window Cross-validation

Another method to check the performance of a time series model is rolling-window cross-validation. This is a method that checks the predictive performance of the model across a sequence of training sets of different sizes. It checks for the error on the prediction for the very next point, relative to the real data. We conducted this analysis for the ETS, SARIMA, and Neural models for each of the two time series and compared graphically. The bagged model was not completing it's run in R; we would have liked to include it here as well - though the neural network does provide sufficient non-linear representation for imports especially.
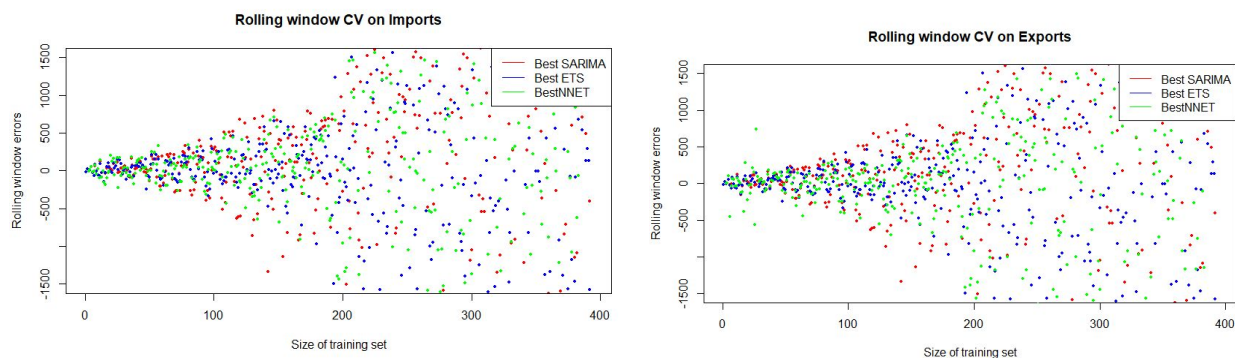


The resulting figures can be interpreted by looking for which series cluster well around 0. In our instance, there isn't a major discernible winner in the sets across any size of training set - though there is a noticeable widening of the error margins with a bigger training set. Our

hypothesis for this is that the highly non-stationary nature of our entire dataset makes "closer" training sets(i.e.) small have such close values to the "tomorrow" value that they naturally perform better, even with less history to draw from.

Rolling window is not one of our more important accuracy checks, however. This is because we do not envision this sort of time series data being important for monthly economic forecasting - this length of data would be more useful for forecasting on the order of years, and as such we lean more heavily on our sigma, MAPE, and MASE metrics to pick among competing non-linear models.

Final Model Selection and Comparison

We conducted a final comparison of all of the top-contender models we produced by producing a tabular comparison of the ETS, ARIMA, and non-linear models for each of imports and exports. The ETS models are quite easily disqualified due to the dependence of residuals and the failure of the nonlinearity tests. The SARIMA suffers the same linearity concern, and dependent residuals for the import series. The export series has an otherwise quite solid SARIMA (2,1,1)(0,1,1)[12] model which was the ARIMA accuracy winner for MAPE and MASE in all areas except the training MAPE.

For the overall imports winner, the best neural network model had better MAPE and MASE values than the bagged version in every category except training MAPE. We were also satisfied with the number of coefficients, though the p=4 value is a little higher than desired. The bagged model for exports had the lowest MAPE and MASE in all respects among the models we made on the series. Interestingly, the lambda BoxCox transformation vrsions of the various models did not improve the results. The winning models are marked with green coloring in the table below. The forecast overlay graphs (Figure x) shows that the models stay quite centered in the range, especially on the export model where the orange line noting the bag model noticeably lacks many of the extreme points that plague the ETS and ARIMA model (Figure x). The best export SARIMA has a more narrow PI (judged from the sigma^2) value than the neural networks, but because the bagged model doesn't provide prediction intervals of the same kind it can't be compared in this manner.

| data | method | model | lambda | sigma**2 | subset | mape | mase | residuals |
|---|---|---|---|---|---|---|---|---|
| import | ets | M,Ad,M | N/A | 0.0763 | train | 5.494712 | 0.3703234 | dependent |
|  |  |  |  |  | test | 7.537235 | 1.763118 |  |
| export | ets | M,Ad,M | N/A | 0.1551 | train | 10.37534 | 0.5103051 | dependent |
|  |  |  |  |  | test | 15.89129 | 2.8818206 |  |

| data | method | model | lambda | sigma**2 | significant parameters | subset | mape | mase | residuals |
|---|---|---|---|---|---|---|---|---|---|
| import | sarima | ARIMA(2,1,1)(2,1,0)[12] | N/A | 1180427 | YES | train | 5.356059 | 0.3627931 | dependent |
|  |  |  |  |  |  | test | 6.900162 | 1.6583602 |  |
| import | sarima | ARIMA(2,1,1)(2,1,0)[12] | 0.1637399 | 0.07768 | YES | train | 4.977908 | 0.3433272 | dependent |
|  |  |  |  |  |  | test | 7.287937 | 1.7651253 |  |
| export | sarima | ARIMA(2,1,1)(0,1,1)[12] | N/A | 119334 | YES | train | 11.35756 | 0.4513094 | independent |
|  |  |  |  |  |  | test | 19.70742 | 3.5138966 |  |
| export | sarima | ARIMA(2,1,1)(2,0,0)[12] with drift | 0.220129 | 0.4778 | YES | train | 10.81068 | 0.4775985 | independent |
|  |  |  |  |  |  | test | 22.87962 | 4.1109044 |  |

| | data | method | model | lambda | sigma**2 | subset | mape | mase |
|---|---|---|---|---|---|---|---|---|
| *imports best nonlinear model->* | import | neural | NNAR(4,1,3)[12] | N/A | 1618448 | train | 7.23142 | 0.4292306 |
| | | | | | | test | 8.17489 | 2.02708 |
| | import | neural | NNAR(1,1,2)[12] | 0.1637399 | 0.1308 | train | 6.597035 | 0.5082465 |
| | | | | | | test | 8.48026 | 2.0782421 |
| | export | neural | NNAR(1,1,2)[12] | N/A | 195589 | train | 12.53733 | 0.5520151 |
| | | | | | | test | 19.45795 | 3.5122214 |
| | export | neural | NNAR(2,1,2)[12] | 0.220129 | 0.5041 | train | 11.04153 | 0.5366247 |
| | | | | | | test | 16.06305 | 2.9532921 |

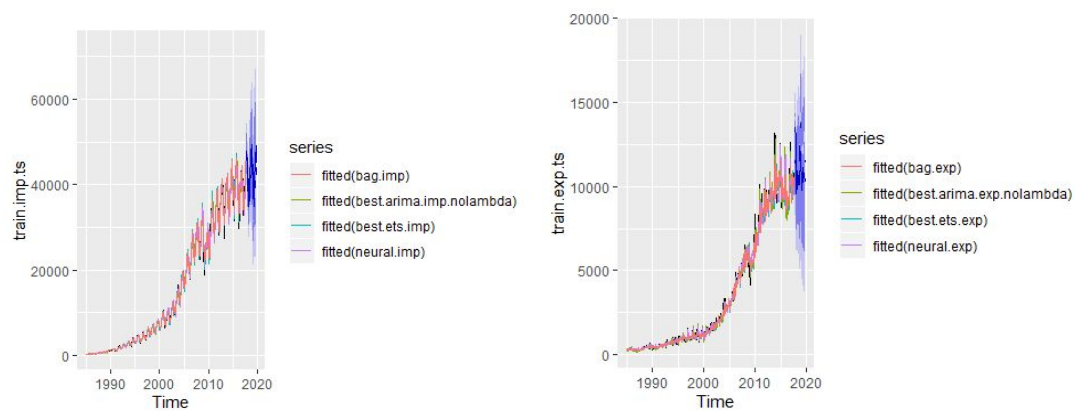| | data | method | lambda | subset | mape | mase |
|---|---|---|---|---|---|---|
| | import | bagged | N/A | train | 5.215448 | 0.3438924 |
| | | | | test | 8.673755 | 2.0504201 |
| | import | bagged | 0.1637399 | train | 60220.0962 | 22417.894 |
| | | | | test | 147209.9 | 62004.77 |
| *exports best nonlinear model->* | export | bagged | N/A | train | 9.4366 | 0.4757732 |
| | | | | test | 15.04068 | 2.7782196 |
| | export | bagged | 0.220129 | train | 13916.27189 | 3543.666 |
| | | | | test | 35757.59 | 10691.656 |

Table:



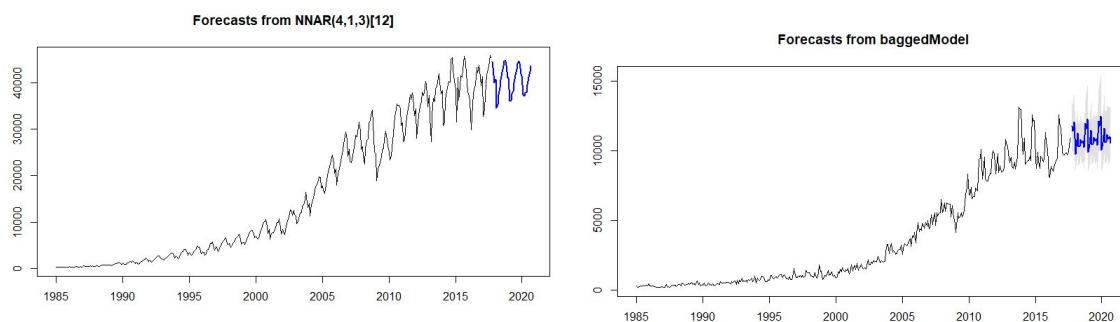Figure: Category-best model Imports and Exports forecast Overlays



Figure: Forecasts of the model winners

When graphing the individual forecast results of the import NNET and the bagged exports, we were pleased to encounter forecasts that were very visually pleasing and consistent with our expectation. They maintained the slight upward trend (though less steep than the early 2000's), and seasonal effect was clearly evident.

# 6 Conclusions and Future Work

Initially we set out to answer several key questions, and we have succeeded in at least addressing them all (or determining a follow-up question to ask). Firstly, we were curious whether this data would be conducive to time series forecasting at all. It ended up being low entropy data, which satisfied this concern. Another key question was simply whether the data would align with certain common-knowledge current events between the U.S. and China that we knew about - critically the early 2000's boom, the Great Recession, and the most recent round of tariffs. All three of these events are apparent visually in the main graph of the time series.

Another takeaway from this investigation, following our model-making process, was that this data was non-linear. It would be interesting to replicate this investigation with other bilateral trade relationships - perhaps the U.S. and another high volume trade partner like Canada, to see if that was still the case. Yet another future investigation we would like to do may have to wait a bit. The recent tariffs fell within the testing window for our model-making, and as such we suspect that their effect and the overall testing accuracy of the models suffers as a result. We would be interested to replicate the study with perhaps a shorter time frame, and with more tariff-active months in the series overall. A logical extension of looking at imports and exports separately would be to difference them and investigate trade balance. The application of this series may be more political than economic, but has been the focus of much of the recent tariff discussions in the United States nonetheless.

Our last future study of interest would be to add regressors into the data, to determine if there are explanatory factors related to GDP, population growth, or other main economic drivers that could enhance the predictive capability of the models.
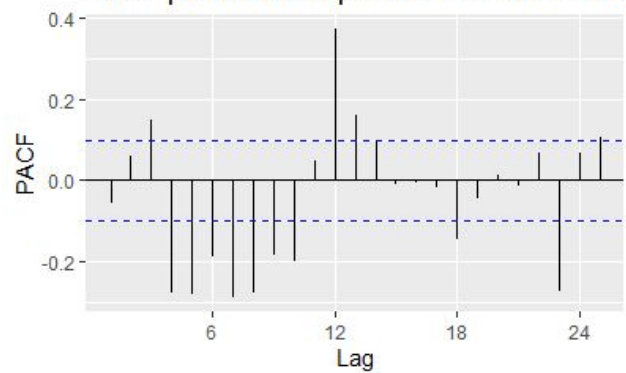
# 7 Appendix

```
ndiffs(train.imp.ts)
## [1] 1
ndiffs(train.exp.ts)
## [1] 1
```
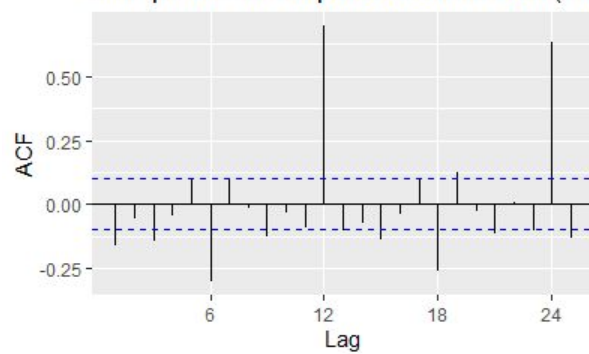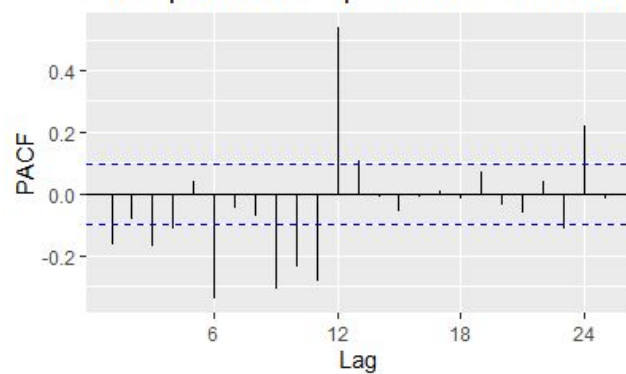
## ACF plot for US Imports of Chinese Goods c
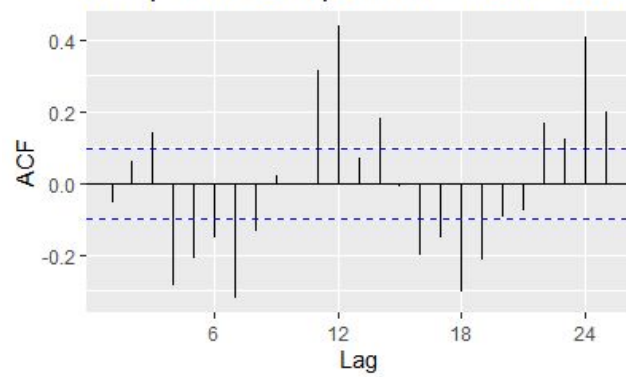


## PACF plot for US Imports of Chinese Goods



## ACF plot for US Exports to China data (Firs



## PACF plot for US Exports to China Goods da

```
nonlinearityTest(train.imp.ts)

##      ** Teraesvirta's neural network test   **
##      Null hypothesis: Linearity in "mean"
##      X-squared =  14.54697  df =  2  p-value =  0.0006936909
##
##      ** White neural network test  **
##      Null hypothesis: Linearity in "mean"
##      X-squared =  14.70372  df =  2  p-value =  0.0006413997
##
##      ** Keenan's one-degree test for nonlinearity   **
##      Null hypothesis: The time series follows some AR process
##      F-stat =  20.80022  p-value =  7.11869e-06
##
##      ** McLeod-Li test  **
##      Null hypothesis: The time series follows some ARIMA process
##      Maximum p-value =  0
##
##      ** Tsay's Test for nonlinearity **
##      Null hypothesis: The time series follows some AR process
##      F-stat =  110.6  p-value =  3.2e-15
##
##      ** Likelihood ratio test for threshold nonlinearity **
##      Null hypothesis: The time series follows some AR process
##      Alternativce hypothesis: The time series follows some TAR process
##      X-squared =  111.4864  p-value =  1.121134e-10
```

```
nonlinearityTest(train.exp.ts)

##      ** Teraesvirta's neural network test   **
##      Null hypothesis: Linearity in "mean"
##      X-squared =  39.29675  df =  2  p-value =  2.929673e-09
##
##      ** White neural network test  **
##      Null hypothesis: Linearity in "mean"
##      X-squared =  44.29962  df =  2  p-value =  2.401379e-10
##
##      ** Keenan's one-degree test for nonlinearity   **
##      Null hypothesis: The time series follows some AR process
##      F-stat =  6.013017  p-value =  0.01470146
##
##      ** McLeod-Li test  **
##      Null hypothesis: The time series follows some ARIMA process
##      Maximum p-value =  0
##
##      ** Tsay's Test for nonlinearity **
##      Null hypothesis: The time series follows some AR process
##      F-stat =  9.493  p-value =  1.722e-06
##
##      ** Likelihood ratio test for threshold nonlinearity **
##      Null hypothesis: The time series follows some AR process
##      Alternativce hypothesis: The time series follows some TAR process
##      X-squared =  62.49455  p-value =  0.002001879
```

```
best.ets.imp <- ets(train.imp.ts, damped = T)
autoplot(best.ets.imp)
```

### Components of ETS(M,Ad,M) method
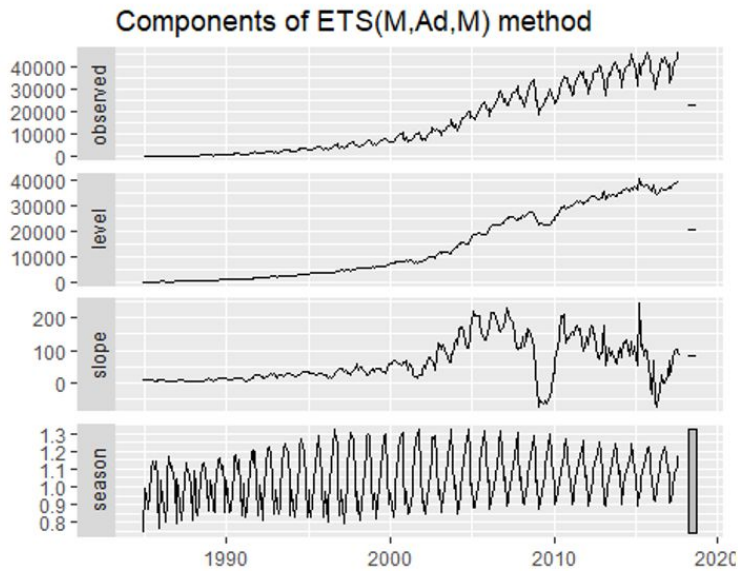


```
accuracy(forecast(best.ets.imp),imp.ts)

##                       ME      RMSE       MAE        MPE     MAPE       MASE
## Training set     54.9893  1162.354  644.2055  0.5429829 5.494712 0.3703234
## Test set       -348.9521  3524.005 3067.0773 -1.5712144 7.537235 1.7631180
##                     ACF1 Theil's U
## Training set -0.06901977       NA
## Test set      0.75490701  1.092759
```
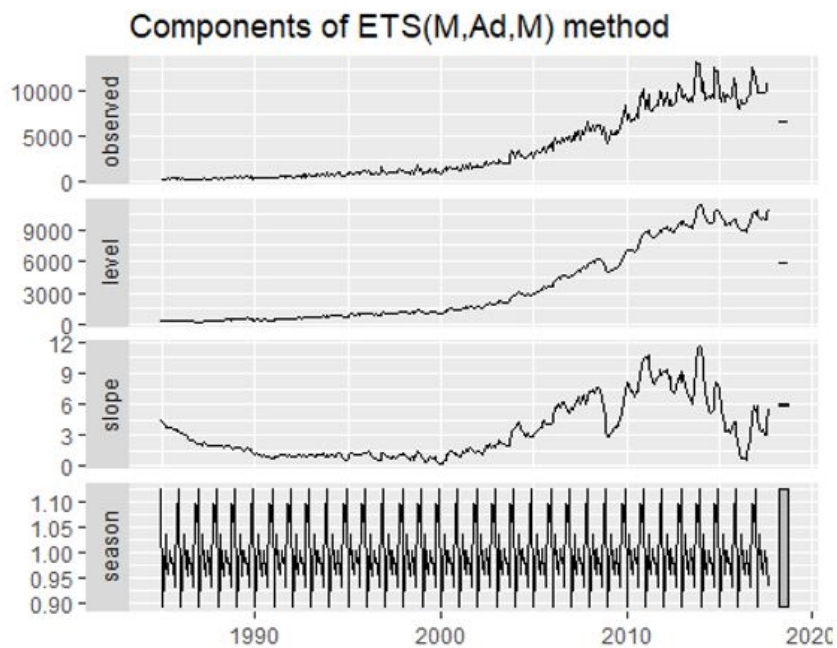
```
checkresiduals(forecast(best.ets.imp))
```



Residuals from ETS(M,Ad,M)
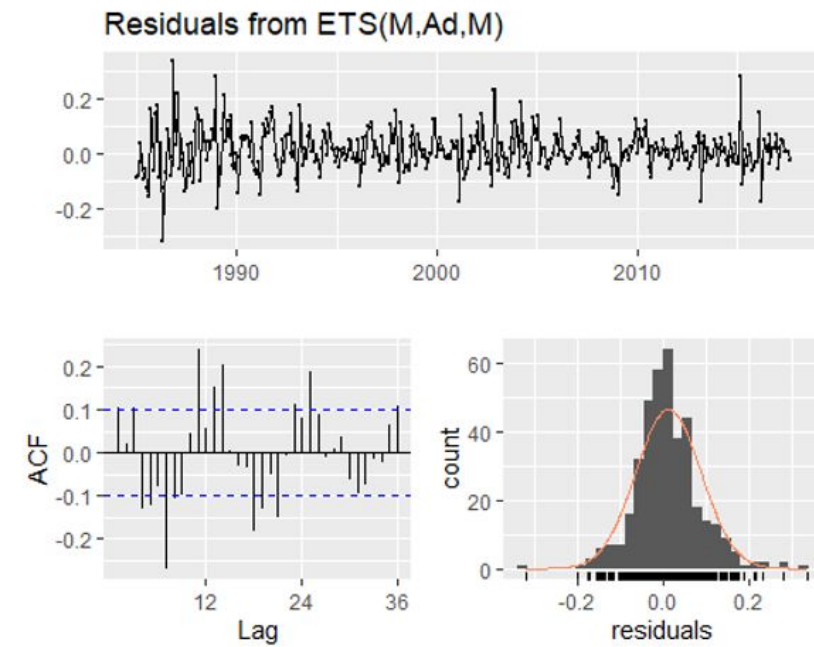
```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(M,Ad,M)
## Q* = 154.31, df = 7, p-value < 2.2e-16
##
## Model df: 17.   Total lags used: 24
```

```
best.ets.exp <- ets(train.exp.ts)
autoplot(best.ets.exp)
```

Components of ETS(M,Ad,M) method



```
accuracy(forecast(best.ets.exp),exp.ts)
```

```
##                         ME      RMSE        MAE         MPE      MAPE       MASE
## Training set      62.92264   420.841   257.0866   0.1297779  10.37534  0.5103051
## Test set       -1045.83546  1742.102  1451.8324 -12.7413460  15.89129  2.8818206
##                       ACF1  Theil's U
## Training set     0.4627870         NA
## Test set         0.6846683   1.369482
```

```
checkresiduals(forecast(best.ets.exp))
```

## Residuals from ETS(M,Ad,M)
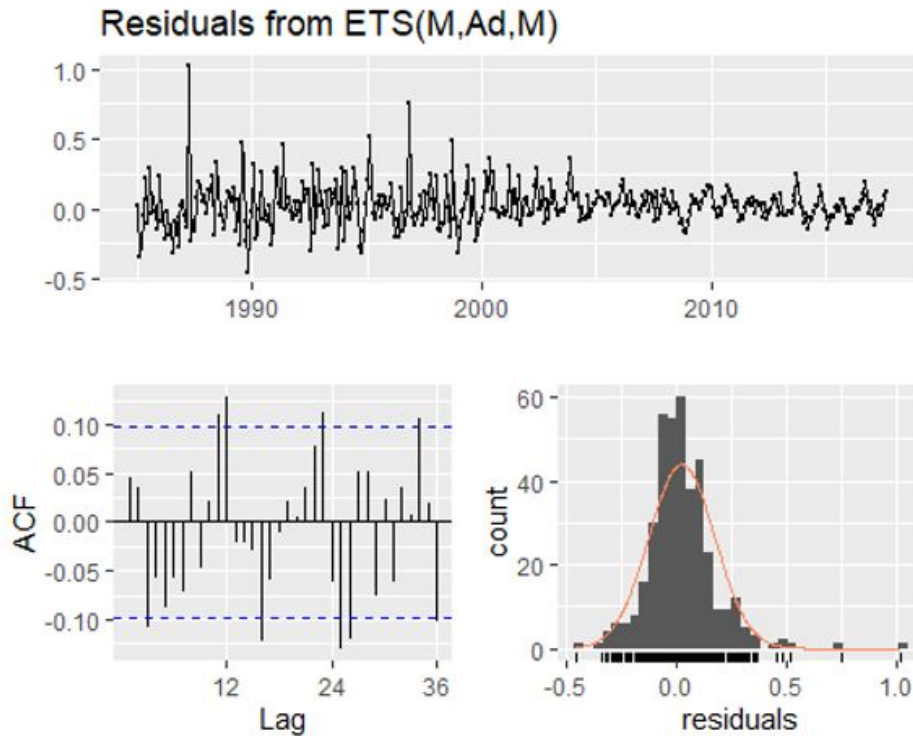


```
##
##   Ljung-Box test
##
## data:  Residuals from ETS(M,Ad,M)
## Q* = 45.992, df = 7, p-value = 8.773e-08
##
## Model df: 17.   Total lags used: 24
```
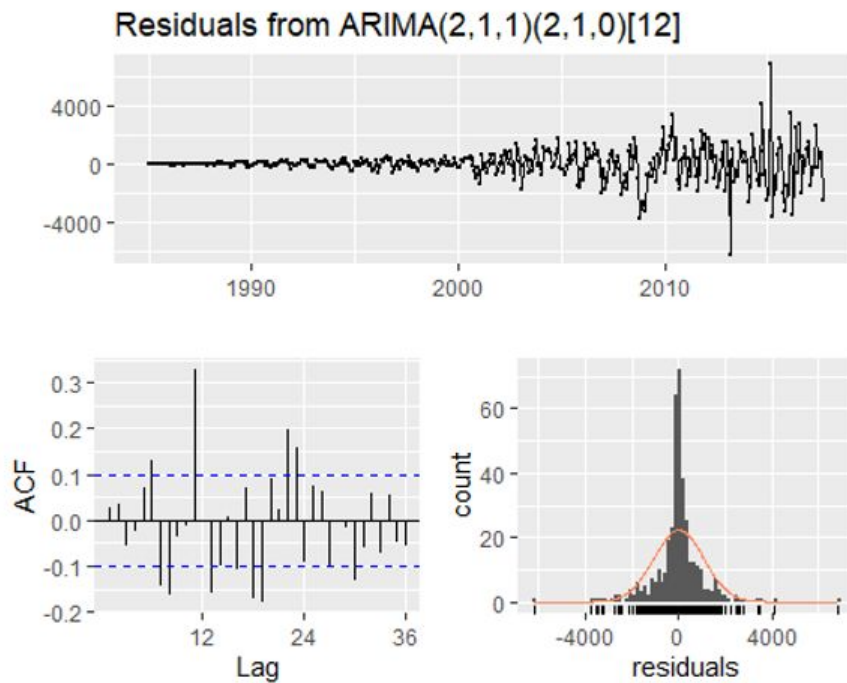
```
summary(best.arima.imp.nolambda)
```

```
## Series: train.imp.ts
## ARIMA(2,1,1)(2,1,0)[12]
##
## Coefficients:
##           ar1      ar2     ma1     sar1     sar2
##       -0.9614  -0.5410  0.4616  -0.7938  -0.5975
## s.e.   0.0731   0.0462  0.0799   0.0466   0.0512
##
## sigma^2 estimated as 1180427:  log likelihood=-3200.48
## AIC=6412.97   AICc=6413.19   BIC=6436.61
##
## Training set error measures:
##                    ME      RMSE      MAE        MPE     MAPE      MASE
## Training set 8.237035 1061.302 631.1061 -0.0213644 5.356059 0.3627931
##                    ACF1
## Training set 0.02655289
```

```
accuracy(forecast(best.arima.imp.nolambda),imp.ts)
```

```
##                       ME      RMSE       MAE        MPE      MAPE      MASE
## Training set   8.237035  1061.302   631.1061  -0.0213644  5.356059  0.3627931
## Test set     390.503477  3280.559  2884.8431   0.2099417  6.900162  1.6583602
##                     ACF1  Theil's U
## Training set  0.02655289         NA
## Test set      0.64841666  0.9497607
```

```
checkresiduals(best.arima.imp.nolambda)
```



Residuals from ARIMA(2,1,1)(2,1,0)[12]

```
##
##   Ljung-Box test
##
## data:  Residuals from ARIMA(2,1,1)(2,1,0)[12]
## Q* = 154.92, df = 19, p-value < 2.2e-16
##
## Model df: 5.    Total lags used: 24
```

```
summary(best.arima.imp.yeslambda)

## Series: train.imp.ts
## ARIMA(2,1,1)(2,1,0)[12]
## Box Cox transformation: lambda= 0.1637399
##
## Coefficients:
##            ar1      ar2     ma1     sar1     sar2
##        -0.8298  -0.4428  0.3331  -0.7430  -0.4380
## s.e.    0.1037   0.0538  0.1119   0.0477   0.0519
##
## sigma^2 estimated as 0.07768:  log likelihood=-55.83
## AIC=123.66   AICc=123.88   BIC=147.3
##
## Training set error measures:
##                     ME     RMSE      MAE        MPE     MAPE      MASE
## Training set -34.37358 1076.89 597.2436 -0.4262426 4.977908 0.3433272
##                    ACF1
## Training set -0.04637189
```

```
accuracy(forecast(best.arima.imp.yeslambda),imp.ts)

##                      ME     RMSE       MAE        MPE     MAPE      MASE
## Training set -34.37358 1076.890  597.2436 -0.4262426 4.977908 0.3433272
## Test set     643.62276 3440.545 3070.5692  0.8346843 7.287937 1.7651253
##                    ACF1 Theil's U
## Training set -0.04637189        NA
## Test set      0.70960777 0.9910815
```

```
checkresiduals(best.arima.imp.yeslambda)
```

## Residuals from ARIMA(2,1,1)(2,1,0)[12]
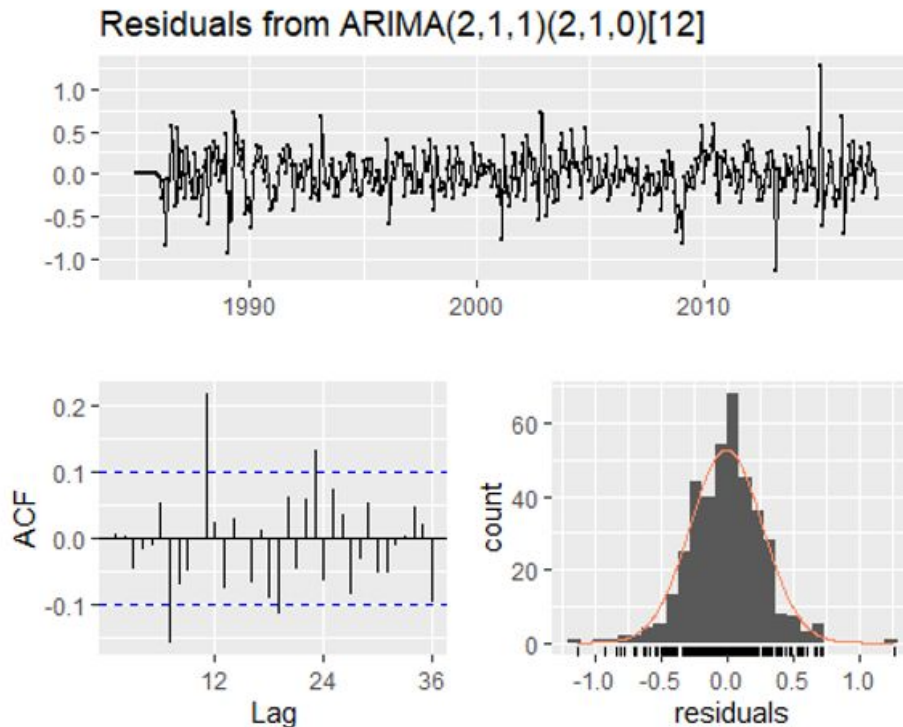


```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(2,1,1)(2,1,0)[12]
## Q* = 60.985, df = 19, p-value = 2.7e-06
##
## Model df: 5.    Total lags used: 24
```
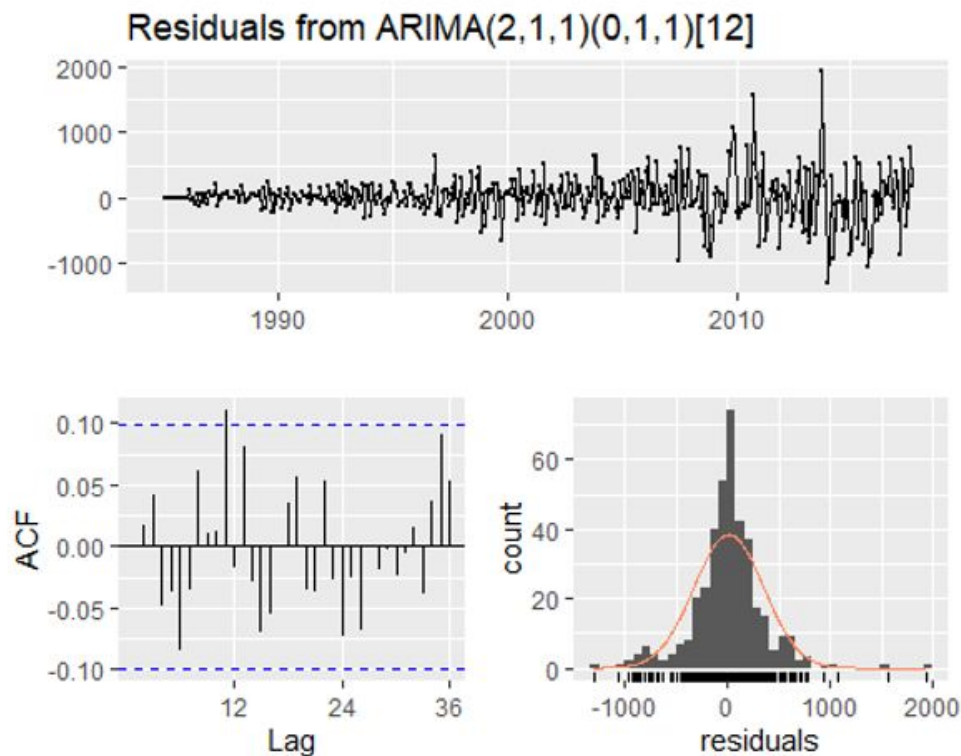
```
summary(best.arima.exp.nolambda)
```

```
## Series: train.exp.ts
## ARIMA(2,1,1)(0,1,1)[12]
##
## Coefficients:
##          ar1     ar2      ma1      sma1
##       0.7114  0.1283  -0.9646  -0.5424
## s.e.  0.0574  0.0559   0.0268   0.0442
##
## sigma^2 estimated as 119334:  log likelihood=-2760.92
## AIC=5531.83   AICc=5531.99   BIC=5551.53
##
## Training set error measures:
##                    ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 11.03621 337.893 227.3651 -0.4317361 11.35756 0.4513094
##                    ACF1
## Training set 0.0001588779
```

```
accuracy(forecast(best.arima.exp.nolambda),exp.ts)
```

```
##                        ME      RMSE       MAE         MPE     MAPE      MASE
## Training set     11.03621   337.893  227.3651  -0.4317361 11.35756 0.4513094
## Test set      -1482.88331  2239.336 1770.2659 -17.4212900 19.70742 3.5138966
##                      ACF1 Theil's U
## Training set 0.0001588779        NA
## Test set     0.6795136848  1.767939
```

```
checkresiduals(best.arima.exp.nolambda)
```



Residuals from ARIMA(2,1,1)(0,1,1)[12]

```
##
##   Ljung-Box test
##
## data:  Residuals from ARIMA(2,1,1)(0,1,1)[12]
## Q* = 25.256, df = 20, p-value = 0.1918
##
## Model df: 4.    Total lags used: 24
```

```
summary(best.arima.exp.yeslambda)

## Series: train.exp.ts
## ARIMA(2,1,1)(2,0,0)[12] with drift
## Box Cox transformation: lambda= 0.220129
##
## Coefficients:
##           ar1     ar2      ma1    sar1    sar2    drift
##        0.3991  0.2344  -0.9395  0.3487  0.1650  0.0480
## s.e.   0.0606  0.0582   0.0312  0.0518  0.0511  0.0117
##
## sigma^2 estimated as 0.4778:  log likelihood=-410.12
## AIC=834.24    AICc=834.53    BIC=862.04
##
## Training set error measures:
##                   ME       RMSE       MAE        MPE      MAPE      MASE
## Training set 10.36284 402.0039 240.6093 -1.331049 10.81068 0.4775985
##                  ACF1
## Training set 0.2891842
```

```
accuracy(forecast(best.arima.exp.yeslambda),exp.ts)

##                        ME       RMSE       MAE        MPE      MAPE      MASE
## Training set    10.36284   402.0039  240.6093  -1.331049  10.81068 0.4775985
## Test set     -1610.97316 2434.7656 2071.0324 -19.342475 22.87962 4.1109044
##                  ACF1 Theil's U
## Training set 0.2891842        NA
## Test set     0.6678145   1.93414
```

```
checkresiduals(best.arima.exp.yeslambda)
```



Residuals from ARIMA(2,1,1)(2,0,0)[12] with drift
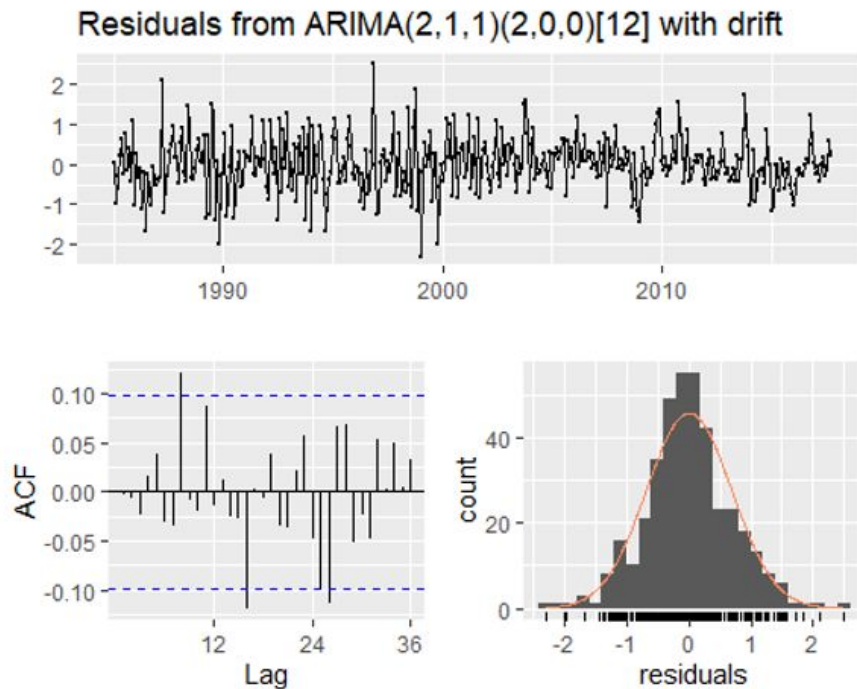
```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(2,1,1)(2,0,0)[12] with drift
## Q* = 21.647, df = 18, p-value = 0.248
##
## Model df: 6.    Total lags used: 24
```

```
neural.imp <- nnetar(train.imp.ts)
neural.imp

## Series: train.imp.ts
## Model:   NNAR(4,1,3)[12]
## Call:    nnetar(y = train.imp.ts)
##
## Average of 20 networks, each of which is
## a 5-3-1 network with 22 weights
## options were - linear output units
##
## sigma^2 estimated as 1618448
```

```
accuracy(forecast(neural.imp),imp.ts)

##                        ME     RMSE      MAE       MPE    MAPE      MASE
## Training set     1.004195 1272.183  746.6791 -2.172185 7.23142 0.4292306
## Test set      2113.309300 3970.815 3526.2591  4.157140 8.17489 2.0270800
##                    ACF1 Theil's U
## Training set 0.1262050        NA
## Test set     0.6928315  1.100258
```

```
neural.imp.boxcox <- nnetar(train.imp.ts, lambda =
BoxCox.lambda(train.imp.ts))
neural.imp.boxcox

## Series: train.imp.ts
## Model:  NNAR(1,1,2)[12]
## Call:   nnetar(y = train.imp.ts, lambda = BoxCox.lambda(train.imp.ts))
##
## Average of 20 networks, each of which is
## a 2-2-1 network with 9 weights
## options were - linear output units
##
## sigma^2 estimated as 0.1319
```

```
accuracy(forecast(neural.imp.boxcox),imp.ts)

##                       ME     RMSE      MAE        MPE     MAPE      MASE
## Training set    39.81596 1514.976  884.1333 -0.4315061 6.597035 0.5082465
## Test set      1795.17829 4444.743 3615.2595  3.0381427 8.485026 2.0782421
##                     ACF1 Theil's U
## Training set 0.1137020        NA
## Test set     0.7510175  1.264006
```

```
neural.exp <- nnetar(train.exp.ts)
neural.exp

## Series: train.exp.ts
## Model:  NNAR(1,1,2)[12]
## Call:   nnetar(y = train.exp.ts)
##
## Average of 20 networks, each of which is
## a 2-2-1 network with 9 weights
## options were - linear output units
##
## sigma^2 estimated as 195589
```

```
accuracy(forecast(neural.exp),exp.ts)

##                        ME      RMSE       MAE        MPE     MAPE
## Training set     0.2292767  442.2549  278.0997  -3.358741 12.53733
## Test set      -1196.3518931 2091.7454 1769.4220 -14.909501 19.45795
##                  MASE      ACF1 Theil's U
## Training set 0.5520151 0.2018676        NA
## Test set     3.5122214 0.6016065  1.652535
```

```
neural.exp.boxcox <- nnetar(train.exp.ts, lambda =
BoxCox.lambda(train.exp.ts))
neural.exp.boxcox

## Series: train.exp.ts
## Model:  NNAR(2,1,2)[12]
## Call:   nnetar(y = train.exp.ts, lambda = BoxCox.lambda(train.exp.ts))
##
## Average of 20 networks, each of which is
## a 3-2-1 network with 11 weights
## options were - linear output units
##
## sigma^2 estimated as 0.5098

accuracy(forecast(neural.exp.boxcox),exp.ts)

##                        ME       RMSE        MAE        MPE      MAPE       MASE
## Training set     15.52981   457.1013   270.3462   -1.369548 11.04153 0.5366247
## Test set       -789.80332  1744.3656  1487.8390  -10.532445 16.06305 2.9532921
##                     ACF1 Theil's U
## Training set 0.2351623         NA
## Test set     0.5333260   1.342548
```

| data | method | model | lambda | sigma**2 | subset | mape | mase |
|------|--------|-------|--------|----------|--------|------|------|
| import | neural | NNAR(4,1,3)[12] | N/A | 1618448 | train | 7.23142 | 0.4292306 |
| | | | | | test | 8.17489 | 2.02708 |
| import | neural | NNAR(1,1,2)[12] | 0.1637399 | 0.1308 | train | 6.597035 | 0.5082465 |
| | | | | | test | 8.48026 | 2.0782421 |
| export | neural | NNAR(1,1,2)[12] | N/A | 195589 | train | 12.53733 | 0.5520151 |
| | | | | | test | 19.45795 | 3.5122214 |
| export | neural | NNAR(2,1,2)[12] | 0.220129 | 0.5041 | train | 11.04153 | 0.5366247 |
| | | | | | test | 16.06305 | 2.9532921 |

```
accuracy(forecast(bag.imp), imp.ts)

##                       ME      RMSE        MAE        MPE      MAPE      MASE
## Training set   9.890236  1001.747   598.2268   0.1107069 5.215448 0.3438924
## Test set      69.670790  4186.723  3566.8610  -0.5733451 8.673755 2.0504201
##                    ACF1 Theil's U
## Training set 0.1788646        NA
## Test set     0.7304160   1.24933

bag.imp.wlambda <- baggedModel(BoxCox(train.imp.ts,lambda =
BoxCox.lambda(train.imp.ts)), bootstrapped_series =
bld.mbb.bootstrap(train.imp.ts, 100))
accuracy(forecast(bag.imp.wlambda), BoxCox(imp.ts,lambda =
BoxCox.lambda(train.imp.ts)))

##                     ME      RMSE       MAE       MPE      MAPE      MASE
## Training set -15365.52  21156.07  15365.52   -60220.1   60220.1  22417.89
## Test set     -42498.90  42738.15  42498.90  -147209.9  147209.9  62004.77
##                    ACF1 Theil's U
## Training set 0.9869763        NA
## Test set     0.6993608   87036.79

accuracy(forecast(bag.exp), exp.ts)

##                      ME      RMSE        MAE        MPE     MAPE      MASE
## Training set   42.11229   391.9716   239.6898  -0.3486852  9.43660 0.4757732
## Test set     -764.05031  1642.8201  1399.6392  -9.9447899 15.04068 2.7782196
##                    ACF1 Theil's U
## Training set 0.5771892        NA
## Test set     0.7268391   1.264623
```

```
bag.exp.wlambda <- baggedModel(BoxCox(train.exp.ts,lambda =
BoxCox.lambda(train.exp.ts)), bootstrapped_series =
bld.mbb.bootstrap(train.exp.ts, 100, block_size = NULL))
accuracy(forecast(bag.exp.wlambda), BoxCox(exp.ts,lambda =
BoxCox.lambda(train.exp.ts)))

##                       ME      RMSE       MAE       MPE     MAPE      MASE
## Training set    -3533.075   5038.574   3533.075  -13916.27  13916.27   3543.666
## Test set       -10659.701  10680.271  10659.701  -35757.59  35757.59  10691.656
##                     ACF1  Theil's U
## Training set   0.98596726         NA
## Test set       0.06434909   9805.401
```
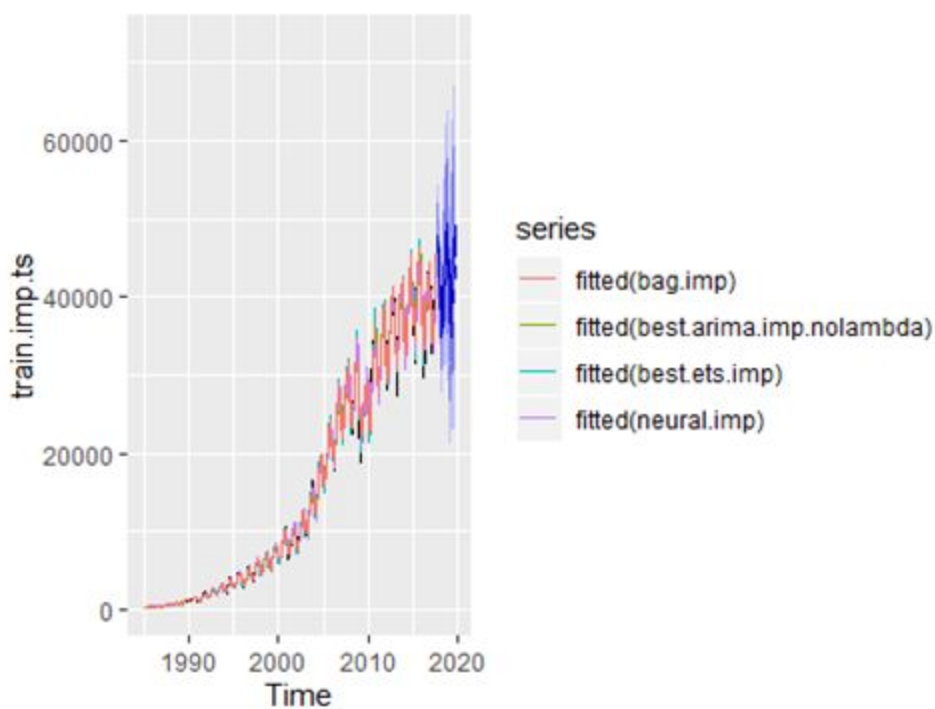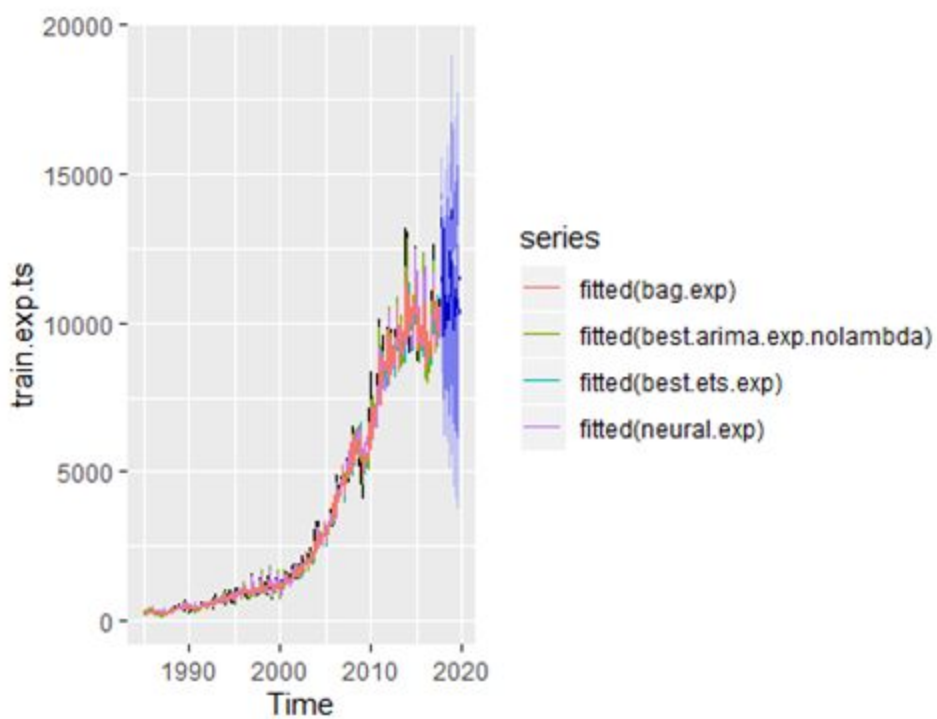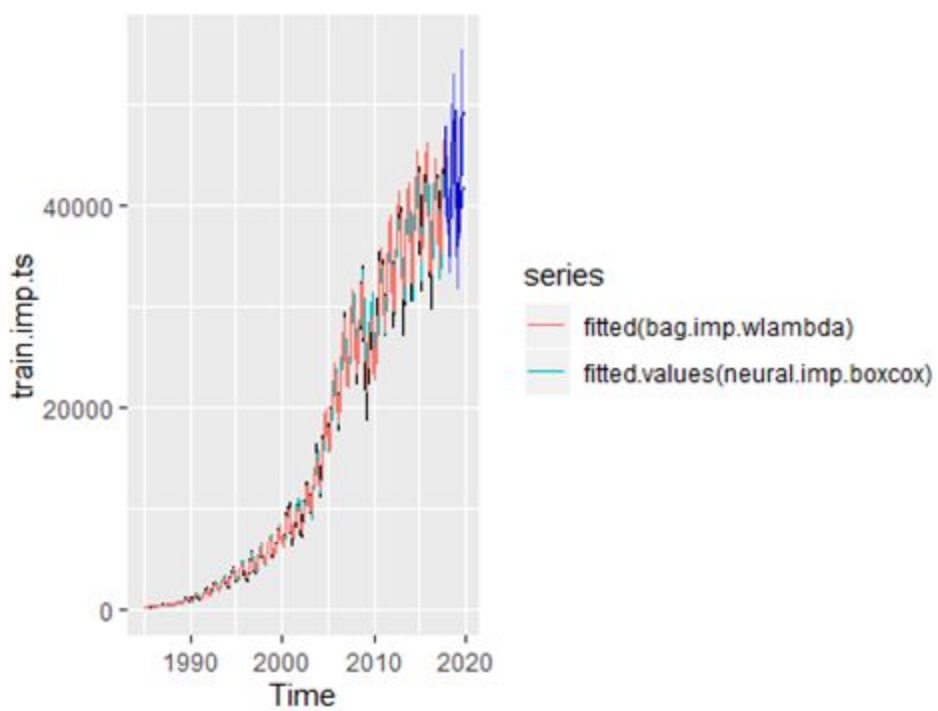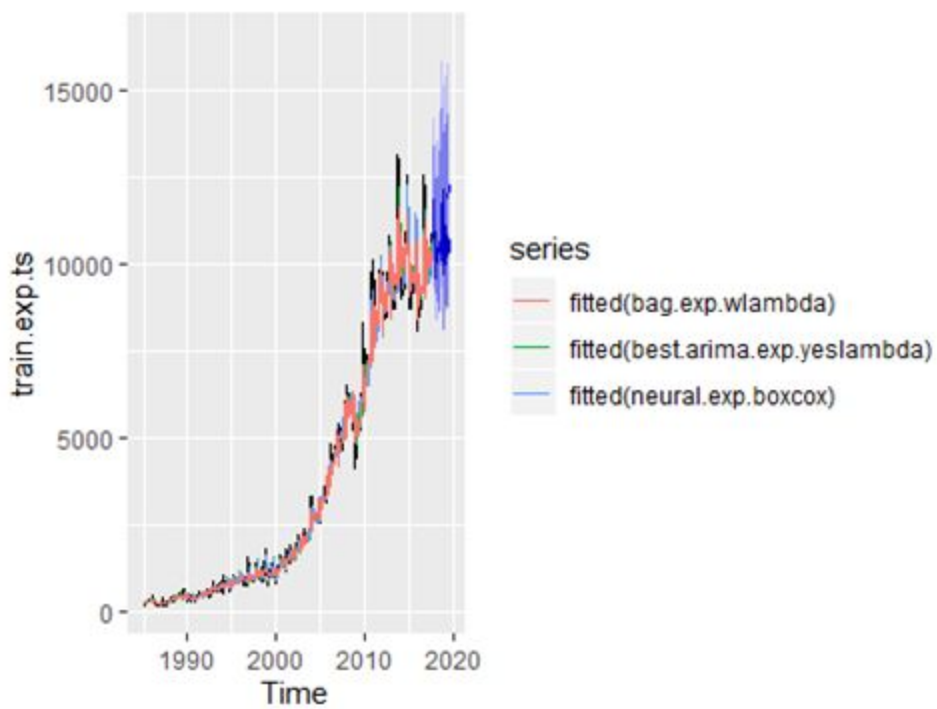
| data | method | lambda | subset | mape | mase |
|------|--------|--------|--------|------|------|
| import | bagged | N/A | train | 5.215448 | 0.3438924 |
| | | | test | 8.673755 | 2.0504201 |
| import | bagged | 0.1637399 | train | 60220.0962 | 22417.894 |
| | | | test | 147209.9 | 62004.77 |
| export | bagged | N/A | train | 9.4366 | 0.4757732 |
| | | | test | 15.04068 | 2.7782196 |
| export | bagged | 0.220129 | train | 13916.27189 | 3543.666 |
| | | | test | 35757.59 | 10691.656 |

series

fitted(bag.imp.wlambda)

fitted.values(neural.imp.boxcox)



series

fitted(bag.exp)

fitted(best.arima.exp.nolambda)

fitted(best.ets.exp)

fitted(neural.exp)

```
diss(impex.ts, METHOD = "EUCL")

##          Imports
## Exports 358571.2

diss(impex.ts, METHOD = "COR")

##           Imports
## Exports 0.2604179
```

```
tsoutliers(imp.ts, lambda = "auto")

## $index
## [1]   15   22 290 363
##
## $replacements
## [1]   277.6325   519.7730 21335.2673 33007.5785
```

```
tsoutliers(exp.ts, lambda = "auto")

## $index
## integer(0)
##
## $replacements
## numeric(0)
```

## References

[1] U.S. Bureau of Economic Analysis and U.S. Census Bureau, U.S. Imports of Goods by Customs Basis from China [IMPCH], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/IMPCH, December 2019

[2] U.S. Bureau of Economic Analysis and U.S. Census Bureau, U.S. Exports of Goods by F.A.S. Basis to China, Mainland [EXPCH], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/EXPCH, December, 2019.

[3] Council on Foreign Relations,  U.S. Relations with China 1949-2019, https://www.cfr.org/timeline/us-relations-china