Time Series Analysis for Chicago's Trade Data

MSCA 31006 IP03 Time Series Analysis and Forecasting

2023, Spring

Group 5

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Goal of Analysis

The goal of prediction for Chicago's import data is to forecast future import trends accurately, enabling businesses / policymakers to make informed decisions, optimize operations, & drive economic growth.

🎯 1

Accurately predict monthly import trends in Chicago

🎯 2

Pre-Covid vs. Post-Covid :
Does the model predict Pre-covid better?

🎯 3

Pre-Covid vs. Post-Covid :
Which model performs better for each period?

Compared ETS, SARIMA, Regression w/ ARMA errors, VAR Models

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Business Opportunity

Accurate import forecasting for Chicago informs *economic planning, trade analysis, infrastructure planning, market opportunities, policy-making, and risk management. It enables informed decisions, capitalizing on opportunities, and fostering sustainable economic growth.*

Economic Planning

Businesses/city officials can plan and allocate resources effectively, and attract investments

Logistics Planning

Logistics capabilities to support the efficient movement of goods

Policy & Regulatory

Develop & implement trade policies, regulations, and incentives that support economic growth, job creation, and sustainable development

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Data Description

1. **Dataset Size**: 254 monthly observations across 9 variables
2. **Target Variable**: 'Import' (in $billion)
3. **Time Span**: January 2002 to February 2023
   - Pre-Covid: 2002 - 2018 for forecasting 2019
   - Post-Covid: 2002 - 2021 for forecasting 2022
4. **Predictor Variables**: Supplemented by the following economic indices from the same time period, i.e.
   - Export (in $billion)
   - CPI (Consumer Price Index)
   - PPI (Producer Price Index)
   - Bond (10-year Government Bond Yield)
   - Sentiment (Consumer Sentiment Indicator from the University of Michigan)
   - USDX (US Dollar Index)
   - Uncertainty (Economic Policy Uncertainty Index for the United States)
5. **Source of Data**: United States Census Bureau (Trade Data) and The Fed St. Louis (Other Economic Data)

Experimental Analysis: Stationarity

1. What Is Stationarity?

- ***Stationarity*** is a fundamental concept in time series analysis. A time series is said to be stationary when its statistical properties—like mean, variance, and autocorrelation—do not change over time. In simpler terms, the series doesn't exhibit trends or seasonality; it looks roughly the same throughout its entirety.

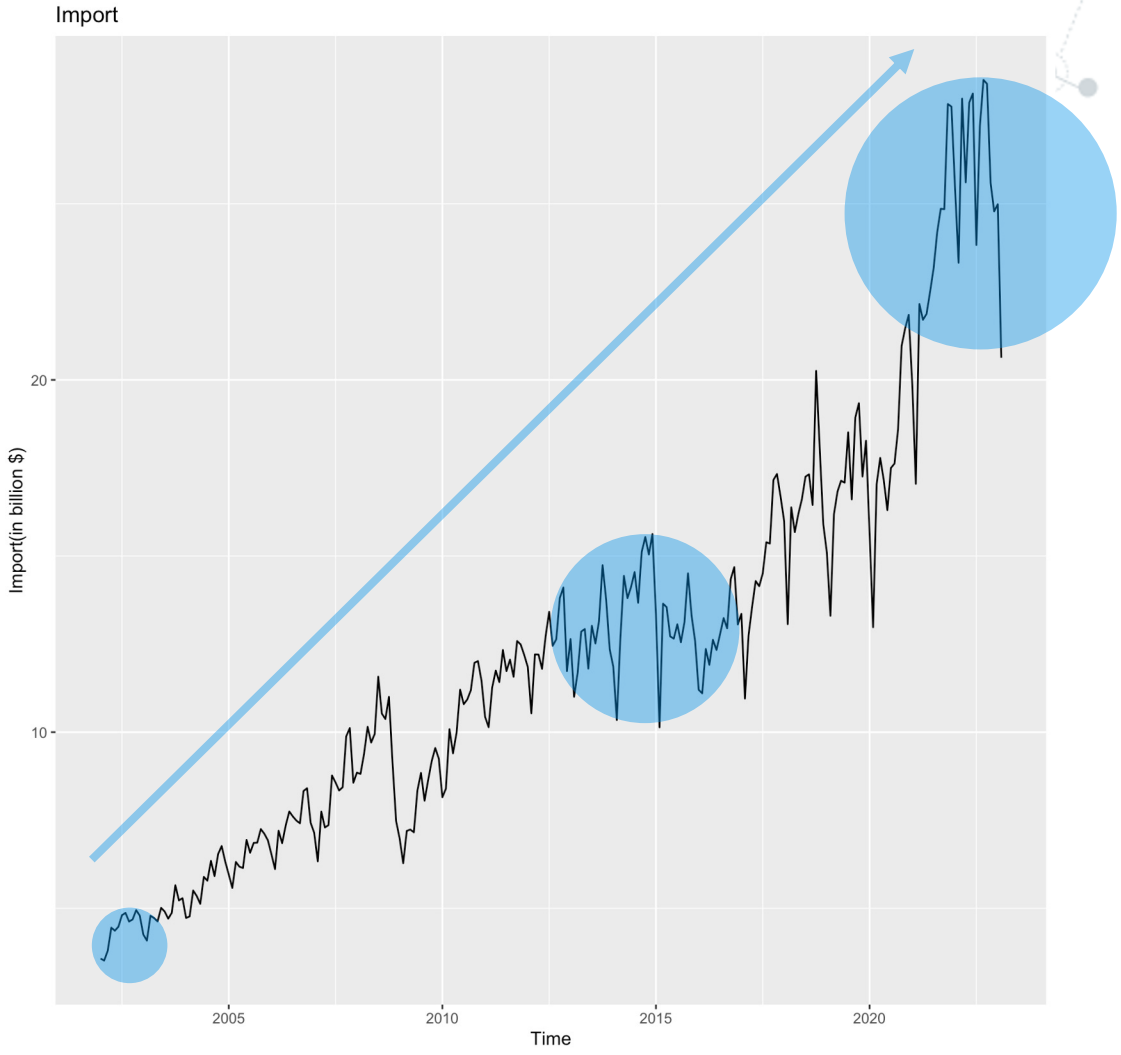
2. Why Is Stationarity Important?

- ***Predictability:*** Stationary time series are easier to model and predict. When a series is stationary, its past behavior can provide insights into its future.
- ***Reliability:*** Forecasting a stationary series is generally more accurate. Non-stationary data can lead to unreliable and spurious results.
- ***Model Assumptions:*** Many time series models, such as ARIMA, have an underlying assumption that the data is stationary. Applying these models to non-stationary data without necessary transformations can yield inaccurate predictions.
- ***Consistent Mean and Variance:*** A stationary time series will have a consistent mean and variance, making the analysis more interpretable and the results more dependable.

Experimental Analysis: Stationarity

Does the Original Data Satisfy the Stationarity Assumption? ***No.***

- Upon visual inspection, it is clear that the original data does not satisfy the stationarity assumption due to an observable ***1) increasing trend*** and ***2) inconsistent variance.***
- The KPSS that assesses the stationarity of a time series confirms the non-stationarity of the data due to ***the p-value of 0.01(<0.05).***



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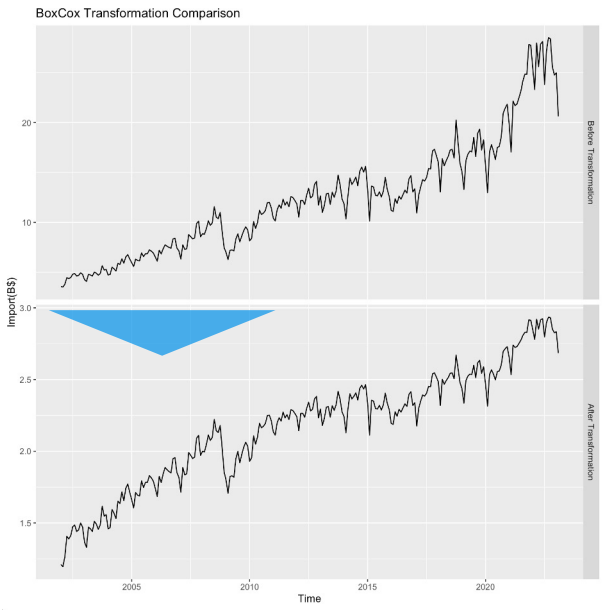
Experimental Analysis: Stationarity

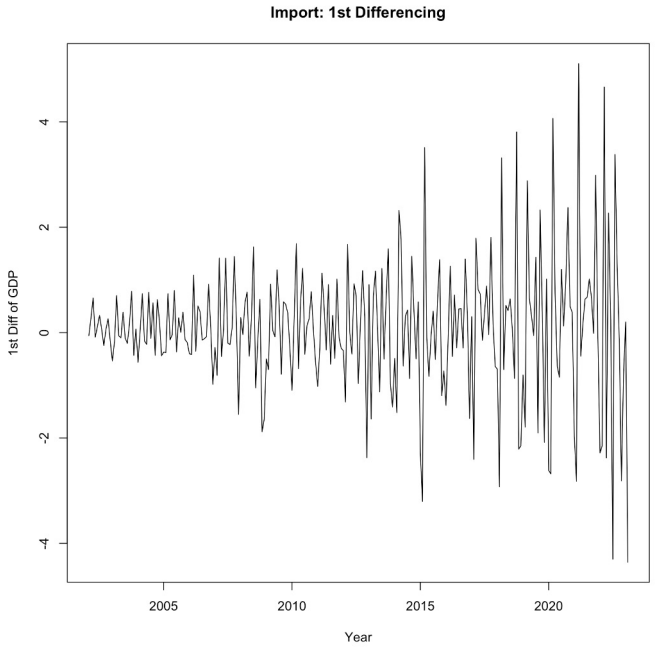
We'll address the non-stationarity in our data through two key steps:

1. ***Box-Cox Transformation*** to stabilize any varying variance.
2. ***1st order differencing*** to mitigate upward trends.

Box-Cox Transformation



1st Order Differencing



Applying the Box-Cox transformation (with λ=-0.081) stabilized our time series. However, the first-order differencing applied to the original data was insufficient to fully eliminate the trend. → ***Combine two methods to achieve stationarity.***

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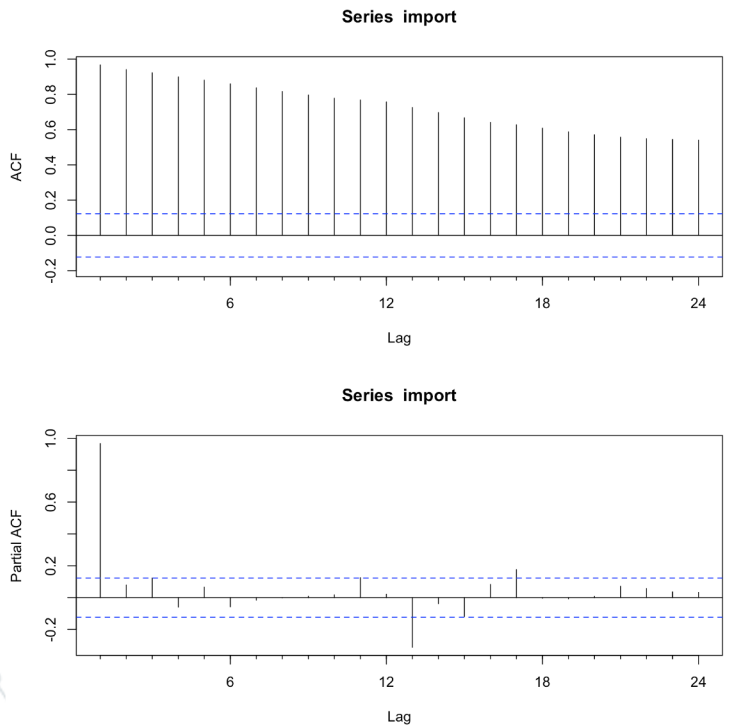
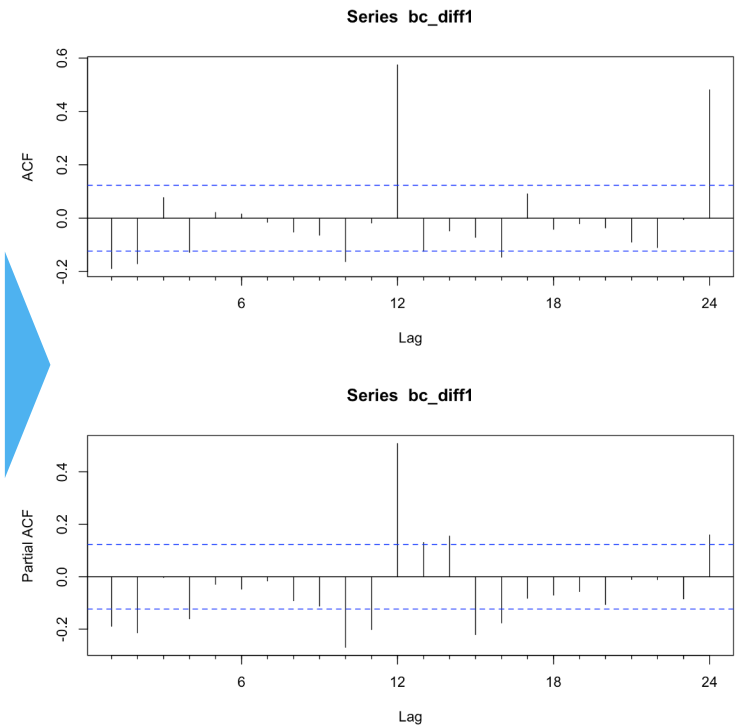
Experimental Analysis: Stationarity

ACF and PACF

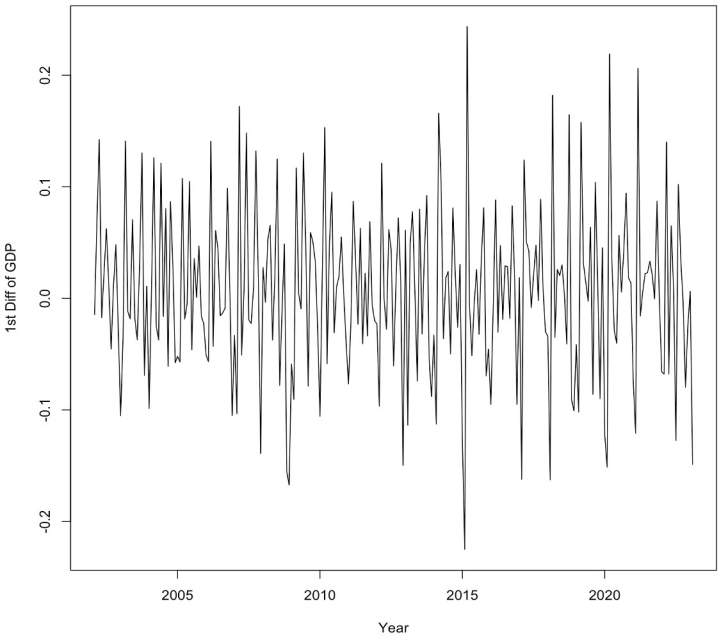
Original Data



BoxCox Trans. + 1st order Differencing



Data after Box-Cox Trans + 1st order Differencing



This data will form the foundation for our upcoming analysis.

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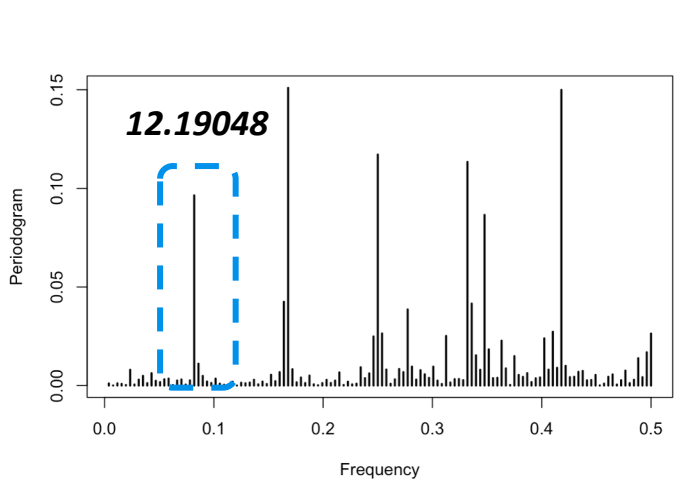
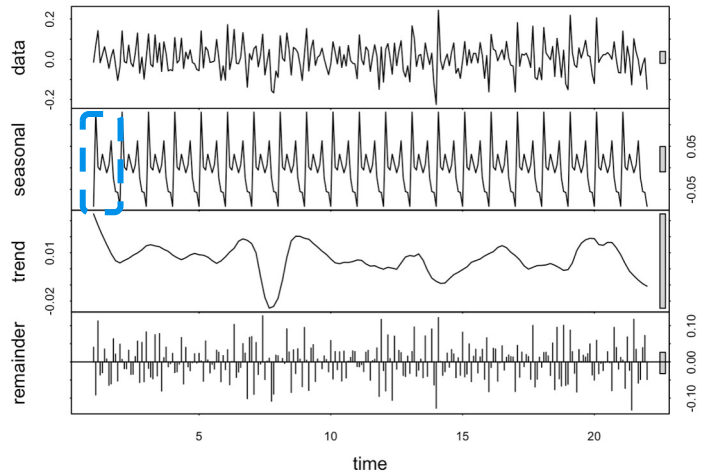
Experimental Analysis: Seasonality

We have confirmed the presence of seasonality with a lag of 12 in our time series data.

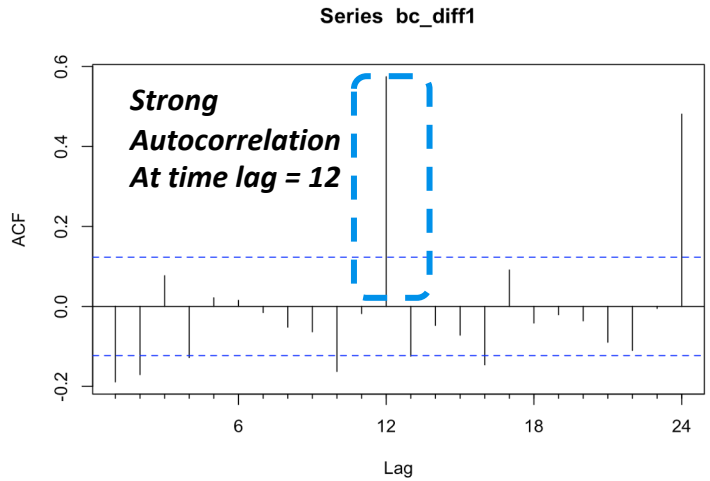
Periodogram



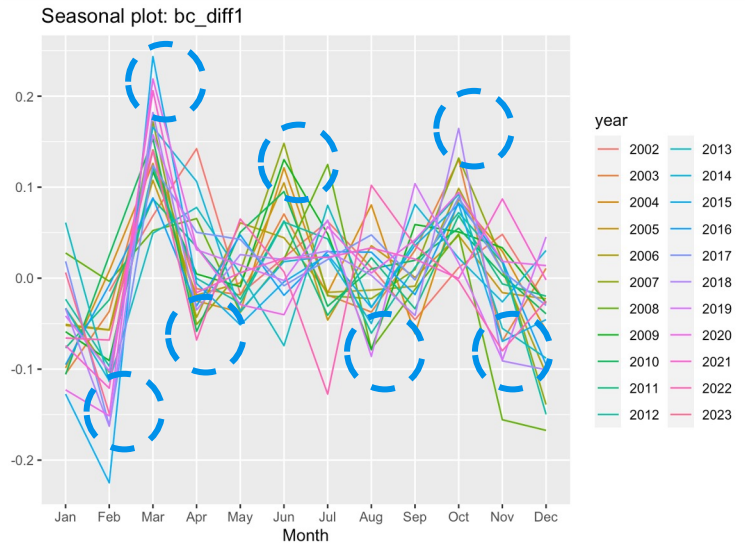
STL



ACF Plot



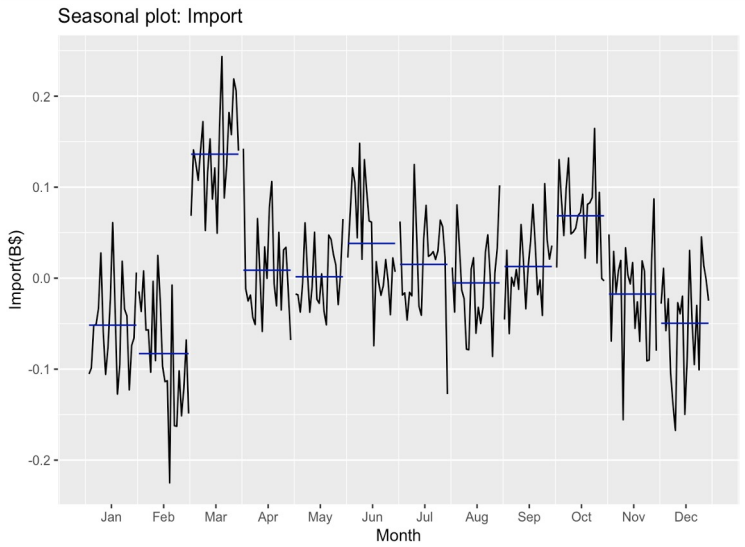
Seasonal Plot



Seasonal Patterns throughout a year

1) high in Mar, Jun, Oct 2) low in Feb, Apr, Aug, and Nov

Subseries Plot (Seasonal Plot)



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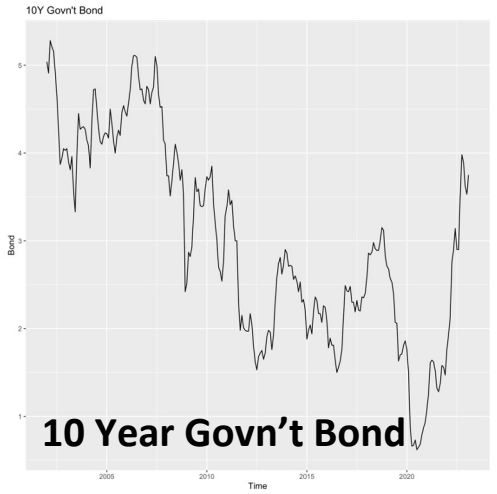
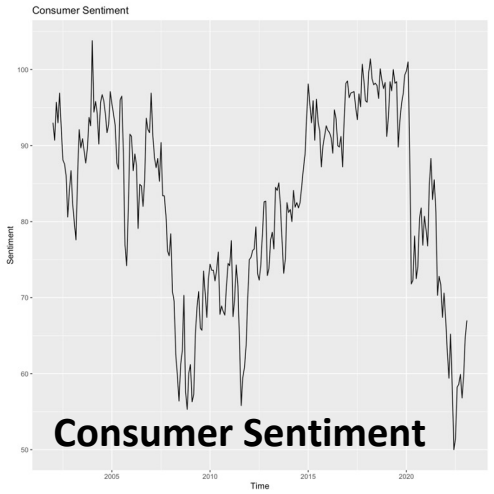
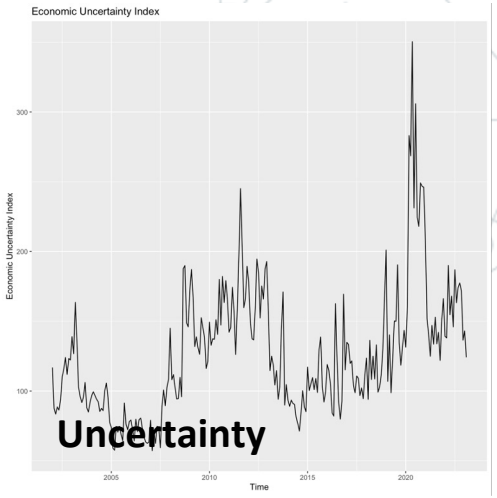
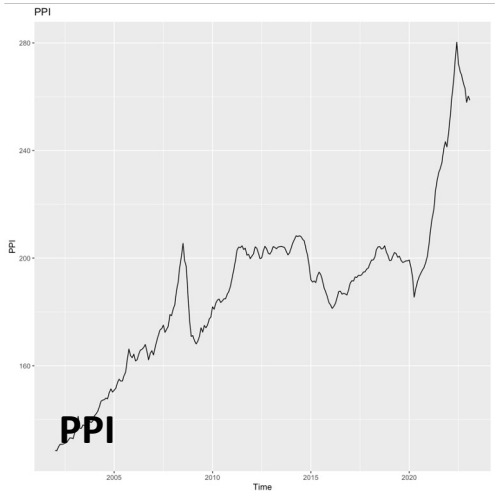
Experimental Analysis: Correlation

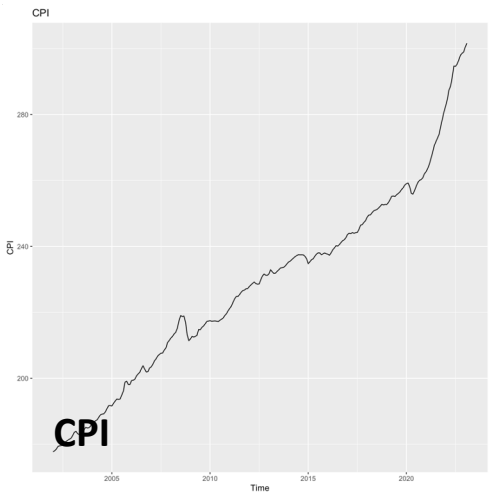
- In our model exploration, we'll be employing advanced techniques, such as Regression with ARIMA error modeling and VAR and VARIMA for handling multivariate time series.
- This necessitates examining time series plots for each variable and assessing their correlations.

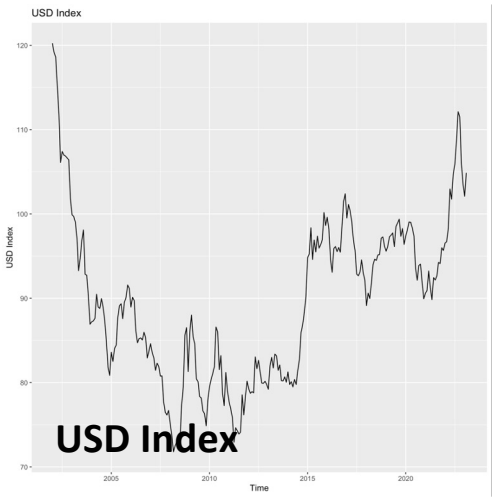












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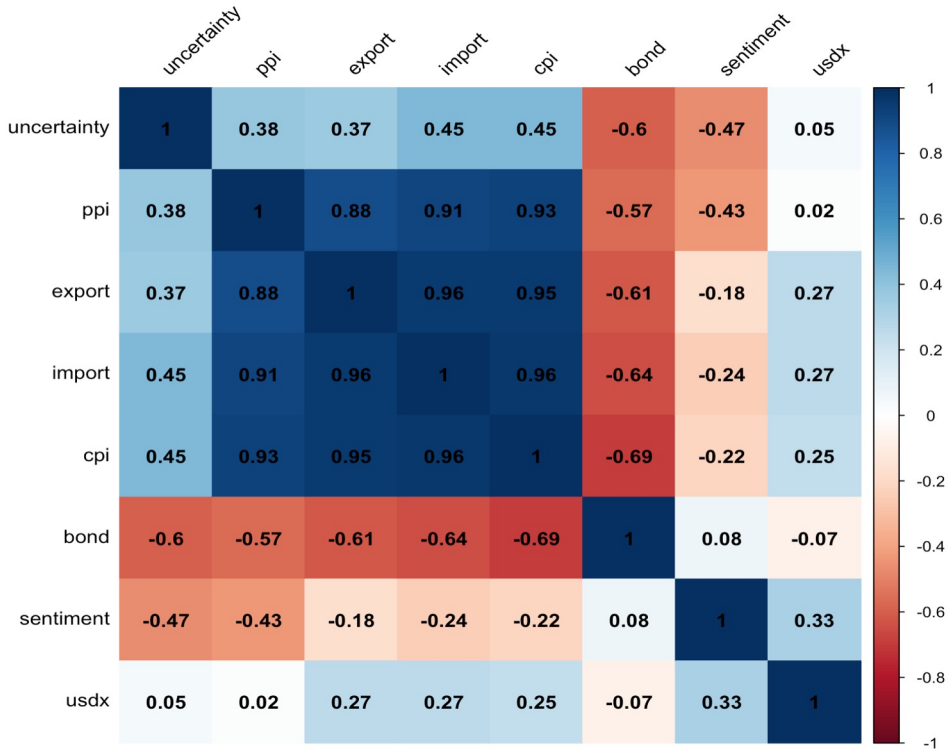
Experimental Analysis: Correlation

The Definition of Variables

Variables	Definition
Import & Export	• The value of goods and services that the US buys from/sells to other countries
10-Year Govn't Bond	• A debt security issued by the US government in 10 years
Consumer Sentiment	• How people feel about the economy and their financial situation • An indicator of consumer spending, essential for economic growth
Economic Uncertainty	• The unpredictability of the future state of the economy
PPI (Producer Price Index)	• The average change over time in selling prices received by domestic producers for their output • A leading indicator of consumer price inflation
CPI (Consumer Price Index)	• The average change over time in prices paid by consumers for a market basket of consumer goods and services, a measure of inflation
USD Index	• The value of the US dollar against a basket of foreign currencies

Correlation among Variables



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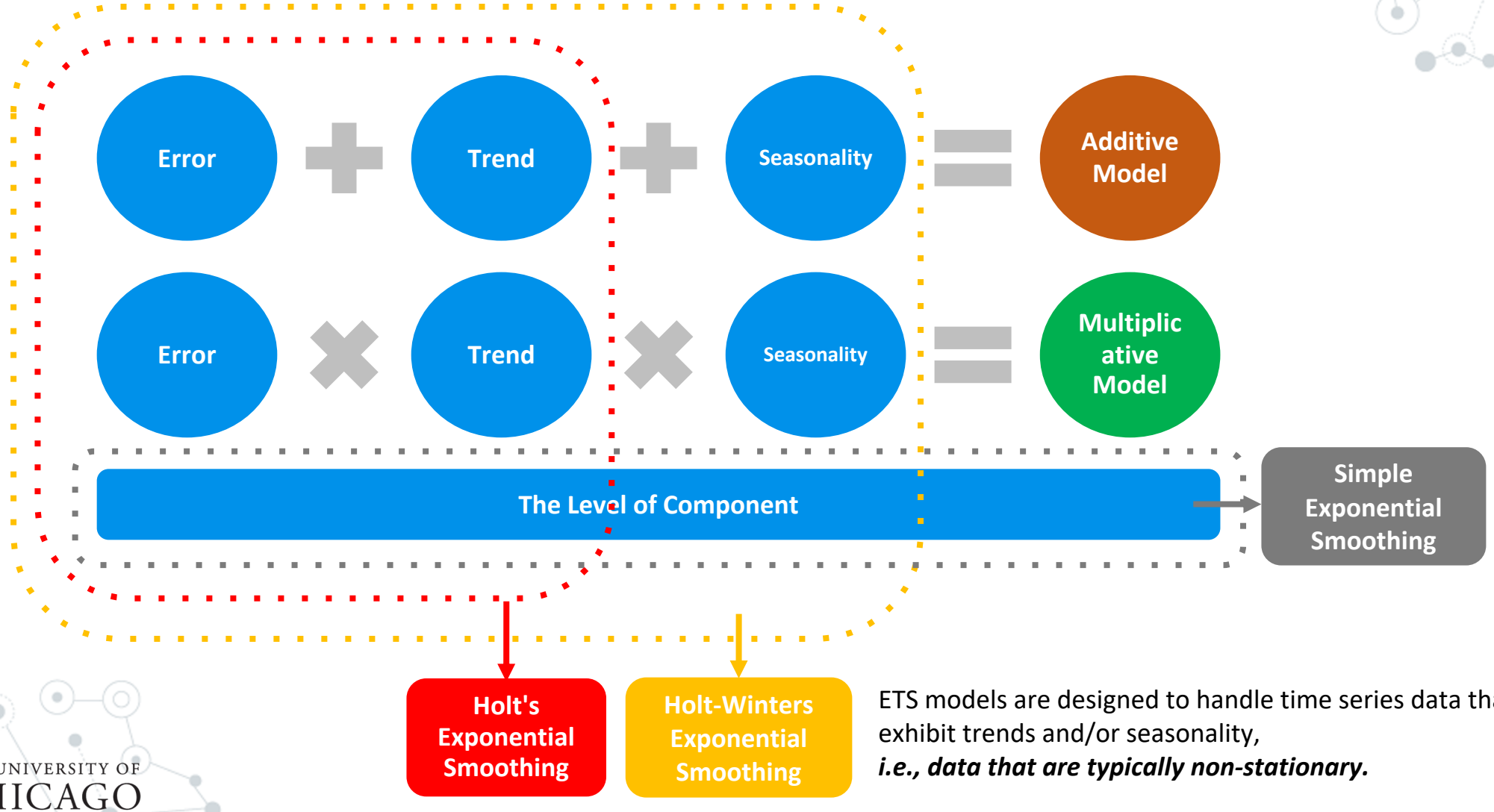
Model Exploration(1) ETS Overview



ETS models are designed to handle time series data that exhibit trends and/or seasonality,
i.e., data that are typically non-stationary.

Model Exploration (1) ETS Before COVID19

TS Models	E/T/S	(α, β, γ)	RMSE (train)	AICc	RMSE (test)	Ljung-Box (P-Value)
Seasonal Naïve	N/A	-	1.527044	-	1.248044	2.2e-16
Simple Exponential Smoothing	(A, N,N)	-	0.9509481	-	1.643461	2.2e-16
Holt's Exponential Smoothing	(A, A,N)	-	0.6488222	-	0.8469332	0.001823
	(A, A_d,N)	-	0.6597823	-	1.105793	0.01986
	(A, M,N)	-	0.5818108	-	0.8660047	0.01154
	(A, M_d, N)	-	0.5807925	-	0.9971667	0.0577
Holt-Winters Exponential Smoothing	(M,A,M)	(0.5353, 1e-04, 2e-04)	0.5906786	851.2826	0.8525379	0.01196
	(A,A,A)	(0.4797, 1e-04, 0.2997)	0.6488222	945.6878	0.8469332	0.001823
	(M,A,A)	(0.5215, 1e-04, 0.206)	0.6566577	884.2588	0.8176148	0.02815
	(M,M,M)	(0.554, 1e-04, 1e-04)	0.5900927	850.9813	0.8680253	0.01866

The Holt-Winters Exponential Smoothing model with (M,A,M) parameters appears to be the best option.
It offers a balanced performance with fairly low training and test RMSE values (0.5906786 and 0.8525379, respectively), a moderate AICc score (851.2826), and a comparatively high Ljung-Box P-value (0.01196), suggesting that its residuals are closer to white noise compared to other models.

Model Exploration (1) ETS After COVID19

TS Models	E/T/S	(α, β, γ)	RMSE(train)	AICc	RMSE(test)	Ljung-Box (P-Value)
Seasonal Naïve	N/A	-	1.926457	-	4.445163	2.2e-16
Simple Exponential Smoothing	(A, N,N)	-	1.118179	-	2.103524	2.2e-16
Holt's Exponential Smoothing	(A, A,N)	-	0.7700349	-	3.432513	0.01716
	(A, A_d,N)	-	0.7972801	-	3.829269	0.0001161
	(A, M,N)	-	0.7014787	-	3.174066	5.467e-05
	(A, M_d, N)	-	0.6975741	-	3.633945	0.0006899
Holt-Winters Exponential Smoothing	(M,A,M)	(0.5311, 1e-04, 1e-04)	0.7294272	1097.287	2.019115	0.004212
	(A,A,A)	(0.4867, 0.0276, 0.346)	0.7700349	1226.677	3.432513	0.01716
	(M,A,A)	(0.5565, 1e-04, 0.2409)	0.773105	1129.110	1.907392	0.06159
	(M,M,M)	(0.5646, 1e-04, 9e-04)	0.7196395	1097.301	2.680248	0.003535

The ETS(M,A,M) model stands out due to its consistently strong performance, as indicated by its favorable AICc and RMSE values for both the training and test sets.

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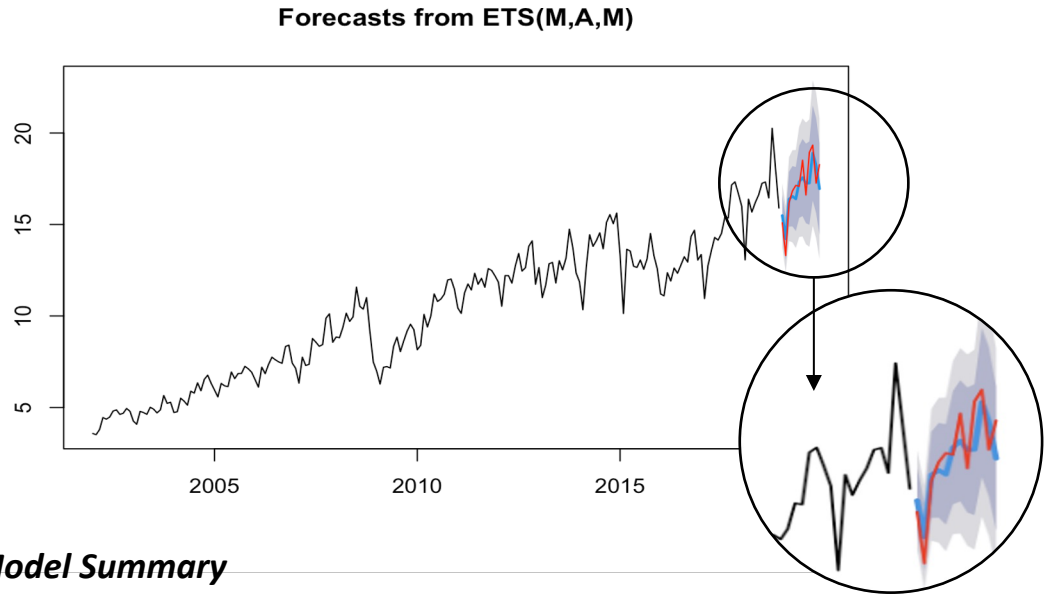
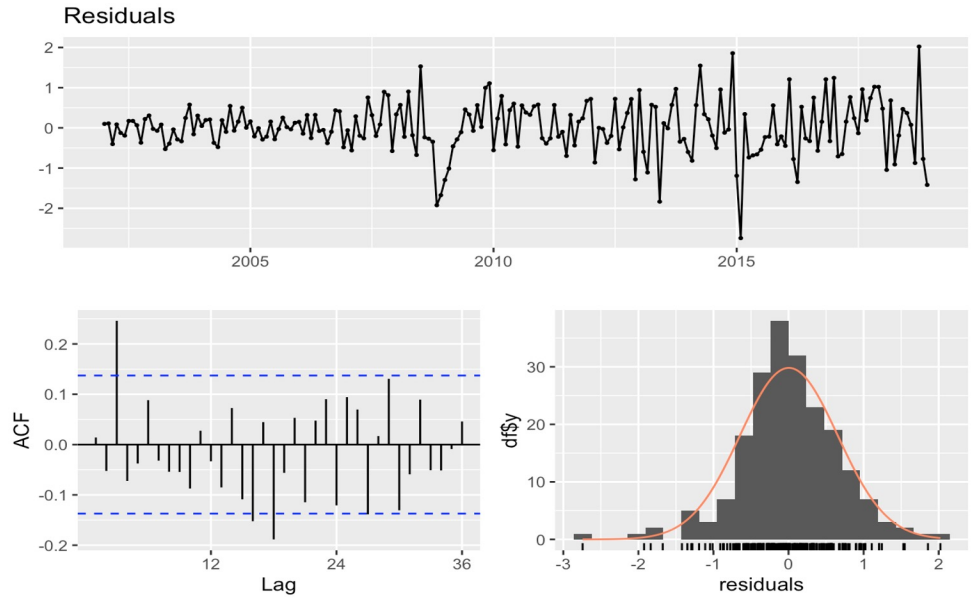
Model Exploration (1) ETS Pre COVID-19



Model Summary

1. ETS(M,A,M): Error(Multiplicative), Trend(Additive), Seasonality(Multiplicative)
2. AICc: 851.2826
3. RMSE: 0.5906786(training), 0.8525379(test)
4. Smoothing Parameters (α, β, γ): (0.5353, 1e-04, 2e-04)



Check Residuals

- Ljung-Box test
- p-value:0.001823 (Total lags used: 24)
- There's autocorrelation in the residuals of a time series model.

Based on the result we see from the Ljung-Box test, this outcome implies that the model fails to sufficiently capture the data's temporal dependencies and inherent patterns.

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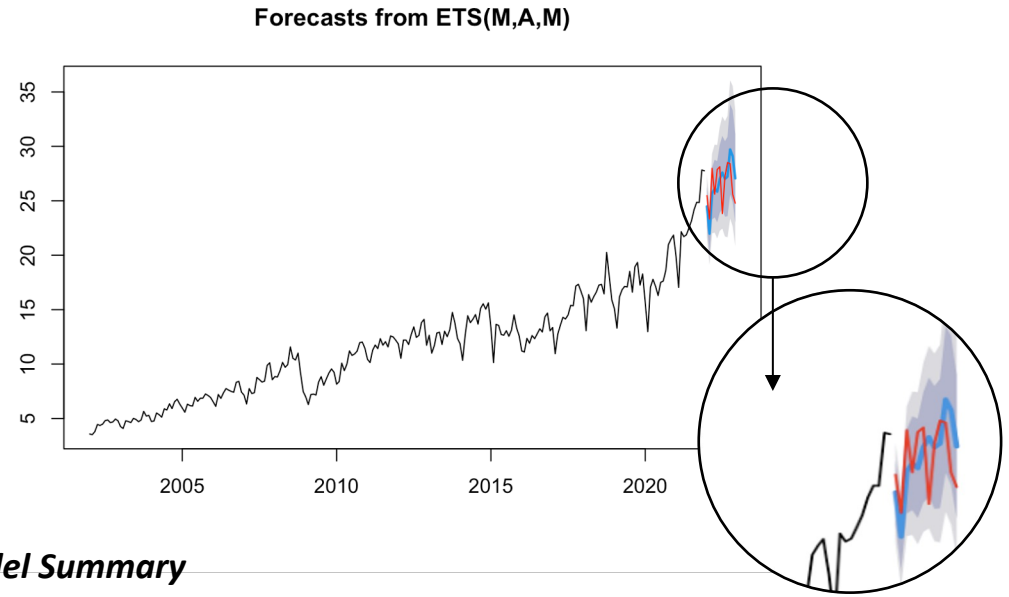
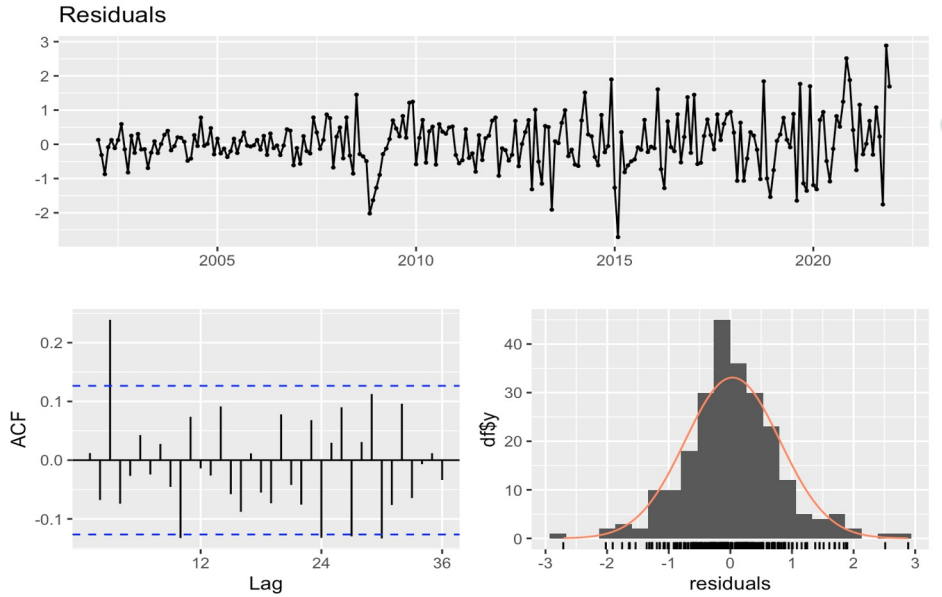
Model Exploration (1) ETS Post COVID-19



Model Summary

1. ETS(M,A,M): Error(Multiplicative), Trend(Additive), Seasonality(Multiplicative)
2. AICc: 1097.287
3. RMSE: 0.7294272 (train); 2.019115 (test)
4. Smoothing Parameters (α, β, γ): (0.5311, 1e-04, 1e-04)



Check Residuals

- Ljung-Box test
- p-value: 0.004212 (Total lags used: 24)
- There's autocorrelation in the residuals of a time series model.

In both predictions before and after the COVID-19 period, the ETS(M,A,M) model consistently outperformed other models. However, we observed a decline in the model's performance when incorporating the COVID-19 pandemic period for prediction.

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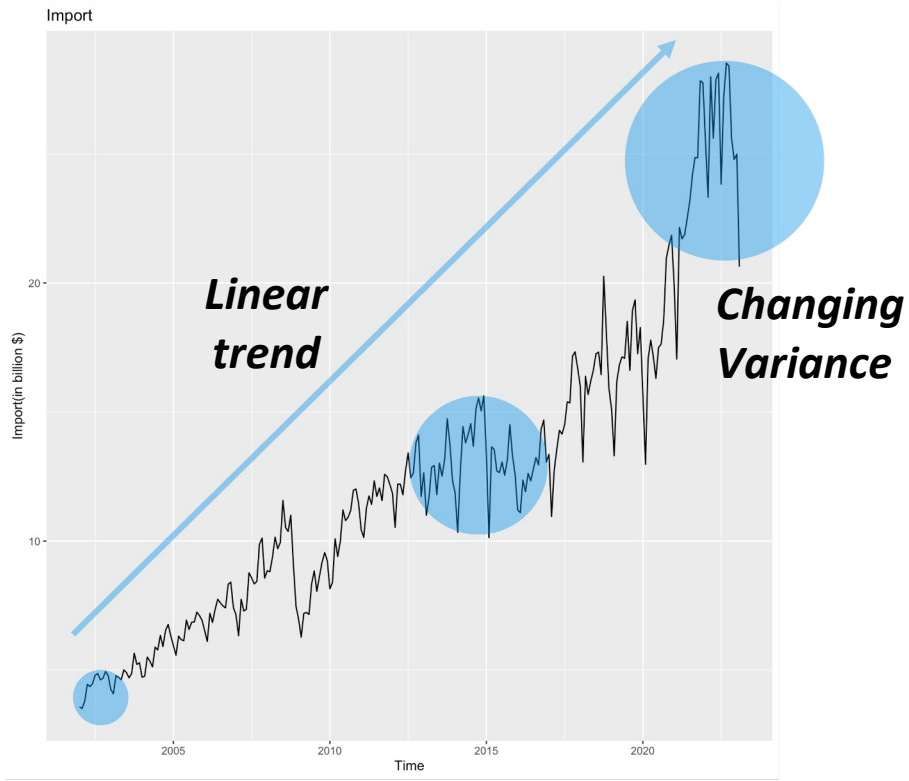
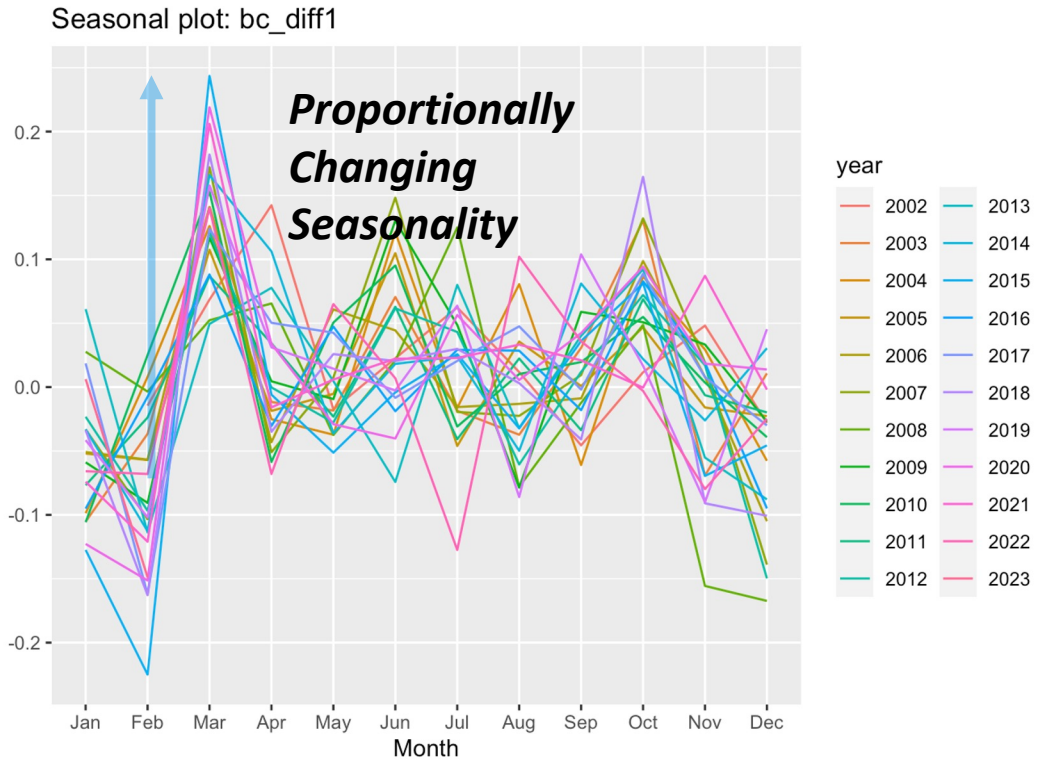
Model Exploration (1) ETS Summary

Model Selection

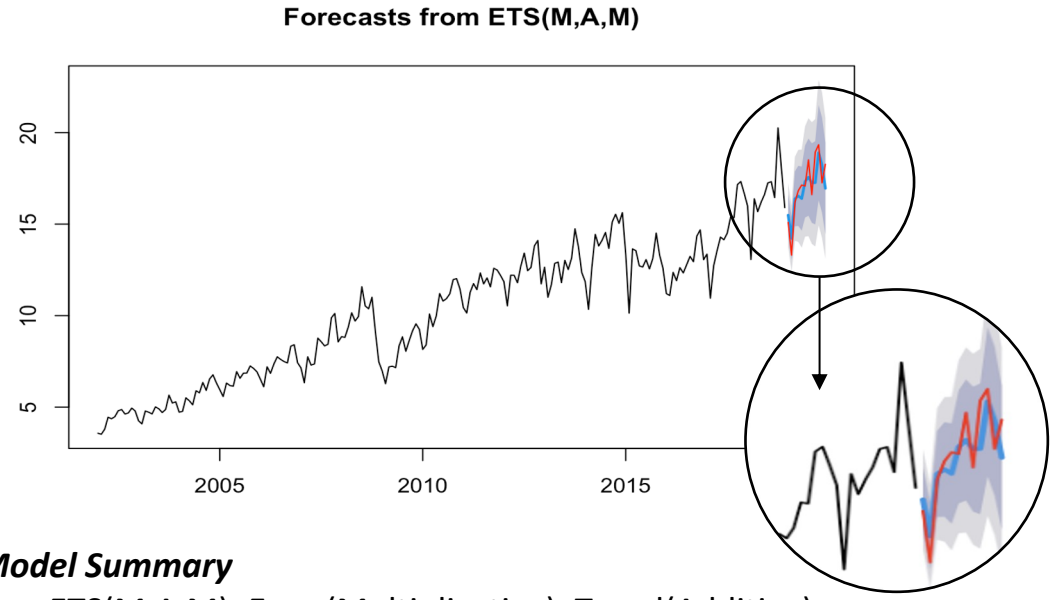
- ***The ETS(M,A,M)*** model is chosen as the best model due to its ability to capture the changing variance over time (Multiplicative Error - M), linear trend (Additive Trend - A), and proportionally changing seasonality pattern (Multiplicative Seasonality - M).





Model Exploration (1) ETS Summary

Pre Covid, ETS(M,A,M)



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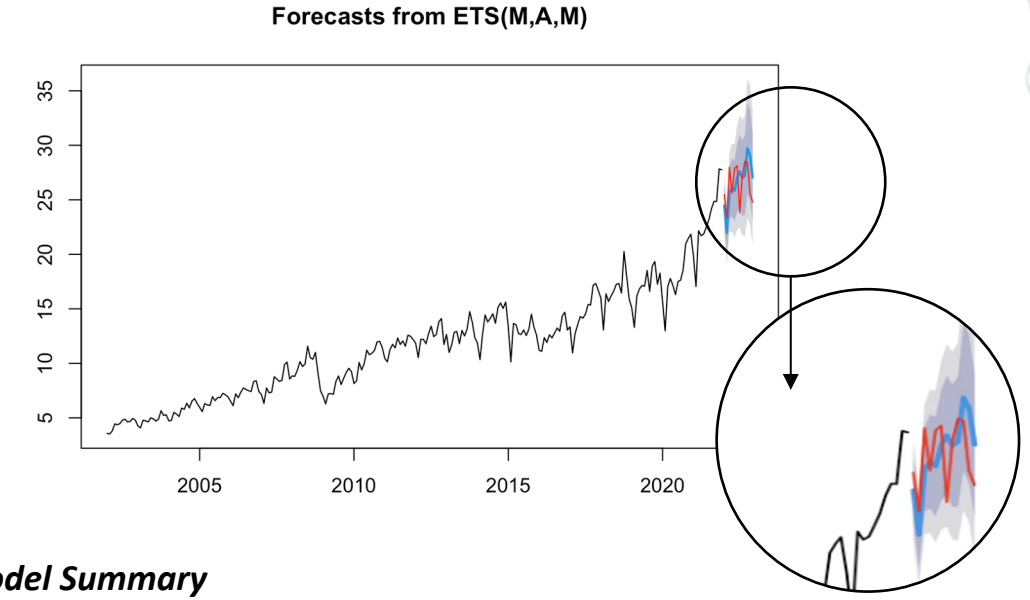
Post Covid, ETS(M,A,M)



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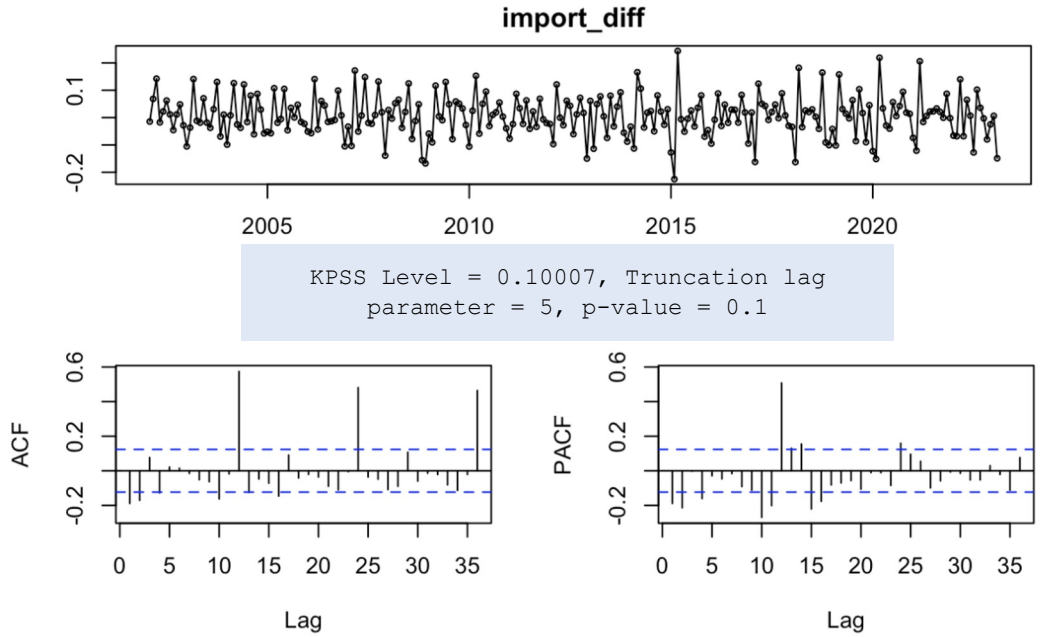
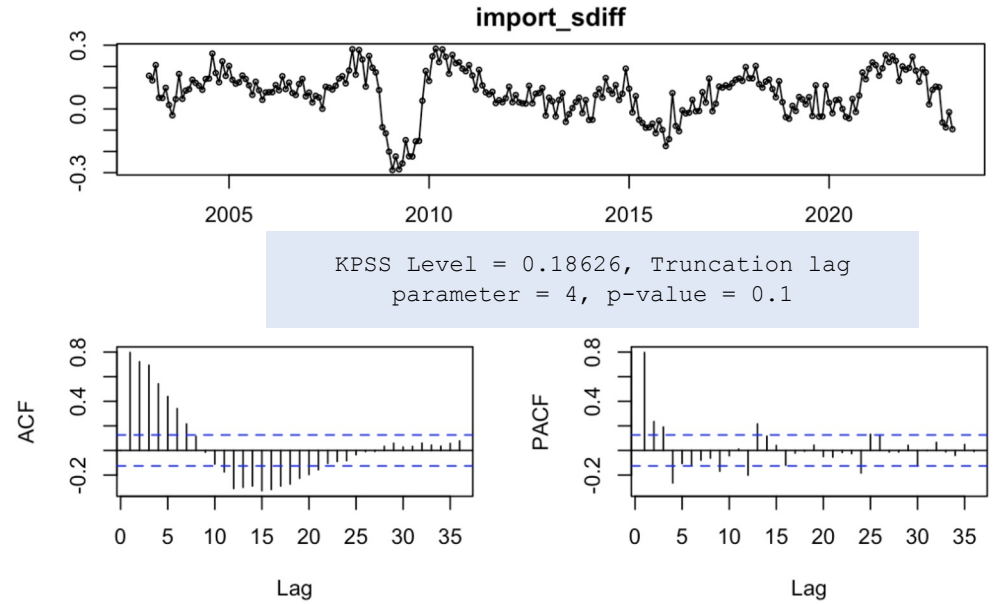
Model Exploration (2) SARIMA

sARIMA Assumption - Time series must be stationary.

d = 1



D = 1



Exploration Method: Auto.Arima() and explore other orders with different differencing.

Model Exploration (2) SARIMA: Pre COVID

No	Model		AICc	RMSE (train)	Ljung-Box (P-Value)	RMSE (test)
	Order (p,d,q)(P,D,Q)[N]	drift				
1	(4,0,0)(1,1,2)[12]	Yes	-470.5	0.5971973	0.4979	0.9223954
2	(4,0,0)(1,1,2)[12]	No	-467.13	0.6043885	0.3191	0.9219941
3	(4,0,0)(0,1,1)[12]	Yes	-474.7	0.5988067	0.6329	0.9224962
4	(4,0,0)(0,1,1)[12]	No	-471.38	0.6054706	0.4527	0.9207406
5	(3,0,1)(0,1,1)[12]	Yes	-471.64	0.5991217	0.199	0.9189453
6	(3,0,1)(0,1,1)[12]	No	-469.23	0.6053335	0.1559	0.8641353
7	(2,0,3)(0,1,1)[12]	Yes	-470.98	0.6009981	0.2485	0.9144917
8	(2,0,3)(0,1,1)[12]	No	-467.07	0.6086834	0.142	0.9842110
9	(4,1,0)(1,0,2)[12]	Yes	N/A	N/A	N/A	N/A
10	(4,1,0)(0,0,1)[12]	Yes	-402.05	0.8027907	4.839e-08	1.1848420
11	(3,1,1)(0,0,1)[12]		-402.36	0.8038033	6.836e-08	1.5335435
12	(2,1,0)(1,0,0)[12]	Yes	-440.15	0.7246152	0.0006764	1.0411485

← from Auto.Arima()

Guide for exploration:

1. tsdisplay()
2. Extended Autocorrelation Function [eacf()]

```
AR/MA
  0 1 2 3 4 5 6 7 8 9 10 11 12 13
0 x x x x x x x x x x  x  x  x
1 x x o x o o o o o o  o  x  o  o
2 x x o x o o o o o o  o  x  o  o
3 o x o x o o o o o o  o  x  x  o
4 o x x x o o o o o o  o  x  x  o
5 x o x x o o o o o o  o  x  o  x
6 x o o x o o o o o o  o  x  o  x
7 x o o x o o o o o o  o  x  o  x
```

1. Significance of parameter
2. CheckResiduals()

Model Exploration (2) SARIMA: Post COVID

No	Model		AICc	RMSE (train)	Ljung-Box (P-Value)	RMSE (test)
	Order (p,d,q)(P,D,Q)[N]	drift				
1	(4,0,0)(1,1,2)[12]	Yes	-701.41	0.706554	0.5409	2.365628
2	(4,0,0)(1,1,2)[12]	No	-697.64	0.7151124	0.3938	2.8653706
3	(4,0,0)(0,1,1)[12]	Yes	-705.38	0.7090993	0.6448	2.3751877
4	(4,0,0)(0,1,1)[12]	No	-701.72	0.7170508	0.5179	2.8429648
5	(3,0,2)(0,1,1)[12]	Yes	-701.83	0.7106919	0.4118	2.4440392
6	(3,0,2)(0,1,1)[12]	No	-698.7	0.718369	0.3459	2.797201
7	(2,0,3)(1,1,2)[12]	Yes	-698.84	0.7060893	0.2978	2.3099154
8	(2,0,3)(1,1,2)[12]	No	-694.07	0.7166455	0.1551	2.9972462
9	(4,1,0)(1,0,2)[12]	Yes	N/A	N/A	N/A	N/A
10	(4,1,0)(0,0,1)[12]	Yes	-613.83	0.9223215	1.108e-10	2.6477560
11	(2,1,3)(1,0,2)[12]	Yes	-723.26	0.7174144	0.2935	3.1392563
12	(2,1,0)(1,0,0)[12]	Yes	-664.68	0.819143	0.0005101	4.117066

← from Auto.Arima()

Guide for exploration:

1. tsdisplay()
2. Extended Autocorrelation

1. Significance of parameter
2. CheckResiduals()

Model Exploration (2) Best SARIMA Model

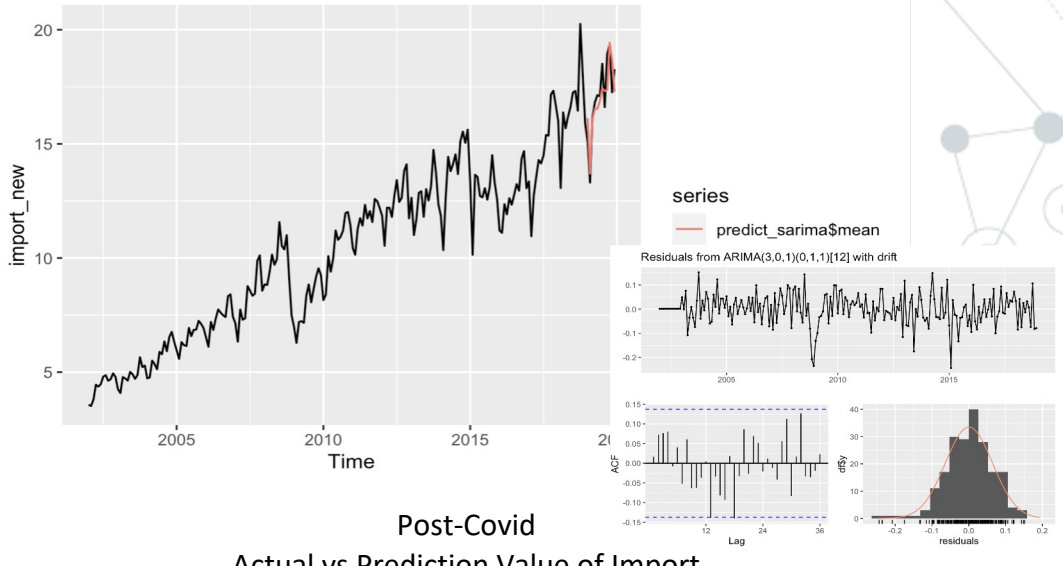
Period	Best sARIMA Model		RMSE (test)
	Order (p,d,q)(P,D,Q)[N]	drift	
Pre-COVID	(3,0,1)(0,1,1)[12]	Yes	0.8641353
Post-COVID	(2,0,3)(1,1,2)[12]	No	2.3099154

Period	Base Model	RMSE (test)
Pre-COVID	Seasonal Naive Forecast	1.248044
Post-COVID	Naive Forecast	2.235439

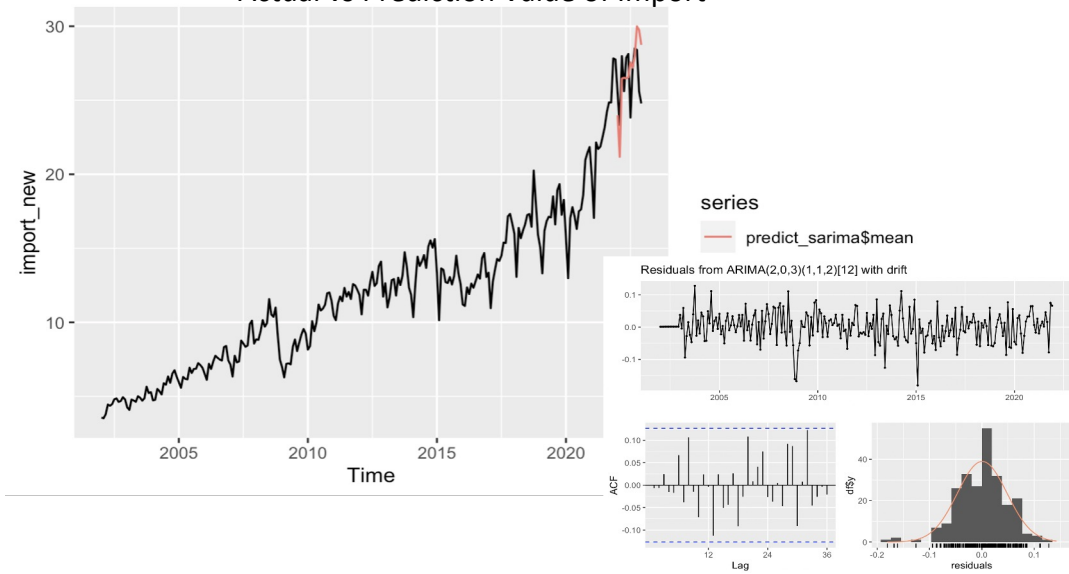
Notes:

- For Pre-COVID, Arima forecast is better than the base model.
- For Post-COVID, Arima forecast is worse than the base model.
- COVID era changes the data generating process that could not be accounted by Arima Model.

Pre-Covid
Actual vs Prediction Value of Import



Post-Covid
Actual vs Prediction Value of Import



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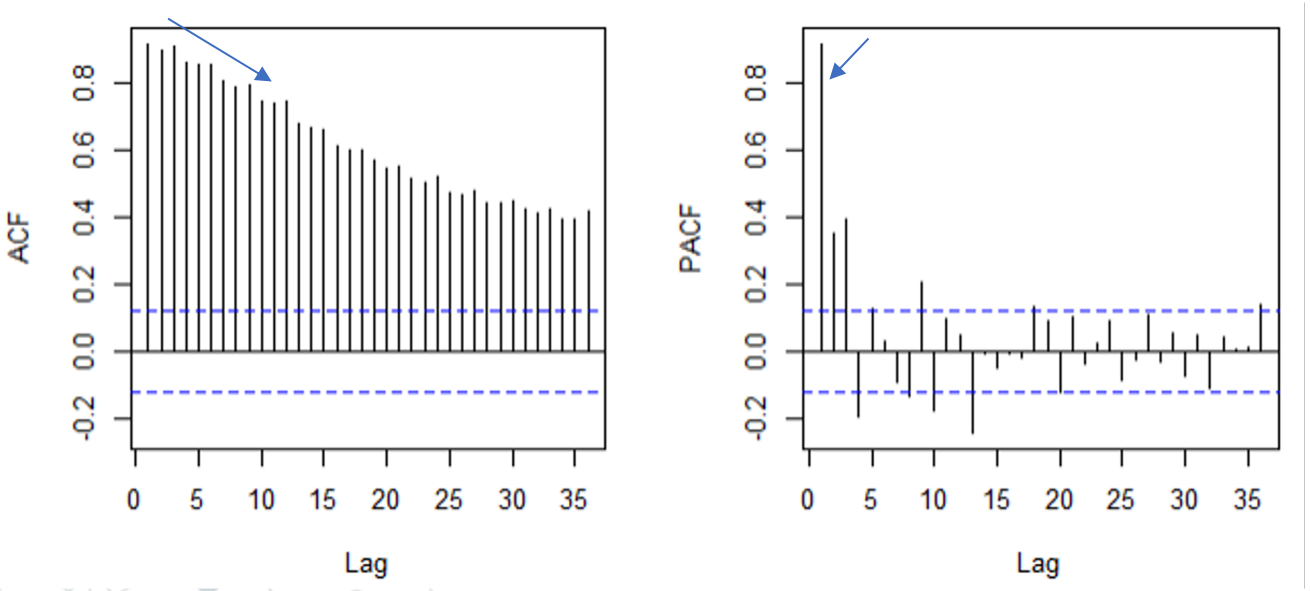
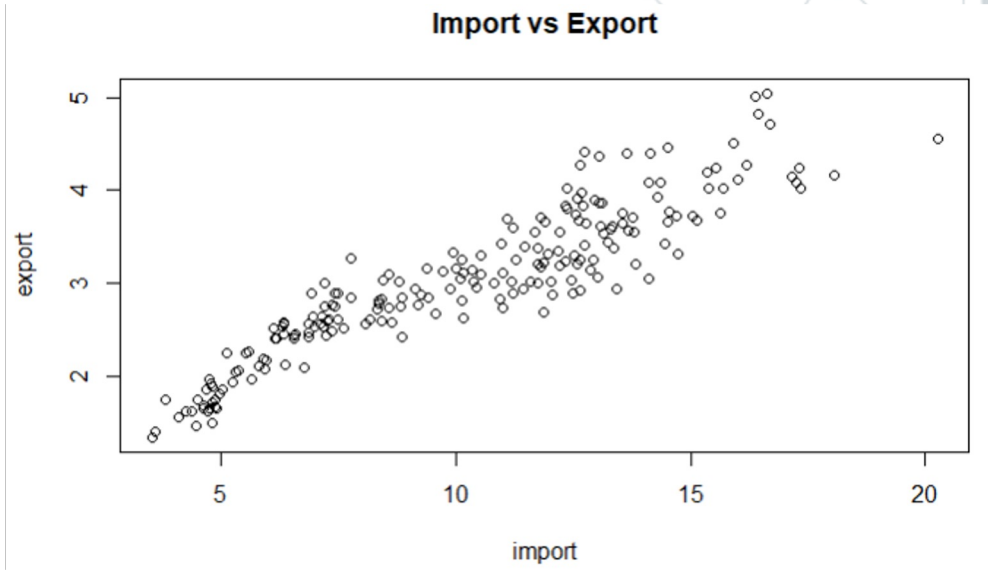
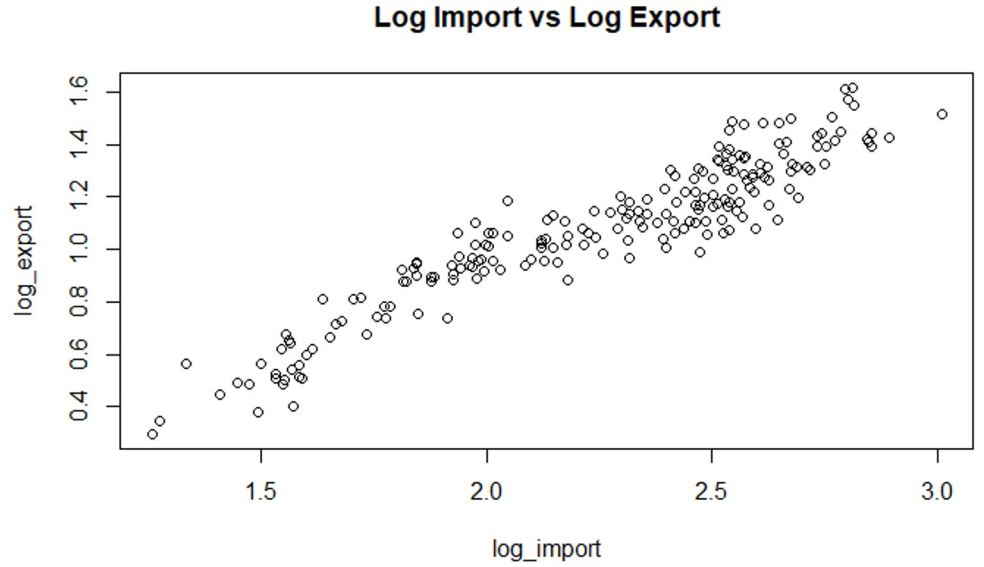
Model Exploration (3) Regression with ARIMA error

Export as the explanatory variable

- Choosing Export as the covariate for the model
- Strong correlation with Import (95.65%)







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Model Exploration (3) Regression with ARIMA error

Pre COVID (2019)

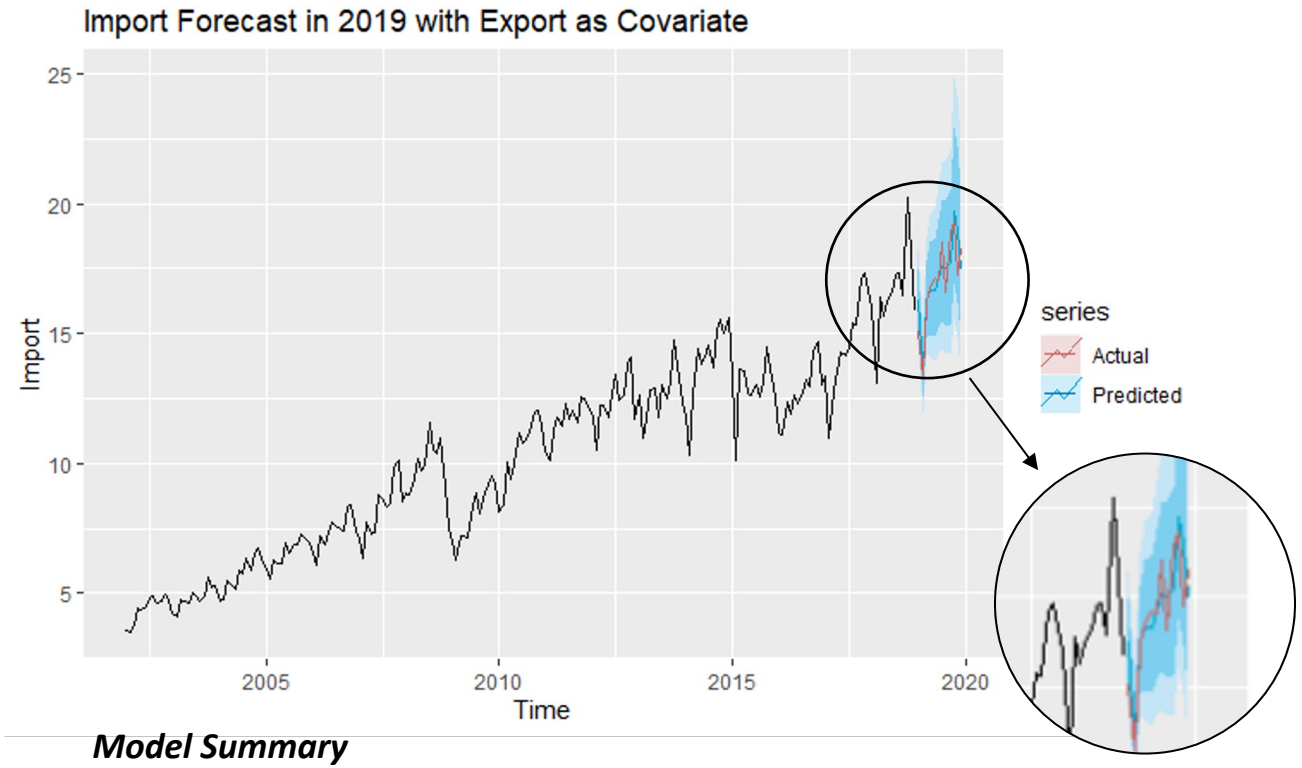
from Auto.Arima()

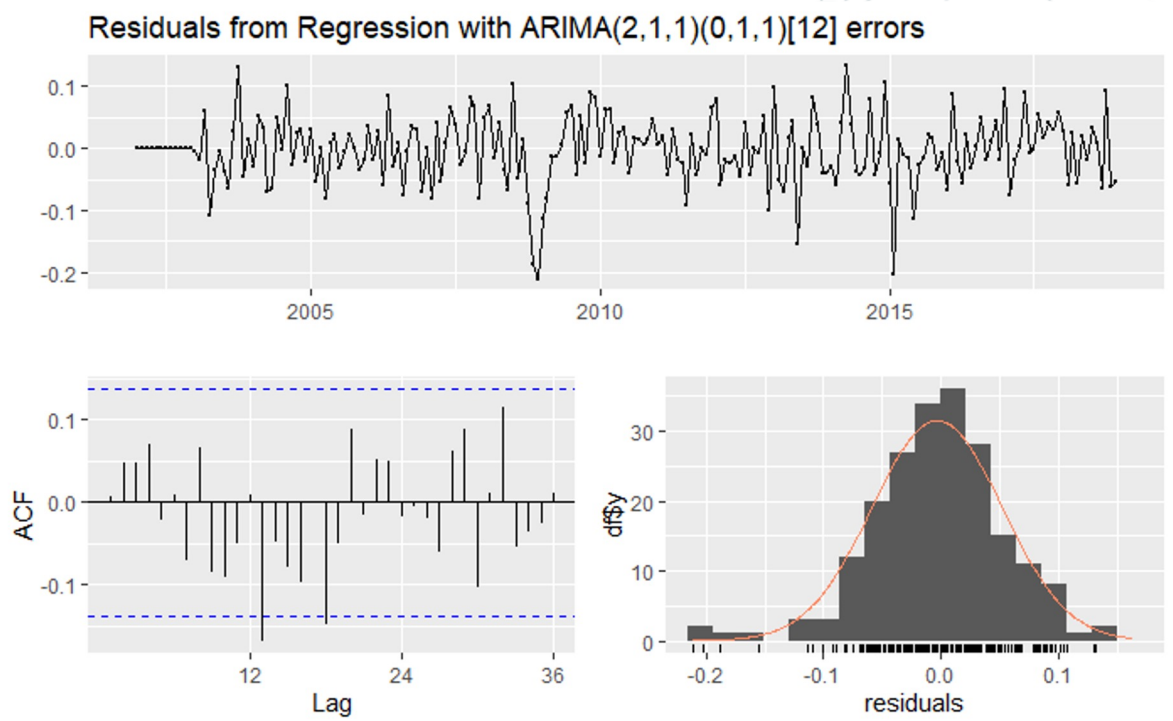
No	Model Order (p,d,q)(P,D,Q)[N]	AICc	RMSE (train)	P-Value (Ljung-Box)
1	(1,0,3)(1,1,2)[12]	-523.6	0.05479793	0.1094
2	(1,0,3)(1,1,1)[12]	-520.98	0.05567779	0.05388
3	(1,0,3)(0,1,1)[12]	-522.96	0.05574829	0.05427
4	(1,1,3)(0,1,1)[12]	-522.42	0.05547876	0.1040
5	(1,0,4)(1,1,2)[12]	-519.15	0.05539141	0.08216
6	(1,0,4)(1,1,1)[12]	-521.08	0.05544364	0.1108
7	(2,1,0)(1,1,1)[12]	-521.39	0.05571836	0.01013
8	(2,1,1)(0,1,1)[12]	**-525.53**	0.05535418	0.1381
9	(2,1,2)(1,1,1)[12]	-522.36	0.05523922	0.1837
10	(2,1,2)(1,1,2)[12]	-520.24	0.05522163	0.1297

Best model

Model Exploration (3) Best Regression with ARIMA error

Model Pre COVID





Model Summary

Regression with ARIMA(2,1,1)(0,1,1)[12] errors

AICc: -525.53

RMSE (train): 0.0554

RMSE (test): 0.8446

Check Residuals

Ljung-Box test: p-value = 0.1381, Total lags used: 24

Autocorrelations still exist

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Model Exploration (3) Regression with ARIMA error

Post COVID (2022)

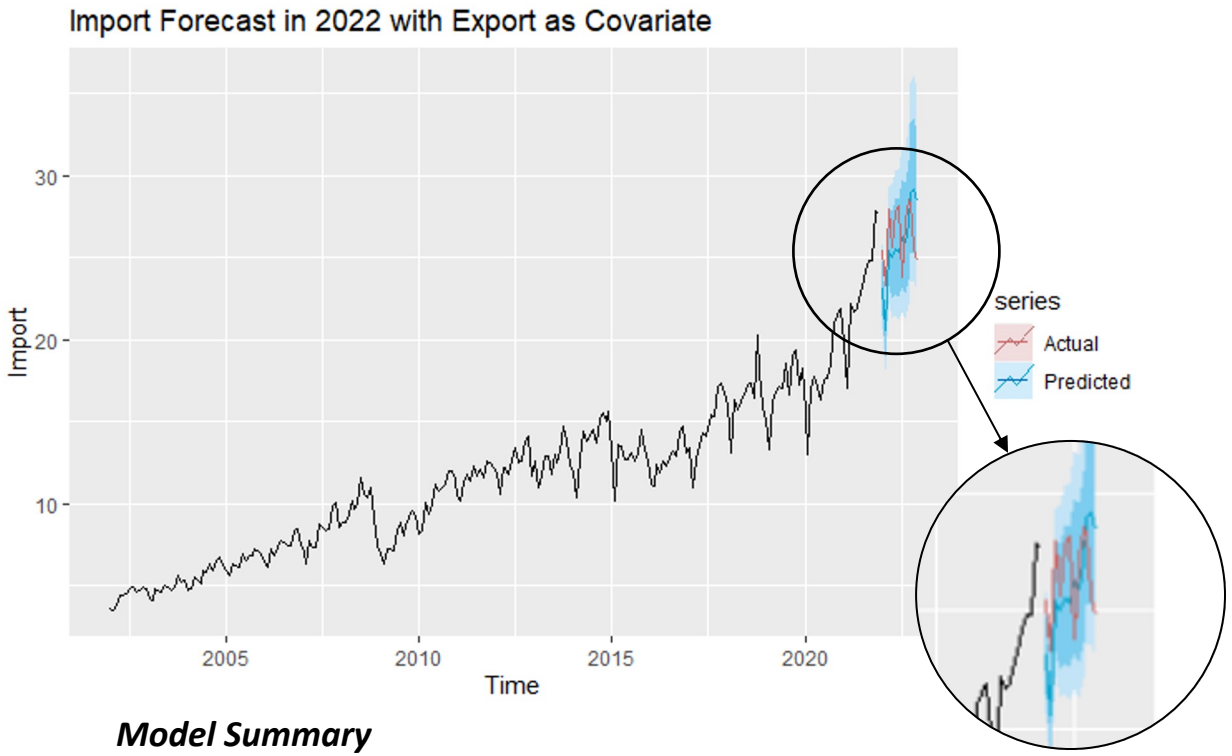
from Auto.Arima()

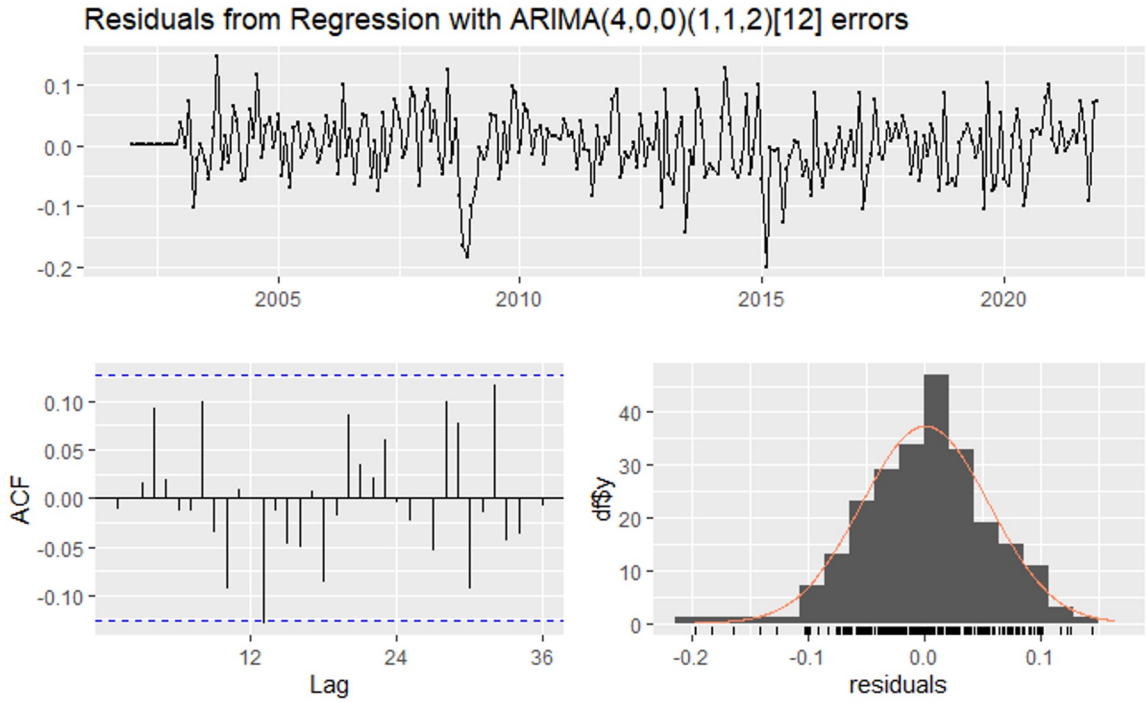
No	Model Order (p,d,q)(P,D,Q)[N]	AICc	RMSE (train)	P-Value (Ljung-Box)
1	(4,0,0)(1,1,2)[12]	**-633.24**	0.05469901	0.3682
2	(2,0,2)(0,1,1)[12]	-614.46	0.05751704	5.092e-05
3	(3,0,1)(0,1,1)[12]	-631.27	0.05553935	0.1713
4	(3,0,1)(1,1,1)[12]	-629.13	0.05553744	0.1362
5	(3,1,0)(0,1,1)[12]	-632.84	0.0553475	0.4102
6	(3,1,1)(0,1,1)[12]	-630.85	0.0553253	0.3841
7	(4,0,0)(0,1,1)[12]	-632.58	0.0554282	0.3754
8	(4,1,1)(1,1,1)[12]	-628.49	0.05483743	0.232
9	(5,0,0)(0,1,1)[12]	-630.49	0.05541923	0.3311
10	(5,1,1)(0,1,1)[12]	-627	0.05525888	0.2825

Best model

Model Exploration (3) Best Regression with ARIMA error

Model Post COVID





Model Summary

Regression with ARIMA(4,0,0)(1,1,2)[12] errors

AICc: -633.24

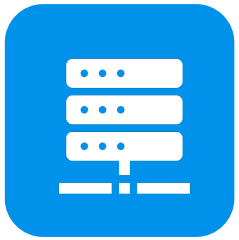
RMSE (train): 0.0547

RMSE (test): 2.3918

Check Residuals

Ljung-Box test: p-value = 0.3682, Total lags used: 24

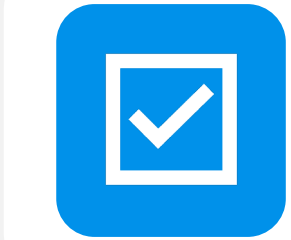
Model Exploration (4) Building VAR Model



01

Create Stationary Data

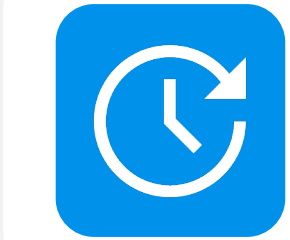
ADF & KPSS Test
Log Diff Method



02

Select Variables

Granger Causality
Cross Correlation



03

Select Optimal Lag

Var Select
Serial Test

04

Model Comparison

AICc

Model Exploration (4) VAR Model: Select Variables

Granger Causality

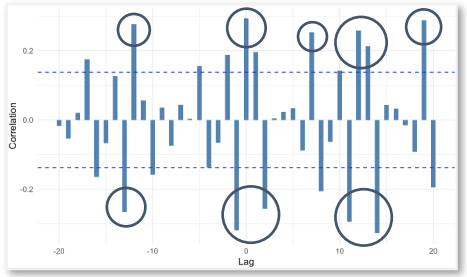
Pre Covid

Variables	P value	Significant
EXPORT	0.00012	Caused
CPI	0.00045	Caused
PPI	0.00064	Caused
…	…	…
UNCERTAINTY	0.39899	Not Caused

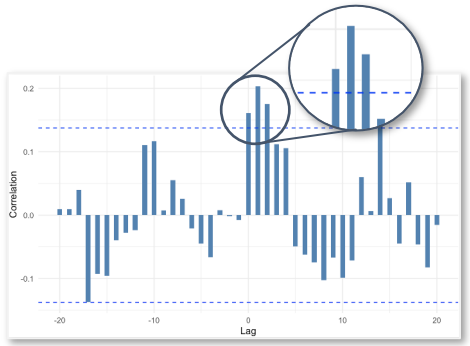
Post Covid

Variables	P value	Significant
EXPORT	0.00000	Caused
CPI	0.00052	Caused
PPI	0.00141	Caused
…	…	…
UNCERTAINTY	0.27819	Not Caused

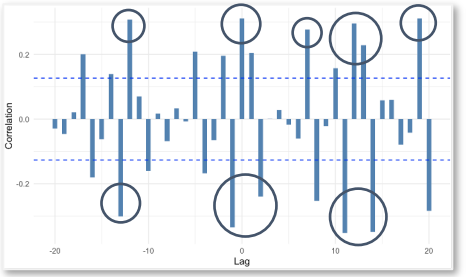
Cross Correlation



< Import vs. Export >



< Import vs. PPI >



< Import vs. Export >

< Import vs. PPI >

Model Exploration (4) VAR Model: Select Optimal Lags

VAR Select

Pre Covid

AIC (n)	HQ (n)	SC (n)	FPE (n)
2	2	2	2

Post Covid

AIC (n)	HQ (n)	SC (n)	FPE (n)
2	2	2	2

Serial Test

Lags	P-value	Autocorrelation
2	0.0969	Not Autocorrelated
3	0.1252	Not Autocorrelated
4	0.19486	Not Autocorrelated
5	0.22673	Not Autocorrelated

Lags	P-value	Autocorrelation
2	0.03088	Autocorrelated
3	0.0337	Autocorrelated
4	0.02565	Autocorrelated
5	0.12602	Not Autocorrelated
6	0.07209	Not Autocorrelated
7	0.0404	Autocorrelated

Model Exploration (4) VAR Model Comparison

Pre Covid

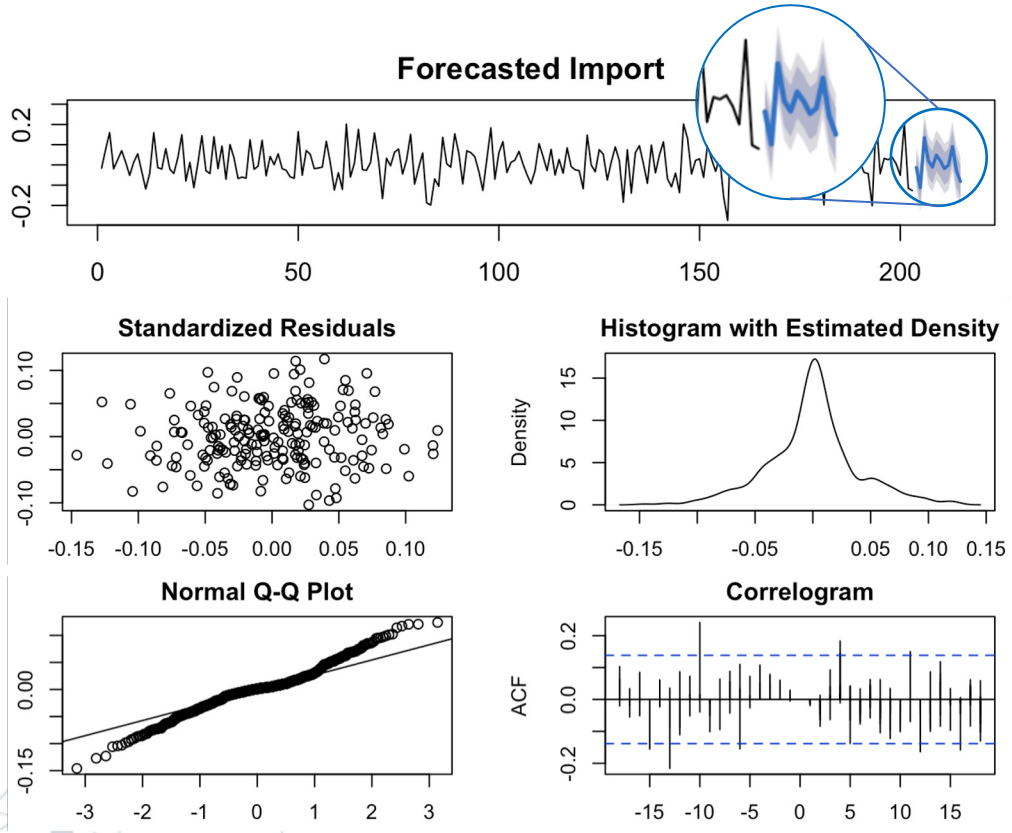
Lags	MAE	MSE	RMSE	AICc	MAPE
2	0.7923706	0.9031720	0.9503536	**-2487.399**	0.04560345
3	0.7850147	0.8518980	0.9229832	-2469.384	0.04571006
4	0.7846202	0.7942794	0.8912235	-2545.401	0.04620134
5	0.8424218	0.9754128	0.9876299	-2433.698	0.04900531

Post Covid

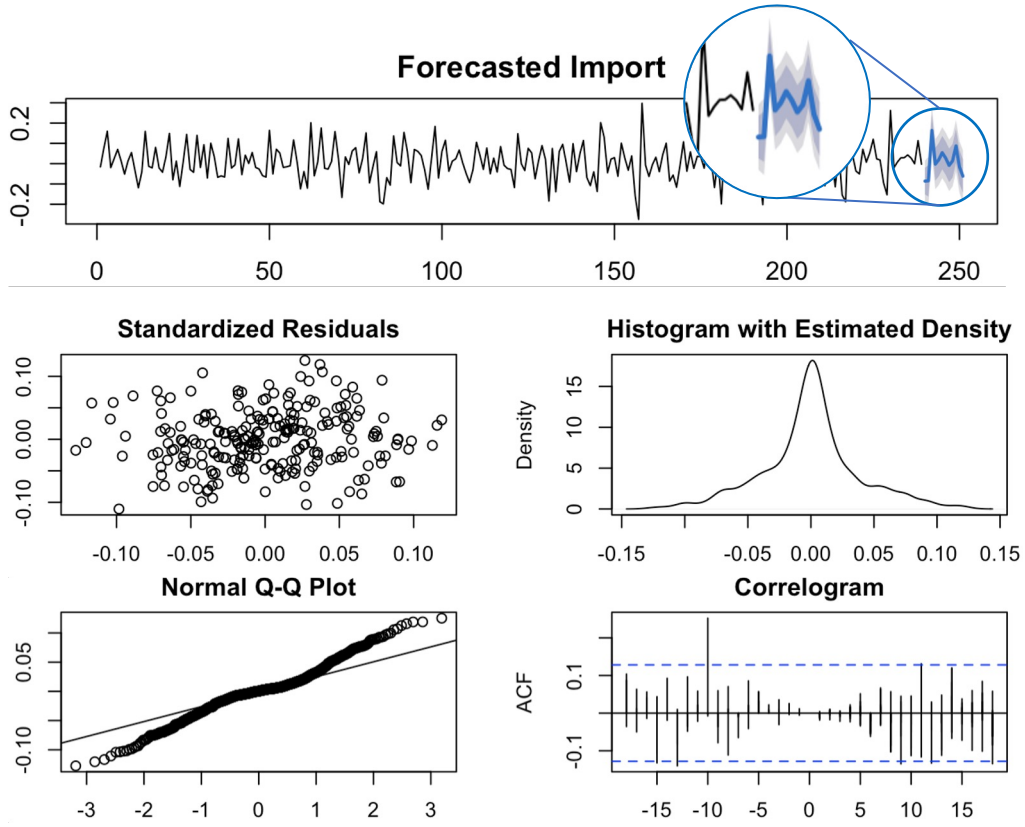
Lags	MAE	MSE	RMSE	AICc	MAPE
5	2.823877	14.67617	3.830949	**-2858.115**	0.1091495
6	2.517569	11.59846	3.405651	-2833.328	0.0974212

Model Exploration (4) VAR Model Comparison

Pre Covid, VAR(2)



Post Covid, VAR(5)



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Model Selection

Best Model:

- Pre COVID forecast (2019): Regression with ARIMA Errors (2,1,1)(0,1,1)[12]
- Post COVID forecast (2022): ETS (M,A,M).

Pre COVID (2019)

Models	RMSE
ETS	0.8525
SARIMA	0.8641
Regression with ARIMA errors	0.8446
VAR	0.9504

Post COVID (2022)

Models	RMSE
ETS	2.0191
SARIMA	2.3099
Regression with ARIMA errors	2.3918
VAR	3.8309

Conclusion and Future Work

Conclusion: Performance of models **reduced** after the COVID-19 period.

- Increased Volatility: Higher volatility and uncertainty were introduced in 2020, making time series models less accurate.
- Model Overfitting: Potential overfitting to the data from 2002-2018 leads to poor generalization when encountering the unique patterns of the 2019-2021 period.
- Seasonality Impact: Increased importance of seasonality during and after the pandemic due to lockdowns, reopening, and changing consumer behavior.

Future Work:

- Examine additional potential explanatory variables.
- Try forecasting using other models (e.g., TBATS, Dynamic Harmonic Regression, ARCH/GARCH, etc.).
- Build the model and forecast based on the industry.

THANK YOU