137 Project

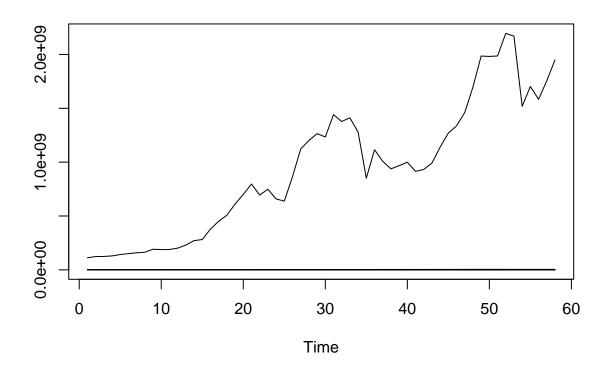
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2025-05-30

```
# Load required libraries
library(tidyverse) # For data manipulation and visualization
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
           1.1.4
## v dplyr
                       v readr
                                    2.1.5
## v forcats
              1.0.0
                        v stringr
                                    1.5.1
## v ggplot2 3.5.1
                       v tibble
                                    3.2.1
## v lubridate 1.9.3
                        v tidyr
                                    1.3.1
## v purrr
              1.0.2
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                    masks stats::lag()
## i Use the conflicted package (<a href="http://conflicted.r-lib.org/">http://conflicted.r-lib.org/</a>) to force all conflicts to become error
library(forecast)
                       # For Box-Cox transformation and time series analysis
## Registered S3 method overwritten by 'quantmod':
    method
                      from
    as.zoo.data.frame zoo
library(tseries)
                   # For additional time series functions
library(ggplot2)
                       # For plotting
library(carData)
library(car)
##
## Attaching package: 'car'
## The following object is masked from 'package:dplyr':
##
##
      recode
##
## The following object is masked from 'package:purrr':
##
##
       some
```

Time Series Plot for the Data

```
load("finalproject.Rdata")
ts.plot(finalPro_data)
```



Quick look:

- Upward trend
- Some fluctuations and short-term volatility
- $\bullet \ \ {\rm Non\text{-}stationary}$

GDP Model

Summary GDP

```
# 1. Diagnose model for GDP
model_gdp <- lm(GDP ~ Year + Growth + CPI + Imports + Exports + Population, data = finalPro_data)
summary(model_gdp)

##
## Call:
## lm(formula = GDP ~ Year + Growth + CPI + Imports + Exports +
## Population, data = finalPro_data)</pre>
```

```
##
## Residuals:
                            Median
##
                     1Q
                                                     Max
## -355647077 -123917222
                          18740212 114338509 328824034
##
## Coefficients:
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.704e+11 1.190e+11 -2.272
                                              0.0307 *
              1.394e+08 6.097e+07
## Year
                                      2.286
                                              0.0297 *
## Growth
               6.543e+06 4.960e+06
                                      1.319
                                              0.1974
## CPI
              -9.881e+06 4.121e+06 -2.398
                                              0.0231 *
## Imports
               1.590e+07
                          1.088e+07
                                      1.461
                                              0.1548
              -7.174e+07 1.240e+07 -5.784 2.89e-06 ***
## Exports
## Population -1.470e+03 7.621e+02 -1.928
                                              0.0636 .
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
##
## Residual standard error: 194300000 on 29 degrees of freedom
    (22 observations deleted due to missingness)
## Multiple R-squared: 0.8316, Adjusted R-squared: 0.7967
## F-statistic: 23.87 on 6 and 29 DF, p-value: 5.499e-10
```

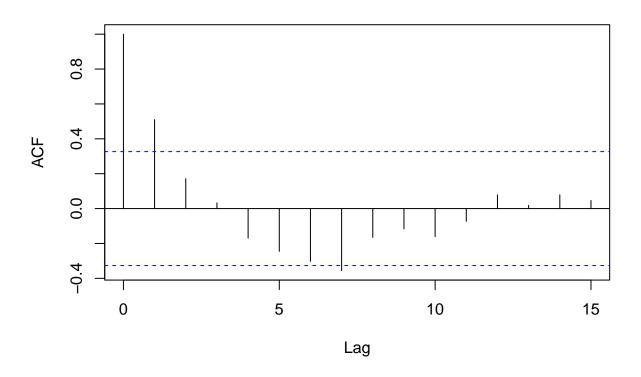
• Significant variables: Year, Exports

Residuals Diagnostic

ACF and Ljung-Box

```
#ACF GDP
acf(residuals(model_gdp), main="ACF of Residuals GDP")
```

ACF of Residuals GDP



```
# L-jung-box
Box.test(residuals(model_gdp), lag = 20, type = "Ljung-Box")
```

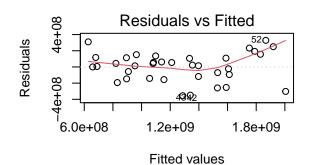
```
##
## Box-Ljung test
##
## data: residuals(model_gdp)
## X-squared = 32.013, df = 20, p-value = 0.04316
```

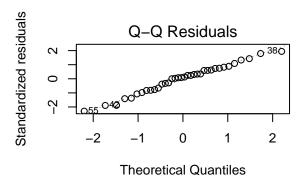
Quick look:

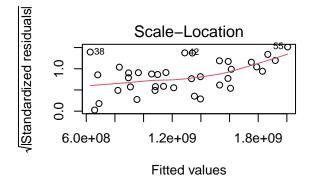
- Autocorrelation remains positive before approaching zero
- The pattern shows strong autocorrelation and persistence in the residuals
- Slow decay -> the data is non-stationary or trending series

Plot GDP

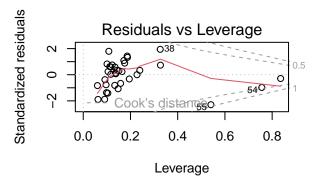
```
# Diagnostic plots for GDP model
par(mfrow = c(2,2))
plot(model_gdp)
```







Shapiro-Wilks for GDP



```
ei_gdp = model_gdp$residuals
the.SWtest_gdp = shapiro.test(ei_gdp)
the.SWtest_gdp
##
##
    Shapiro-Wilk normality test
##
## data: ei_gdp
## W = 0.97508, p-value = 0.5794
# Brown/Levene test
# Extract residuals from your model
res <- residuals(model_gdp)</pre>
# Make a grouping variable (e.g., you can split by median fitted value)
fit <- fitted(model_gdp)</pre>
group <- ifelse(fit > median(fit), "High", "Low")
# Levene's Test (Brown-Forsythe is a median-centered version of Levene's test)
```

Warning in leveneTest.default(y = y, group = group, ...): group coerced to ## factor.

leveneTest(res ~ group, center=median) # Brown-Forsythe test

Quick note:

- Residuals vs fitted: looks good, no obvious pattern suggests linearity
- QQ plot: residuals are close to the line, suggests approximately normally distributed
- Scale-Location: slightly upward trend, meaning the variance of errors is not constant
- Residuals vs Leverage: most points have low leverage so this is good
- Shapiro-Wilk test: W = 0.98882, p-value = 0.8709 -> met normality assumption
- Brown test: p-value = 0.002518, so constant variance assumption is not met

Recommendations:

• Transforming the dependent variable; considering Box-Cox or log transformation

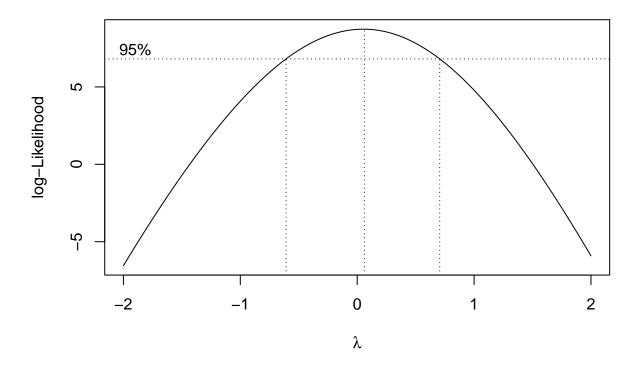
Box-Cox for GDP (Draft)

```
library(MASS)

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
## select

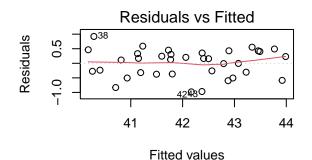
# Perform Box-Cox transformation
bc <- boxcox(model_gdp, lambda = seq(-2, 2, by = 0.1))</pre>
```

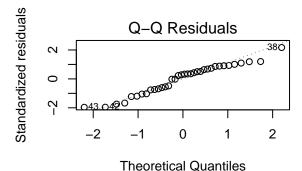


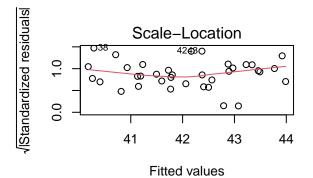
```
# Find the best lambda
best_lambda <- bc$x[which.max(bc$y)]</pre>
\#cat("Best\ lambda:",\ best\_lambda,\ "\n")
# Refit using the Box-Cox transformed GDP:
finalPro_data$GDP_boxcox <- (finalPro_data$GDP^best_lambda - 1) / best_lambda</pre>
model_gdp_boxcox <- lm(GDP_boxcox ~ Year + Growth + CPI + Imports + Exports + Population, data = finalP.
summary(model_gdp_boxcox)
##
## Call:
## lm(formula = GDP_boxcox ~ Year + Growth + CPI + Imports + Exports +
##
       Population, data = finalPro_data)
##
## Residuals:
##
       Min
                1Q Median
                                3Q
                                       Max
## -0.9805 -0.3315 0.1426 0.3662 0.9210
##
## Coefficients:
##
                 Estimate Std. Error t value Pr(>|t|)
## (Intercept) -8.288e+02 3.168e+02 -2.616 0.01398 *
                4.474e-01 1.623e-01
## Year
                                       2.757 0.00999 **
## Growth
                1.540e-02 1.320e-02
                                       1.166
                                               0.25295
## CPI
               -2.445e-02 1.097e-02 -2.229 0.03373 *
## Imports
               1.188e-02 2.898e-02
                                       0.410 0.68487
               -1.901e-01 3.302e-02 -5.755 3.12e-06 ***
## Exports
```

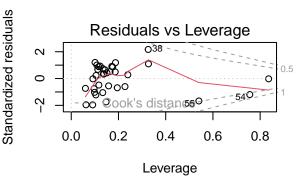
```
## Population -5.099e-06 2.029e-06 -2.513 0.01777 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5172 on 29 degrees of freedom
## (22 observations deleted due to missingness)
## Multiple R-squared: 0.847, Adjusted R-squared: 0.8154
## F-statistic: 26.76 on 6 and 29 DF, p-value: 1.41e-10

par(mfrow = c(2,2))
plot(model_gdp_boxcox)
```









```
# Check variance again
res_boxcox <- residuals(model_gdp_boxcox)

# Make a grouping variable
fit_boxcox <- fitted(model_gdp_boxcox)
group_boxcox <- ifelse(fit_boxcox > median(fit_boxcox), "High", "Low")

# Levene's Test (Brown-Forsythe is a median-centered version of Levene's test)
leveneTest(res_boxcox ~ group_boxcox, center=median) # Brown-Forsythe test
```

Warning in leveneTest.default(y = y, group = group, ...): group coerced to ## factor.

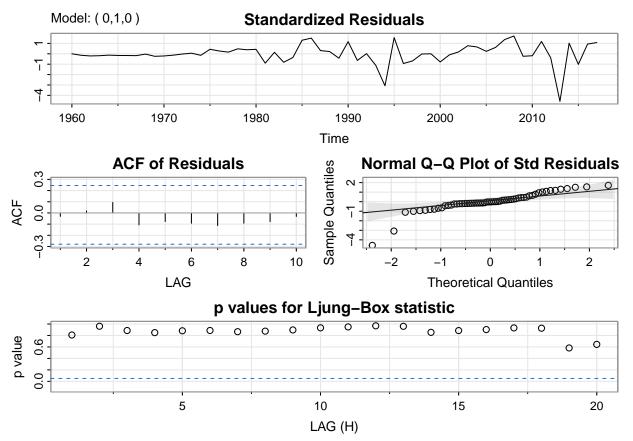
```
## Levene's Test for Homogeneity of Variance (center = median)
## Df F value Pr(>F)
## group 1 0.3973 0.5327
## 34
```

The variance for model GDP improved after transforming

(Draft) Use auto.arima()

```
# GDP time series covers years 1960-2017:
GDP_ts <- ts(finalPro_data$GDP, start = 1960, frequency = 1)
# Use auto.arima to find the best ARIMA model
best_arima_gdp <- auto.arima(GDP_ts)</pre>
# Show model summary
summary(best_arima_gdp)
## Series: GDP_ts
## ARIMA(0,1,0) with drift
##
## Coefficients:
##
            drift
         32232562
## s.e. 19852873
## sigma^2 = 2.269e+16: log likelihood = -1153.71
## AIC=2311.42 AICc=2311.64
                               BIC=2315.51
##
## Training set error measures:
                      ME
                              RMSE
                                        MAE
                                                   MPE
                                                           MAPE
                                                                     MASE
## Training set 1377.983 148026421 93710161 -2.966937 11.05622 0.9363027
## Training set -0.03099395
# Plot diagnostics:
#checkresiduals(best_arima_gdp)
library(astsa)
## Attaching package: 'astsa'
## The following object is masked from 'package:forecast':
##
##
       gas
arima_010 = sarima(GDP_ts, 0, 1, 0)
```

```
## initial value 18.821597
## iter
          1 value 18.821597
## final value 18.821597
## converged
## initial
           value 18.821597
          1 value 18.821597
## iter
## final value 18.821597
## converged
   <><><><><>
##
##
   Coefficients:
##
                           SE t.value p.value
            Estimate
   constant 32232562 19852873 1.6236 0.1101
##
##
##
  sigma<sup>2</sup> estimated as 2.229624e+16 on 56 degrees of freedom
##
## AIC = 40.55125 AICc = 40.55252 BIC = 40.62293
##
```



Summary: - ARIMA(0,1,0) model fits the GDP time series pretty well - Residuals show no significant autocorrelation - Errors appear approximately normal - Good baseline so far

Imports Model

Summary Imports

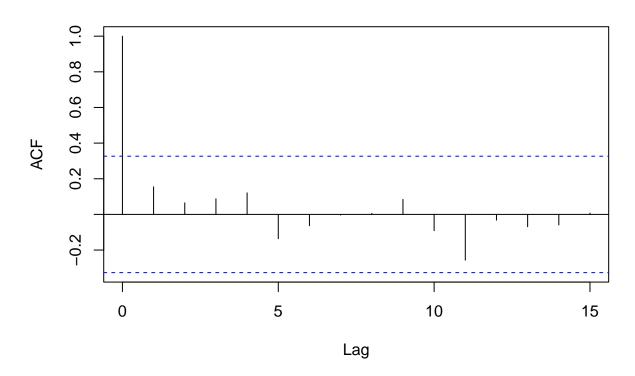
```
# 2. Diagnose model for Imports
model_imports <- lm(Imports ~ Year + GDP + Growth + CPI + Exports + Population, data = finalPro_data)
summary(model_imports)
##
## Call:
## lm(formula = Imports ~ Year + GDP + Growth + CPI + Exports +
##
      Population, data = finalPro_data)
##
## Residuals:
##
      Min
               1Q Median
                               3Q
## -5.8591 -1.7526 -0.4215 1.2413 8.9778
##
## Coefficients:
                Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 8.762e+02 2.121e+03 0.413 0.68251
              -4.330e-01 1.088e+00 -0.398 0.69347
## Year
## GDP
              4.311e-09 2.951e-09
                                     1.461 0.15484
## Growth
              -5.806e-02 8.339e-02 -0.696 0.49179
## CPI
              2.359e-01 5.998e-02
                                     3.933 0.00048 ***
## Exports
               5.924e-01 2.788e-01
                                     2.125 0.04226 *
## Population -5.022e-06 1.330e-05 -0.378 0.70842
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Residual standard error: 3.199 on 29 degrees of freedom
    (22 observations deleted due to missingness)
## Multiple R-squared: 0.7213, Adjusted R-squared: 0.6636
## F-statistic: 12.51 on 6 and 29 DF, p-value: 6.306e-07
```

• Significant variables: Year, CPI, Exports, Population

Residuals Diagnostics

```
#ACF Imports
acf(residuals(model_imports), main="ACF of Residuals Imports")
```

ACF of Residuals Imports



```
# L-jung-box
Box.test(residuals(model_imports), lag = 20, type = "Ljung-Box")
```

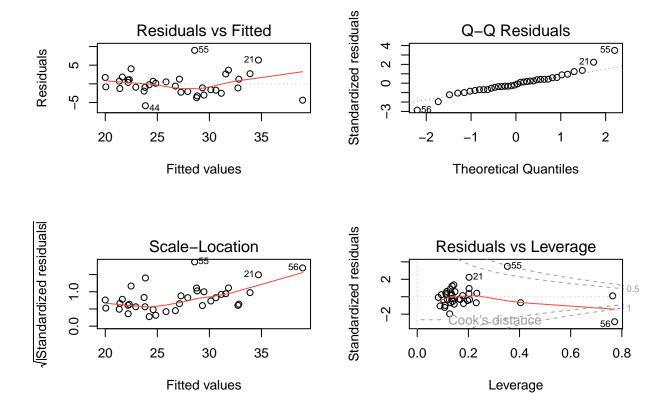
```
##
## Box-Ljung test
##
## data: residuals(model_imports)
## X-squared = 12.965, df = 20, p-value = 0.8789
```

Quick look:

- ACF plot shows no significant autocorrelation at higher lags
- Possible AR(1) model
- Ljung-box p-value > 0.1, so residuals are likely white noise

Plot Imports

```
# Diagnostic plots for Imports model
par(mfrow = c(2,2))
plot(model_imports)
```



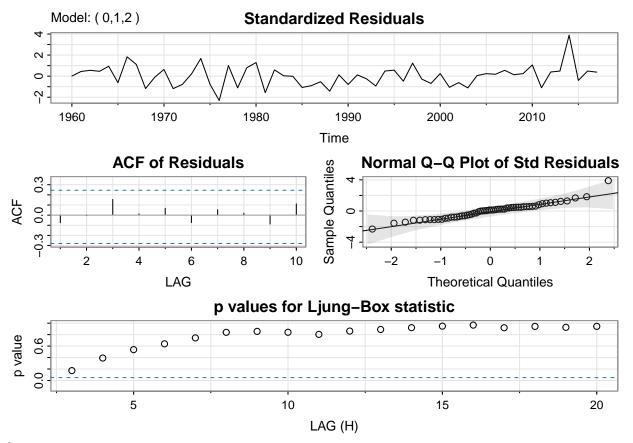
Quick interpretation:

- Residuals vs fitted: linearity assumption is reasonably met
- QQ plot: approximately normally distributed
- Scale-Location: variance of the residuals is roughly constant
- Residuals vs Leverage: most points have low leverage

(Draft) auto.arima() for Imports

```
# Imports time series covers years 1960-2017:
Imports_ts <- ts(finalPro_data$Imports, start = 1960, frequency = 1)</pre>
# Use auto.arima to find the best ARIMA model
best_arima_imports <- auto.arima(Imports_ts)</pre>
# Show model summary
summary(best_arima_imports)
## Series: Imports_ts
## ARIMA(0,1,2)
##
##
  Coefficients:
##
             ma1
                       ma2
##
         -0.0463
                  -0.4473
```

```
## s.e. 0.1307 0.1361
##
## sigma^2 = 12.33: log likelihood = -151.68
## AIC=309.37 AICc=309.82 BIC=315.5
## Training set error measures:
                             RMSE
                                                MPE
                                                        MAPE
                      ME
                                      MAE
## Training set -0.1397995 3.419567 2.587628 -1.299382 8.423651 0.883748
##
## Training set -0.08094744
# Plot diagnostics:
#checkresiduals(best_arima_imports)
arima_010 = sarima(Imports_ts, 0, 1, 2)
## initial value 1.338143
## iter 2 value 1.244114
## iter 3 value 1.243039
## iter 4 value 1.240054
## iter 5 value 1.239916
## iter 6 value 1.239904
## iter 7 value 1.239904
## iter 7 value 1.239904
## iter 7 value 1.239904
## final value 1.239904
## converged
## initial value 1.240322
## iter 2 value 1.240244
## iter 3 value 1.240231
## iter 4 value 1.240162
## iter 5 value 1.240162
## iter 5 value 1.240162
## iter 5 value 1.240162
## final value 1.240162
## converged
## <><><><>
##
## Coefficients:
##
                       SE t.value p.value
          Estimate
          -0.0528 0.1300 -0.4065 0.6860
           -0.4622 0.1416 -3.2636 0.0019
## ma2
## constant -0.1157 0.2333 -0.4960 0.6219
## sigma^2 estimated as 11.84284 on 54 degrees of freedom
## AIC = 5.458552 AICc = 5.466496 BIC = 5.601924
##
```



Summary:

- ARIMA(0,1,2) model fits the Imports time series well
- Residual diagnostics shows good model fit with no significant autocorrelation left