Advanced Macroeconometrics – Assignment 1

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Contents

The executable code that was used in compiling the assignment is available on GitHub at https://github.com/maxmheinze/macrometrics.

Exercise 1

First, we read in the data set, removing the first column indicating the recommended transformation.

```
# Header ---------------------------------------------------------------------

rm(list = ls())
gc()

pacman::p_load(tidyverse, urca, vars)


# Read in Data ---------------------------------------------------------------

fred <- read.csv("./assignment1/data/fred.csv")[-1, ]

kpdata <- read.table("./assignment1/data/data_kilian_park_2009.txt", header = FALSE)
colnames(kpdata) <- c("oil_prod_change", "econ_act_real", "oil_price_real",
"div_growth_change_real")
```

Creating the Function

Next, we create the desired function[1] `ts_explode()`. Along with the vector to be transformed, it asks for a specification of whether the data is ordered with the latest or earliest value first. It takes the earliest value first as default.

```
# Create the function --------------------------------------------------------

ts_explode <- function(input_vector, start_with_latest = FALSE) {
    # The function is called ts_explode because a single vector explodes into
    # an entire data frame. Boom!

    # Package dplyr required for lag() function
    require(dplyr)

    # Reverse input vector if user specifies it is sorted latest to earliest
    input_vector <- if (start_with_latest == FALSE) {
        input_vector
    } else {
        rev(input_vector)
    }

    # Do the transformations, assign transformed vectors
    original <- input_vector
    log_transformed <- log(input_vector)
    mom_growth <- input_vector/dplyr::lag(input_vector, 1) - 1
    mom_growth_log <- log(input_vector/dplyr::lag(input_vector, 1))
    yoy_growth <- input_vector/dplyr::lag(input_vector, 12) - 1
    yoy_growth_lagged <- dplyr::lag(input_vector, 12)/dplyr::lag(input_vector, 24) -
        1

    # Create a data frame to export, reverse ordering back to original in case
    # start_with_latest = TRUE was specified
    export_df <- if (start_with_latest == FALSE) {
        data.frame(original, log_transformed, mom_growth, mom_growth_log, yoy_growth,
            yoy_growth_lagged)
    } else {
        data.frame(original = rev(original), log_transformed = rev(log_transformed),
            mom_growth = rev(mom_growth), mom_growth_log = rev(mom_growth_log), yoy_growth =
            rev(yoy_growth),
```

[1] In addition to the transformations asked in the assignment, we let it calculate log month-on-month growth, wich we use in Question 2 for the creation of the stock returns variable.

```
            yoy_growth_lagged = rev(yoy_growth_lagged))
    }

    # Display warnings regarding ordering and units of growth rates
    warning("By default, ts_explode() assumes that values are ordered from earliest to
    latest. If your vector is ordered from latest to earliest, specify `start_with_latest =
    TRUE`!")
    warning("Growth rates are given in decimals, not in percent!")

    # Return the data frame
    return(export_df)
}
```

Preparing the Data Frame

Using `ts_explode()`, we create the data frame `ind_prod` including all transformations of the `INDPRO` variable. We bind the data frame together with the date column, which we transform from character to date. All other changes in the resulting data frame are of cosmetic nature.

```
# Prepare Industrial Production Data Frame --------------------------------

ind_prod <- fred$sasdate %>%
    cbind(ts_explode(fred$INDPRO)) %>%
    as_tibble() %>%
    mutate(date = lubridate::mdy(.)) %>%
    dplyr::select(-.) %>%
    relocate(date, .before = original)
```

Plots

Next, we plot both the logged variable and the year-on-year growth rate.

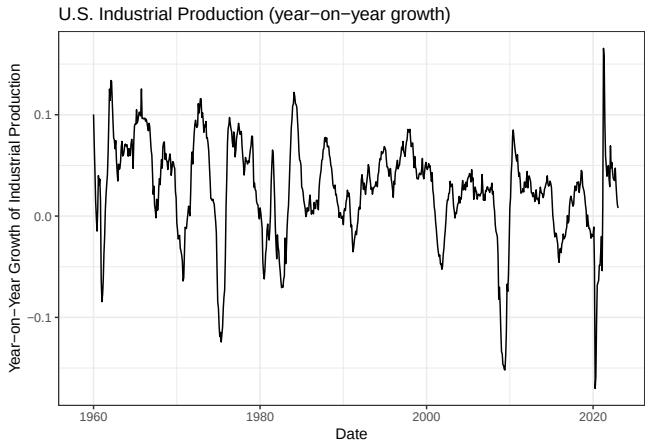
```
# Create Log Plot ---------------------------------------------------------

ind_prod %>%
    ggplot() + geom_line(aes(x = date, y = log_transformed)) + labs(title = "U.S. Industrial
    Production (logged)",
    x = "Date", y = "Log of Industrial Production") + ylim(3, 5) + theme_bw()
```

```
## Warning: Removed 1 row containing missing values (`geom_line()`).
```


```
# Create Growth Plot ------------------------------------------------------

ind_prod %>%
    ggplot() + geom_line(aes(x = date, y = yoy_growth)) + labs(title = "U.S. Industrial
    Production (year-on-year growth)",
```

```
    x = "Date", y = "Year-on-Year Growth of Industrial Production") + theme_bw()
```

```
## Warning: Removed 13 rows containing missing values (`geom_line()`).
```

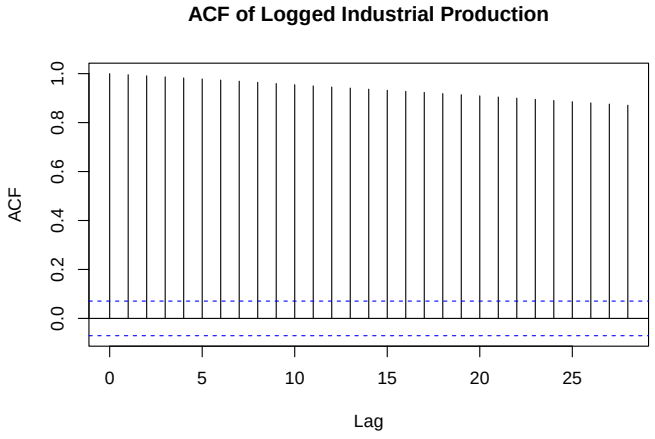


The plots above depict the logged time series of U.S. industrial production and its year-on-year growth rates. The logged time series of U.S. industrial production appears to exhibit a generally upward trend over time. The logged time series of U.S. industrial production also shows evidence of cyclical patterns, with periods of expansion and contraction occurring in a cyclical manner. There are also periodic fluctuations in the year-on-year growth rates, which suggests the presence of seasonality in U.S. industrial production.

Assessing Properties

Next we assess the properties of both logged industrial production and its yearly growth rate. We start with logged industrial production:

```
# ACF plot of Logged Industrial Production

stats::acf(ind_prod$log_transformed[!is.na(ind_prod$log_transformed)], main = "ACF of Logged
Industrial Production")
```



The ACF of Logged Industrial Production reveals a highly persistent nature of the time series with significant autocorrelation coefficients, particularly between Logged Industrial Production and its first five lags, which are extremely close to 1. The autocorrelation coefficients remain highly significant in the displayed lags. This highly persistent nature suggests potential non-stationarity in the series. For a more appropriate procedure, we apply the Augmented Dickey-Fuller (ADF) unit root tests.

Type: "trend" (urtest1a)

- H_0 : The time series is random walk around a trend
- H_1 : The time series is trend-stationary

```
# ADF test 1a) of Logged Industrial Production
urtest1a = ur.df(ind_prod$log_transformed[!is.na(ind_prod$log_transformed)], type = "trend",
```

```
    selectlags = "AIC")
summary(urtest1a)
```

```
##
## ###############################################
## # Augmented Dickey-Fuller Test Unit Root Test #
## ###############################################
##
## Test regression trend
##
##
## Call:
## lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.131711 -0.003784  0.000414  0.004158  0.054957
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.923e-02  1.006e-02   1.911   0.0564 .
## z.lag.1     -4.932e-03  2.998e-03  -1.645   0.1004
## tt           6.338e-06  6.121e-06   1.036   0.3007
## z.diff.lag   2.889e-01  3.458e-02   8.353 3.12e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.009501 on 763 degrees of freedom
## Multiple R-squared:  0.0963, Adjusted R-squared:  0.09275
## F-statistic:  27.1 on 3 and 763 DF,  p-value: < 2.2e-16
##
##
## Value of test-statistic is: -1.6449 7.7617 3.7276
##
## Critical values for test statistics:
##       1pct  5pct 10pct
## tau3 -3.96 -3.41 -3.12
## phi2  6.09  4.68  4.03
## phi3  8.27  6.25  5.34
```

As the coefficient of trend (tt) is insignificant, we never apply the ADF test with drift and trend. Instead, we move on to the second equation including only the drift component.

Type: "drift" (urtest2a)

- H_0 : The time series is random walk around a drift
- H_1 : The time series is (log-level) stationary around a drift

```
# ADF test 2a) of Logged Industrial Production
urtest2a = ur.df(ind_prod$log_transformed[!is.na(ind_prod$log_transformed)], type = "drift",
    selectlags = "AIC")
summary(urtest2a)
```

```
##
## ###############################################
## # Augmented Dickey-Fuller Test Unit Root Test #
## ###############################################
##
## Test regression drift
##
##
```

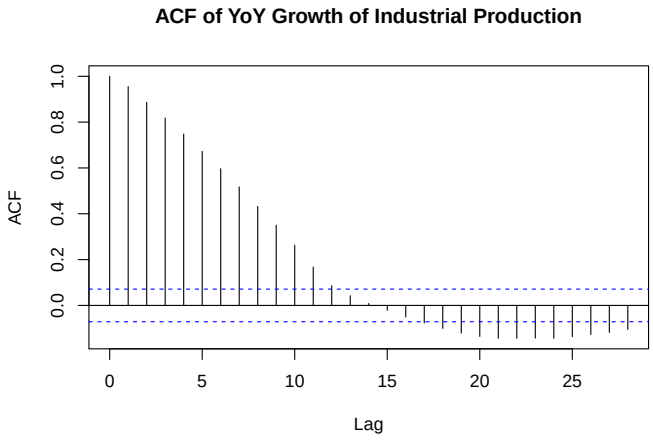
```
## Call:
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.131010 -0.003791  0.000361  0.004097  0.055859
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.0093366  0.0031640   2.951  0.00327 **
## z.lag.1     -0.0019295  0.0007638  -2.526  0.01173 *
## z.diff.lag   0.2866319  0.0345154   8.304 4.55e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.009501 on 764 degrees of freedom
## Multiple R-squared:  0.09503,    Adjusted R-squared:  0.09266
## F-statistic: 40.11 on 2 and 764 DF,  p-value: < 2.2e-16
##
##
## Value of test-statistic is: -2.5263 11.1054
##
## Critical values for test statistics:
##       1pct  5pct 10pct
## tau2 -3.43 -2.86 -2.57
## phi1  6.43  4.59  3.78
```

As the drift component is significant, and the absolute value of the test-statistic (2.5263) is below all the critical values for conventional significance levels, we conclude that we fail to reject the null hypothesis that the time series is random walk around a drift.

Thus, we conclude that Logged Industrial Production is $I(1)$.

Next we assess the ACF of the yearly growth rate of Instustrial production:

```
# ACF plot of Year-on-Year Growth Rate
stats::acf(ind_prod$yoy_growth[!is.na(ind_prod$yoy_growth)], main = "ACF of YoY Growth of
Industrial Production")
```



The ACF of YoY Growth rate of Industrial Production shows positive persistence, but to a lesser degree than the former series. The correlation coefficient decreases relatively quickly and even turns significantly negative after the 17th lag, indicating the presence of a pattern or cycle in the data at specific time lags. Now we apply the Augmented Dickey-Fuller (ADF) unit root tests.

Type: "trend" (urtest1b)

- H_0 : The time series is random walk around a trend
- H_1 : The time series is trend-stationary

```r
# ADF test 1b) of Year-on-Year Growth Rate
urtest1b = ur.df(ind_prod$yoy_growth[!is.na(ind_prod$yoy_growth)], type = "trend",
    selectlags = "AIC")
summary(urtest1b)
```

```
##
## ###############################################
## # Augmented Dickey-Fuller Test Unit Root Test #
## ###############################################
##
## Test regression trend
##
##
## Call:
## lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.112205 -0.005982  0.000166  0.005728  0.134883
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.846e-03  1.088e-03   2.615   0.0091 **
## z.lag.1     -6.130e-02  1.047e-02  -5.852 7.24e-09 ***
## tt          -3.507e-06  2.295e-06  -1.528   0.1268
## z.diff.lag   3.272e-01  3.435e-02   9.527  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01324 on 751 degrees of freedom
## Multiple R-squared:  0.1286, Adjusted R-squared:  0.1251
## F-statistic: 36.94 on 3 and 751 DF,  p-value: < 2.2e-16
##
##
## Value of test-statistic is: -5.8523 11.4203 17.1258
##
## Critical values for test statistics:
##       1pct  5pct 10pct
## tau3 -3.96 -3.41 -3.12
## phi2  6.09  4.68  4.03
## phi3  8.27  6.25  5.34
```

As the coefficient of trend (tt) is insignificant, we never apply the ADF test with drift and trend. Instead, we move on to the second equation including only the drift component.

Type: "drift" (urtest2b)

- H_0 : The time series is random walk around a drift
- H_1 : The time series is stationary around a drift

```r
# ADF test 2b) of Year-on-Year Growth Rate
urtest2b = ur.df(ind_prod$yoy_growth[!is.na(ind_prod$yoy_growth)], type = "drift",
    selectlags = "AIC")
summary(urtest2b)
```

```
##
## ###############################################
## # Augmented Dickey-Fuller Test Unit Root Test #
## ###############################################
##
## Test regression drift
```

```
##
##
## Call:
## lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.113192 -0.006224  0.000028  0.005802  0.133866
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.0014075  0.0005468   2.574   0.0102 *
## z.lag.1     -0.0570068  0.0100998  -5.644 2.35e-08 ***
## z.diff.lag   0.3246308  0.0343372   9.454  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01325 on 752 degrees of freedom
## Multiple R-squared:  0.1259, Adjusted R-squared:  0.1235
## F-statistic: 54.14 on 2 and 752 DF,  p-value: < 2.2e-16
##
##
## Value of test-statistic is: -5.6443 15.934
##
## Critical values for test statistics:
##       1pct  5pct 10pct
## tau2 -3.43 -2.86 -2.57
## phi1  6.43  4.59  3.78
```

As the drift component is significant, and the absolute value of the test-statistic (5.6443) is above all the critical values for conventional significance levels, we conclude that we reject the null hypothesis that the time series is random walk around a drift.

Thus, we conclude that the YoY Growth of Industrial Production is $I(0)$.

Estimating an AR Model

```
# Estimate AR model ------------------------------------------------------------

ar_model_yoygrowth = ar.ols(ind_prod$yoy_growth[!is.na(ind_prod$yoy_growth)])
summary(ar_model_yoygrowth)
```

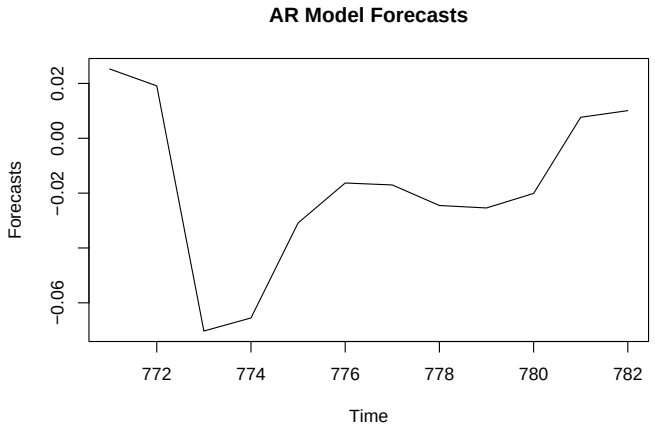
```
##             Length Class  Mode
## order         1    -none- numeric
## ar           26    -none- numeric
## var.pred      1    -none- numeric
## x.mean        1    -none- numeric
## x.intercept   1    -none- numeric
## aic          29    -none- numeric
## n.used        1    -none- numeric
## n.obs         1    -none- numeric
## order.max     1    -none- numeric
## partialacf    0    -none- NULL
## resid       757    -none- numeric
## method        1    -none- character
## series        1    -none- character
## frequency     1    -none- numeric
## call          2    -none- call
## asy.se.coef   2    -none- list
```

```
# Generate forecasts for the next year
forecasts <- predict(ar_model_yoygrowth, n.ahead = 12)
```

```
print(forecasts)
```

```
## $pred
## Time Series:
## Start = 758
## End = 769
## Frequency = 1
##  [1]  0.025269455  0.019107977 -0.070284530 -0.065514117 -0.030876699
##  [6] -0.016306685 -0.017024809 -0.024510326 -0.025405957 -0.020109857
## [11]  0.007656505  0.010083272
##
## $se
## Time Series:
## Start = 758
## End = 769
## Frequency = 1
##  [1] 0.01016206 0.01654370 0.02111975 0.02485038 0.02826507 0.03122660
##  [7] 0.03401918 0.03654871 0.03859429 0.04052347 0.04271988 0.04482780
```

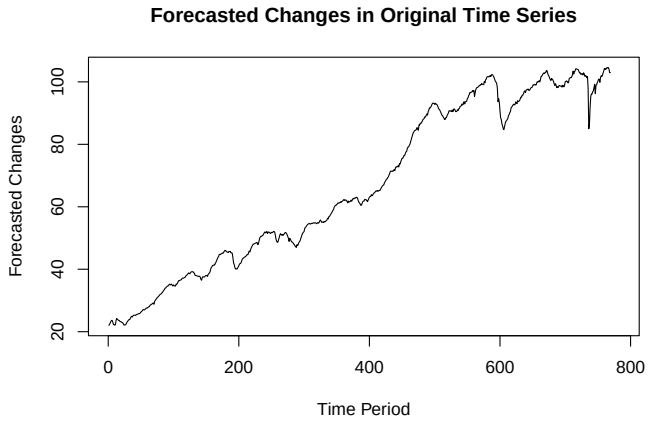
```
# Extract the forecasted values and the corresponding time period
forecasted_values <- as.vector(forecasts$pred)
time_period <- seq_along(forecasted_values) + length(ind_prod$yoy_growth)

# Plot the forecasts
plot(time_period, forecasted_values, type = "l", main = "AR Model Forecasts", xlab = "Time",
    ylab = "Forecasts")
```




```
# Average YoY growth rate
mean(ind_prod$yoy_growth[!is.na(ind_prod$yoy_growth)])
```

```
## [1] 0.02552905
```

```
# Forecast change in original time series based on forecasted year-on-year
# growth rate
last_observed_original <- tail(ind_prod$original, n = 1)
forecasted_change <- last_observed_original * forecasted_values

# Combine original time series with forecasted change
forecasted_original <- c(ind_prod$original, forecasted_change)

# Define time periods for forecasted changes
time_period_forecasted_change <- seq_along(forecasted_original)

# Plot forecasted changes
plot(time_period_forecasted_change, forecasted_original, type = "l", xlab = "Time Period",
    ylab = "Forecasted Changes", main = "Forecasted Changes in Original Time Series")
```



The lag order is determined by default in the `ar.ols()` function using the Akaike Information Criterion (AIC) as the method for order selection. AIC is a model selection criterion that balances model goodness of fit and complexity. Lower AIC values are preferred. The `ar.ols()` function computes the AIC value for different lag orders and selects the lag order that minimizes the AIC as the optimal lag order for the AR model.

If the AR model is capturing the underlying patterns well, then as the YoY growth rate of industrial production is stationary, the forecasts are likely to converge towards their long-run average of around 0.026 (2.6%).

Bonus Question

```
# Bonus (AR Model of (Logged) Industrial
# Production-----------------------------

# Define function to calculate RMSE for AR model with given lag order
calculate_rmse <- function(lag_order, holdout_period, ind_prod) {

    # Exclude the holdout period from the end of the sample
    train_data <- ind_prod$log_transformed[1:(length(ind_prod$log_transformed) -
        holdout_period)]

    # Estimate AR model
    ar_model <- ar.ols(train_data, aic = FALSE, order.max = lag_order)

    # Produce forecasts for the holdout period
    forecasts <- predict(ar_model, n.ahead = holdout_period)

    # Extract predicted values for the holdout period
    predicted_values <- forecasts$pred

    # Extract realized values for the holdout period
    realized_values <- ind_prod$log_transformed[(length(ind_prod$log_transformed) -
        holdout_period + 1):length(ind_prod$log_transformed)]

    # Remove missing values from predicted_values and realized_values
    predicted_values <- na.omit(predicted_values)
    realized_values <- na.omit(realized_values)

    # Check and adjust length of predicted_values and realized_values
    if (length(predicted_values) > length(realized_values)) {
        predicted_values <- predicted_values[1:length(realized_values)]
    } else if (length(realized_values) > length(predicted_values)) {
        realized_values <- realized_values[1:length(predicted_values)]
    }

    # Compute RMSE
    rmse <- sqrt(mean((predicted_values - realized_values)^2))
    return(rmse)
```

```
}

# Specify lag orders to compare
lag_orders <- c(1, 2, 3, 4, 5, 6, 7, 8)

# Specify holdout periods to compare
holdout_periods <- c(6, 12, 24)

# Initialize matrix to store RMSE results
results <- matrix(NA, nrow = length(lag_orders), ncol = length(holdout_periods))

# Iterate over lag orders and holdout periods to calculate RMSE for each model
for (i in 1:length(lag_orders)) {
    for (j in 1:length(holdout_periods)) {
        rmse <- calculate_rmse(lag_orders[i], holdout_periods[j], ind_prod)
        results[i, j] <- rmse
    }
}

# Print RMSE results
print(results)
```

```
##             [,1]        [,2]       [,3]
## [1,] 0.01083095 0.009360575 0.05575435
## [2,] 0.01020996 0.007806726 0.07005326
## [3,] 0.01017002 0.008160002 0.06738367
## [4,] 0.01018277 0.008012830 0.06806190
## [5,] 0.01018192 0.007866010 0.06822266
## [6,] 0.01007486 0.008113162 0.06834463
## [7,] 0.01016670 0.008140459 0.07030717
## [8,] 0.01027124 0.008264455 0.07092213
```

The AR Model with a holdout period of 12 months and a lag order of 2 performs the based among the alternatives as it minimizes the RMSE. When specifying a holdout period of 6 (24) months, we would, based on minimizing the RMSE, select an AR model with 6 (1) lags. Thus, the preferred specification (i.e. optimal lag order) depends on the selected holdout period.

Exercise 2

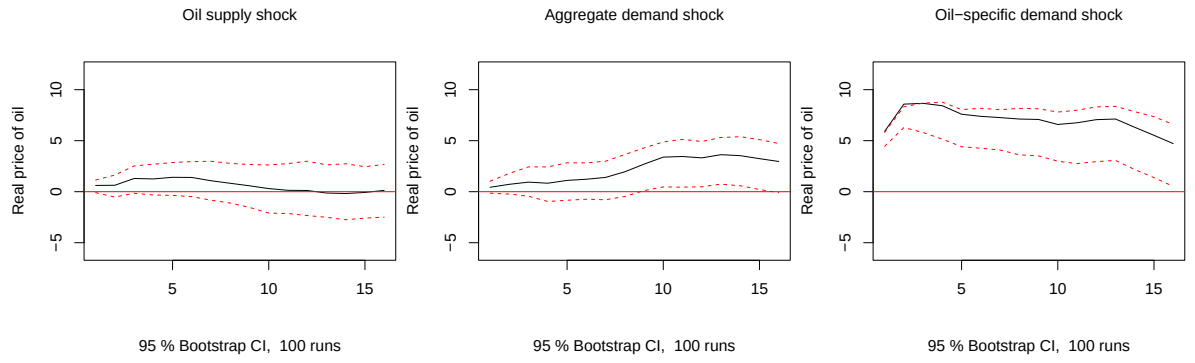
We begin by estimating the VAR model the way Kilian & Park (2009) did:

```
# Estimating the VAR -------------------------------------------------------

var_model <- VAR(kpdata, p = 24, type = "const")
coefficients <- coef(var_model)
residuals <- resid(var_model)
```

Replicating Figure 1

To replicate Figure 1, we compute impulse response functions the way the paper described and plot them:

```
# Replicating Figure 1 -----------------------------------------------------

# Computing impulse response function with recursive-design wild bootstrap

set.seed(123)  # for reproducibility

nboot <- 1000  # number of bootstrap replications
irf1 <- irf(var_model, impulse = "oil_prod_change", response = "oil_price_real",
    n.ahead = 15, boot = TRUE, nboot = nboot, ci = 0.95, boot.type = "rdwb")
irf1$irf$oil_prod_change <- irf1$irf$oil_prod_change * (-1)  # Switching signs of shock
irf1$Lower$oil_prod_change <- irf1$Lower$oil_prod_change * (-1)  # and of the CIs
irf1$Upper$oil_prod_change <- irf1$Upper$oil_prod_change * (-1)

irf2 <- irf(var_model, impulse = "econ_act_real", response = "oil_price_real", n.ahead = 15,
    boot = TRUE, nboot = nboot, ci = 0.95, boot.type = "rdwb")

irf3 <- irf(var_model, impulse = "oil_price_real", response = "oil_price_real", n.ahead =
15,
    boot = TRUE, nboot = nboot, ci = 0.95, boot.type = "rdwb")


plot(irf1, ylim = c(-6, 12), main = "Oil supply shock", ylab = "Real price of oil")

plot(irf2, ylim = c(-6, 12), main = "Aggregate demand shock", ylab = "Real price of oil")

plot(irf3, ylim = c(-6, 12), main = "Oil-specific demand shock", ylab = "Real price of oil")
```



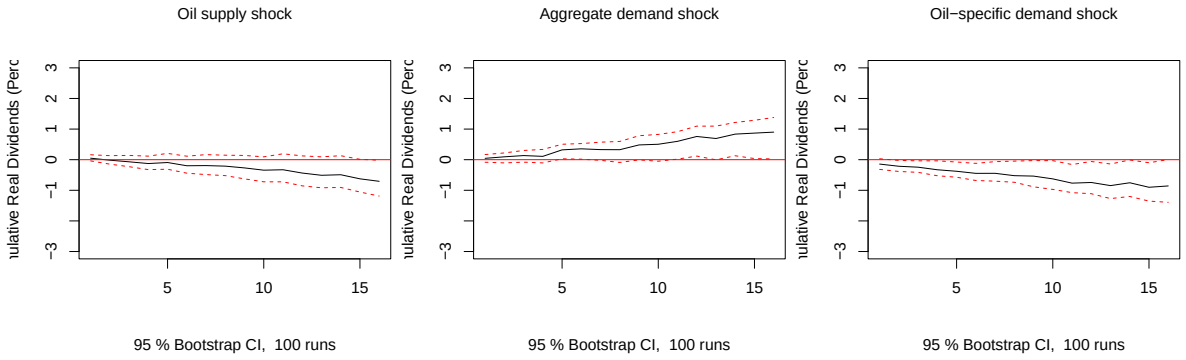
The IRF plots show the responses of the real price of oil to the oil supply shock, the aggregate demand shock, and the oil-market specific demand shock.The oil supply shock is represented by a negative one standard deviation shock, while the other two shocks are positive and would raise the real price of oil. Differently from Kilian and Park (2009), the plots display only the two-standard error bands. The confidence intervals were constructed using a recursive-design wild bootstrap.

Similar to the results in Kilian and Park (2009), the key finding is that the three shocks have different impacts on the real price of oil.

Replicating the Lower Panel of Figure 3

Next, we replicate the plots in the lower panel of Figure 3:

```
# Replicating Figure 3 ----------------------------------------------------

set.seed(123)  # for reproducibility

nboot <- 1000  # number of bootstrap replications
irf4 <- irf(var_model, impulse = "oil_prod_change", response = "div_growth_change_real",
    cumulative = TRUE, n.ahead = 15, boot = TRUE, nboot = nboot, ci = 0.95, boot.type =
    "rdwb")

irf4$irf$oil_prod_change <- (-1) * irf4$irf$oil_prod_change  # Switching signs of shock
irf4$Lower$oil_prod_change <- (-1) * irf4$Lower$oil_prod_change  # and of the CIs
irf4$Upper$oil_prod_change <- (-1) * irf4$Upper$oil_prod_change

irf5 <- irf(var_model, impulse = "econ_act_real", response = "div_growth_change_real",
    cumulative = TRUE, n.ahead = 15, boot = TRUE, nboot = nboot, ci = 0.95, boot.type =
    "rdwb")

irf6 <- irf(var_model, impulse = "oil_price_real", response = "div_growth_change_real",
    cumulative = TRUE, n.ahead = 15, boot = TRUE, nboot = nboot, ci = (0.95), boot.type =
    "rdwb")


plot(irf4, ylim = c(-3, 3), main = "Oil supply shock", ylab = "Cumulative Real Dividends
(Percent)")

plot(irf5, ylim = c(-3, 3), main = "Aggregate demand shock", ylab = "Cumulative Real
Dividends (Percent)")

plot(irf6, ylim = c(-3, 3), main = "Oil-specific demand shock", ylab = "Cumulative Real
Dividends (Percent)")
```



The above code replicates the cumulative responses of the dividend-growth rate to each shock. Differently from Kilian and Park (2009), the plots display only the two-standard error bands. The confidence intervals were constructed using a recursive-design wild bootstrap. From the plots, we observe that an oil supply shock result in a significant and negative impact on real dividends, which becomes apparent after five months. Positive aggregate demand shocks have a persistent positive effect on real dividends, with the effect being significant in most horizons. Conversely, positive shocks to precautionary demand lead to a persistent negative effect on real dividends, with the impact being significant across all horizons.

Replicating Table 2

Finally, we replicate Table 2. Note that, in accordance with the paper, we output values as percentages (i.e., multiplied by 100):

```
# Replicating Table 2 -----------------------------------------------------

table_2 <- fevd(var_model, n.ahead = 1000)$div_growth_change_real %>%
```

```
    magrittr::multiply_by(100) %>%
    cbind(horizon = 1:1000) %>%
    as_tibble() %>%
    dplyr::relocate(horizon, .before = oil_prod_change) %>%
    dplyr::filter(horizon %in% c(1, 2, 3, 12, 1000)) %>%
    mutate(horizon = ifelse(horizon == 1000, Inf, horizon))

knitr::kable(table_2)
```

horizon	oil_prod_change	econ_act_real	oil_price_real	div_growth_change_real
1	0.1999480	0.1635769	1.691515	97.94496
2	0.5509699	0.3610968	2.089788	96.99815
3	0.7611886	0.4840789	2.119006	96.63573
12	2.7957267	6.8331769	4.532478	85.83862
Inf	6.6274588	8.3817303	7.932067	77.05874

The dividend growth shock has the highest contribution to the forecast error variance, with a percentage of 77.1% at an infinite horizon, while the oil supply shock, oil demand shock, and oil-specific demand shock have smaller contributions. This suggests that the dividend growth shock is the most important factor driving the variability of U.S. real dividend growth over the long run, while oil-related shocks play a relatively smaller role. Specifically, as noted by Kilian and Park (2009), in the long run, shocks affecting the crude oil market account for 23% of the variability in real divident growth, and more than two-thirds of this variability is attributed to oil demand shock. However. the combined impact of these shocks is only 2%.

Creating a Stock Returns Variable

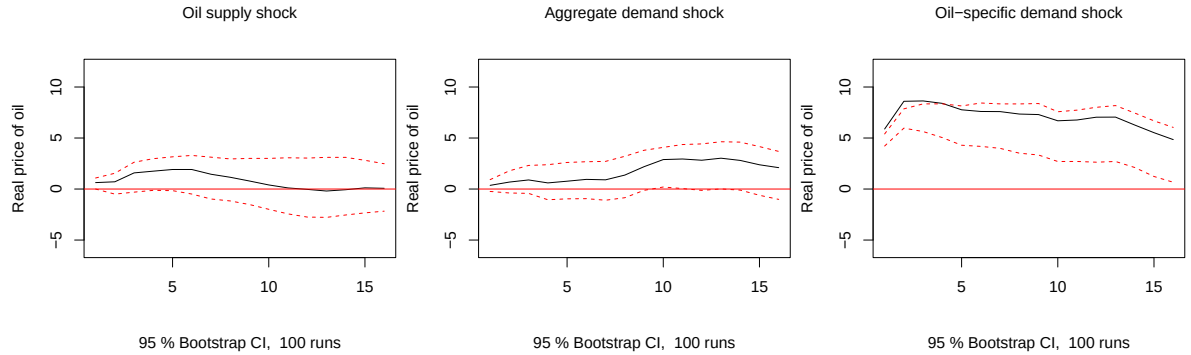
```
# Stock Market Returns ----------------------------------------------------

fred <- read.csv("./assignment1/data/fred.csv")[-1,]


fred_kp <- fred[169:576,] %>% # only choosing 1.1973 to 12.2006
  as_tibble() %>%
  dplyr::select(S.P.500, CPIAUCSL)


sp_kp <- ts_explode(fred_kp$S.P.500) %>%
  magrittr::set_colnames(c("sp500", "sp500_log", "sp500_mom", "sp500_momlog", "sp500_yoy",
"sp500_yoylag")) %>%
  magrittr::extract(-1,) %>%
  as_tibble()

cpi_kp <- ts_explode(fred_kp$CPIAUCSL) %>%
  magrittr::set_colnames(c("cpi", "cpi_log", "cpi_mom", "cpi_momlog", "cpi_yoy",
"cpi_yoylag")) %>%
  magrittr::extract(-1,) %>%
  as_tibble()

real_stock_returns <- sp_kp$sp500_momlog-cpi_kp$cpi_mom

kpdata_2 <- cbind(kpdata, real_stock_returns = 100*real_stock_returns)
```

```
# Re-estimating the model -------------------------------------------------

var_model_2 <- VAR(kpdata_2, p = 24, type = "const")
```

Replicating Figure 1

Using our newly estimated VAR model, we replicate Figure 1 again:

```
# Replicating Figure 1 ----------------------------------------------------

set.seed(123)  # for reproducibility

nboot <- 1000  # number of bootstrap replications
irf7 <- irf(var_model_2, impulse = "oil_prod_change", response = "oil_price_real",
    n.ahead = 15, boot = TRUE, nboot = nboot, ci = 0.95, boot.type = "rdwb")
irf7$irf$oil_prod_change <- irf7$irf$oil_prod_change * (-1)  # Switching signs of shock
irf7$Lower$oil_prod_change <- irf7$Lower$oil_prod_change * (-1)  # and of the CIs
irf7$Upper$oil_prod_change <- irf7$Upper$oil_prod_change * (-1)

irf8 <- irf(var_model_2, impulse = "econ_act_real", response = "oil_price_real",
    n.ahead = 15, boot = TRUE, nboot = nboot, ci = 0.95, boot.type = "rdwb")

irf9 <- irf(var_model_2, impulse = "oil_price_real", response = "oil_price_real",
    n.ahead = 15, boot = TRUE, nboot = nboot, ci = 0.95, boot.type = "rdwb")


plot(irf7, ylim = c(-6, 12), main = "Oil supply shock", ylab = "Real price of oil")

plot(irf8, ylim = c(-6, 12), main = "Aggregate demand shock", ylab = "Real price of oil")

plot(irf9, ylim = c(-6, 12), main = "Oil-specific demand shock", ylab = "Real price of oil")
```



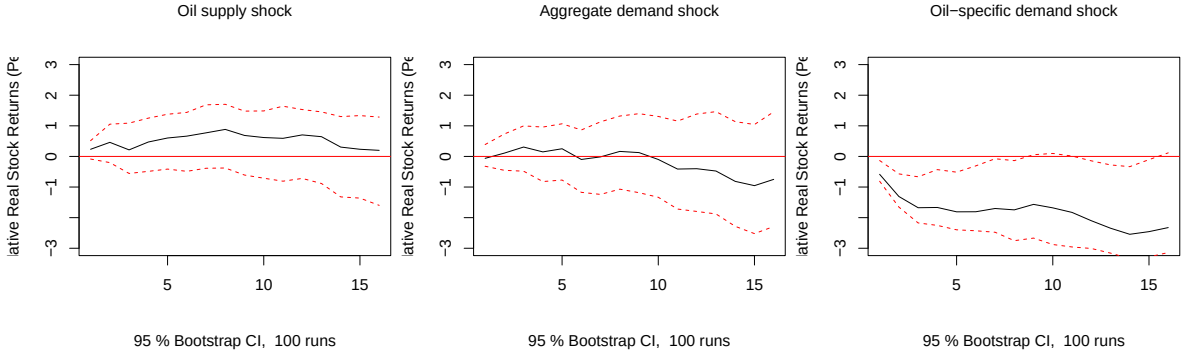
Looking at the results, we conclude that the plots have not changed since we first replicated them before re-estimating the VAR model.

Replicating the Upper Panel of Figure 3

Next, we replicate the upper panel of Figure 3:

```
# Replicating Figure 3 ----------------------------------------------------

set.seed(123)  # for reproducibility

nboot <- 1000  # number of bootstrap replications

irf10 <- irf(var_model_2, impulse = "oil_prod_change", response = "real_stock_returns",
    cumulative = TRUE, n.ahead = 15, boot = TRUE, nboot = nboot, ci = 0.95, boot.type =
    "rdwb")

irf10$irf$oil_prod_change <- (-1) * irf10$irf$oil_prod_change  # Switching signs of shock
irf10$Lower$oil_prod_change <- (-1) * irf10$Lower$oil_prod_change  # and of the CIs
irf10$Upper$oil_prod_change <- (-1) * irf10$Upper$oil_prod_change

irf11 <- irf(var_model_2, impulse = "econ_act_real", response = "real_stock_returns",
    cumulative = TRUE, n.ahead = 15, boot = TRUE, nboot = nboot, ci = 0.95, boot.type =
    "rdwb")
```

```
irf12 <- irf(var_model_2, impulse = "oil_price_real", response = "real_stock_returns",
    cumulative = TRUE, n.ahead = 15, boot = TRUE, nboot = nboot, ci = 0.95, boot.type =
    "rdwb")


plot(irf10, ylim = c(-3, 3), main = "Oil supply shock", ylab = "Cumulative Real Stock
Returns (Percent)")

plot(irf11, ylim = c(-3, 3), main = "Aggregate demand shock", ylab = "Cumulative Real Stock
Returns (Percent)")

plot(irf12, ylim = c(-3, 3), main = "Oil-specific demand shock", ylab = "Cumulative Real
Stock Returns (Percent)")
```



The upper panel of figure 3 displays the cumulative impulse responses of the created variable real stock returns to the three demand and supply shocks in the crude oil market. The results are qualitatively similar to the ones from Kilian and Park (2009). Oil supply shocks still have little effect on cumulative U.S. stock returns while a positive shock in global demand has a smaller effect, and turns negative sooner. Similar to the results in Kilian and Park (2009), an increase in the precautionary demand for oil causes persistently negative U.S. stock returns.

Replicating Table 1

Finally, we replicate Table 1:

```
# Replicating Table 1 ----------------------------------------------------

table_1 <- fevd(var_model_2, n.ahead = 1000)$real_stock_returns %>%
    magrittr::multiply_by(100) %>%
    cbind(horizon = 1:1000) %>%
    as_tibble() %>%
    dplyr::relocate(horizon, .before = oil_prod_change) %>%
    dplyr::select(-div_growth_change_real) %>%
    dplyr::filter(horizon %in% c(1, 2, 3, 12, 1000)) %>%
    mutate(horizon = ifelse(horizon == 1000, Inf, horizon))

knitr::kable(table_1)
```

horizon	oil_prod_change	econ_act_real	oil_price_real	real_stock_returns
1	0.4825399	0.0341007	3.012370	96.45241
2	0.8239363	0.2569623	6.751464	92.05562
3	1.2693408	0.5531023	7.658378	90.37831
12	2.3320103	2.9279609	8.213784	83.77642
Inf	5.9049610	6.9272703	9.827450	72.04405

Table 1 reveals that, similar to the results in Kilian and Park (2009), in the short run, the impact of oil supply, aggregate demand, and oil-specific demand shocks is very small with around 96% of the variation in U.S. stock returns associated with other shocks than those in the global crude oil market. However, we also see that as the

horizon increases, the explanatory power of the oil shocks increases.