

# Assignment 1

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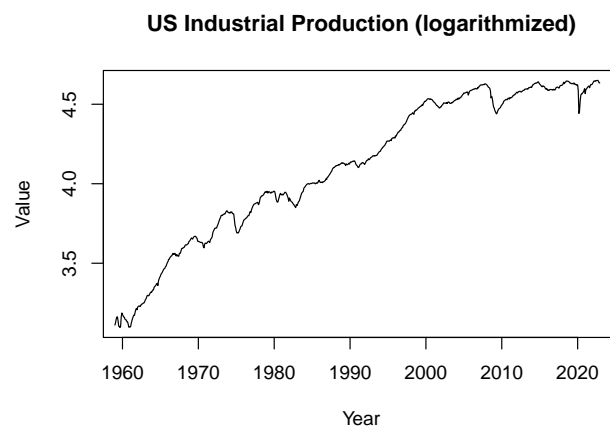
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## 1 Exercise I

### 1.1 Properties of the Time Series

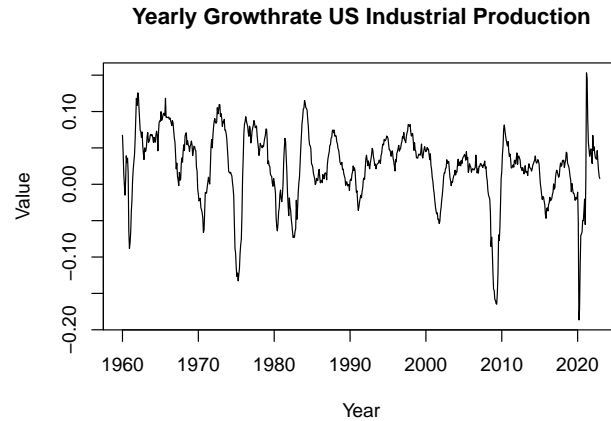
The plot of the logged time series of US industrial production has an upward sloping trend. This trend declines over time, especially when comparing the period from 1960 until 2000 (steeper) to the one from 2000 until now (flatter). The big economic crises (in 1973, 1983, 2008 and 2020) are prominent while cyclical and seasonal changes are unapparent.

Figure 1: Logged Industrial Production Time Series



The plot of the yearly changes in production displays the seasonal changes better than the first plot, while being mostly positive with only occasional negative fluctuations/shocks. Between 1980 and 2008 the fluctuations are less severe/pronounced (lower variance), while the fluctuations before and after this period have a higher amplitude/variance (due to crises of 1973, 2008 and 2020). However, the curve varies around zero, such that the mean seems to be rather constant over time.

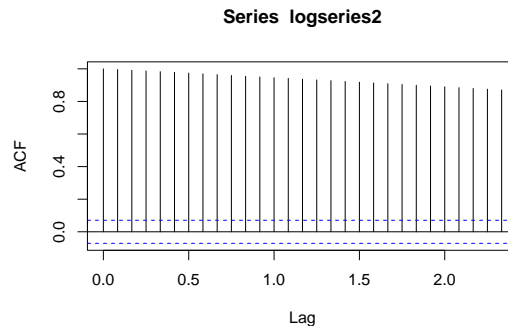
Figure 2: Yearly Growth Rate Of Industrial Production



## 1.2 Plot of Autocorrelation Functions and Dickey-Fuller Test

It cannot be falsified that the logged production time series is not stationary, as the resulting p-value of the Dickey-Fuller test ( $p = 0.4829$ ) lies above the critical p-value of 0.05, such that the  $H_0$  can not be falsified. This also holds true when adding a drift to the specification of the Dickey-Fuller test. When adding a drift, we cannot reject the null hypothesis that the timeseries has a unit root and hence conclude that it is most likely not stationary. When adding a trend, our p-value 0.0564 lies just above the critical p-value of 0.05 and hence we can at the 5% error level not reject the null-hypthesis of non-stationarity. The plot additionally demonstrates the characteristics of a random walk (/non-stationary time series) with the variance converging to  $\infty$  over time, the mean depending on time and an autocorrelation slowly decaying over the lags (see figure 1: "Autocorrelation US Industrial Production").

Figure 3: Autocorrelation US Industrial Production

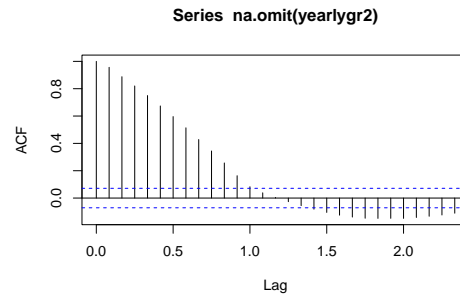


The growth rate on the other hand seems to be a stationary time series, as mean and variance are roughly constant/independent of time. Hence, the curve varies around a certain value (here 0.024) without continuously drifting away or apart.

Figure 4 displays an autocorrelation decaying much faster over lags than the autocorrelation of logged production time series. These properties indicate stationarity. The Dickey-Fuller test supports this, as the resulting p-value ( $p = 0.01$ ) lies below the critical

p-value of 0.05, such that the  $H_0$  is rejected. Hence, we can conclude - given no other forms of non-stationarity are present - that the time series is stationary. We then again add a drift and a trend and also here, the results imply stationarity.

Figure 4: Autocorrelation Yearly Growth Rate



### 1.3 Forecasting value of next years growth rate (stationary time series)

The default setting for lag order is 26 in the AR model. The curve converges to the mean ( $=0.024006$ ) of the AR model, while having a negative tendency relative to the year before.

Figure 5: Overview of Forecast

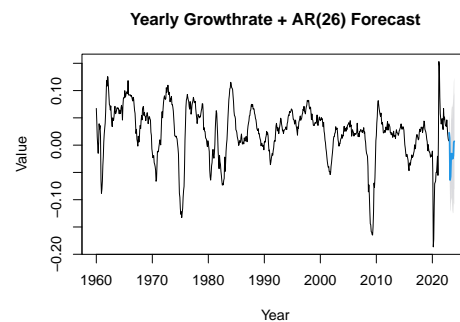
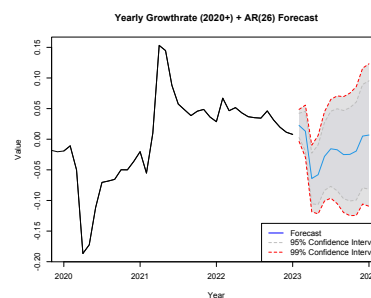


Figure 6: Period 2020 + Forecast



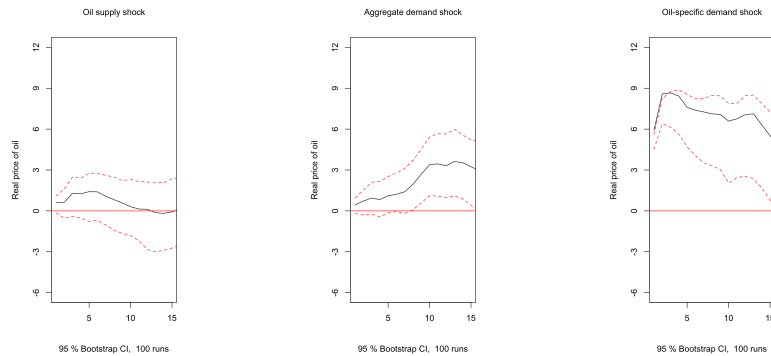
## 1.4 Bonus Question

After calculating the values of an RMSE with different horizons (6 vs. 12) and lag orders (6 vs. 12), the one with a period of 6 months and 6 lags seems to be the one with the highest predictive performance. Comparing the results of a RMSE with 6 month and 6 lags to a RMSE with 6 month and 12 lags as well as a RMSE with 12 month and 12 lags, we conclude that a lower forecasting horizon leads to a better prediction.

## 2 Exercise II

### 2.1 Replicated Figure 1 and Lower Panel of Figure 3

Figure 7: Replicated Figure 1

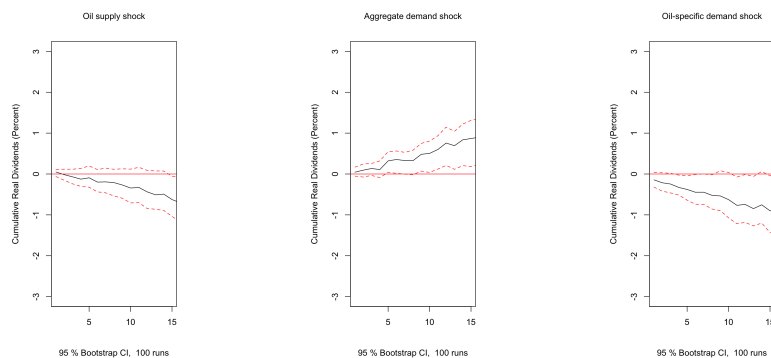


The replicated graphs of figure 1 show the effect of different types of shocks on the real price in oil. The first one is a negative shock of oil supply, which leads to an increase in the real oil price. The price level increases in the first year, after which it falls even below the initial level.

The second graph displays the effect of a positive shock in aggregate demand, which affects the real oil price also positively. However, in this case the reaction has a delay of a few months before the price increases continuously. The real oil price only decreases slowly at the end of the time horizon.

The last plot in figure 1 captures the effect of a positive shock of oil-specific demand on real oil price. This shock leads to an increase in the price, which remains for nearly one year, followed by a progressive decline.<sup>1</sup>

Figure 8: Replicated Lower Panel of Figure 3



The replicated lower panel of figure 3 shows the cumulated responses of dividend-growth rates following the three different shocks. The oil supply shock and oil specific demand shock both lower real dividends. An aggregate demand shock on the other hand increases real dividends.

<sup>1</sup>At the first part of the replicated figure 1 we see a slight difference compared to Kilian & Park at the 15th period estimated ahead, as it slightly converges towards zero.

## 2.2 Replicated Table 2

Table 2 captures the impact/importance of each shock for the variance in dividend growth. It shows that the three observed shocks have a low explanatory impact (around 2 percent at horizon of 1, increasing over length of horizon) on the variance of dividend growth compared to other shocks.

Horizon	Oil Supply Shock	Aggregate Demand Shock	Oil-specific Demand Shock	Other Shock
1	0.200	0.164	1.692	97.945
2	0.551	0.361	2.090	96.998
3	0.761	0.484	2.119	96.636
12	2.796	6.833	4.532	85.839

Table 1: Replicated Table 2

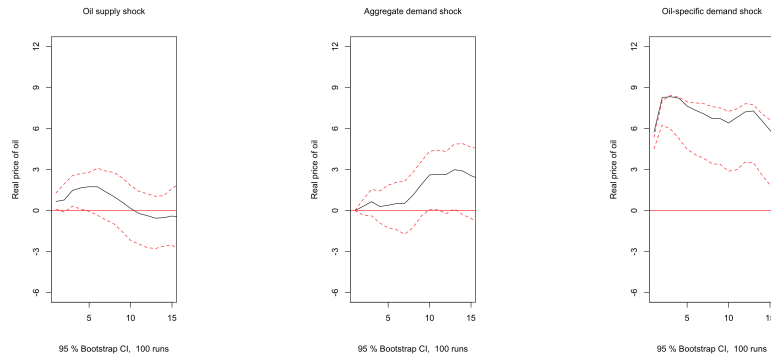
## 2.3 Re-estimated Figure 1, Top Panel of figure 3 and Table 1

We used the data S&P500 from Fred-MD to evaluate the stock market returns and transformed it in order to calculate the growth rates. By using the CPI variable from Fred-MD, we evaluated real stock market returns.

In this new setting the direction of the effects are roughly the same compared to the first case but show a few differences. With the re-estimated model the oil supply shock leads to a slightly higher variance in the real oil price curve. In this case, the curve increases to a slightly higher level following the shock, as well as it decreases more afterwards compared to the previous model.

The aggregate demand shock in contrast leads to a less pronounced reaction, meaning the real oil price increases less than in the first model. However, the effect of a shock in oil-specific demand on real oil price is roughly the same as for the previous model.

Figure 9: Re-estimated Figure 1



The top panel of figure 3 accounts for the accumulated responses of stock returns to the different shocks. All three shocks seem to lead to some fluctuations, but the plots show no significant trend or tendency for an in- or decrease of real stock returns. The plot for the oil-specific demand shock in the paper, in contrast, shows a clear negative tendency for the reaction of stock returns.

Figure 10: Re-estimated Upper Panel of Figure 3

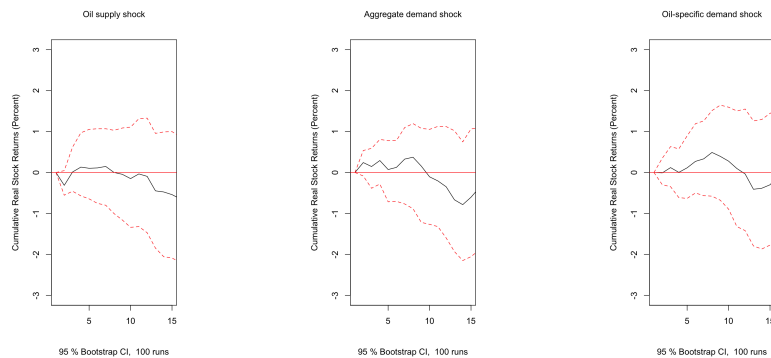


Table 1 captures the impact/importance of each shock for the variance in real stock returns. Compared to the original table 1, in the re-estimated model the explanatory power

of the three observed shocks together decreased slightly in the long run, but increased in short run. The effect of the oil-specific demand shock has decreased, whereas the impact of oil supply and aggregate demand shock on real stock returns has increased mostly.

Horizon	Oil Supply Shock	Aggregate Demand Shock	Oil-specific Demand Shock	Other Shock
1	0.001	0.334	3.458	96.207
2	0.781	1.006	3.486	94.727
3	1.624	1.054	3.586	93.736
12	2.044	3.002	4.654	90.300

Table 2: Re-estimated Table 1

This means that the data on US stock market returns makes the oil supply and aggregate demand appear more important for the variance of real stock returns, while oil-specific demand appears to be less important than assumed before (in table 1 of the paper). However, in general the focus in the longer run shifts more to the other shocks, when taking the US stock market data into account.