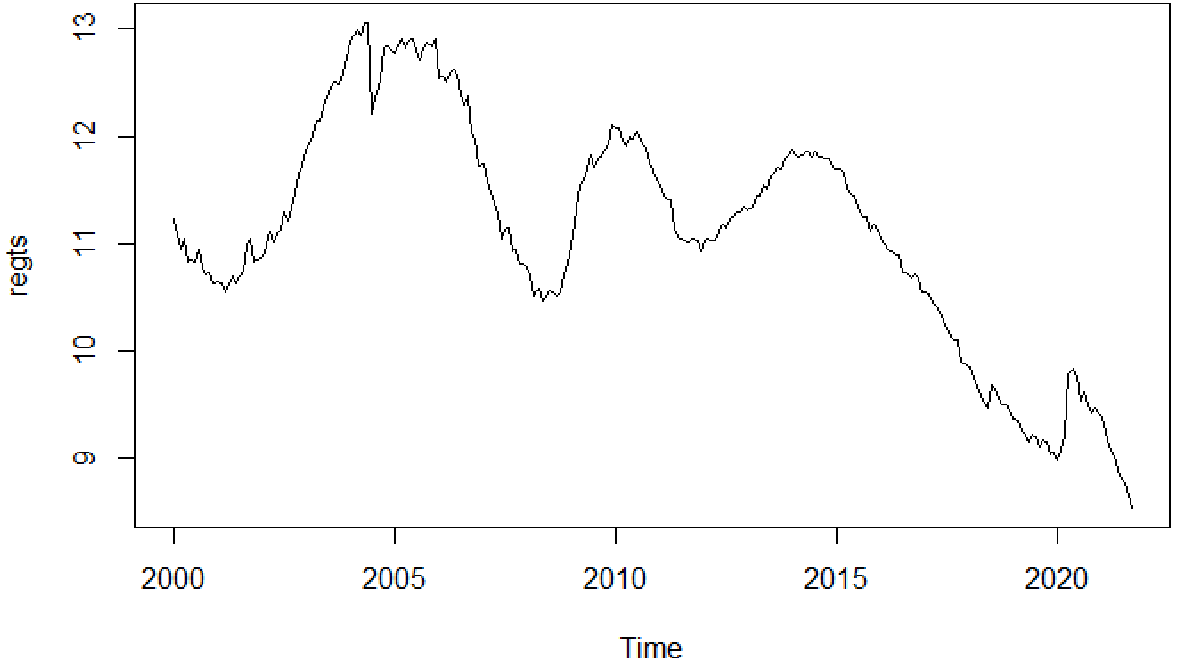
Definition of the time series

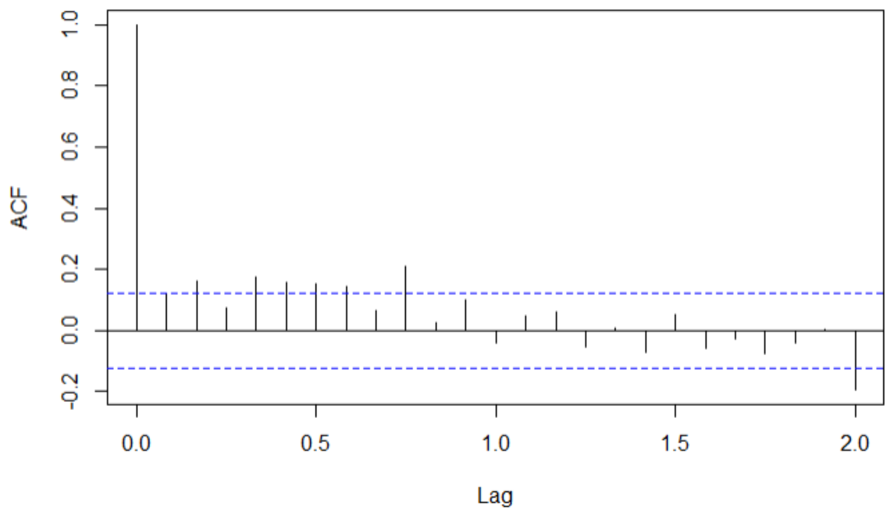


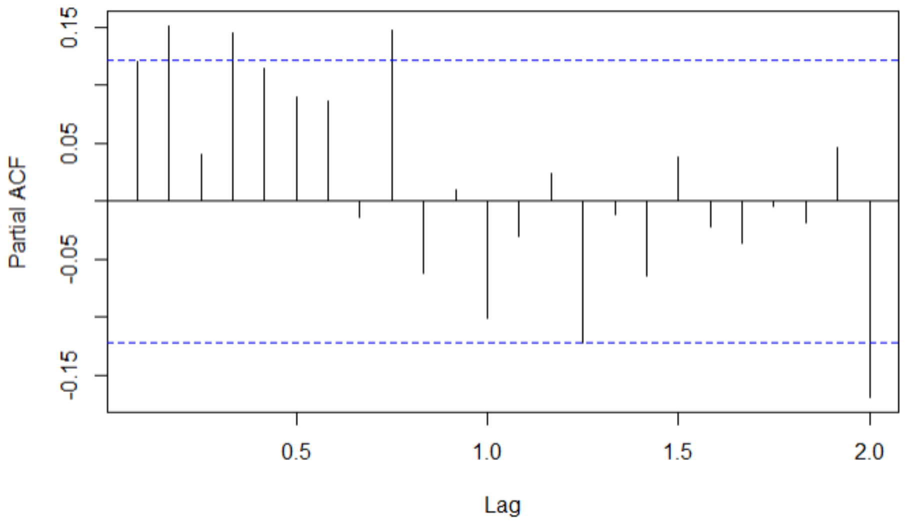
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
8.542	10.557	11.136	11.111	11.821	13.060

- Registered unemployment rate in Belgium (deseasonalized)
- Monthly data from January 2000 – September 2021
- Data is measured in percentages
- Source: Federal Reserve Economic Data (FRED)

Univariate analysis

- The series in levels shows strong persistency and is non-stationary, but the series in differences is stationary as evidenced by the ADF test (p = 2,08 x 10^-13).





- Correlograms of the differenced series suggest possible MA(9) or AR(8) specifications.
- Alternatively, we can use the most parsimonious ARIMA specification that can be validated, this turns out to be ARIMA(1, 1, 1). The data is deseasonalized so we do not concern ourselves with SARIMA modeling.

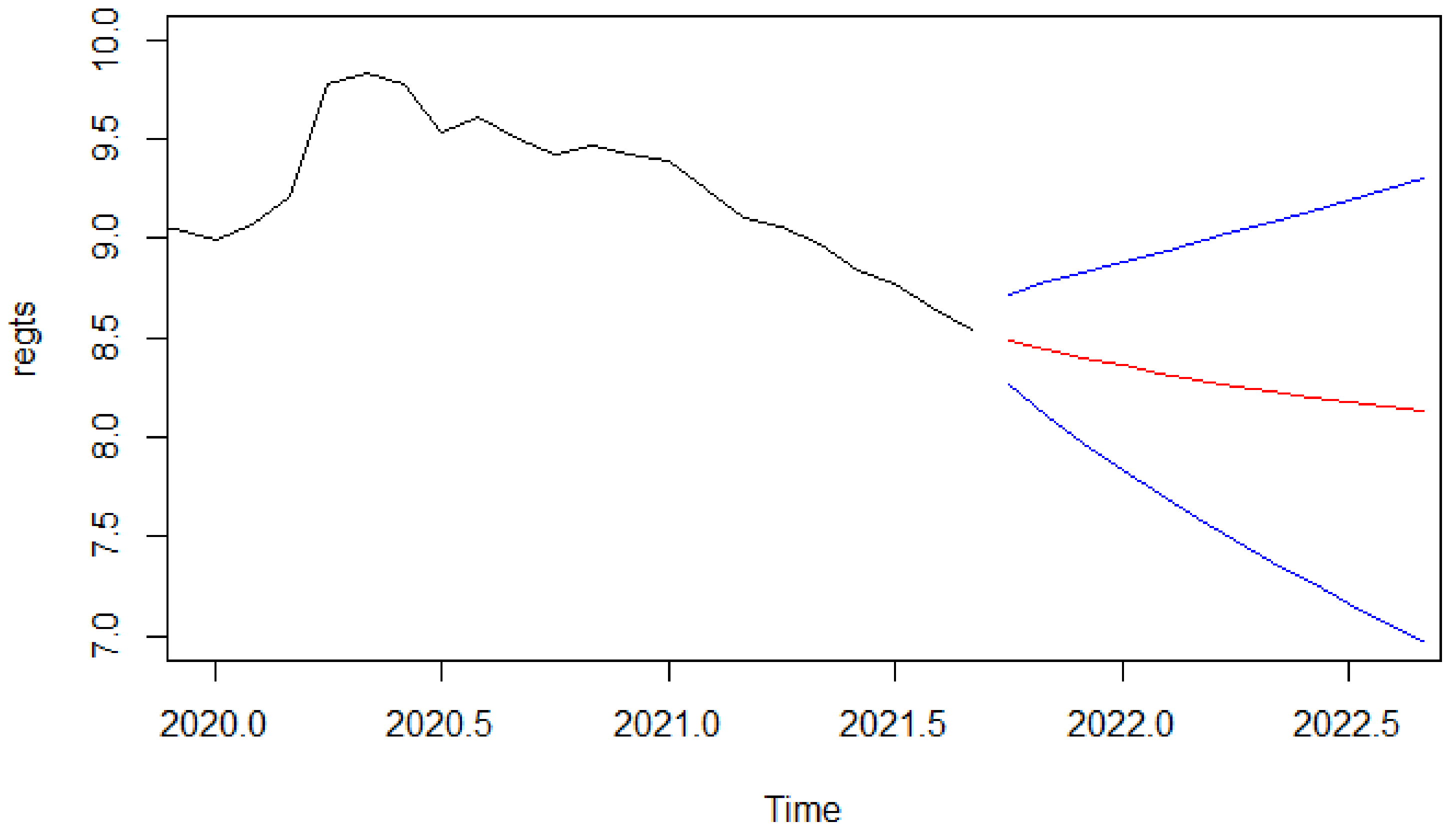
Model comparison

Model	MA(9)	AR(8)	ARIMA(1,1,1)
MAE (horizon = 1 month)	0,104	0,100	0,099
MAE (horizon = 6 months)	0,449	0,490	0,479
MAE (horizon = 12 months)	0,694	0,789	0,730
Highest order term significant?	Yes	No	Yes
Ljung-Box p-value on residuals	0,99	0,73	0,28
BIC	-345,69	-346,19	-373,74

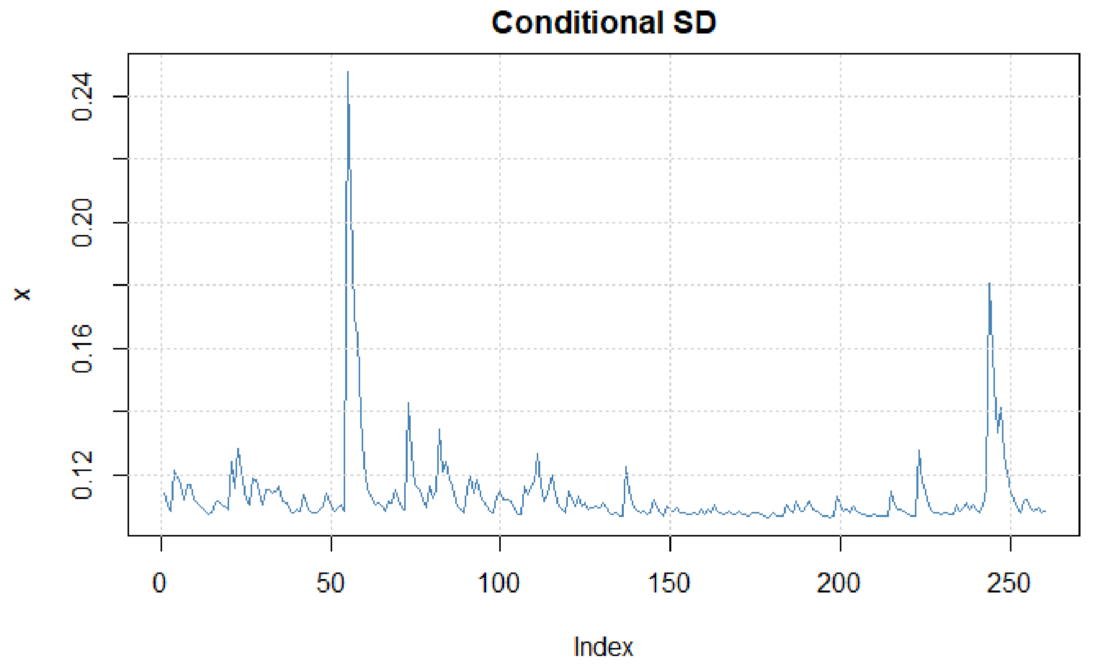
Table 1: In-sample and out-of-sample comparison of 3 ARIMA models

- All 3 proposed models are validated.
- Diebold-Mariano testing between all 3 models over all 3 horizons only shows significant differences in MAE between MA(9) and AR(8) for h=6 and h=12.
- We conclude that AR(8) performs significantly worse than the other models at longer forecast horizons.
- For forecasting, we will use ARIMA(1,1,1) because its out-of-sample performance is not significantly different from MA(9), while being more parsimonious. It also has lower BIC.

ARIMA(1,1,1) 12 month forecast, with 95% prediction interval

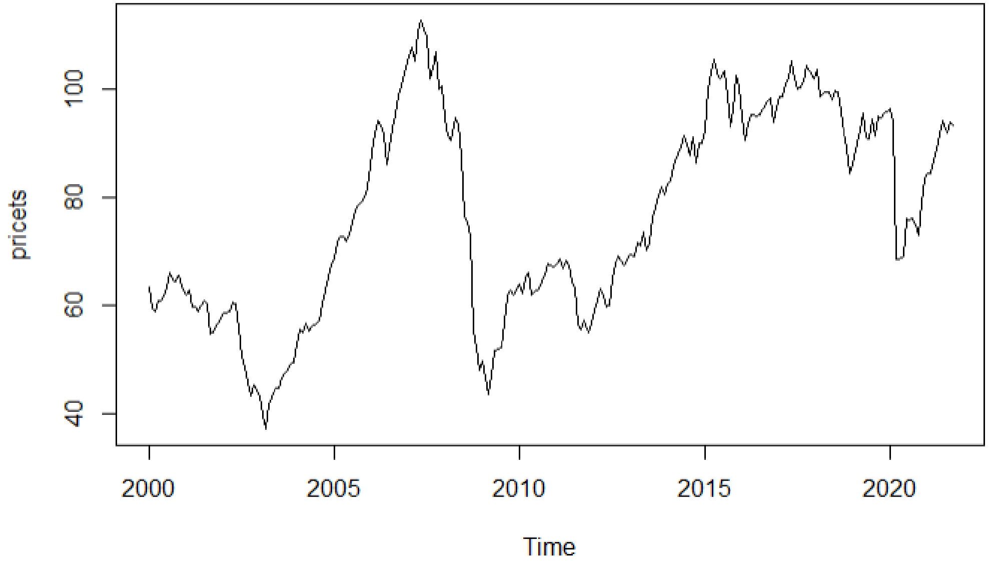


GARCH effects



- Fitting an ARMA(1,1)-GARCH(1,1) to the differenced series reveals significant conditional heteroscedasticity.
- There is a large spike in the conditional SD at the start of the COVID pandemic in Belgium, as well as an unexplained spike in July 2004.

Multivariate analysis



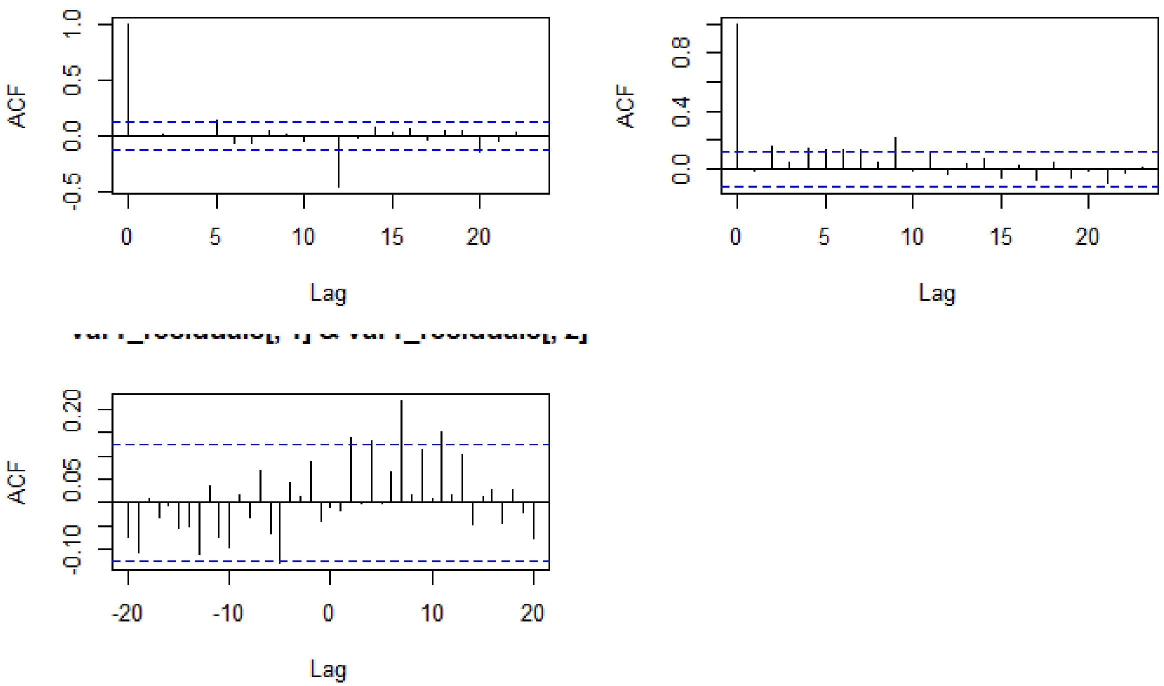
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
37.23	60.86	75.11	76.73	94.09	112.84

- Second series: total share price for all shares in Belgium, index (2015 = 100). Monthly data Jan 2000 - Sept 2021.
- Source: Federal Reserve Economic Data (FRED)
- Total share price acts as a proxy for investors’ trust in the Belgian financial markets.
- We may be interested in whether investors’ trust impacts general unemployment rates.
- We go in logs because we are interested in percent change. The log-differenced series is stationary (ADF p<2,2x10^-16).
- The monthplot shows some seasonality, so we also go in seasonal differences with lag 12.

Multivariate analysis (Granger causality)

- An Engle-Granger test finds no cointegration relationship between the two series, so we test for Granger causality between the (stationary) series.
- We predict unemployment rate with an ADLM(5) containing lags of both unemployment rate and total share price. (it took 5 lags for the residuals to look like white noise by the Q-test).
- This model is then compared with the nested ADLM(5) containing lags of only unemployment rate itself, we find a significant difference between the models ($p = 0.045$). Lagged total share price provides incremental explanatory power in predicting unemployment rate.
- We conclude that there is Granger causality from total share price to unemployment rate.

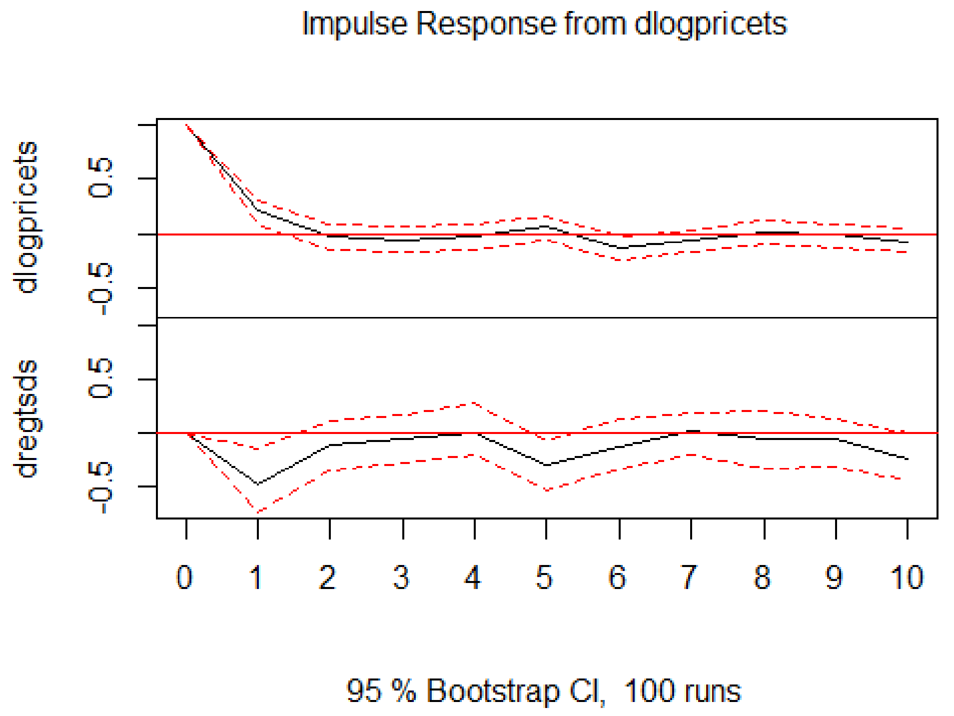
VAR modeling



VAR(1) correlograms

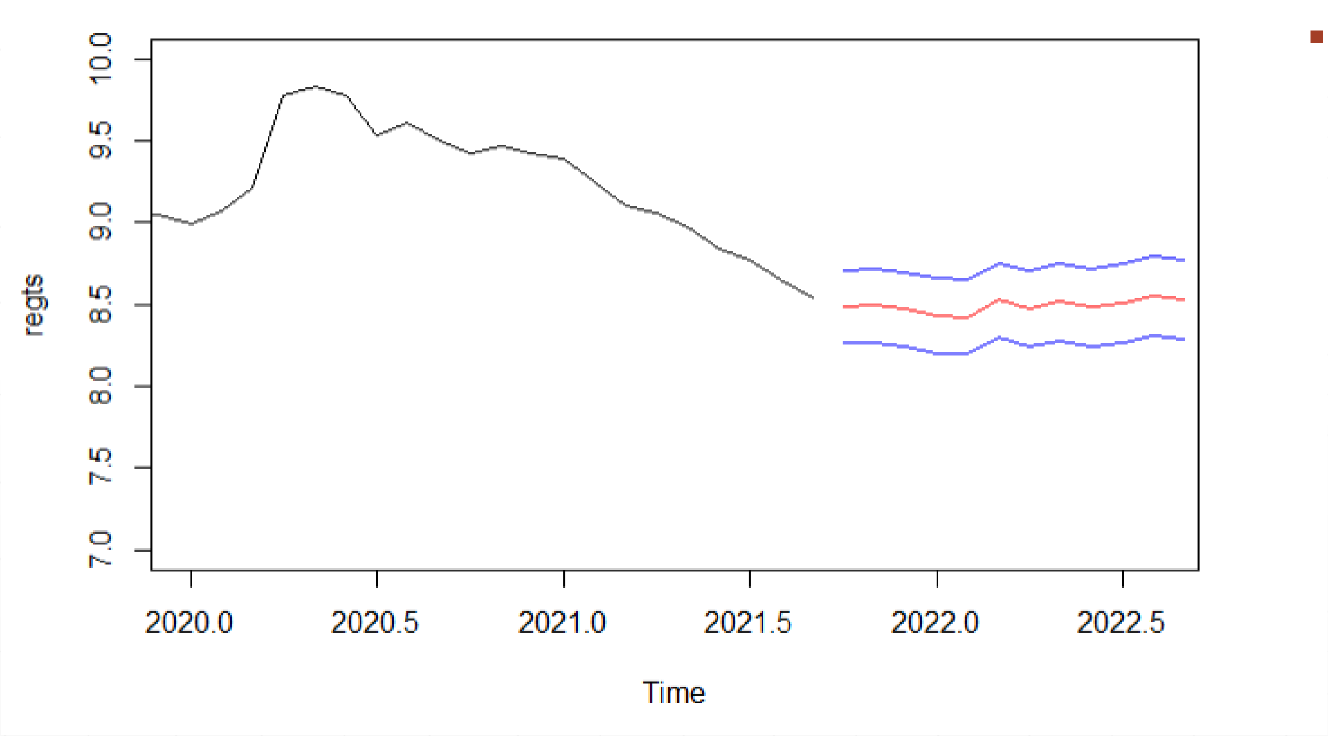
- Initially we choose VAR(1) because it minimizes the BIC. However, this specification leaves several significant autocorrelations and cross-correlations in the residuals, so we cannot validate it.
- AIC is minimized by VAR(13), this model has no notable correlation structure or cross-correlation structure left in the residuals, they look like multivariate white noise. We will continue with VAR(13), even though this model has a lot of parameters.
- The VAR(13) model is significant (p=0.0009) with multiple R-squared = 0.22

Impulse-Response function



- We are primarily interested in the result on registered unemployment due to an impulse from total share price. This is the bottom figure to the left.
- Given a unitary impulse from log share price at time t, we see a significant negative response in unemployment at time t+1 and t+5.

VAR(13) 12 month unemployment forecast with 95% PI, keeping total share price constant.



- The added information from total share price in this scenario increases the accuracy of the prediction (prediction interval is much narrower than in the univariate case).