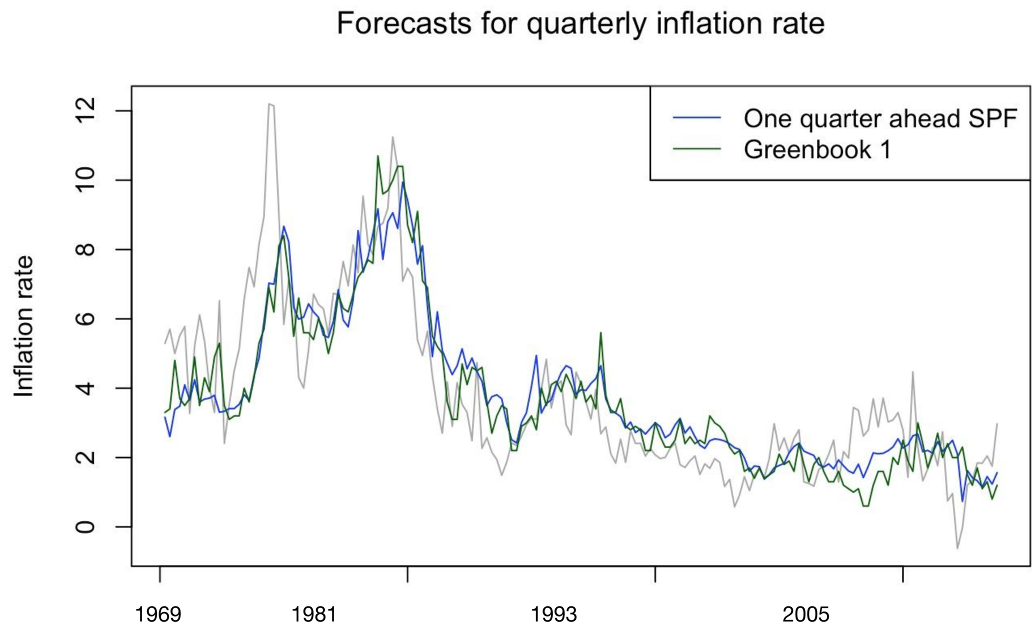
Final Exam, March 2017
MgtF 405 Forecasting
Prof.: Allan Timmermann
Student: Anton Prokopyev

To answer questions 1-5, use the sample 1969Q1-2011Q1.

1. How accurate were the one-quarter-ahead SPF and Greenbook inflation forecasts (columns D and F)? For each of the forecasts, report estimates of predictive accuracy.

Deliverables: Brief explanation of measures of predictive accuracy —DONE
Estimated values of measures of predictive accuracy —DONE



Measures of predictive accuracy are a big topic in the forecasting. There are broadly used measures that depend on the 'scale' of the data: Mean Error, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Median Absolute Error(MdAE), and others. These measures are a good tool for comparing different models on the same data. However, it is advisable not to use these across different datasets because of the different scales. Indicators Like Mean Absolute Percentage Error (MAPE), Mean Absolute Scales Error (MASE) may be used for different scale datasets.

MSE and RMSE remain to be the most popular measures due to simplicity of computation. However, due to squaring MSE put a very big weight on large errors. Thus, an MSE-optimized prediction may have many small errors. Luckily, RMSE allows us to address this issue due to a nature of the square root. It should be noted that in real life settings the cost of committing a forecasting error should be calculated. Depending on which errors are more 'costly' to the research, big or smaller ones, a decision on the criterion should be made.

It should be clarified that MSE notation a lot of the time is used for measuring the expected squared distance between the true value and an estimating *parameter*. In this work under MSE I also understand Mean Square Forecast Error (MSFE): a *forecasted* value subtracted from actual value.

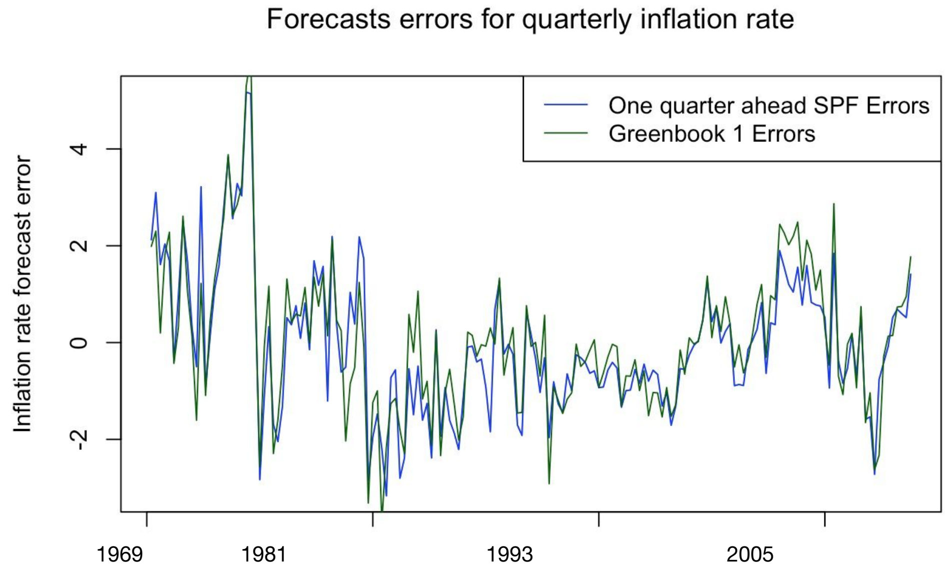
In this exam we operate under an assumption of a squared error loss function, thus I will focus on RMSE. Lower values will be synonymous to a better forecast.

Forecast	RMSE
SPF, One quarter ahead	1.451363
Greenbook, One quarter ahead	1.484430

Based on these results, one quarter ahead SPF produces a slightly more accurate predictions than Greenbook (difference = 0.033067).

2. Evaluate if the one-quarter-ahead SPF and Greenbook inflation forecasts are optimal under MSE loss. Use graphical plots to convey a sense of forecasting performance and evaluate forecast optimality more formally by testing for bias and serial correlation in the forecast errors.

Deliverables: Graphics: plots of forecast errors, scatter plots (forecast vs realized value) —DONE
Explanation of statistical tests of bias, optimality (Mincer-Zarnowitz) —DONE
Regression estimates and tests —DONE
Interpretation of empirical results —DONE

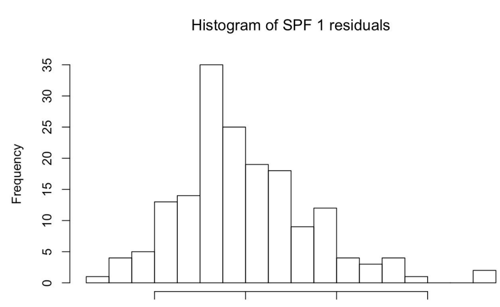


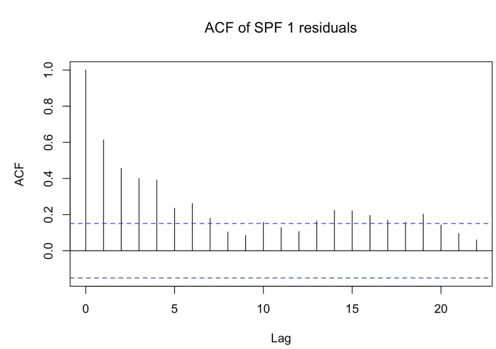
An optimal forecasts exhibits minimum error variance during its forecast horizon. In other words, an optimal forecast creates lowest possible sum of squared errors. The horizon is understood as the number of periods over which the data is forecasted. However, this method forgets to penalize models for their complexity. For that, we used AIC of BIC information criteria.

To consider a forecast to be unbiased, I would like to know if the residuals are white noise (for simplicity assume residuals and errors are terms that are used interchangeably). This will allow me to assume that the forecast is optimal in having used all of the available information properly, with a pure white noise coming out in residual form. My go-to tests for this are the 1) visual inspection of residuals 2) histogram 3) ACF autocorrelation plot. In addition to the ACF plot, I normally do a more formal test for autocorrelation called a general Ljung-Box test. A small p-value (< 0.05) will show the possibility of non-zero autocorrelation within the specified number of lags. Some researchers use the Box-Pierce test and the Durbin-Watson test based on the first autocorrelation.

Then, I test for forecast optimality using the Mincer-Zarnowitz test. An optimal forecast has the following properties 1) it is unbiased 2) its 1-step-ahead errors are white noise 3) the Forecast Errors should be unpredictable as well 4) its *horizon*-step-ahead errors are MA (*horizon*-1) at most 5) variance of *h*-step-ahead error is increasing in *h.*

Looking at the SPF and Greenbook errors in the line plot above I see that the errors do not fully follow a white noise process. Because of the spikes in the beginning and certain cyclicity in the rest of the graph I conclude that there may be some structure to the errors. The variation of residuals does not look the same across time either.

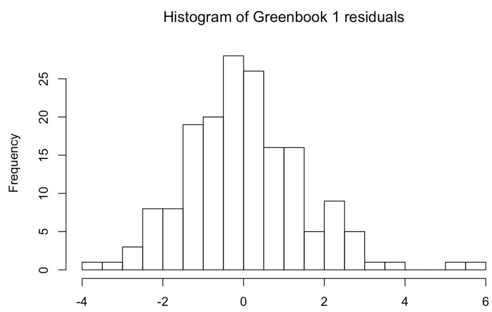


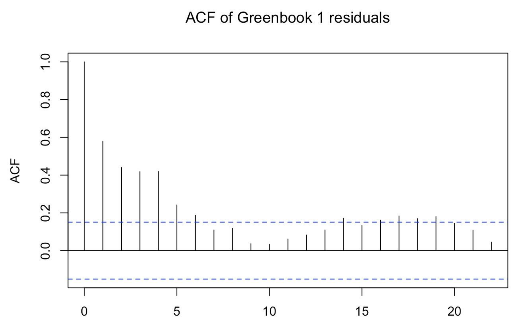


For SPF 1 the histogram shows the residuals do not follow a normal distribution, and the mean is not close to zero. The ACF time plot of errors shows significant autocorrelation during 5+ lags. Therefore, I conclude that SFP 1 does not account for all available information.

Box-Pierce test for SPF 1 shows at df = 10, p-value < 2.2e-16
Ljung-Box test for SPF 1 shows: at df = 10, p-value < 2.2e-16

With P-Values close to zero, I reject the null hypothesis of lack of serial correlation. SPF 1 may still be an acceptable forecast, but the prediction intervals computed with assumption of normal distribution may turn out to be inaccurate.

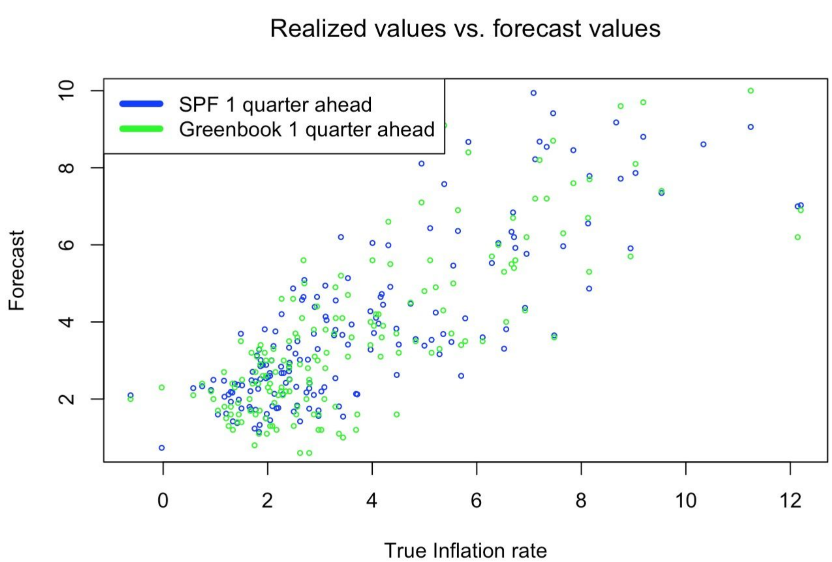




For Greenbook 1 the histogram shows the residuals do follow a normal distribution closely, but the right tail is a bit too long. The ACF time plot of errors shows significant autocorrelation during 5+ lags. Therefore, I conclude that Greenbook 1 does not account for all available information. It may still be an acceptable forecast, but the prediction intervals computed with assumption of normal distribution may turn out to be inaccurate.

Box-Pierce test for Greenbook 1 shows at df = 10, p-value < 2.2e-16
Ljung-Box test for Greenbook 1 shows: at df = 10, p-value < 2.2e-16

With P-Values close to zero, I reject the null hypothesis of lack of serial correlation. Greenbook 1 may still be an acceptable forecast, but the prediction intervals computed with assumption of normal distribution may turn out to be inaccurate.



Examination of the scatterplot above tells me that 1) both forecasts *generally* work as a linear fit can be made easily 2) SPF looks better here as its values are a little more 'condensed' in [0;4] true values range. 3) the correlation coefficient will be positive and > ½. Calculate correlation coefficients: SPF1 & True values: 0.8102083; Greenbook 1 & True values: 0.8058561.

R-squared is the squared correlation between the actual data and the predictions. Therefore, if I run a regression, I for SPF 1 I should see R-squared of 0.6564 and for Greenbook 1 I should see 0.6494. Running a simple linear regression:

```
                                    Dependent variable:
                                ----------------------------
                                      Inflation Rate
                                     (1)            (2)
------------------------------------------------------------
SPF.t.t.1.                         0.958***
                                   (0.054)

Greenbook.t.t.1.                                 0.891***
                                                  (0.051)

Constant                            0.115         0.469**
                                   (0.233)        (0.219)

------------------------------------------------------------
Observations                         169            169
R2                                  0.656          0.649
Adjusted R2                         0.654           0.647
Residual Std. Error (df = 167)      1.457           1.472
F Statistic (df = 1; 167)         319.083***    309.332***
============================================================
Note:                            *p<0.1; **p<0.05; ***p<0.01
```

Et voila. Formally speaking, both forecasts explain – or, rather, predict – about 65% of the variation in true inflation rates. Good first approximation, but I continue the search for a model to better predict inflation. Before we proceed, let's implement the Mincer-Zarnowitz test for optimality.

The idea of this test is to regress realized values on forecasts: $\sigma_{t+1} = \beta_0 + \beta_1 \widehat{\sigma}_{t+1}$

And then the next step is to test the joint null hypothesis: $\beta_0 = 0, \beta_1 = 1$

An intercept of zero means that the forecast is not biased. The slope needs to be 1 in order to perfectly explain the realized values. If the intercept is, for example, 1.3, then the algorithm will on average add to 1.3 to its forecast in order for the equation to settle. This results in continuous underestimation of the realized values.

Mincer-Zarnowitz regression for SPF 1 via Linear Fit and Linear Hypothesis Test functions in R:

```
Hypothesis: SPF.t.t.1.SLID = 1; Intercept = 0
Model 1: restricted model
Model 2: datas$Inflation.rate ~ datas$SPF.t.t.1.SLID
  Res.Df    RSS Df Sum of Sq      F Pr(>F)
1    168 283.72
2    166 283.38  2   0.33934 0.0994 0.9054
```

P-value is highly insignificant, therefore we fail to reject H0. The performance of this model is unbiased under Mincer-Zarnowitz assumptions.

Mincer-Zarnowitz regression for Greenbook 1 via Linear Fit and Linear Hypothesis Test functions in R:

```
Hypothesis: datas$Greenbook.t.t.1.SLID = 1; Intercept = 0
Model 1: restricted model
Model 2: datas$Inflation.rate ~ datas$Greenbook.t.t.1.SLID
  Res.Df    RSS Df Sum of Sq      F Pr(>F)
1    168 284.75
2    166 281.20  2    3.5464 1.0468 0.3534
```

P-value is insignificant, therefore we fail to reject H0. The performance of this model is unbiased under Mincer-Zarnowitz.

3. Which forecasts were most accurate during the sample, the SPF or the Greenbook forecasts? Explain how you can formally test which of those forecasts is most accurate and report the outcome of such a test. Does one forecast dominate the other? Deliverables:
Description and explanation of tests —DONE
Regression estimates, test statistics —DONE
Interpretation of empirical results —DONE

Such test is called Diebold and Mariano test. What is needed are the two competing predictions and the realized values. Squared error loss must be specified. Then one will be able to calculate measures of predictive accuracy embedded in the test to test for null hypothesis of equal accuracy. As part of this test, the mean difference of the loss criterions for the two predictions is 0. A long run estimation of variance of difference between series is used.

Diebold-Mariano forecast comparison test for actual inflation rate:

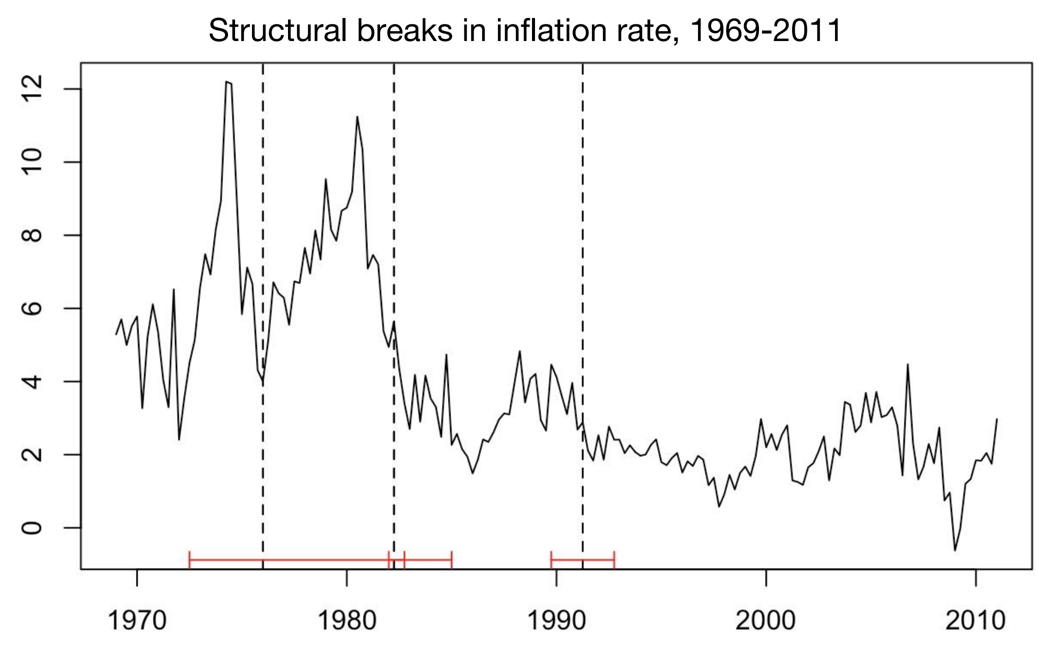
```
Competing forecasts:  SPF tt1 versus Greenbook tt1
Criterion: MSE over 169 observations
Maxlag = 13 chosen by Schwert criterion   Kernel : uniform

Series                  MSE
______________________________
spftt1                  2.106
greenbooktt1            2.204
Difference            -.09708
H0: Forecast accuracy is equal.
S(1) =       -.47  p-value = 0.6383
```

SPF would have been the better forecast by MSE criterion if p-value was low and we rejected the H0.

4. Is there evidence of instability in the forecasting performance of the SPF forecasts during the sample or in the relative forecast accuracy of the SPF versus the Greenbook forecasts?
Deliverables: Discussion of instability tests —DONE
Results from empirical tests and/or graphical analysis —DONE

Instability is also known as structural change. It can be understood as whether there are structural differences in how high or low inflation values when shocks are generated by the market. Because of such events models may become unreliable due to tremendously increased forecasting errors. The Chow test checks if coefficients in 2 linear regressions are the same. If there are structural breaks regression on subsets of data may provide a better model than the combined regression across all the time.



The dotted vertical lines indicate the dates when breaks in inflation rate occurred. Horizontal red lines show their confidence intervals. They are overlapping for the first two indicated breaks. Let's test these dates:

Year	Chow test
1976	F = 6.5769, p-value = 0.001786
1981	F = 53.102, p-value < 2.2e-16
1991	F = 9.3996, p-value = 0.000136
2008	F = 1.5641, p-value = 0.2124

In most cases p-value is < 0.05. Therefore at 95% confidence level we reject the null and confirm that these dates are indeed break points. I've intentionally included 2008, where there is no reported break, and p-value is indeed > 0.05 there.

5. Are the one-quarter-ahead SPF forecasts in column D more accurate than the two-quarter-ahead SPF inflation forecasts in column E? How can you test formally if this holds?

Deliverables: Explanation of test —DONE, Empirical findings and interpretation of results —DONE

Forecast	RMSE
SPF, One quarter ahead	1.451363
SPF, Two quarters ahead	1.631019

Forecast encompassing tests would have helped us greatly in assessing models with more and less information. However, these are mostly model-based, and I don't have the models. Therefore, I am using model-free Diebold-Mariano test again given our limited information set with actual and predicted values only.

```
Competing forecasts:  spftt1 versus spftt2
Criterion: MSE over 169 observations
Series                      MSE
______________________________
spftt1                     2.106
spftt2                      2.66
Difference                -.5538
By this criterion, spftt1 is the better forecast

H0: Forecast accuracy is equal.
S(1) =     -2.01   p-value = 0.0445
```

SPF1 is still the better forecast by MSE criterion since p-value is low and we reject the H0. In addition, I also ran a different encompassing test from "A Companion to Economic Forecasting" edited by Michael P. Clements, David F. Hendry, see Eq (14.2) on p. 302. First run a simple regression with both forecasts:

$$y_{t+1} = \alpha_0 + \alpha_1 \hat{y}_{1,t+1} + \alpha_2 \hat{y}_{2,t+1} + u_{t+1}$$

where yhat_1 and yhat_2 are competing forecasts for actual observations y:

```
                        Dependent variable:
                          Inflation Rate
-----------------------------------------------
SPF.t.t.1.                   1.412***
                              (0.198)
SPF.t.t.2.                   -0.502**
                              (0.211)
Constant                      0.297
                              (0.242)
-----------------------------------------------
Observations                   169
R2                            0.668
Adjusted R2                   0.664
Residual Std. Error      1.437 (df = 166)
F Statistic          166.798*** (df = 2; 166)
===============================================
```

```
Note:               *p<0.1; **p<0.05; ***p<0.01
```

We see that SPF 1 is more statistically significant and positively associated with inflation. However, what we want to do now is to test joint Null Hypothesis that SPF1 coefficient = 0 and SPF2 coefficient = 1. In other words Null Hypothesis is whether SPF2 fully encompasses SPF1.

```
Linear hypothesis test: datas$SPF.t.t.1. = 0; datas$SPF.t.t.2. = 1

Model 1: restricted model
Model 2: datas$Inflation.rate ~ datas$SPF.t.t.1. + datas$SPF.t.t.2.

  Res.Df    RSS Df Sum of Sq      F    Pr(>F)
1    168 449.25
2    166 342.75  2     106.5 25.789 1.765e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

P-value is statistically significant at 95% confidence level. Thus, reject the null. The result of the test is that, SPF2 does not fully encompass SPF1 according to the Michael P. Clements, David F. Hendry encompassing test.

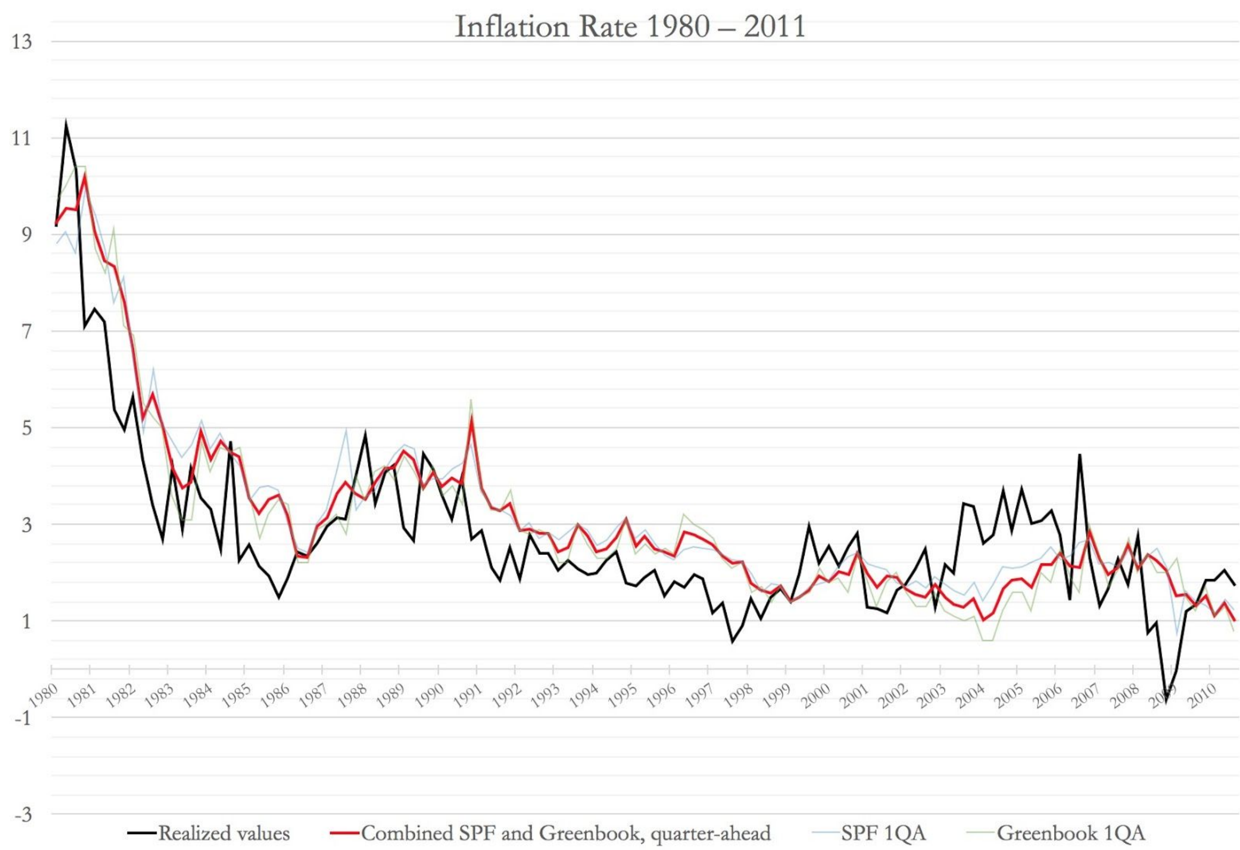
Questions 6-10 use the out-of-sample period 1980Q1-2011Q1.

6. Assess whether combining the one-quarter-ahead Greenbook and SPF forecasts leads to better overall out-of-sample forecasting performance over the period 1980Q1-2011Q1.

Deliverables: Explanation of combination method —DONE
Empirical performance results for combination —DONE
Interpretation of results —DONE

Combination of forecast models has been known to consistently improve predictive results. This is possible because many forecasts possess unique features that other models are unable to grasp. By combining them we are able to 'preserve' the unique information, which is usually reflected in lowered residuals: a sign, that new information has been absorbed. To do this, first I perform a simple forecast where I average the two forecasts while assigning equal weights. This indeed results in an improvement in terms of lowering RMSE.

Forecast	RMSE
Combined SPF 1 & Greenbook 1	1.161464
SPF 1	1.164474
Greenbook 1	1.232882



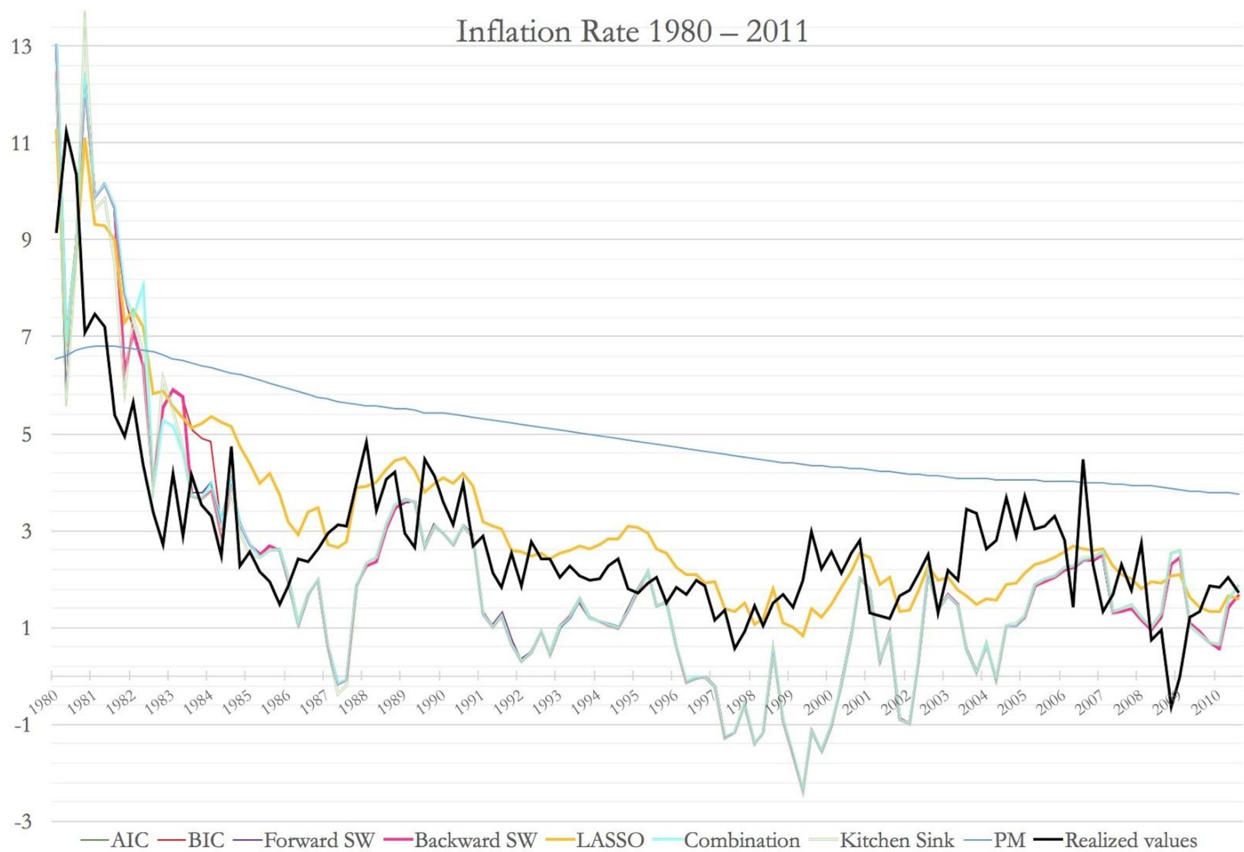
Visual inspection of the results does not provide many insights into the improvement in performance, except for the fact that the combined forecast's errors indeed seem lower in many cases due to averaging of the two extremes effect.

Other combination methods exist. In 1969 Bates and Granger wrote a famous paper on "The Combination of Forecasts". They proved that combination of forecasts leads to better forecast accuracy in many cases. The mixture functions usually create weights after combining forecasts. It is based on performance of a forecast or prediction up until the current point.

Many methods take into account all intervals produced by individual models. With only one bad model the entire combination may be ruined. prediction intervals are screwed. That is why covariances between forecasting errors need to be taken into account to estimate the variance expression for the linear combination of methods of interest.

7. Next, using lagged values of inflation and any of the predictor variables listed in columns I-L, estimate time-series models and use them to generate a series of out-of-sample inflation forecast for the period 1980Q1-2011Q1. Specifically, generate one-step-ahead forecasts recursively by using data up to 1979Q4 to select and estimate a model and generate forecasts for 1980Q1. Next, add data for 1980Q1, select and re-estimate a forecasting model, and predict inflation for 1980Q2. Continue this way up to 2011Q1. Note that your preferred forecasting model may change over time. Show graphs of your time-series forecasts and evaluate their predictive performance and optimality.

Deliverables: Explanation of model selection – which variables get selected and how often? —Done
Graphical evaluation of time-series forecasts —Done
Empirical estimates of forecast accuracy —Done
Forecast optimality tests (Mincer-Zarnowitz) —Done + Interpretation of results —Done



On the graph above we can see true inflation values in black ink. The rest of the colors represent different forecasts. LASSO forecast on average looks like the closest to true values. A variety of other forecasts show very similar performance, and thus cannot be clearly seen due to overlapping effect. I have done my best to resolve this issue. It is not surprising that Kitchen Sink and Stepwise forecasts are similar as there are only a few predictor variables to chose from. It is likely that one of them got preference most of the time. The prevailing mean forecast habitually perform quite poorly as it is unable to grasp structural changes and quick fluctuations very well.

Here is how often some variables get selected as predictors using AIC and BIC models:

Forecast	T-Bill rate	Treasury bill	Unemployment	S&P 500 Index
AIC	123	117	1	109
BIC	123	115	0	106

Clearly, unemployment is the least favorite predictor variable in this case. In case of T-Bill, we have to be cautious of endogeneity problems. As stated in Investopedia: “T-Bills are still subject to inflation risk.” It can affect T-Bill rates, so the high preference for T-Bill may also be connected with mutual feedback of the two variables.

	AIC	BIC	Forward SW	Backward SW
RMSE	1.896839477	1.90105234	1.888385554	1.878297101
	LASSO	**Combo**	**Kitchen Sink**	**Prev. Mean**
RMSE	1.340895223	1.898420396	1.902892535	2.622212806

The table above contains estimates of forecast accuracy. The best model out of 8 so far is LASSO, with the lowest RMSE of 1.34. It is on par and very close to our special combined SPF and Greenbook forecast with RMSE of 1.16.

Mincer-Zarnowitz regression for LASSO via Linear Fit and Linear Hypothesis Test functions in R:

```
Hypothesis: forlasso90$LASSO.SLID = 1; Intercept = 0
Model 1: restricted model
Model 2: forlasso90$inflations.1 ~ forlasso90$LASSO.SLID
  Res.Df    RSS Df Sum of Sq      F    Pr(>F)
1    122 157.23
2    120 115.16  2    42.071 21.921 7.682e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

With P-values < 0.05 at 95% confidence level I reject H0 of MZ test. Therefore, LASSO model is biased. Since it is my best model, I assume others' performance will be even worse.

To further confirm LASSO's optimality I test it against every other forecast using the Diebold-Mariano test:

LASSO vs.	AIC	BIC	Forward SW	Backward SW
p-value	0.0339	0.0247	0.0371	0.0426
	LASSO vs.	**Combo**	**Kitchen Sink**	**Prev. Mean**
	p-value	0.0312	0.0352	0.0000

In every single case I reject H0, which means that LASSO is better than any other forecast model in this case.

8. Evaluate if your time-series forecasts from question 7 are significantly more or less accurate than the SPF and Greenbook forecasts over the period 1980Q1-2011Q1.

Deliverables: Explanation of tests — DONE
Empirical results and interpretation of findings — DONE

For test explanation please see above. Diebold-Mariano test of SPF 1 against new forecasts:

SPF 1 vs.	AIC	BIC	Forward SW	Backward SW
p-value	0.0071	0.0047	0.0069	0.0066
SPF 1 vs.	**LASSO**	**Combo**	**Kitchen Sink**	**Prev. Mean**
p-value	0.3209	0.0063	0.0074	0.0000

All p-values are < 0.05, therefore we reject H0 every time. This means SPF 1 is better than any of these models.

For test explanation please see above. Diebold-Mariano test of Greenbook 1 against new forecasts:

Greenbook 1 vs.	**AIC**	**BIC**	**Forward SW**	**Backward SW**
p-value	0.0182	0.0138	0.0179	0.0168
Greenbook 1 vs.	**LASSO**	**Combo**	**Kitchen Sink**	**Prev. Mean**
p-value	**0.6448**	0.0164	0.0184	0.0000

Greenbook 1 is better than any of these models, except for LASSO! In this case p-value is > 0.05, therefore I do not reject H0 that Greenbook is the forecast accuracy is equal.

9. Use the time-series model from question 7 to generate out-of-sample 90% interval forecasts for the period 1980Q1-2011Q1. State and motivate any assumptions made to generate the 90% interval forecasts and evaluate if they are correctly specified.

Deliverables: Description of methodology used to generate the 90% interval forecasts —DONE
Evaluation of interval forecasts —DONE
Empirical findings and interpretation of results —DONE

When forecasting, we estimate the very middle of a range of possible values the variable in question can. In economics forecasts are often accompanied by an interval giving a range of values such variable can assume with certain high probability. Most common are 95%, 90% 80%, 66% prediction intervals. They contain a range of values that can be realized with corresponding probabilities. Alternatively, we expect the true value to lie within this interval with this specified probability.

To forecast intervals forecasts I first calculate the Root Mean Square Forecast Error (RMSFE) using the following formula:

$$\text{RMSFE} = \sqrt{E[(Y_{T+1} - \hat{Y}_{T+1|T})^2]}$$

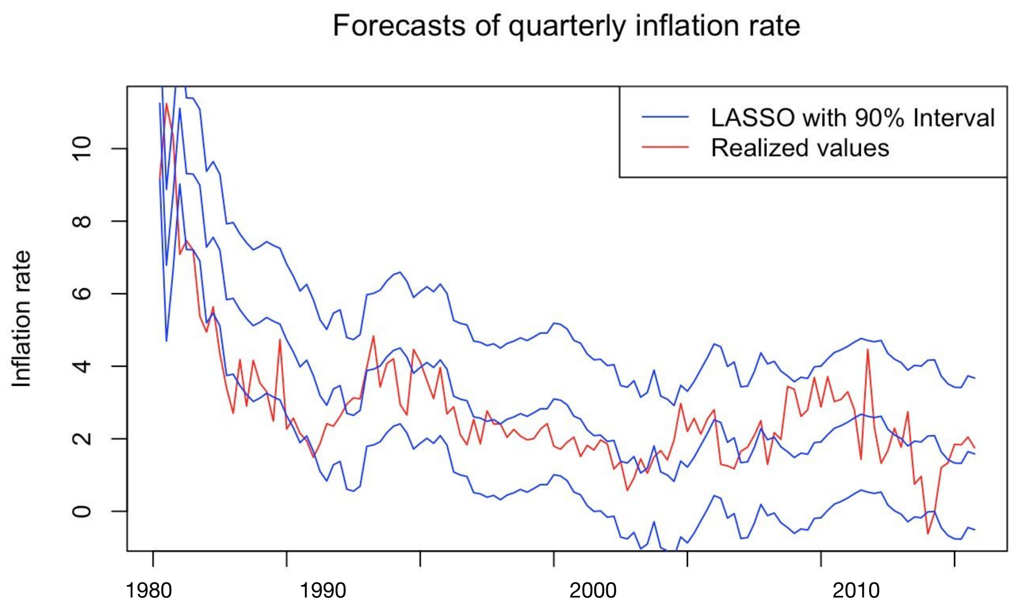
In short, I subtract the forecasted value in time *t* from the realized value in the same time *t* to get Forecast Errors. I then square FEs (variance) and take a mean value of all of them. Extract the square root to get RMSFE.

Under the working assumption of normal distribution of the residuals I then use the following formula for interval forecasts:

$$FCI_t = F_t \pm 1.96 * \sqrt{MSFE}$$

I make an adjustment: as the professor did not ask for 95% interval, I replace 1.96 with 1.64 for 90% interval forecast.

To evaluate interval forecasts one needs to check if they have to assume that the residuals are showing strong signs of normal distribution and are not correlated. If any of these conditions doesn't hold, then this method may need to be adjusted. Especially when dealing with financial data, researchers may find that the residuals' tails are quite fat. If the distribution is not normal, oftentimes a t-Distribution may become a reasonable alternative.



With these results, it is safe to say that 90% interval LASSO forecast includes realized values in its range more than 90% of the forecasted time. However, it is still somewhat lacking in the directional accuracy. In fact, most of the times when realized values are outside of the 90% bands, the direction of forecast if wrong. To further prove this claim, one would use a directional accuracy test, such as the Directional Accuracy Test of Pesaran and Timmermann (currently unavailable in 'rugarch' package for R).

10. Use the time-series model from question 7 to generate out-of-sample density forecasts for the period 1980Q1-2011Q1. State and motivate any assumptions made to generate the forecasts and evaluate if the density forecasts are correctly specified.

Deliverables: Description of methodology used to generate the density forecasts — DONE
Evaluation of density forecasts — DONE
Empirical findings and interpretation of results — DONE

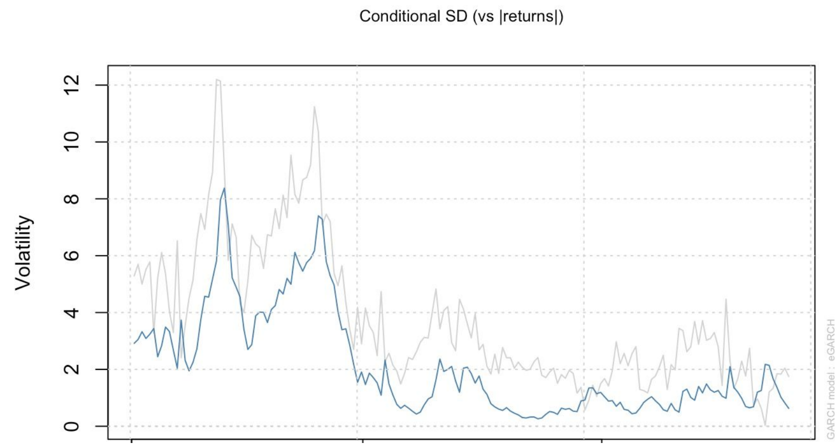
To identify the presence of ARCH volatility effects in inflation, I use the ARCH LM-test; where null hypothesis is no ARCH effects. The results are:

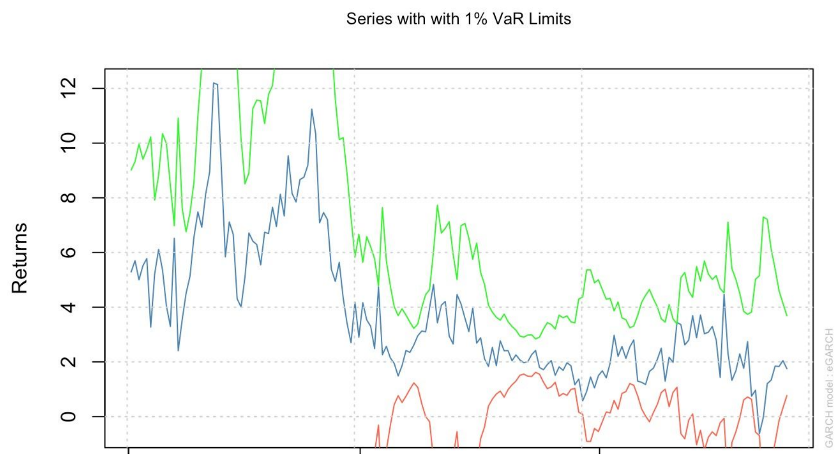
```
Chi-squared = 100.21, df = 1, p-value < 2.2e-16
```

P-value is very low, reject H0. Therefore, there are ARCH effects in inflation. This means GARCH model is recommended. Proceed to density forecasting using ruGARCH package.

Information criteria	**Model: fGARCH** Order: (1,1) Submodel: GARCH	**Model: eGARCH** Order = c(1,1)	**Model: fGARCH** Order =(1,1) Submodel: GJRGARCH
Akaike (AIC)	4.149486	3.706188	3.717404
Bayes (BIC)	4.205272	3.799163	3.810379

To evaluate the three forecasts I used AIC and BIC criteria. Small values represent a better fit of a model. Here we see that according to both AIC and BIC eGARCH model is the best at the most popular order of (1,1). I now proceed to examine if the conditional variance of eGARCH exhibits asymmetrical features.



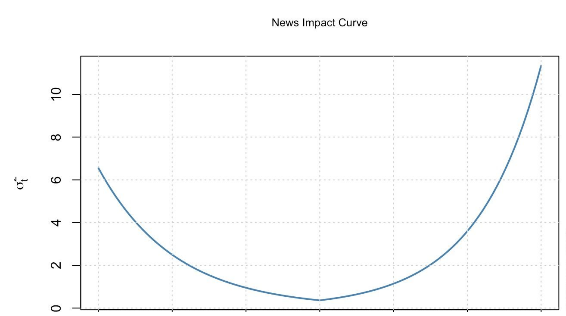


According to conditional standard deviation estimates and series with 1% VaR limits, no asymmetry identified. The news impact curve below is also highly symmetrical, good signs overall.

Proceeding to examine the output:
Optimal Parameters

```
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      2.227920    0.060798 36.64447  0.00000
omega  -0.026134    0.055810 -0.46827  0.63959
alpha1  0.079345    0.100273  0.79129  0.42878
beta1   0.908287    0.044115 20.58896  0.00000
gamma1  0.916529    0.169072  5.42094  0.00000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      2.227920    0.096866 23.00001  0.00000
omega  -0.026134    0.050677 -0.51571  0.60606
alpha1  0.079345    0.091743  0.86486  0.38712
beta1   0.908287    0.038955 23.31648  0.00000
gamma1  0.916529    0.151514  6.04914  0.00000
```



As we see from the output, alpha_1 is highly statistically insignificant. Therefore, it is not different from zero, and volatility may be constant. However, for this to hold true, beta_1 would have to be equal to 1. It is very close and highly statistically significant at 95% confidence. Therefore, a strong volatility in inflation may be expected, but not for indefinite amount of time. In other words, alpha + beta < 1, therefore there's cov stationarity. What this essentially has been is a hypothesis test that assumes homoscedasticity and informs us that there may be heteroscedasticity.

Additional sources used:

- http://stats.stackexchange.com/questions/93529/dummies-instead-of-the-chow-test/93548
- http://stats.stackexchange.com/questions/18880/how-to-interpret-coefficients-from-a-garch-model
- http://stats.stackexchange.com/questions/95719/chow-structural-test-in-r
- http://blog.stata.com/2016/06/01/tests-of-forecast-accuracy-and-forecast-encompassing/
- http://quant.stackexchange.com/questions/22499/gjr-garch-with-alpha-0-as-parameter-estimate
- http://quant.stackexchange.com/questions/23286/rugarch-interpret-test-results
- http://stats.stackexchange.com/questions/154346/fitted-confidence-intervals-forecast-function-r
- https://rpubs.com/Bio-Geek/71339
- http://eranraviv.com/volatility-forecast-evaluation-in-r/
- http://robjhyndman.com/hyndsight/
- http://robjhyndman.com/hyndsight/forecast-combinations/
- http://www.stata.com/meeting/uk10/UKSUG10.Yaffee.pdf
- https://www.otexts.org/fpp/2/7
- http://www.r-tutor.com/elementary-statistics/simple-linear-regression/prediction-interval-linear-regression
- Browser history available upon request.