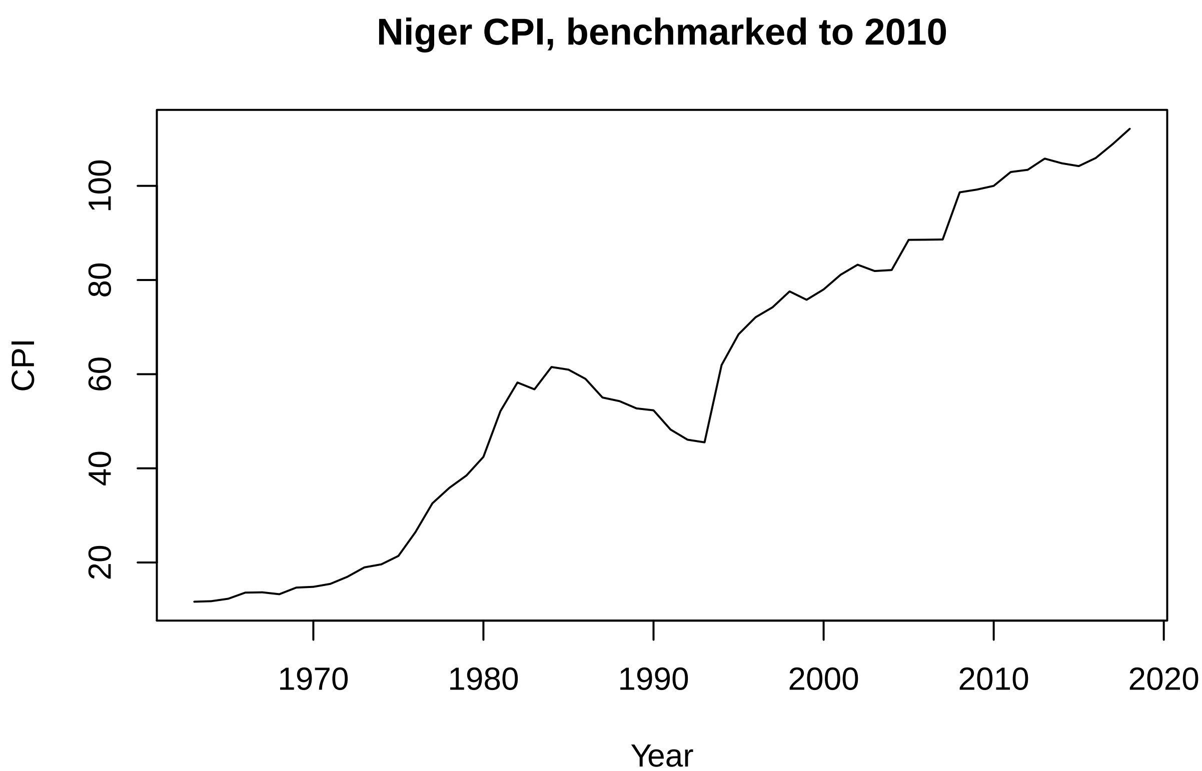
CPI of Niger: rise or fall?

Premilinary Analysis of the data

TS used in this work as an annually Consumer Price Index of Niger every year from 1963 to 2017 which is gathered by the World Bank. CPI could be considered as a proxy of the inflation, so in our work, we want to make short-run predictions of this indicator.

CPI shows how much money people usually need for buying a standard basket of goods which are necessary to fulfill all essential needs, that's why CPI is easy for interpretation. Also, as you know, CPI is one of the most important indicators for consumers in terms of their expectations about future, especially, how much of their disposable income they should save for future consumption or spend in current period, so our work will give consumers an opportunity to plan their budget in more rational way.

Considering the country, nowadays Niger is one of the poorest countries in the world (the last position in the World HDI ranking), so problems of developing countries are aggravated. Prediction of the future value of CPI in short-run may be a step towards solving the global problem of the economic gap of developing countries.



As we can see from visual analysis, the TS is not stationary (there is an obvious trend). Also, we can see that during the period from 1963 to 1984 the CPI grew, but after 1984 there was a decline for nine years, and after that, there was approximately linear growth.

By its economic definition, CPI is an index that measures inflation, and according to the basic economic theory, the inflation rate is essentially dependent on the growth rate of the money supply relative to the growth of the economy. Due to the reason that 2010 is stated as a benchmark year, under normal circumstances we should observe a clear trend of growth. The overall change in values of the TS is under 120% (this increase is usually considered as normal).

However, in 1984 there was a drought in Niger, also accompanied by structural economic transformation based on the change in political leadership. That actually could affect the pace of economic development, what explains the observed decline of CPI during the period from 1984 to 1993.

There's no prerequisites for CPI to show the value out of trend in the nearest future, that's why we expect the continuation of the increase with differences similar to the last available years.

Stationarity

Visual analysis

Looking at a raw data it can be seen that there is an obvious upward trend throughout the period. In 1984 − 1993 there is decline which we have explained earlier. The trend itself seems to be linear rather than exponential, hence non-stationarity is observed.

Essential analysis

As prices have a tendency to rise each year in comparison with previous ones, the numerator in the formula of CPI will be higher, than the denominator. So CPI should be higher every year, that gives us a suggestion that due to the economic sense of CPI this Time Series can't be stationary.

Formal analysis

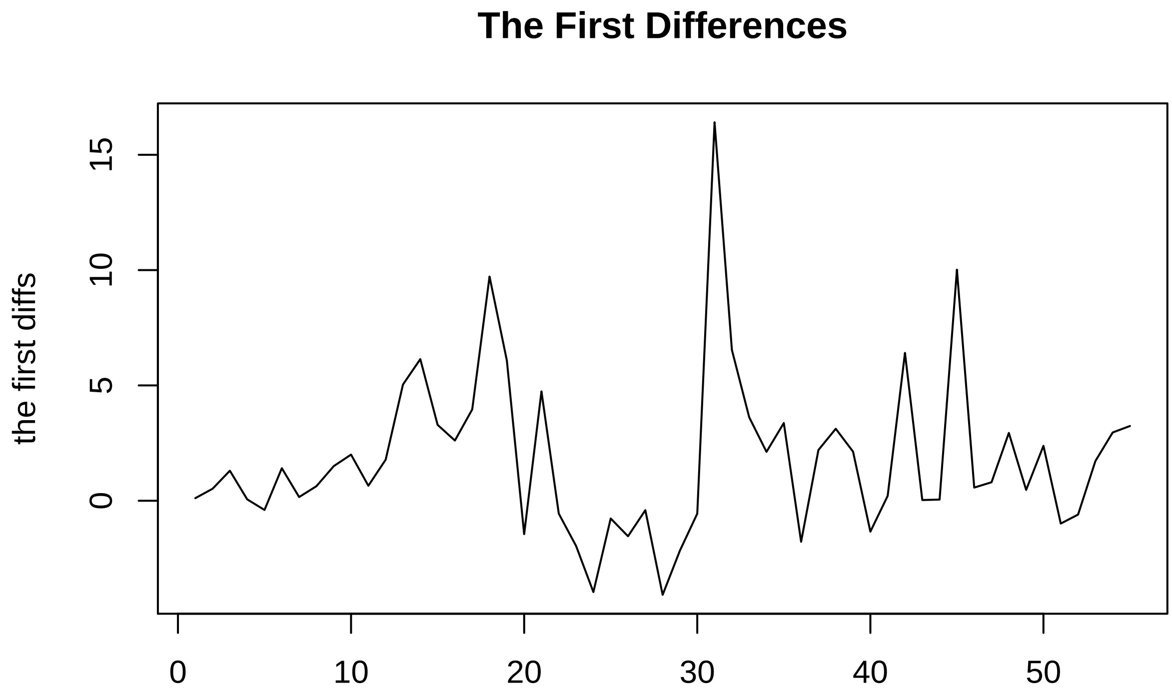
Visual and essential analysis give us a strong evidence that raw data is non-stationary, that is why there is no need in formal testing. However, for training purposes, the ADF and KPSS tests are going to be conducted.

Formal tests show mixed results: according to ADF test we reject the null (unit root), hence the test is in favour of stationarity, whereas KPSS test rejects the null (stationarity) and the test is in favour of non-stationarity.

However, as essential and visual analysis are more important than formal analysis, we ignore the results of formal testing, since the data is experiencing obvious trend that leads to non-stationarity.

Stationary transformations

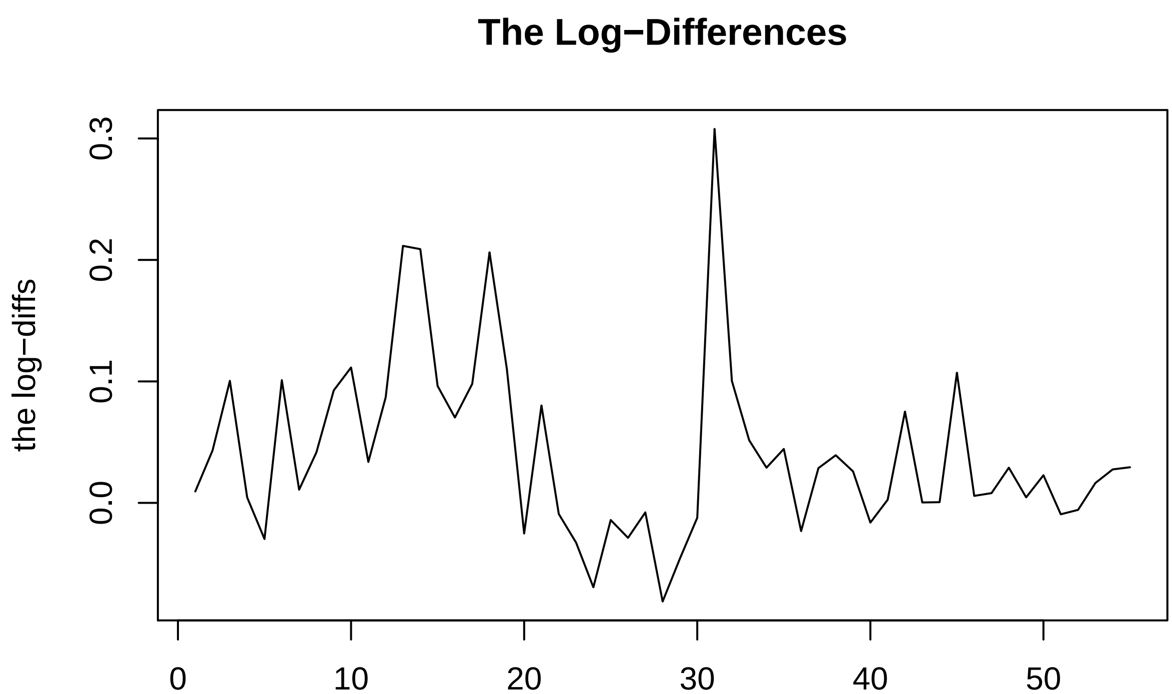
Firstly, to make data stationary we decided to choose the first differences, as it has appropriate economic sense. The main reason is that CPI is measured in percantage to the base year (2010), so using the first diffs is meaningful.



It seems that transformed data is stationary, according to visual analysis, but for being sure conduct the formal testing. We have made ADF and KPSS tests.

Formal tests again show mixed results: in accordance to KPSS test we can not reject the null hypothesis, so TS is stationary.

For studying purposes let us using log diffs to transform initial data and check the result in a formal way.



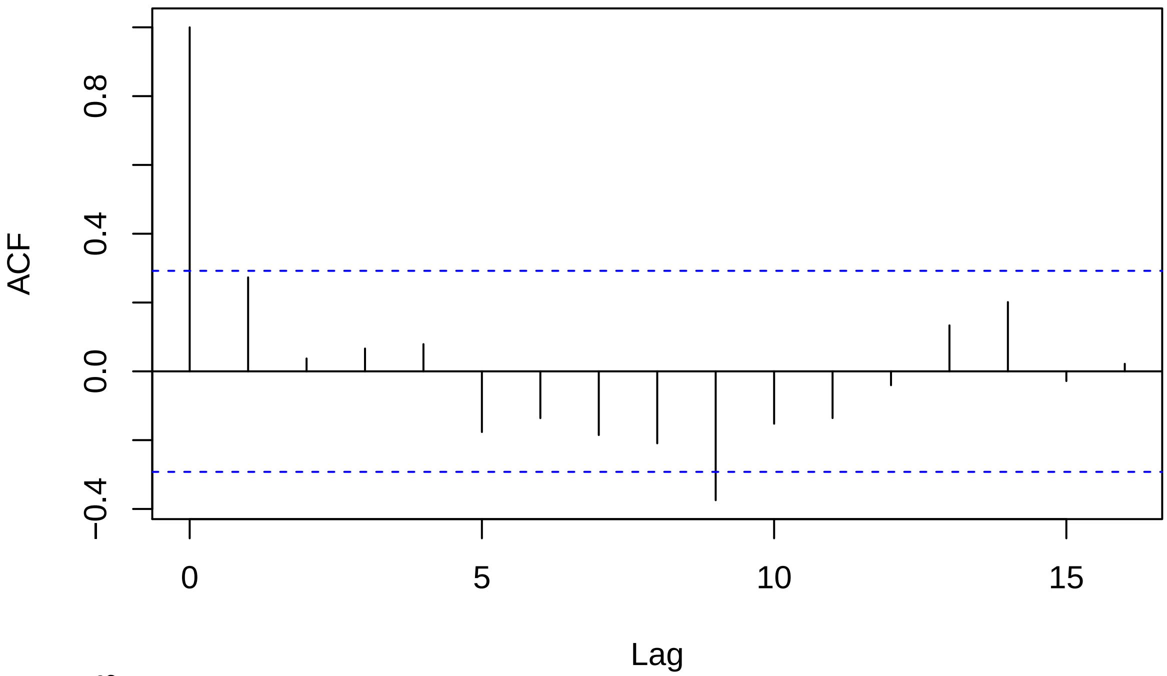
In this case both ADF and KPSS show that our transformed data is not stationary.

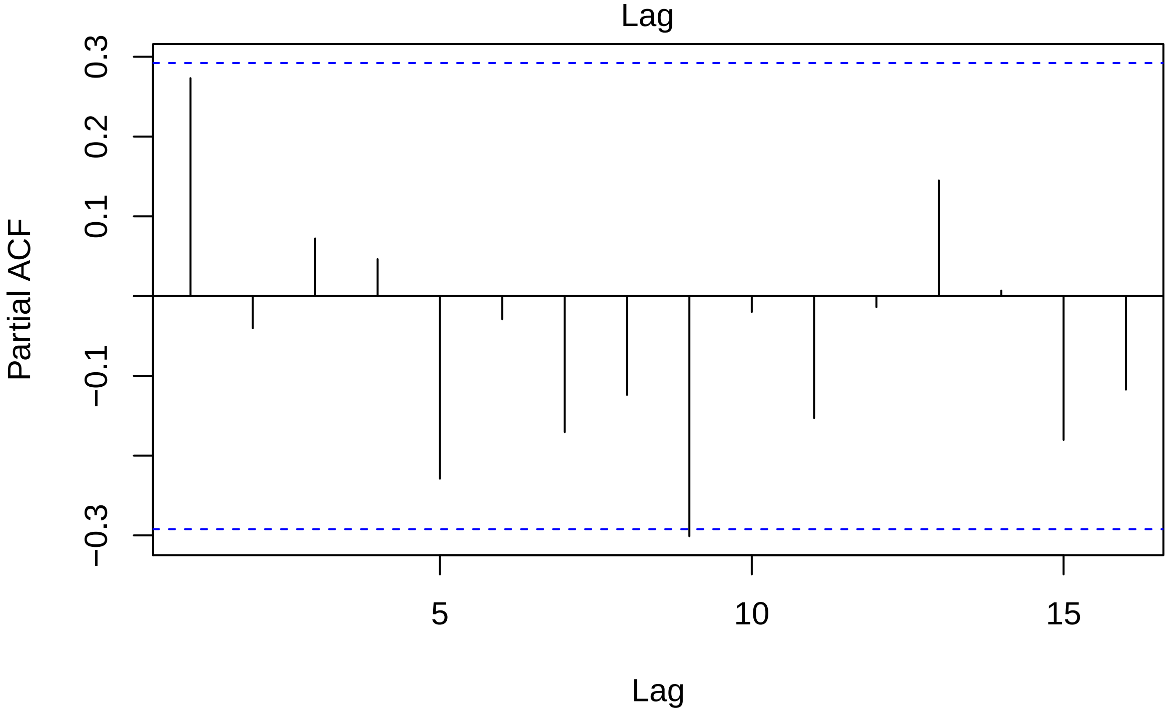
Finally, we decided to choose the 1st diffs in further research.

Modelling

Firstly, divide our sample on three parts: fit subsample, validation subsample and test subsample.

Let us plot ACF and PACF of our fit subsample to choose an appropriate range of p and q.





Keeping in mind ACF, PACF and common sense we decided to consider all ARMAs up to p = 3 and q = 3. Our next step will be checking all the models whether their residuals resemble white noise, consequently we keep models that experience no autocorrelation in residuals for further diagnostics. Future modelling will show us that p = 3 and q = 3 are sufficient to choose a few models, which fit the data in a good way.

According to the residuals of ARMAs we will continue further diagnostic with the following 11 models: AR(1), MA(1), AR(2), MA(2), AR(3), MA(3), ARMA(1,1), ARMA(2,1), ARMA(2,2), ARMA(2,3), ARMA(1,3).

Let us also use information criteria and check AR parts for stationarity. For convinient use, we will combine all the results for 11 ARMAs into a table.

model	p	q	stationarity	LB	AIC	SBIC
AR(1)	1	0	TRUE	0.3032969	250.0361	255.4561
MA(1)	0	1	TRUE	0.1925292	249.8853	255.3053
AR(2)	2	0	TRUE	0.1733988	251.8775	259.1041
MA(2)	0	2	TRUE	0.1717873	251.8197	259.0464
AR(3)	3	0	TRUE	0.1138294	253.6242	262.6575
MA(3)	0	3	TRUE	0.1040973	253.6234	262.6567
ARMA(1,1)	1	1	TRUE	0.1695393	251.8280	259.0546
ARMA(2,1)	2	1	TRUE	0.1118957	253.8268	262.8601
ARMA(2,2)	2	2	TRUE	0.3644836	246.4696	257.3096
ARMA(2,3)	2	3	TRUE	0.1074627	252.3188	264.9655
ARMA(1,3)	1	3	TRUE	0.1700639	253.2024	264.0424

It is convinient to sort the table in accordance to Akaike Information Criterion.

model	p	q	stationarity	LB	AIC	SBIC
ARMA(2,2)	2	2	TRUE	0.3644836	246.4696	257.3096
MA(1)	0	1	TRUE	0.1925292	249.8853	255.3053
AR(1)	1	0	TRUE	0.3032969	250.0361	255.4561
MA(2)	0	2	TRUE	0.1717873	251.8197	259.0464
ARMA(1,1)	1	1	TRUE	0.1695393	251.8280	259.0546
AR(2)	2	0	TRUE	0.1733988	251.8775	259.1041
ARMA(2,3)	2	3	TRUE	0.1074627	252.3188	264.9655
ARMA(1,3)	1	3	TRUE	0.1700639	253.2024	264.0424
MA(3)	0	3	TRUE	0.1040973	253.6234	262.6567
AR(3)	3	0	TRUE	0.1138294	253.6242	262.6575
ARMA(2,1)	2	1	TRUE	0.1118957	253.8268	262.8601

It is seen from the table that it would be meaningful to choose six AIC-best models, for instance ARMA(2,2), MA(1), AR(1), MA(2), ARMA(1,1) and AR(2).

Let us also sort out the results basing on Bayesian Information Criterion.

model	p	q	stationarity	LB	AIC	SBIC
MA(1)	0	1	TRUE	0.1925292	249.8853	255.3053
AR(1)	1	0	TRUE	0.3032969	250.0361	255.4561
ARMA(2,2)	2	2	TRUE	0.3644836	246.4696	257.3096
MA(2)	0	2	TRUE	0.1717873	251.8197	259.0464
ARMA(1,1)	1	1	TRUE	0.1695393	251.8280	259.0546
AR(2)	2	0	TRUE	0.1733988	251.8775	259.1041
MA(3)	0	3	TRUE	0.1040973	253.6234	262.6567
AR(3)	3	0	TRUE	0.1138294	253.6242	262.6575
ARMA(2,1)	2	1	TRUE	0.1118957	253.8268	262.8601
ARMA(1,3)	1	3	TRUE	0.1700639	253.2024	264.0424
ARMA(2,3)	2	3	TRUE	0.1074627	252.3188	264.9655

Analyzing this quality criterion, we get the same bundle of six BIC-best models.

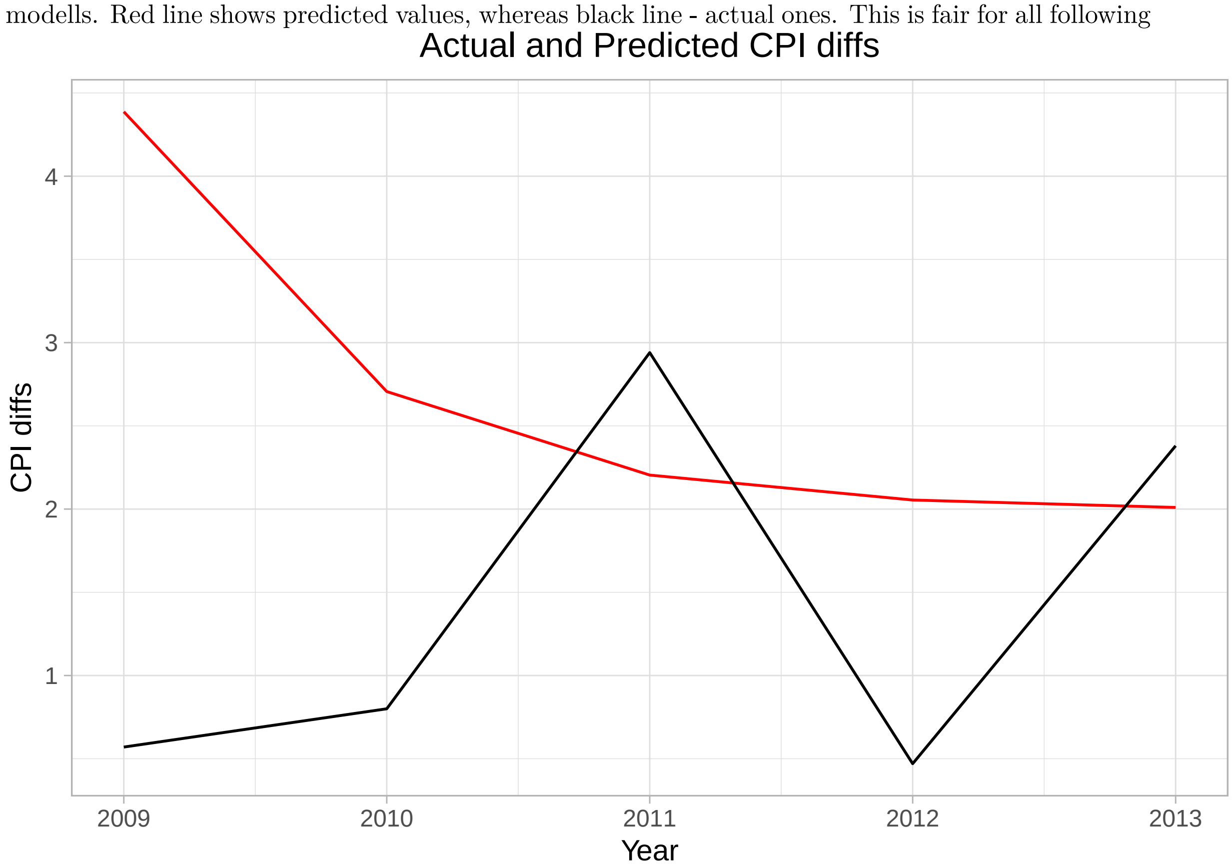
To conclude, an output of the modeling part would be six models: AR(1), MA(1), AR(2), MA(2), ARMA(1,1), ARMA(2,2).

Prediction

Validation

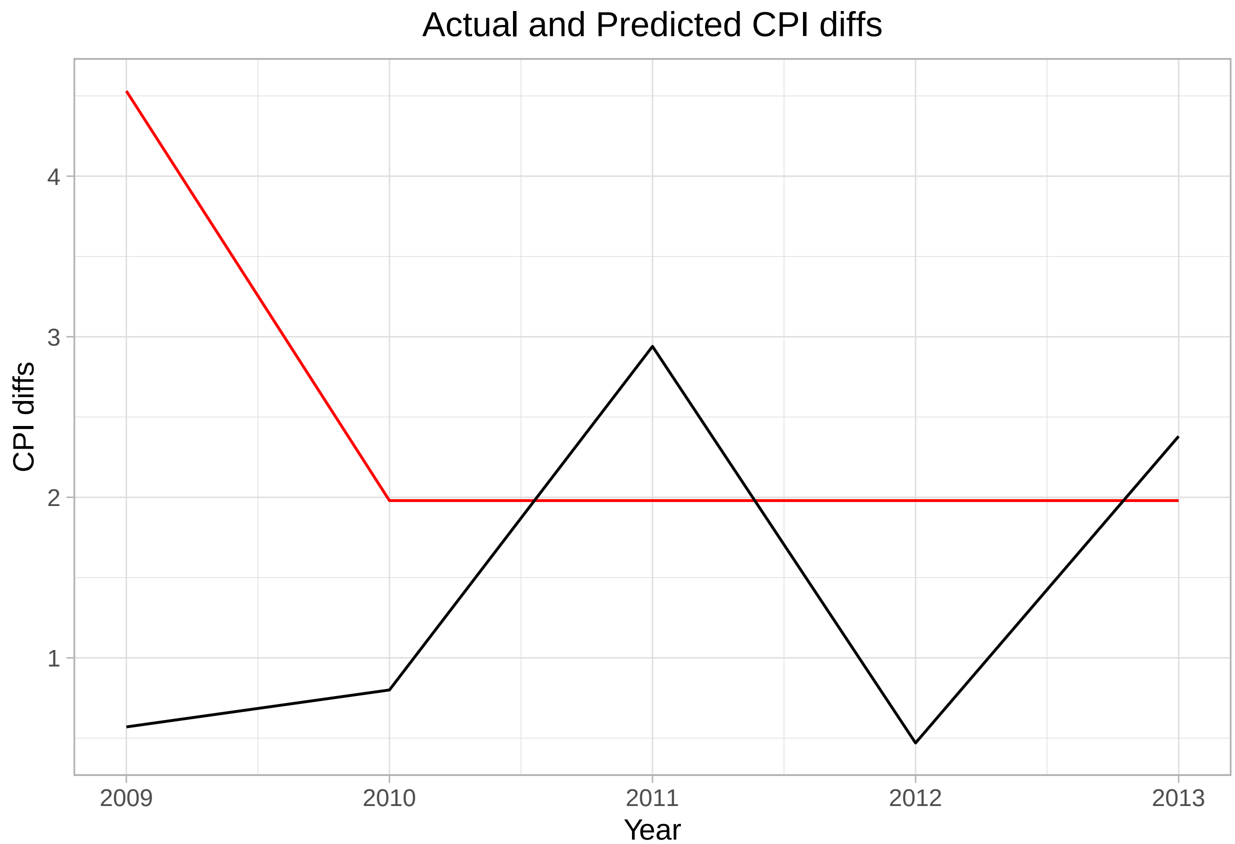
AR(1)

On the following graphs we can see the forecasting values for 5 years in comparison with their actual ones for different modells. Red line shows predicted values, whereas black line - actual ones. This is fair for all following graphs.



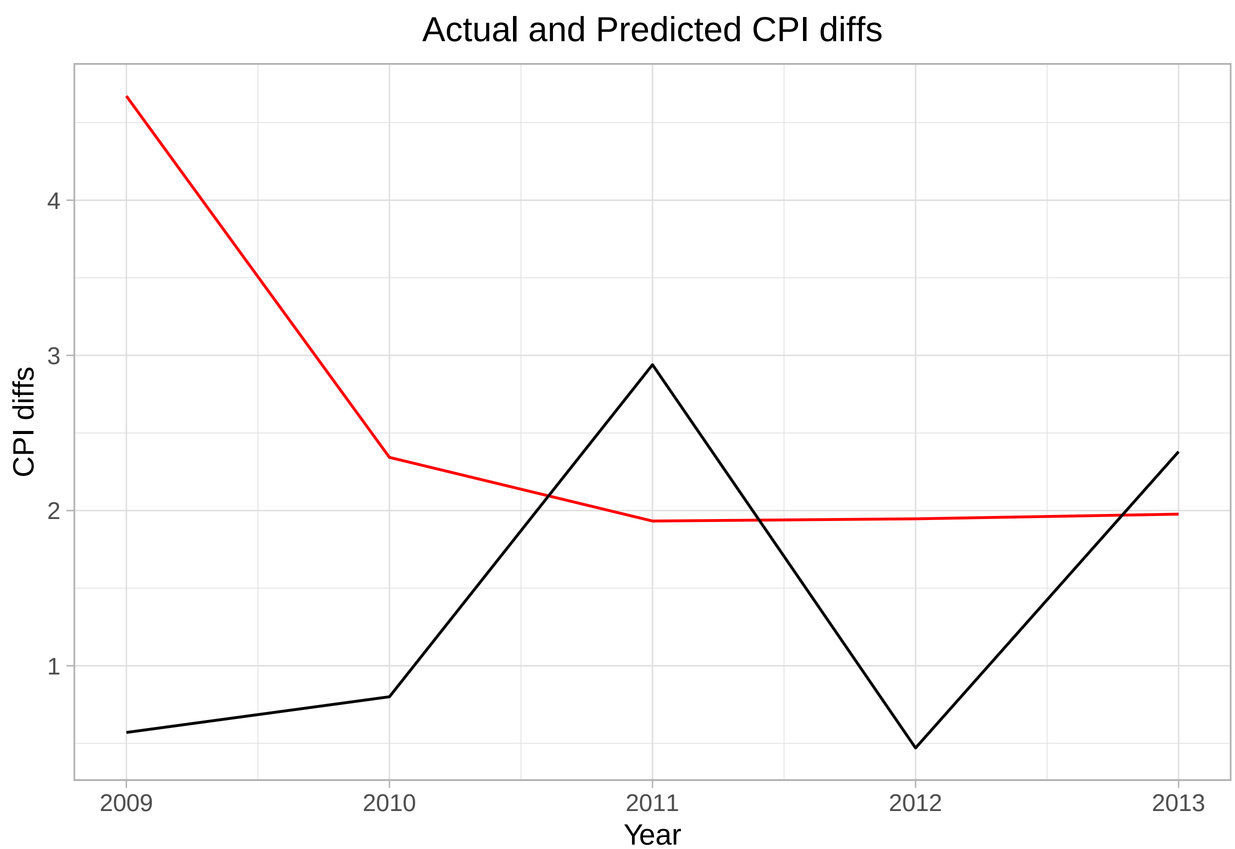
year	validation	AR(1) prediction
2009	0.57	4.387160
2010	0.80	2.705899
2011	2.94	2.204084
2012	0.47	2.054305
2013	2.38	2.009600

MA(1)



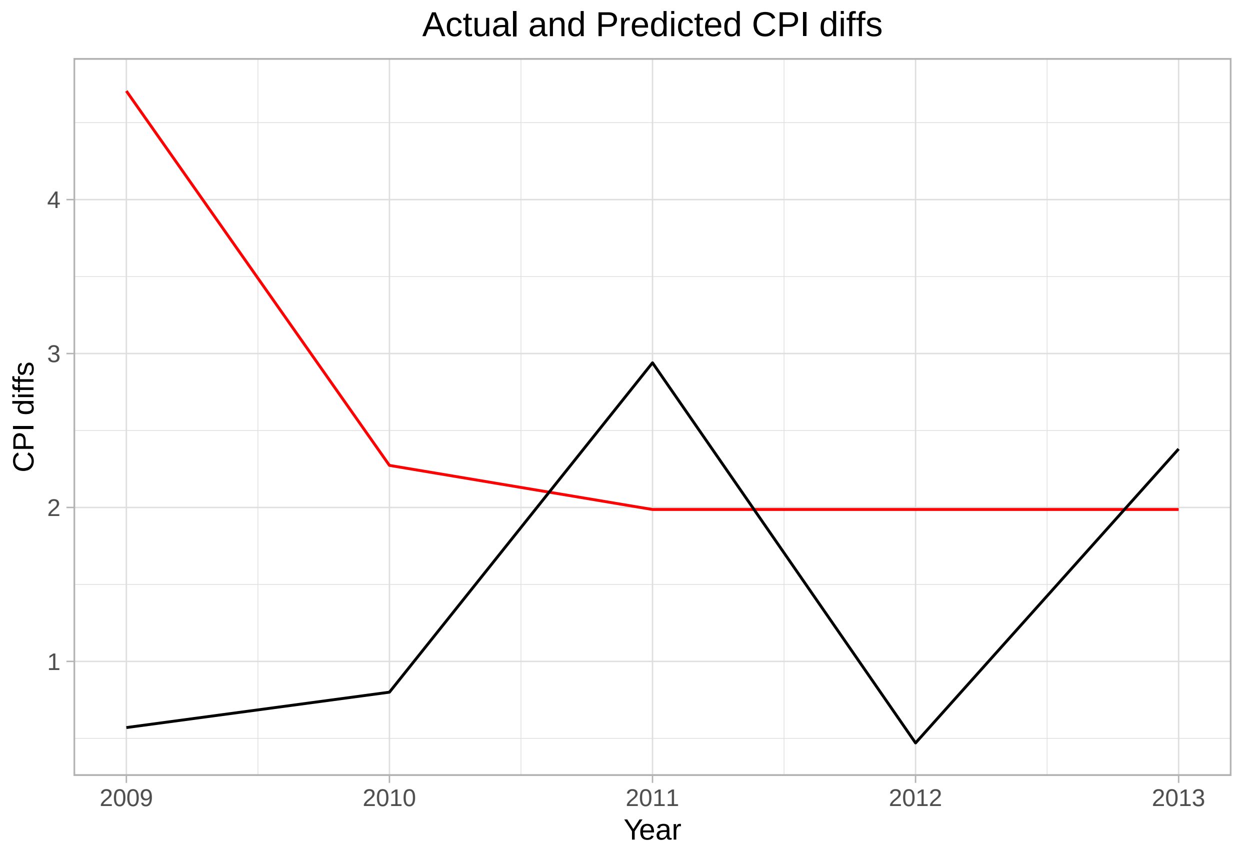
year	validation	MA(1) prediction
2009	0.57	4.530379
2010	0.80	1.979474
2011	2.94	1.979474
2012	0.47	1.979474
2013	2.38	1.979474

AR(2)



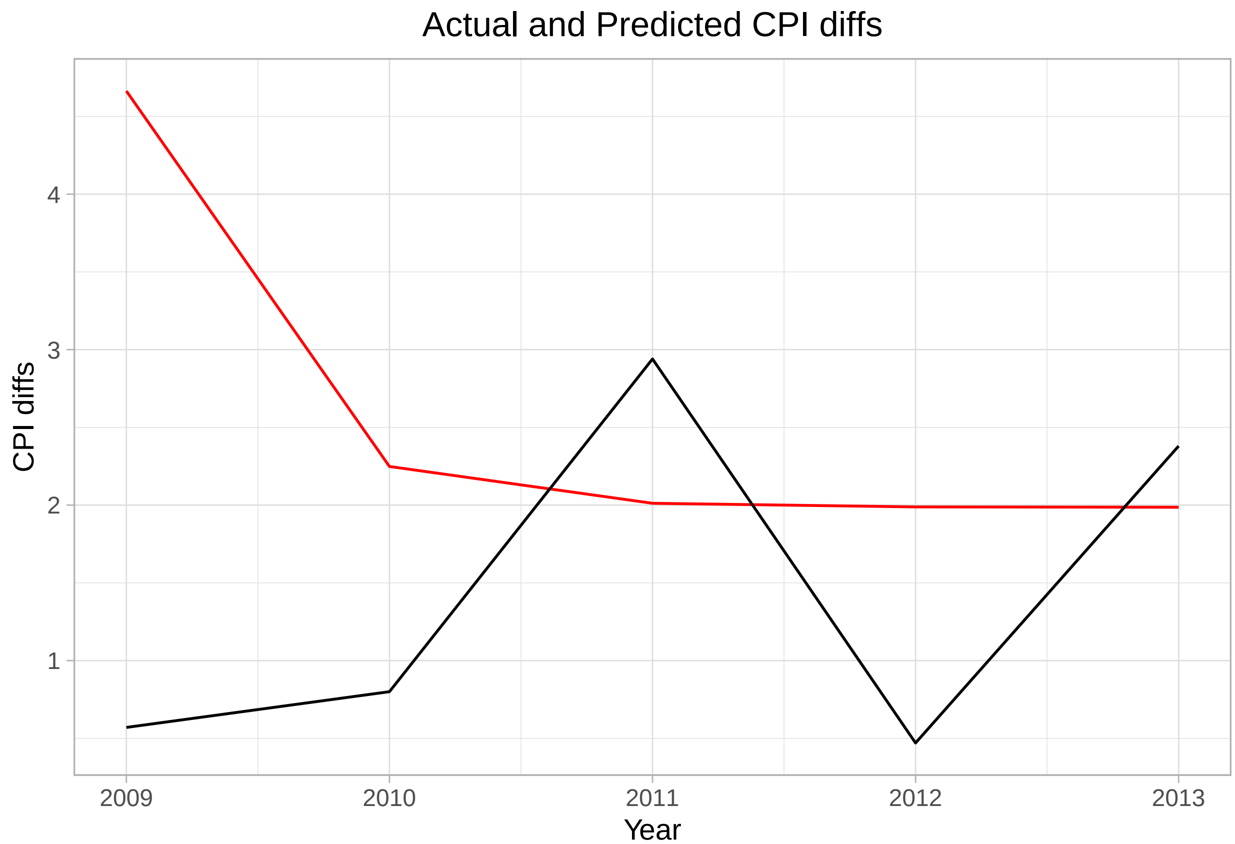
year	validation	AR(2) prediction
2009	0.57	4.671699
2010	0.80	2.342894
2011	2.94	1.932663
2012	0.47	1.946809
2013	2.38	1.976888

MA(2)



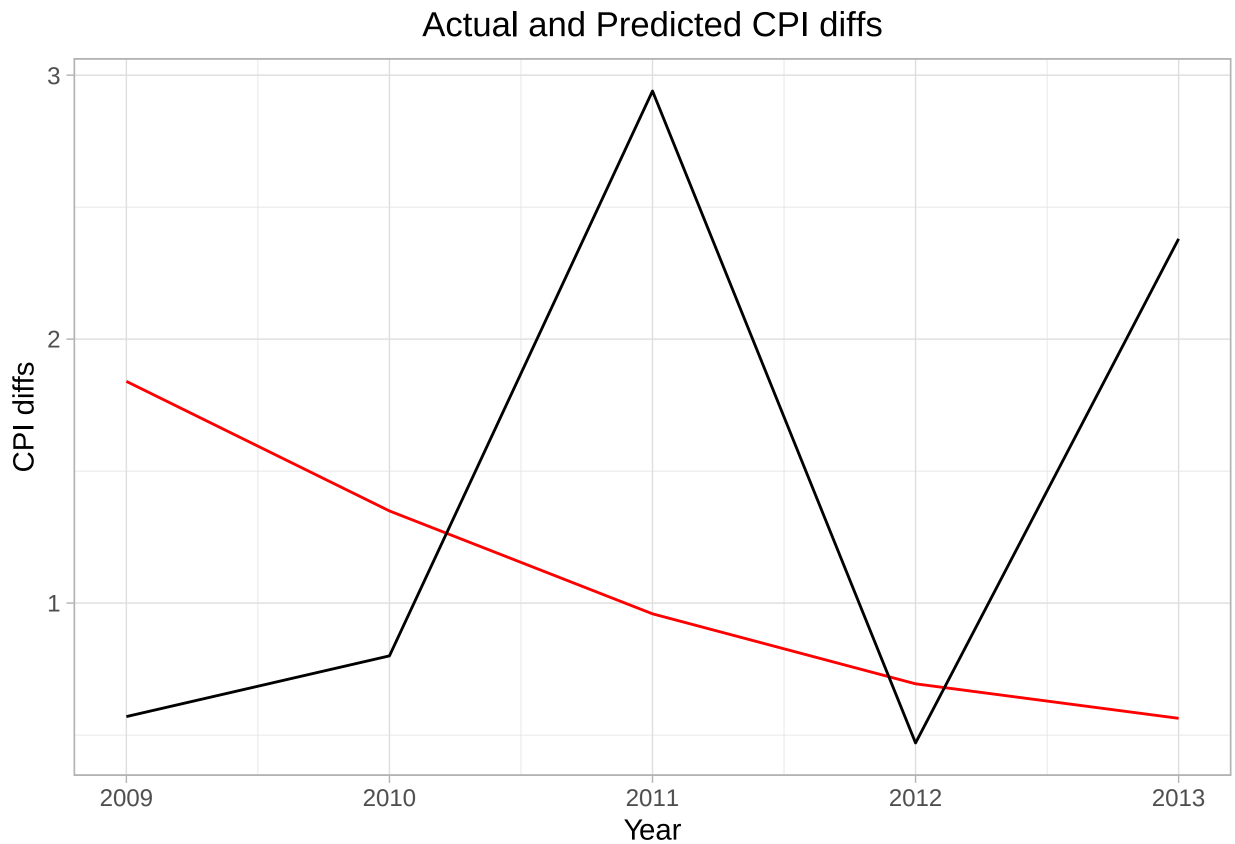
year	validation	MA(2) prediction
2009	0.57	4.705542
2010	0.80	2.273312
2011	2.94	1.986812
2012	0.47	1.986812
2013	2.38	1.986812

ARMA(1,1)



year	validation	ARMA(1,1) prediction
2009	0.57	4.663565
2010	0.80	2.248451
2011	2.94	2.011675
2012	0.47	1.988462
2013	2.38	1.986186

ARMA(2,2)



year	validation	ARMA(2,2) prediction
2009	0.57	1.8400063
2010	0.80	1.3491138
2011	2.94	0.9593590
2012	0.47	0.6941290
2013	2.38	0.5634317

Comparing quality

model	MSE	MAE
ARMA(2,2)	1.84	1.17
MA(1)	4.09	1.60
AR(1)	4.28	1.68
ARMA(1,1)	4.44	1.68
AR(2)	4.51	1.71
MA(2)	4.53	1.69

ARMA(2,2) has the least mean squared error.

model	MSE	MAE
ARMA(2,2)	1.84	1.17
MA(1)	4.09	1.60
AR(1)	4.28	1.68

model	MSE	MAE
ARMA(1,1)	4.44	1.68
MA(2)	4.53	1.69
AR(2)	4.51	1.71

Again, ARMA(2,2) has the best quality in terms of mean absolute error.

Taking into account specificity of our data, it might be reasonable to use MAE as base parameter of quality, because it is more important to make precise predictions for points in time in particular (MAE), than have a good forecast for some period in general (MSE). So for furher steps we can consider also MA(2) due to the fact that it has low MAE.

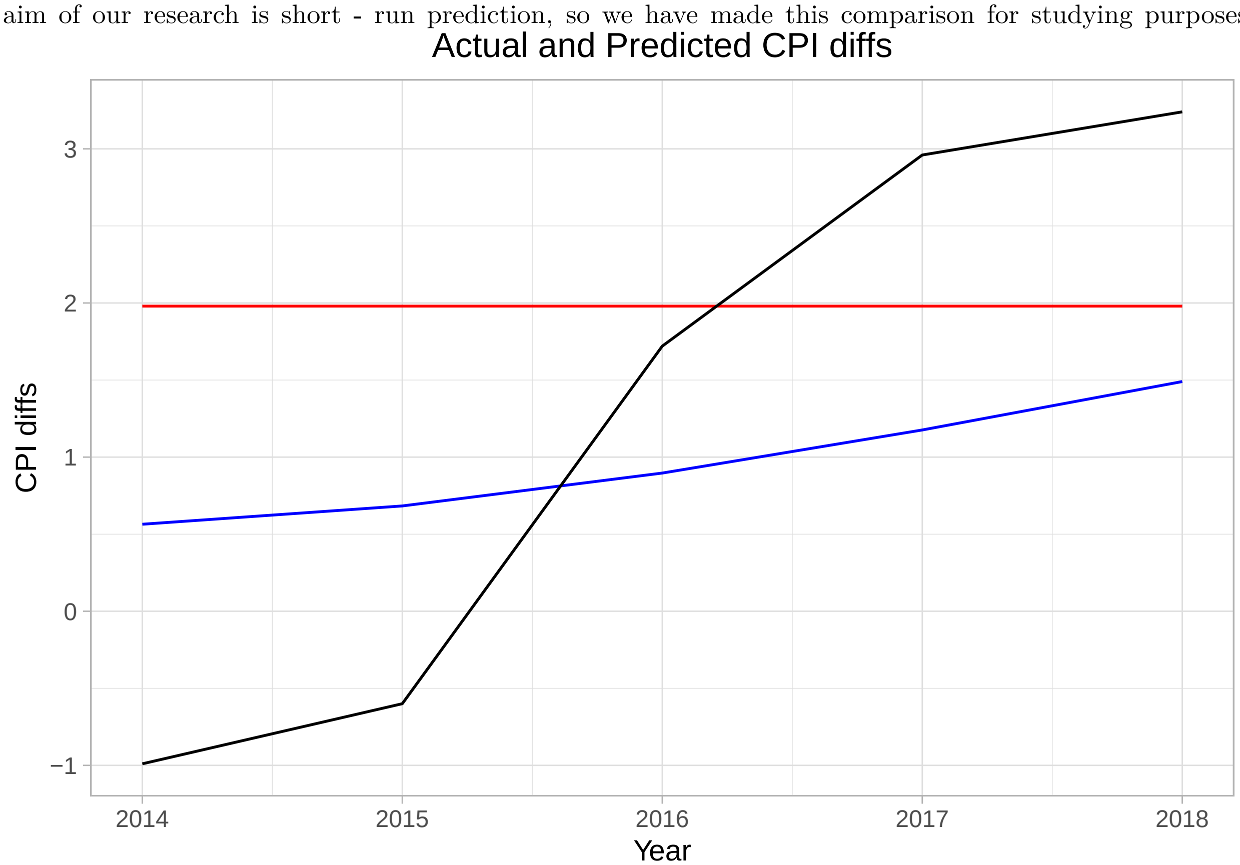
As the result, after the process of validation, we will take ARMA(2,2) and MA(1) for further research.

Testing

For checking our models working on test sample, we may choose several options.

Fixed scheme

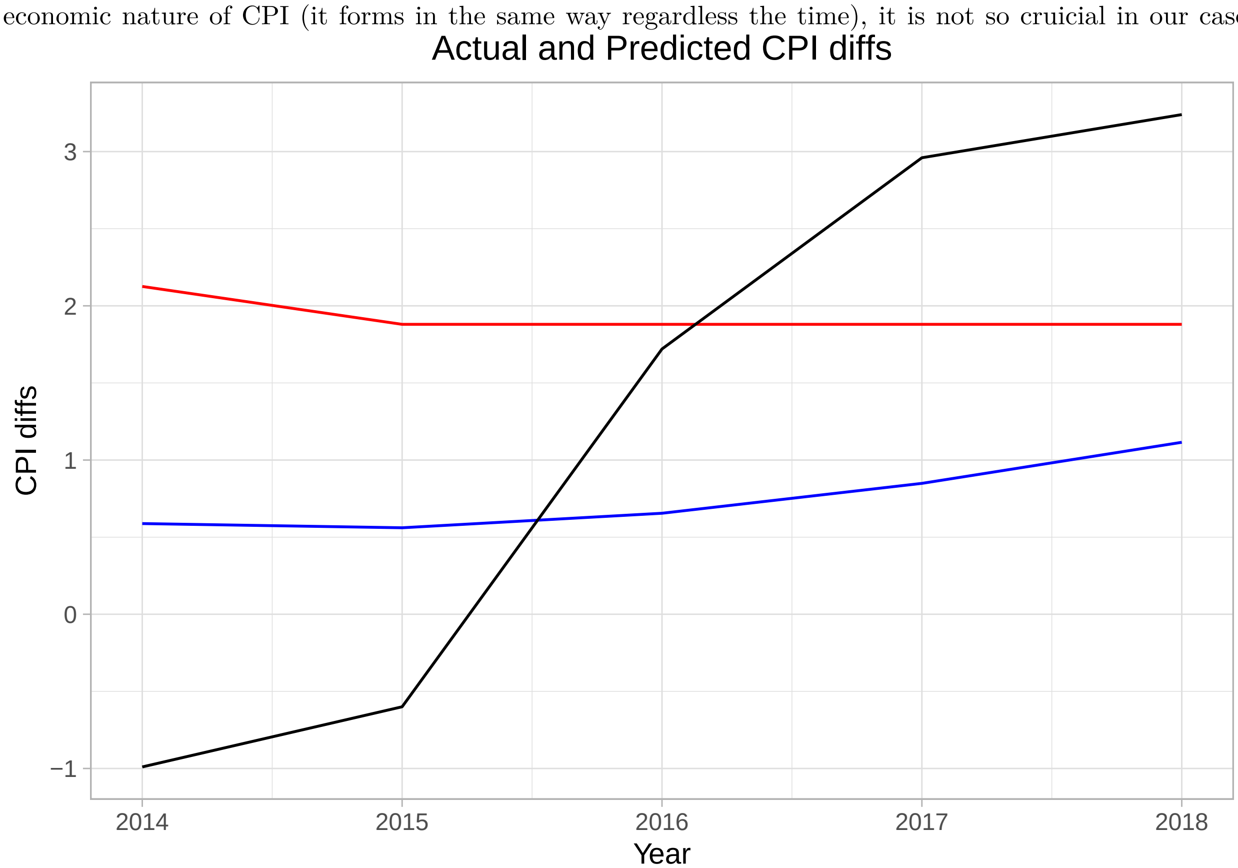
On the following graphs we are going to compare actual values with our prediction for two models under different scenarios. Firstly, it is possible to use the model "fixed", i.e. as it was estimated at the previous steps. If our main objective is long - run forecast, "fixed" scheme is an appropriate choice, but the aim of our research is short - run prediction, so we have made this comparison for studying purposes.



year	test	MA(1) fixed prediction	ARMA(2,2) fixed prediction
2014	-0.99	1.98	0.56
2015	-0.60	1.98	0.68
2016	1.72	1.98	0.90
2017	2.96	1.98	1.18
2018	3.24	1.98	1.49

Recursive scheme

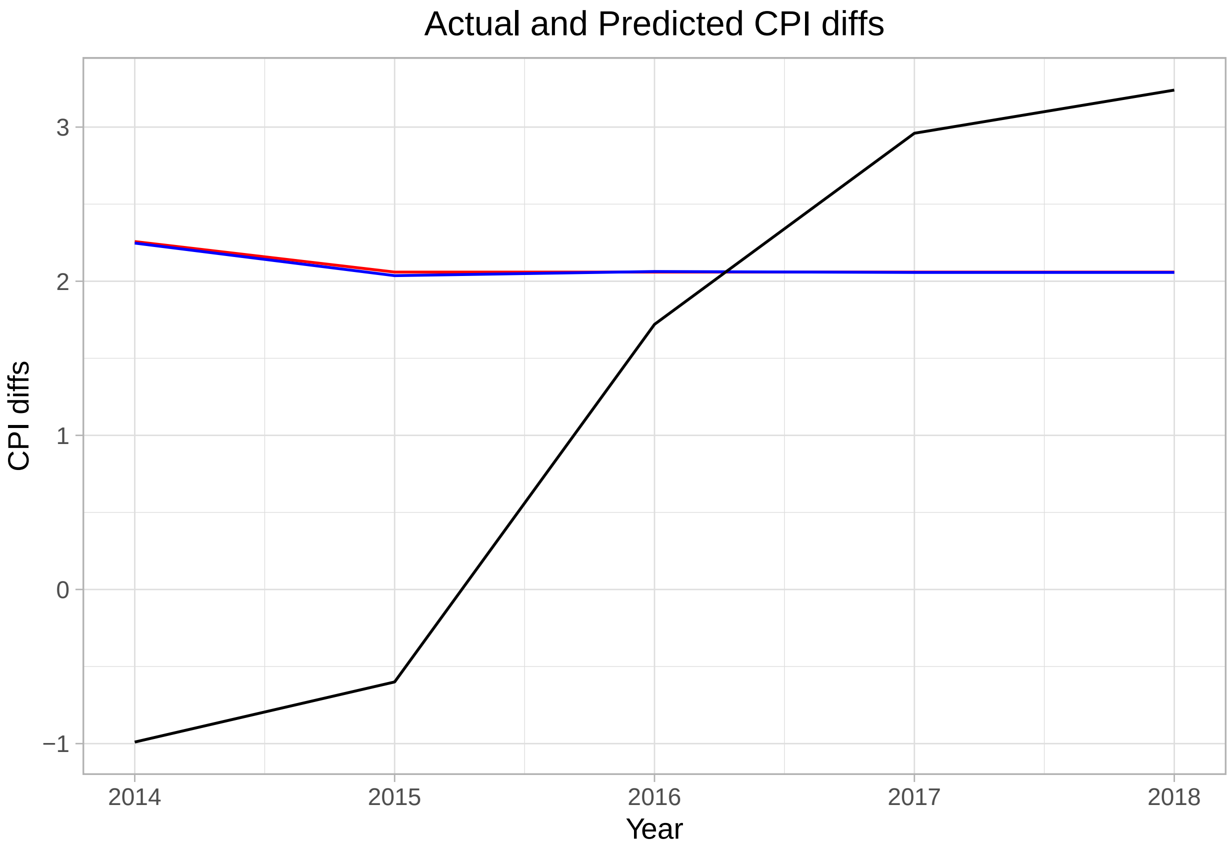
Secondly, we can check the predictive power of our models by re-estimating them on train subsample and validation subsample. This approach can be more beneficial for us due to the fact that our model will be fitted on larger sample, so usually the more data we get the better forecast we will finally have. Furhermore, this way of refitting gives us the opportunity to include in our model fresh data, but in accordance with economic nature of CPI (it forms in the same way regardless the time), it is not so cruicial in our case.



year	test	MA(1) recursive prediction	ARMA(2,2) recursive prediction
2014	-0.99	2.13	0.59
2015	-0.60	1.88	0.56
2016	1.72	1.88	0.65
2017	2.96	1.88	0.85
2018	3.24	1.88	1.11

Rolling scheme

Finally, for testing our models we may re-estimate them on fitting and validation samles, but without older data. In our case it is difficult to say that older data resembles something unussual, so there is no need to eliminate it from our sample. But we want to check this approach on our data, and, finally, choose scheme, which gives us an appropriate results.



year	test	MA(1) rolling prediction	ARMA(2,2) rolling prediction
2014	-0.99	2.26	2.25
2015	-0.60	2.06	2.04
2016	1.72	2.06	2.06
2017	2.96	2.06	2.06
2018	3.24	2.06	2.06

Comparing quality

scheme	MSE MA(1)	MAE MA(1)	MSE ARMA(2,2)	MAE ARMA(2,2)
Fixed	4.52	2.01	2.75	1.80
Recursive	4.72	2.05	3.49	2.01
Rolling	4.98	2.08	4.94	2.08

It can be seen from the table that fixed scheme shows best results, however essentially recursive scheme is better, because it is more appropriate to use the latter option when we deal with short-term forecasts. Moreover, the quality of rolling scheme shows that older data is important for precise prediction (in terms of errors: rolling scheme has the largest MSE and MAE in both models).

Conclusion and ideas for further research

Prediction of CPI could be quite an important objective for modelling society.Accurate assessment of this indicator will hugely benefit the economy. But the set of techniques, which we used in our work, can not provide us with precise results. As for the further possible steps, which will develop our research and make our prediction more accurate, we can use assymetric function. In our specific case, it is not obvious what is more violating for people's expectations whether to underestimate or overestimate the CPI. The underestimation of this indicator leads to the tremendous money loss due to the incentive to save money in spite of spending them. The overestimation can lead to overconsumption and the increase in product demand what will drive the prices, leaving production the same, what will accelerate the inflation rate. Another possible way to improve the accuracy of our predictions is to eliminate the shock in our data, because it is not a strucural shift, it is only the conseqence of political changes, which didn't change the properties of CPI formation.

Team assessment

Overall, the teamwork in our group was well-coordinated, productive and respectful. Maria and Ivan did the premilinary data analysis, visual analysis, essential analysis and made a conclusion of our work. Aleksandra worked on formal analysis and stationary transformations of the data. The responsibilities of Nikita included working on modeling and estimation. Valeria and Pavel did the forecasting part of our work. I evaluate the contribution of each member in our team equally.