UNIVERSITAT POMPEU FABRA

FORECASTING TECHNIQUES

Time Series Project

Predicting Economic Policy Uncertainty in the United States

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Abstract

Markets are characterized by volatility. Volatility can be caused by different factors including uncertainty of future development. The aim of this paper is to examine a potential relationship between market development and economic policy uncertainty (EPU) by quantifying movements in policy-related economic uncertainty. After carrying out a descriptive analysis of the EPU time series, other predictors were identified in order to carry out in-sample analyses and out-of-sample prediction of market performance employing past EPU (and possibly other predictors) and vice versa. A number of linear models were used to forecast the EPU, including ARMA models and models that combine AR components with external covariates. In the out-of-sample analysis the latter strongly outperformed the former and indicated the necessity of accounting for external variables for predicting the EPU. Models specified to capture the underlying dynamics of industrial production growth lead to the conclusion, that the additional explanatory value of EPU growth for industrial production growth is limited. For the linkage of EPU growth and stock market volatility we find statistically significant effects which we consider to be interesting and with potential for deeper exploration.

Contents

1 Milestone I

Uncertainty is challenging to quantify, but always part of the market. It is clear that markets do not react positively to uncertainty. However, in recent times the global economic uncertainty supposedly reached record numbers according to Rees (2019): ”It’s a well-worn truism that is trotted out every time the pound plunges on the latest Brexit twist or stocks swoon on another Twitter tirade from Donald Trump. But one index empirically shows that businesses and investors are facing a level of uncertainty never seen before and that could be hurting the world economy.”

The index mentioned in this article refers to the Global Economic Policy Uncertainty Index, which was constructed by Baker, Bloom & Davis in 1997 and is still updated at the time of the writing of this paper (Baker et al., 2016)[1].

1.1 Definition of Time Series

We focus on the analysis of the continuous development of Economic Policy Uncertainty (EPU) in the USA. Initially, we have chosen the daily time series of the EPU from 1985 until February 2020 with 12826 observations. However, as most indicators are aggregated monthly, we consequently made a transition to monthly data that holds 419 observations. A plot of the EPU and growth rate is included in the appendix (see Figure 2).

The index consists of three types of underlying components:

1. Newspaper coverage of policy-related economic uncertainty
2. Number of federal tax code provisions set to expire in future years
3. Disagreement among economic forecasters as a proxy for uncertainty

As Equation 1 shows, the components are not equally weighted and ”disagreement among economic forecasters” can be partitioned into two sub components.

$$EPU_t = \frac{1}{2} \cdot NEWS_t + \frac{1}{6} \cdot TEI_t + \frac{1}{6} \cdot CPIDM_t + \frac{1}{6} \cdot PDM_t \tag{1}$$

where

- EPU_t is the broad news-based policy uncertainty index
- TEI_t is the tax expirations index
- $CPIDM_t$ is the CPI forecast disagreement measure
- PDM_t is the federal/state/local purchases disagreement measure

[1] Baker et al. (2016) were aware of the challenges of constructed an index to quantify such an elusive variable. They address the reliability concerns via evaluation and refer to a strong relationship between this and other *economic* respectively *policy* uncertainty measures, trends that are robust to political orientation and an audit study of 12,000 articles to assess EPU evidence.

1.1.1 Newspaper coverage of policy-related economic uncertainty

1. Time-series variance σ_i^2 for each newspaper i
2. $Y_{it} = \frac{X_{it}}{\sigma_i}$ for each t as standardisation
3. $Z_t = \frac{1}{10}\sum_{i=1}^{10} Y_{it}$ for each t as mean
4. $M = \frac{1}{419}\sum_{t=1}^{419} Z_t$
5. $NEWS_t = Z_t \cdot \frac{100}{M}$ for each t as the final index

where

- X_{it}, EPU frequency US for newspaper i and day t
- Newspaper $i = 1, ..., 10$, the newspaper out of US media pool
- Month $t = 1, ..., 419$, month from $T_1 = 01/01/1985$ to $T_2 = 06/02/2020$

1.1.2 Number of federal tax code provisions set to expire in future years

As for the second component of the EPU, the Congressional Budget Office (CBO) compiles lists of temporary federal tax code provisions that expire over the next ten years, which will then be dollar-weighted and aggregated annually.

Baker et al. (2016) justify including this as part of the consolidated EPU measure as a source of uncertainty for "businesses and households due to last-minute extensions undermining stability in and certainty about the tax code".

1.1.3 Disagreement among economic forecasters as a proxy for uncertainty

The last component of the EPU tries to capture any dispersion between individual forecasters' predictions about future levels of the CPI, Federal Expenditures, and State/Local Expenditures within the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters using quarterly forecasts for one year ahead in time. Forecasts according to Baker et al. (2016) are directly influenced by monetary policy and fiscal policy actions, hence shall provide a reasonable proxy for economic uncertainty.

1.2 Relevance of Time Series

Political uncertainty can be viewed as a signal of the strength of the ruling party. Therefore, if people are assuming that their government is not consistent in its decisions, the role of volatility in the decision-making of firms should be more conservative. As a result, this uncertainty can lead to a drastic decrease in major macroeconomic variables. Therefore, the effect of political uncertainty can be seen in the production sectors and stop the economy from growing. For example, we can see that there is a decline in economic growth and employment when uncertainty is increasing. Ability to predict if the uncertainty decreases or increases in the next periods can help to smooth the reaction of businesses and prevent the economy from breaking into recession. Figure 1 links uncertainty spikes to global events that occurred in the corresponding dates and at least given the interpretation of Baker et al. (2016).

1.3 Descriptive Analysis of Time Series

In order to be able to do any meaningful analysis in- or out-of-sample, the usual descriptive analysis that precedes such process has been carried out. Firstly, distributional properties have been examined and secondly dynamic properties.

1.3.1 Distributional Properties of the Series

The process of the EPU itself is not stationary, however when transforming it to growth rate the series becomes stationary. The Dickey Fuller Test in Table 1 shows that H_0 can be rejected at a significance level of 0.05 (see Table 2 and 3 for test results of in- and respectively out-of-sample).

After transforming the time series the distribution obviously shifts. The mean of the EPU growth rate is zero and in comparison with the normal distribution has a right tail skew (skewness = 0.508) and fatter tails (leptokurtic distribution with kurtosis = 5.933 >3). All moments are displayed in Table 1, whereas the kernel densities of the original EPU and EPU growth rate are displayed side by side in Figure 3.

1.3.2 Dynamic Properties of the Series

Autocorrelation plots provide futher insights about the time series i.e. are spikes statistically significant from zero or not as would be case for white noise data. The original EPU data may in fact be correlated, returns/growth rates might still be uncorrelated. In this specific case, the data is significantly different from zero for the original data, but also at specific instances for the growth rates rendering a prediction by model possible and desirable.

2 Milestone II

For the following analyses the data was divided into two samples, the first consists of 335 observations and is used for the in-sample prediction, the last 84 observations are being used for the out-of-sample prediction. The results for all OLS regressions below have been obtained using Newey-West standard errors.

2.1 Predicting Economic Policy Uncertainty

Figure 4 shows that only the first lag autocorrelation is significant. This is an indicator that adding the first lag of fitted residuals to the linear time series model can improve the predicting ability of the model – other lags are unlikely to improve fit. At the same time, Figure 5 reveals that the partial autocorrelations are significant for not more than six lags. Hence, it is worth using a few lags of the dependent variable as regressors. However, not more than six. In this section we carry out the in-sample analysis of the EPU using five models: ARMA(1,1), ARMA(4,1) and three versions of AR(4) that are different in the set of external covariates used.

AR(4) with Covariates

As the uncertainty of economic policy is highly affected not only by the actions of the political authorities but also by the economic environment, we decided to examine in more detail possible explanatory variables. Our final set of external variables consists of unemployment rate, industrial production index, consumer price index and time before the next elections. The variables were taken due to the analyzed literature and economic intuition.

After the preliminary analysis of the explanatory variables due to their non-stationarity and in order to achieve more applicable results all variables except for the time before the new elections were transformed into the growth rates. The usage of the growth rate is justified not only by the properties of the data but also by the economic intuition. People tend to pay more attention to the changes, not to the absolute levels.

Three main specifications are used. The results of the estimation of these three models are provided in table 7. The models differ in the terms of used variables and the number of lags used. For the majority of the macroeconomic indicators are updated quarterly the number and the reaction of the people to these changes are not immediate we use four lags of the uncertainty itself in all models.

It turned out that the best model in terms of adjusted R^2 and MSE is the model with one two lags of all variables exept for the time before the next elections. The time before the new election is not significant in any specifications and this variable was dropped in the final model. While the significance of the lags of the dependent variable is stable for all specifications, all other explanatory variables lost their significance. The Newey-West estimator was used to get more reliable results. However, the signs before all the lags of EPU are the same they are not what way expected. The growth of uncertainty in the previous periods decreases uncertainty in the future. Such results can be caused by the fact that people tend to think that after the big shock situation will stabilize or by the fact that after a realization of the new policy people need time to adjust their understanding and, therefore, the effect of shock is decreasing over time.

In order to check the stability of the results and the correctness of the specification residuals analysis was carried for the last model. As the Jarque-Bera test says the residuals are not normally distributed but they do not exhibit any serial dependence according to the Box-Ljung test. Furthermore, the ACF and PACF show no serial dependence. From the distributional properties of the residuals, it can be seen the mean of the residuals is zero. This result is significant which can be checked by the simple t-test. The graph of the residuals shows no dependence and visually confirm that the mean of the residuals is zero.

ARMA Models

Due to the fact that the ACF analysis (Figure 4) indicates a possibility that the lags of residuals can improve the quality of our models, we do not want to limit our analysis with AR models and decide to add lags of fitted residuals as regressors. To be specific, we use an ARMA(1,1) as a benchmark and an ARMA(4,1) as a comparable model for the one with 4 lags of the EPU and external covariates. We estimate the two ARMA models without external covariates as otherwise it would require distinct specifications of data generating processes for all external covariates. Table 5 presents the results of these two regressions in comparison with three OLS models. In ARMA(1,1) the first lags of both the dependent variable and the residuals are significant as the case in ARMA(4,1). However, in ARMA(4,1) other lags are not significant. This means that conditional on the first lags of the EPU and the residuals, lags of the EPU of higher order are not significant. As for the goodness of fit, MSE is lower for ARMA(4,1) by a small margin. Moreover, it is the lowest among all five models.

The residual analysis follows. According to the Jarque-Bera normality test, residuals for both models are not distributed according to the Gaussian distribution (Table 7). Nevertheless, the Ljung-Box test with 12 lags indicates lack of serial dependence in residuals for both models (Table 7). As this condition is crucial we do not reject ARMA(1,1) or ARMA(4,1) even though residuals are not normal. Finally, ACF and PACF of residuals illustrate the lack of serial dependence of fitted residuals (Figures 18). All in all, ARMA(4,1) is not a significant improvement of ARMA(1,1). In terms of the Akaike information criteria, it is slightly worse (2745.37) than the benchmark (2740.94). It is not clear which of the two models is better – different indicators provide different results. Therefore both of the models are tested on the data.

2.2 Predicting Industrial Production

The development of economic policy uncertainty is interesting to analyse and explain, but it may be more relevant with regard to its explanatory power for macroeconomic indicators. Against this backdrop, we examine economic policy uncertainty as an explanatory variable for the growth of industrial production. Exploratory analyses of the growth of industrial production suggested to fit an ARMA(1,3) for prediction of industrial production growth. As this target variable is plausibly driven by more than just its past development, we build two additional models: The first builds just on two lags of growth of EPU, whereas the second is extended with two more lags each of first differences of CPI and unemployment growth.

The estimation results reported in Table 8 confirm the expected relevance of the autoregressive and moving-average terms. Further, Model 2 reveals significance in the second lag for the negative effect of uncertainty growth on the development of industrial production. The extended model (3) confirms this while controlling for relevant lags of CPI and unemployment. Interestingly, the second lag of growth of industrial production as well as uncertainty growth is particularly high in magnitude and significance. This may be due to the the slower adjustments processes within industrial production compared to e.g. stock markets.

To validate this result, detailed diagnostics of the residuals are conducted: The plots of the in-sample forecast (Figure 21) suggest a better fit of Model 1 compared to the first linear model. The third model however outperforms both of the former. The in-sample residuals of all three models exhibit normal behavior in terms of their mean and variance (Figure 22). The residual QQ-plots show that the residuals of all models are close to a normal distribution (Figure 23). Model 1 exhibits little skewness and is slightly light-tailed compared to a normal distribution. The same goes for the linear models, which however are slightly skewed to the left (Figure 24). Concerning the ACF and the PACF of the residuals, the ARMA(1,3) performs best as none of the residuals are significant. Model 3 clearly outperforms our basic linear model with little signs of autocorrelation in the error term (Figure 25). Despite the ARMA(1,3) appearing the most promising, we do not want to reject any of our models at this point, but evaluate them in more depth during the out-of-sample analyses. Test statistics and information criteria will be discussed for the out-of-sample performance of the models.

2.3 Predicting S&P 500 Volatility

To further investigate the impact of uncertainty on the economy we move on from direct macroeconomic outcomes to more general market characteristics and pose a third question: Does growth in economic policy uncertainty explain the volatility of stock market returns?

To find an answer to this question we make use of the US stock index S&P 500 and calculate the monthly return series from its price data and then derive the monthly volatility of these returns from January 1985 until December 2019 (see: sub-sample shown in Figure 31). Based on the ACF and PACF we choose an ARMA(2,1) to compare with a simplistic OLS model including two lags of growth in EPU plus an extended OLS model with additional lags of S&P 500 volatility and controlling lags of CPI and unemployment development.

Table 10 reports the obtained results. The first lag of the monthly volatility of the S&P

500 but also the first lag of uncertainty (EPU) growth have a sizable and significant positive effect on present volatility with the latter effect plausibly being smaller in magnitude. Remarkably, the effect of uncertainty growth measured via the development of the EPU index persists when adding both lagged volatility of stock returns and growth in EPU while adding further lags of other variables (OLS 2). Thus, growth in EPU may help to predict monthly volatility outcomes of the S&P 500.

The in-sample prediction depicted in Figure 32 confirms the promising numerical results of the extended OLS model visually. Figure 33 features normal residuals for all of the models. The QQ-plots again confirm the positive performance of the OLS2 Model as its residuals are closest to a normal distribution (Figure 34). Figure 35 however reveals the limitations of the models as neither matches the normal distribution in terms of skewness nor kurtosis. The plots of the ACF and PACF reassure visually that the ARMA(2,1) and the OLS2 do not feature any serial dependence (Figure 36).

Overall, we conclude that volatility in EPU may serve to explain volatility in real-world markets even though benefits are small however significant. It is clearly demonstrated that it does not work as a predictor on its own but may be important to factor in with other variables.

3 Milestone III

3.1 Predicting Economic Policy Uncertainty

In order to check the validity of the results from the previous milestone the out-of-sample predictions was made using the last 84 observation from our initial data. The comparison between simple OLS model with additional regressors and the MLE model will be provided in the end of this section. Firstly, the comparison between three specifications of the OLS model will be considered.

Three OLS models, which were discussed during the second milestone, perform significantly worse in terms of the MSE than they did in case of in-sample predictions. Furthermore, the ranking of models is not preserved as the second models shows the highest MSE for out-of-sample prediction (table 7).

The static prediction was made and plotted. The model performs well in cases of the non-extreme values. The conditional intervals are quietly narrow. The residuals do not exhibit serial dependence in the case of OLS models, the normality is not achieved, the zero-mean condition for residuals is satisfied.

The analysis of ARMA models for the dynamic forecast is similar, though their performance is much worse. MSE has grown almost two times for the out-of-sample prediction (Table 7). Ranking of models is preserved. Even though for the in-sample analysis ARMA models performed better in terms of MSE than AR(4)-based models, for the out-of-sample analysis they turned out to be much worse. For the static forecast, the situation is the same in principle, still MSE for ARMA is a little less (Table 7).

Residual analysis of ARMA(1,1) and ARMA(4,1) follows. According to the Ljung-Box test with 12 lags, residuals of both models forecasts do not exhibit serial dependence neither for dynamic nor for static forecasts (Table 7). As for the normality of residuals, the Jarque-Bera test indicates that for the static forecast in both ARMA models, we do not reject the hypothesis that residuals are normal at the 5% confidence level (Table 7). For the dynamic forecast, normality is not rejected at the 5% confidence level, though p-value is still very small (Table 7).

It is evident from Table 7 that AR(4)-based models perform significantly better in terms of MSE, even though for the in-sample analysis they were worse than ARMA (Table 7). Hence, the external regressors we add to the models are useful for getting better fit and account for the portion of variance that own lags of the dependent variable do not account for. Without external covariates MSE is remarkably higher for the out-of-sample forecast.

3.2 Predicting Industrial Production

Now we examine the out-of sample performance of the estimated models to predict growth of industrial production.

The visual inspection is in light favor of the fitted OLS models as they seem closer to a normal distribution than the ARMA specifications (Figure 26-30). However, the Jarque-Bera test indicates that skewness and kurtosis of all models match a normal distribution. For the static ARMA(1,3) forecast the evidence still is considerably weak (p-value = 0.125). The ADF-test including four lags provides significant evidence both for the residuals of the ARMA(1,3) static forecast and for the extended OLS forecast to be non-stationary. The Ljung–Box test does not provide evidence of serial correlation of the residuals for any of the models (Table 9).

The MSE of the ARMA models is the lowest, however the results of all models are close. In conclusion, we have limited confidence that either of the models specified captures the underlying dynamics of industrial production growth very well. We further conclude that the additional explanatory value of EPU growth for industrial production growth is limited as we struggle to beat a model based on lags of industrial production growth and respective residuals.

3.3 Predicting S&P 500 Volatility

Finally, we analyse the out-of sample results of the estimated models to predict monthly volatility of the S&P 500.

Visually, in particular the static ARMA(2,1) and the second OLS model look promising (Figure 37). However, the residuals of the ARMA forecasts diverge visibly from a normal distribution and further feature some serial dependence in the residuals (Figure 38 - 41).

Table 11 summarizes the test statistics for the fitted models. For all models concerns are being raised with regard to the normality of their distribution. With regard to MSE, the dynamic ARMA(2,1) performs best, closely followed by the extended OLS model. Since several diagnostic results violate the underlying assumptions of time series analysis, we take the obtained result of a statistical significant effect of EPU growth on stock market volatility with a grain of salt. However, we consider them to be interesting and with potential for deeper exploration.

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4 Appendix

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Milestone I

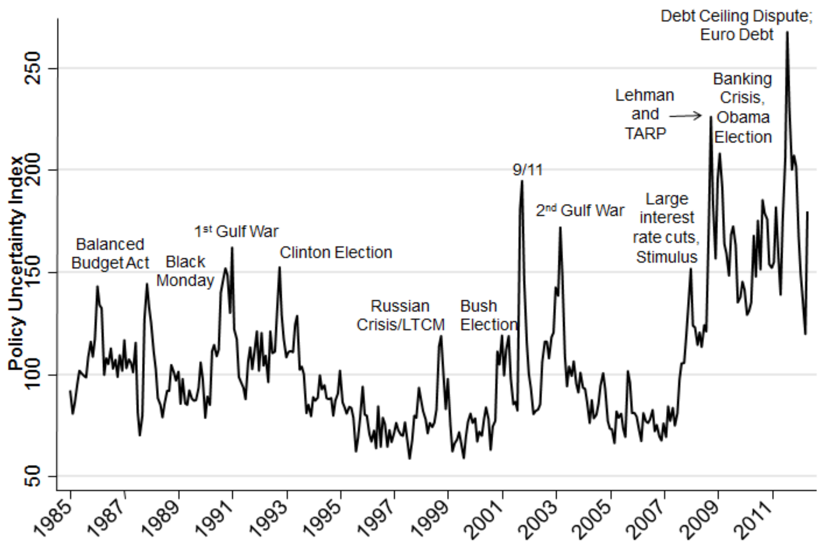


Figure 1: Effect of Global Events on Political Uncertainty Index (Baker et al., 2016)

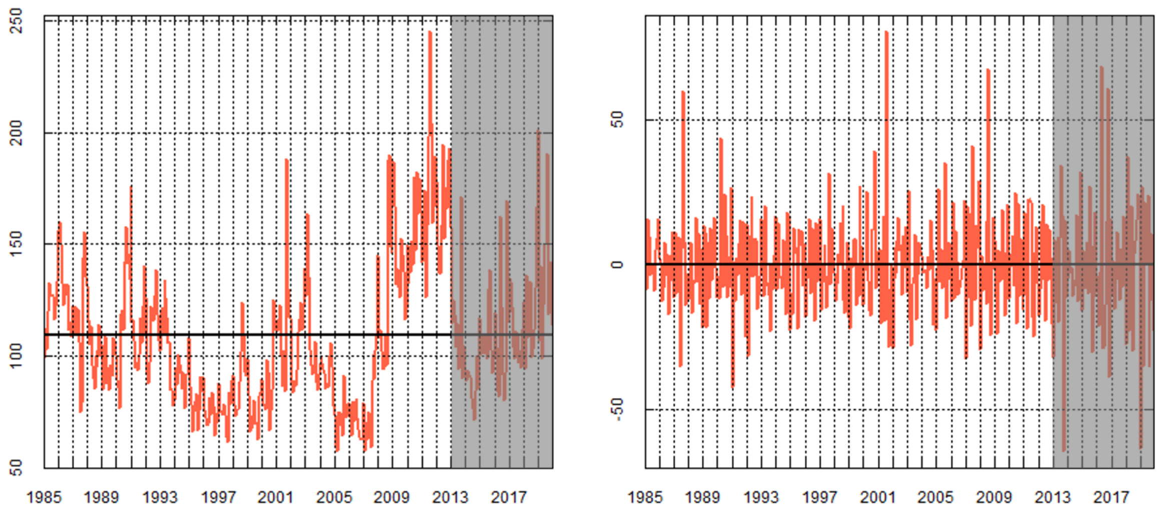


Figure 2: Monthly EPU and EPU Growth Rates for US (1985 - 2020)

Milestone II

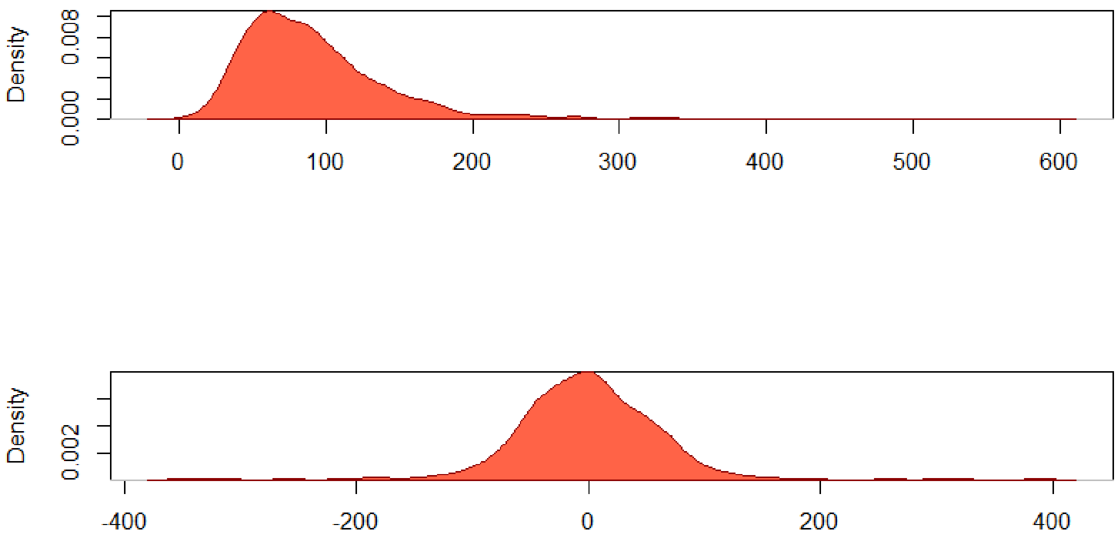


Figure 3: Kernels of Original (upper kernel) and Growth Rate Data (lower kernel)

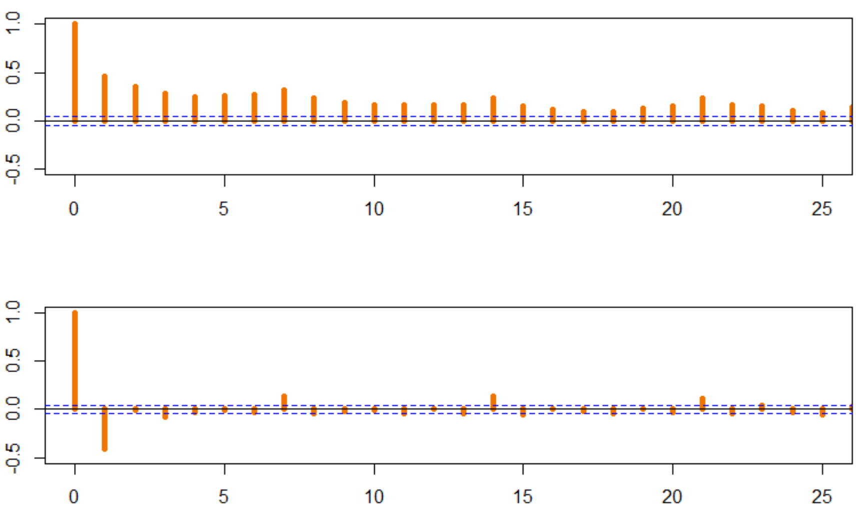


Figure 4: Autocorrelations for Original (upper) and Growth Rate (lower)

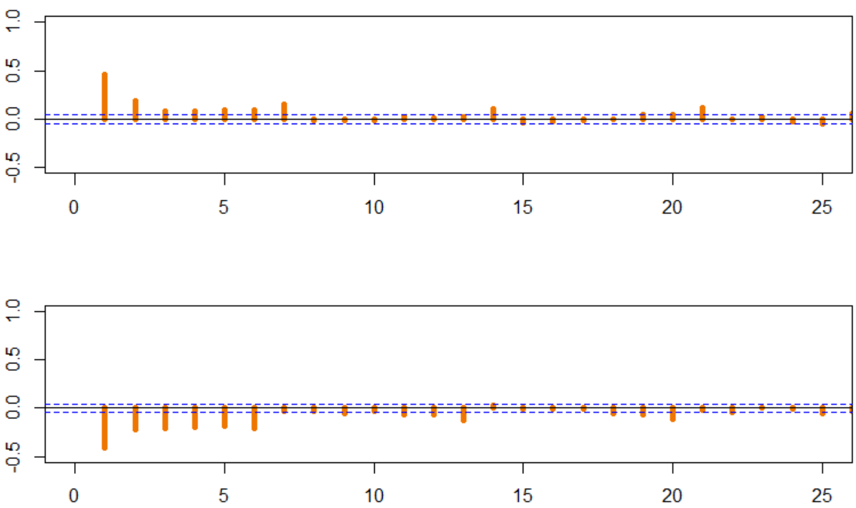


Figure 5: Partial Autocorrelations for Original (upper) and Growth Rate (lower)

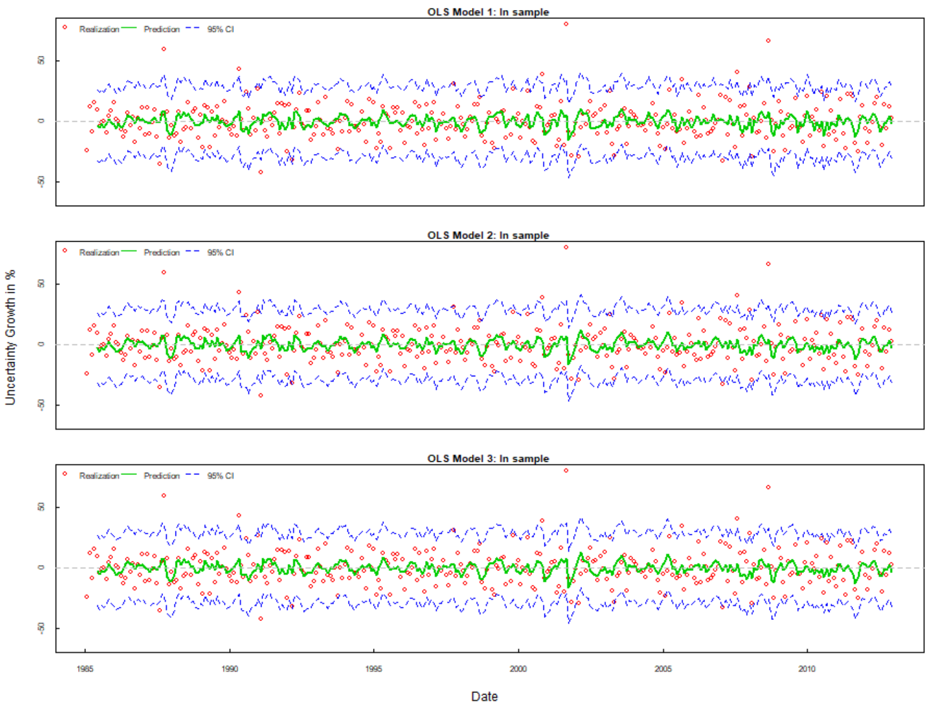


Figure 6: In-sample forecast of Economic Policy Uncertainty for OLS models 1 - 3.

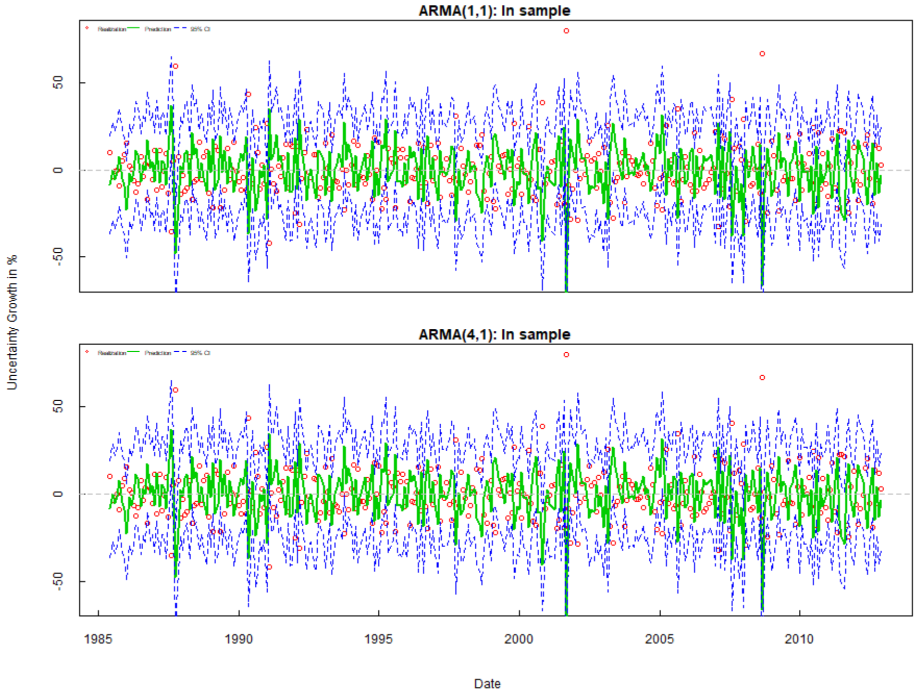


Figure 7: In-sample forecast of Economic Policy Uncertainty for ARMA(1,1) and (4,1)

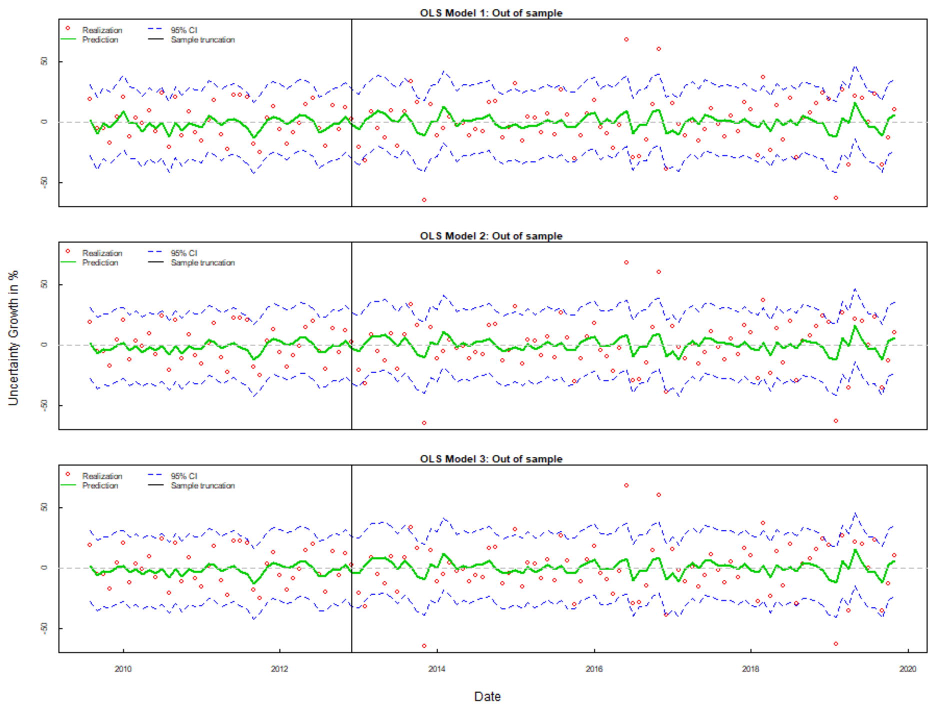


Figure 8: Out of sample forecast of Economic Policy Uncertainty for OLS models 1 - 3.

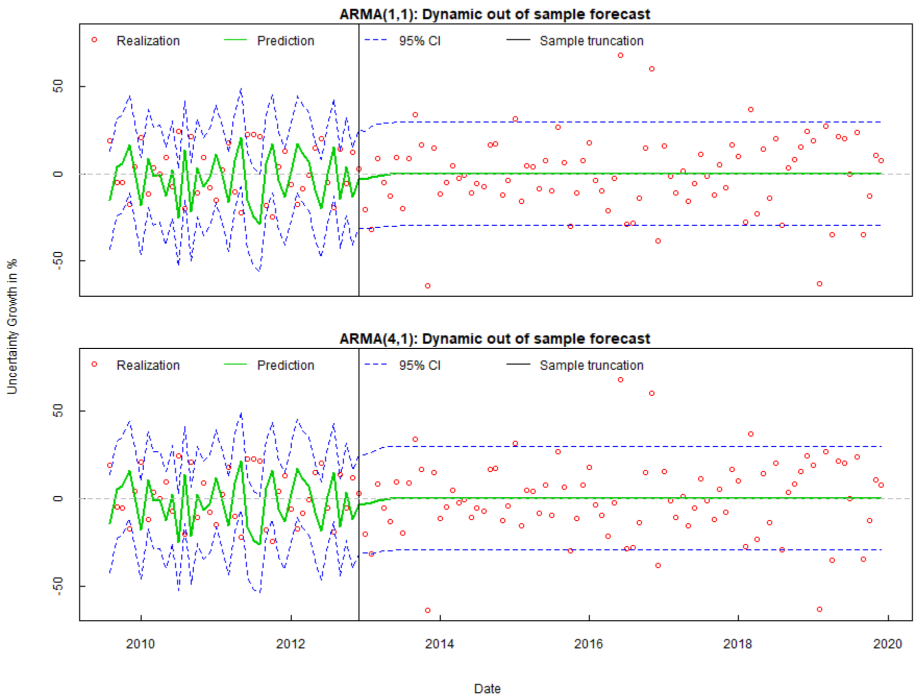


Figure 9: Dynamic out of sample forecast of Economic Policy Uncertainty for ARMA(1,1) and (4,1)

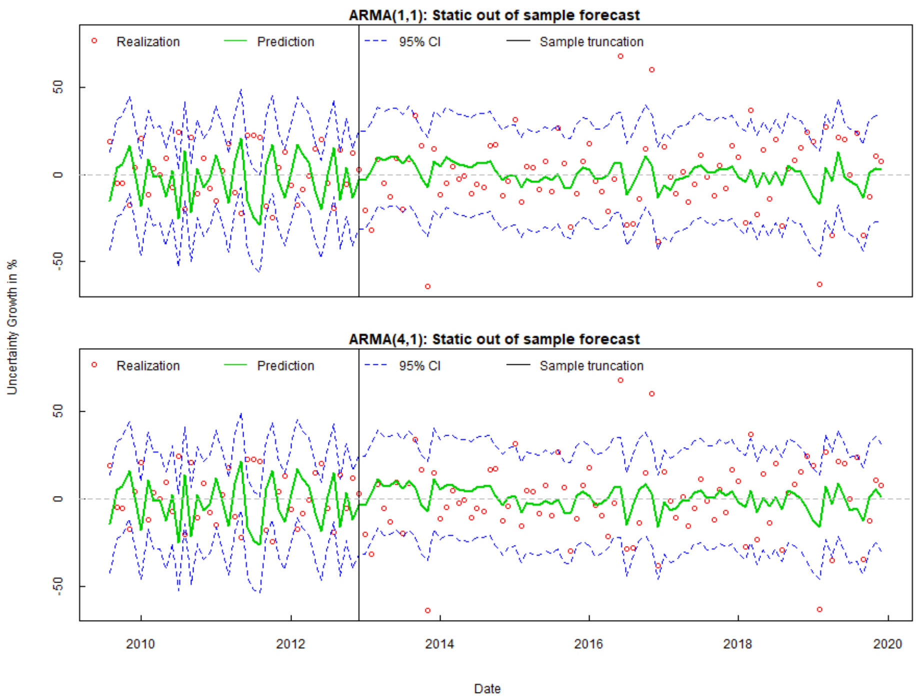


Figure 10: Static out of sample forecast of Economic Policy Uncertainty for ARMA(1,1) and (4,1)

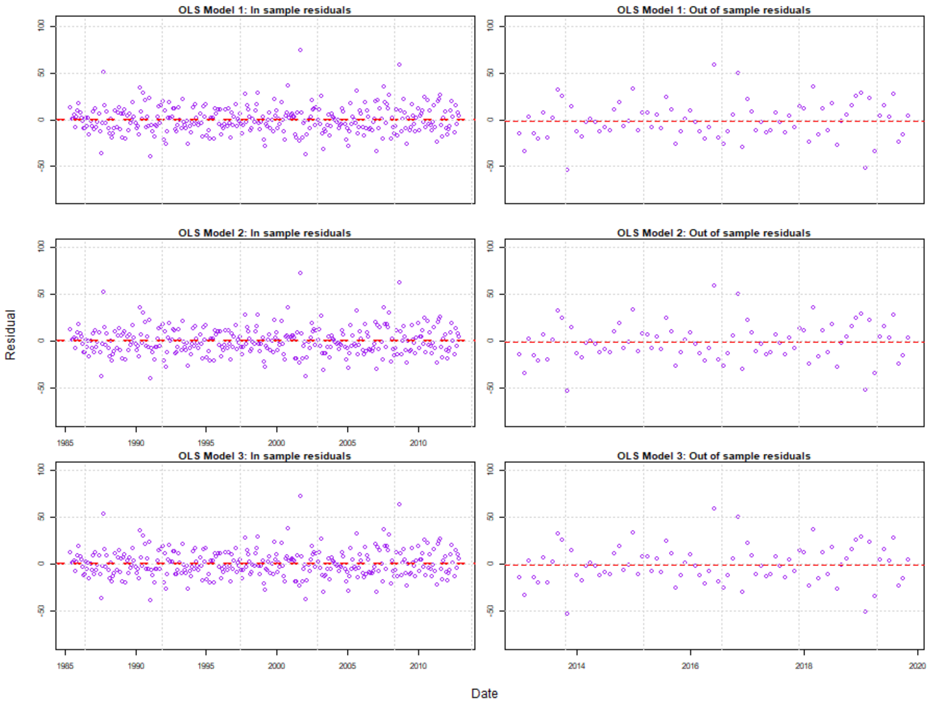


Figure 11: Residuals of Economic Policy Uncertainty for OLS models 1 - 3.

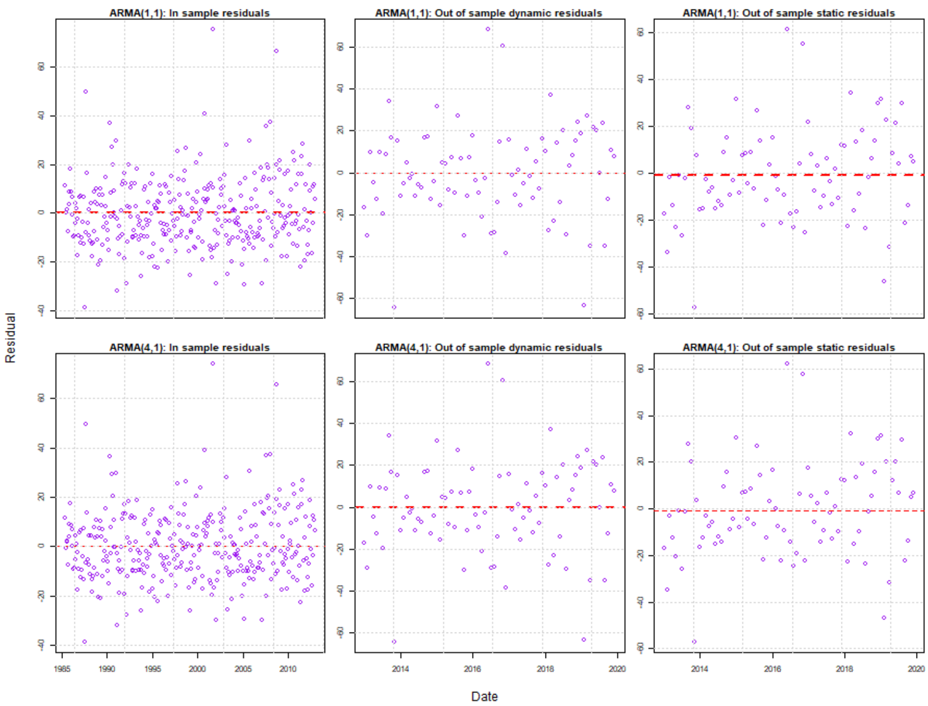


Figure 12: Residuals of Economic Policy Uncertainty for ARMA(1,1) and (4,1)

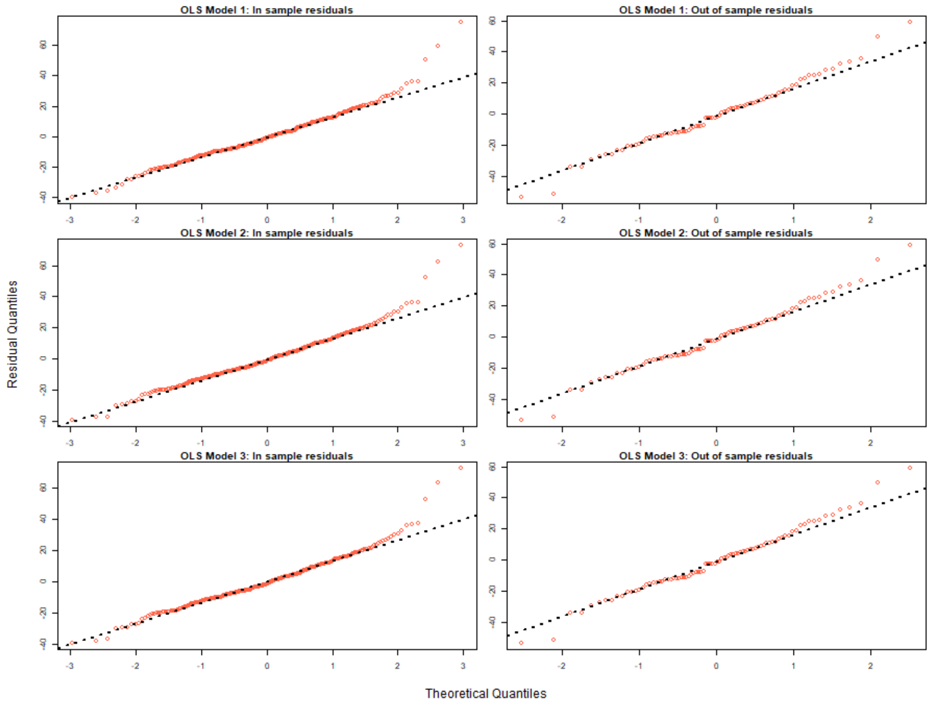


Figure 13: Residuals QQ-Plots of Economic Policy Uncertainty for OLS models 1 - 3.

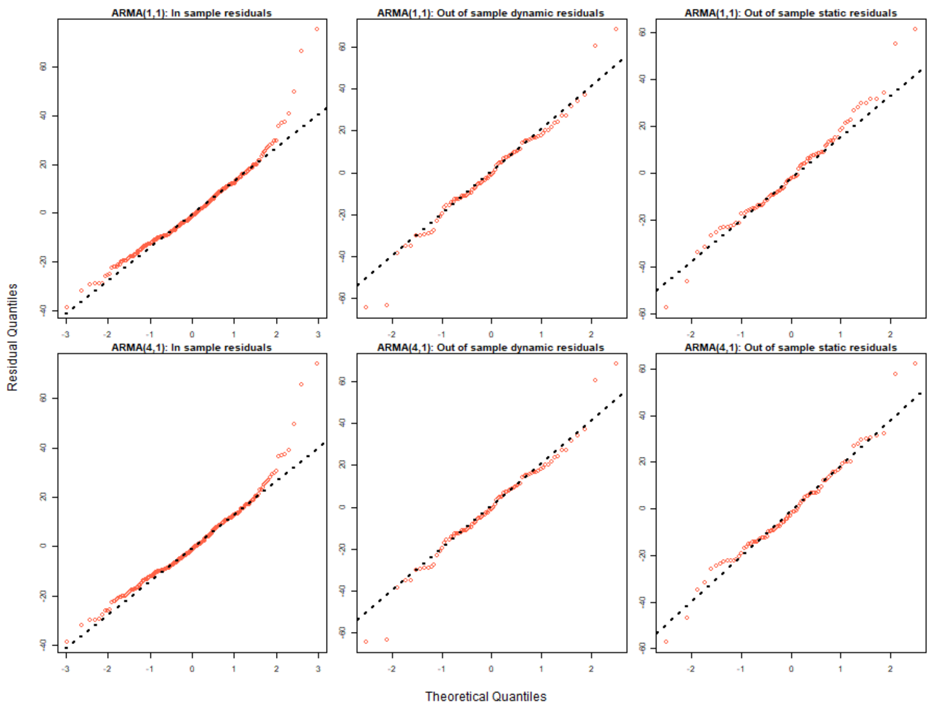


Figure 14: Residuals QQ-Plots of Economic Policy Uncertainty for ARMA(1,1) and (4,1)

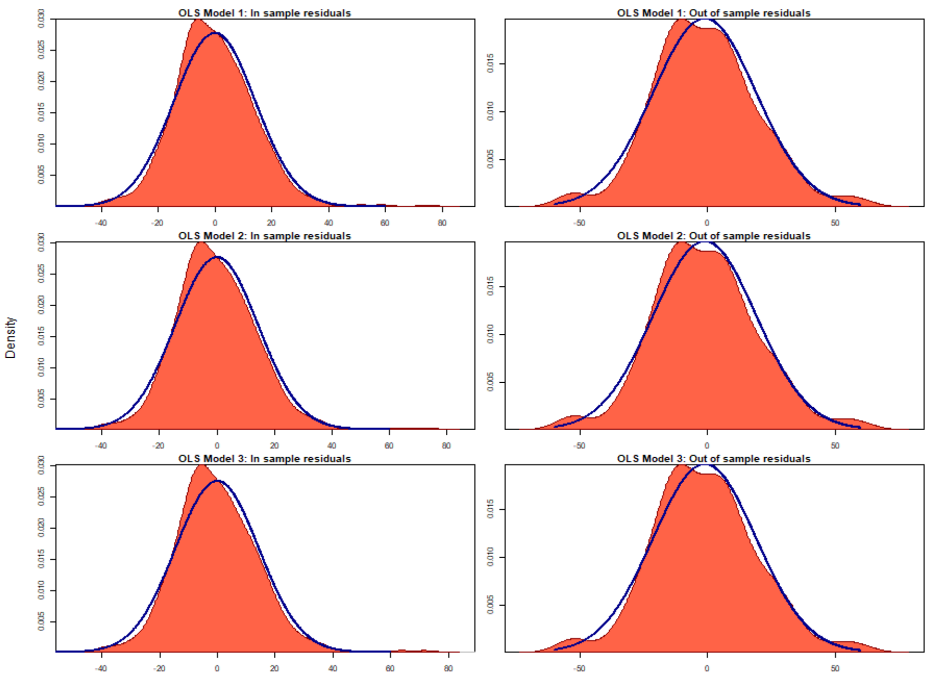


Figure 15: Residuals Kernel of Economic Policy Uncertainty for OLS models 1 - 3.

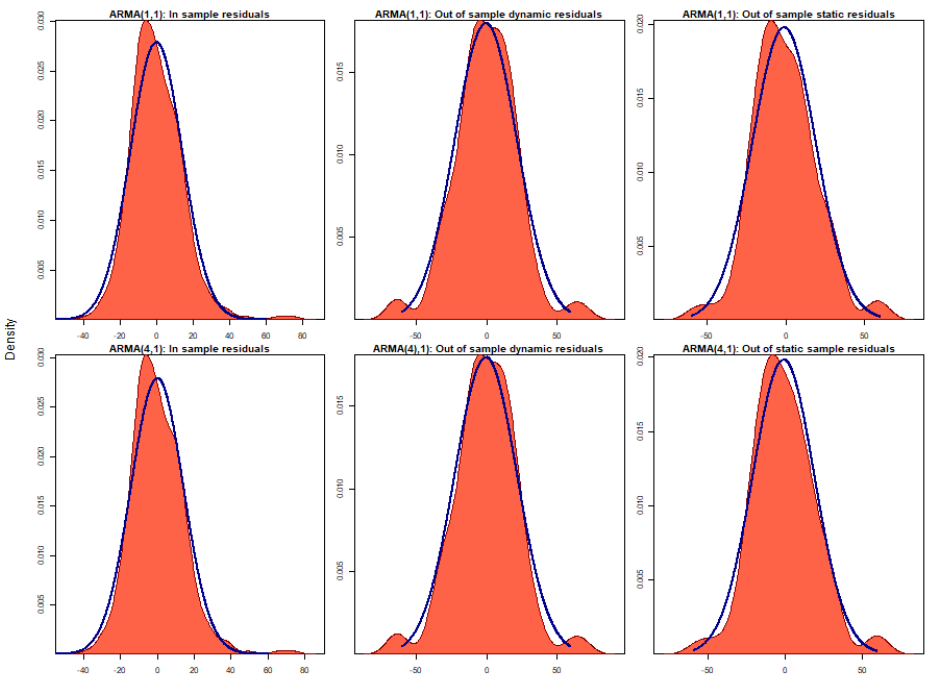


Figure 16: Residuals Kernel of Economic Policy Uncertainty for ARMA(1,1) and (4,1)

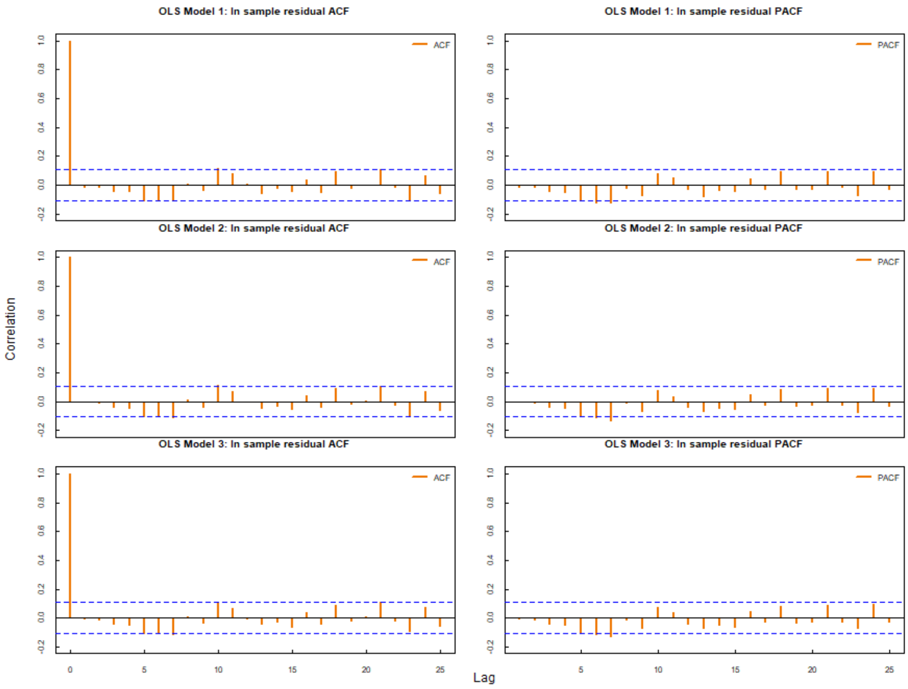
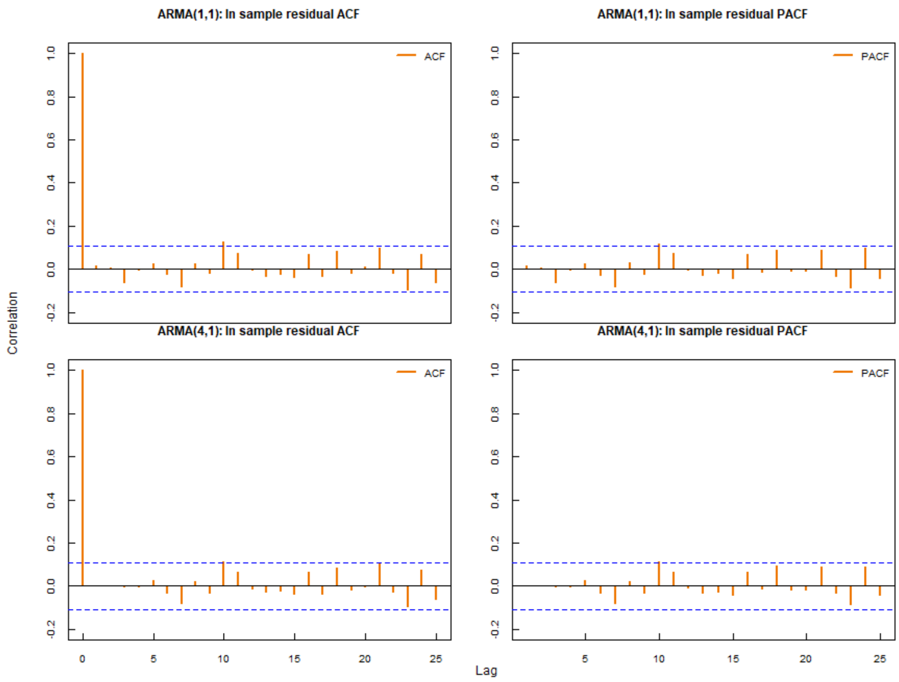


Figure 17: In-sample residual ACF of Economic Policy Uncertainty for OLS models 1 - 3.



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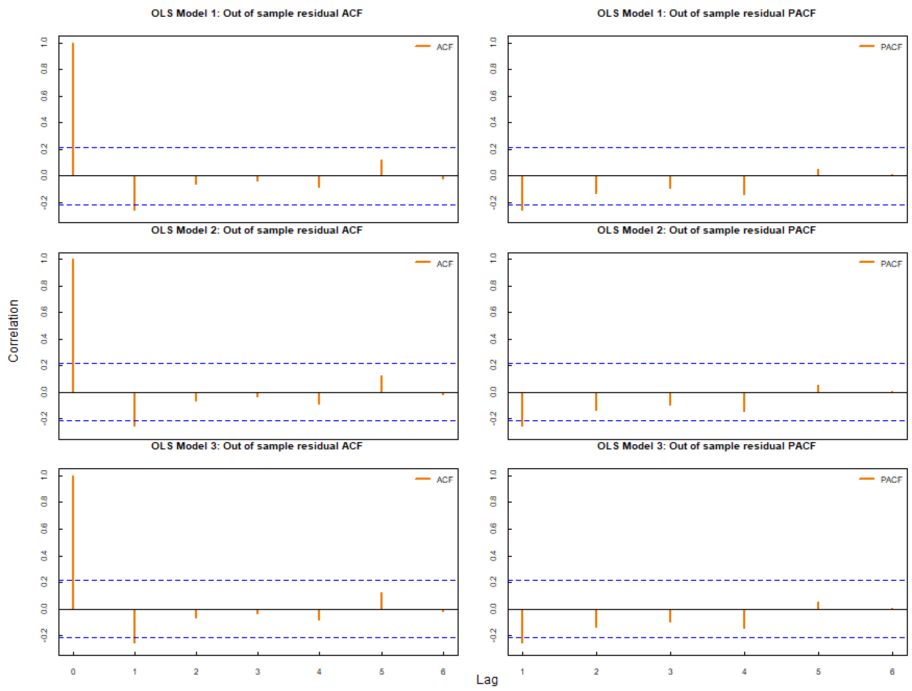

Figure 19: Out of sample residual ACF of Economic Policy Uncertainty for OLS models 1 - 3.

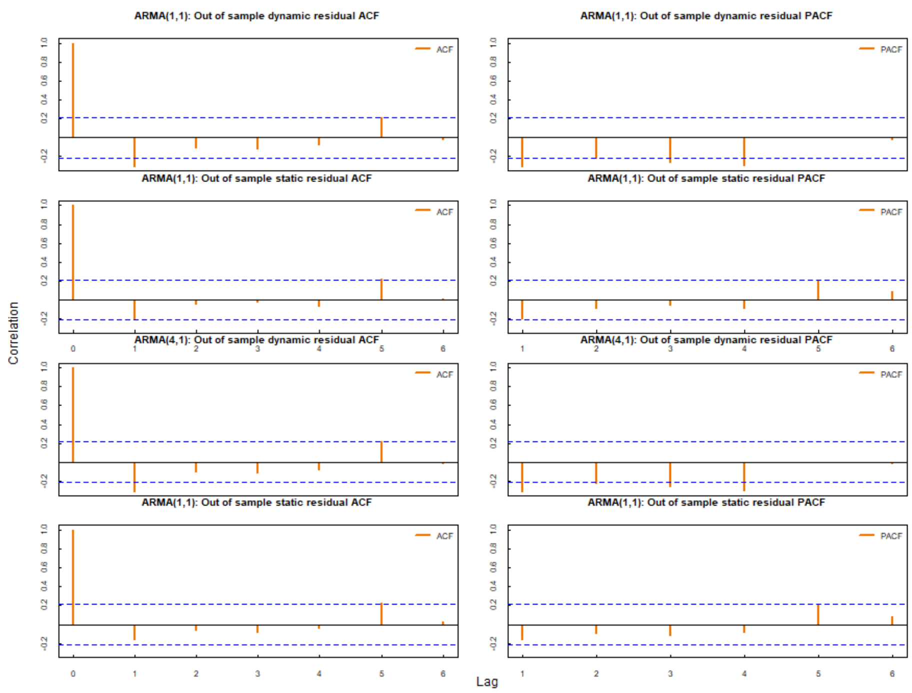

Figure 20: Out of sample residual ACF of Economic Policy Uncertainty for ARMA(1,1) and ARMA(4,1).

Figure 21: In-sample forecast of Industrial Production Growth for Models (1) - (3)

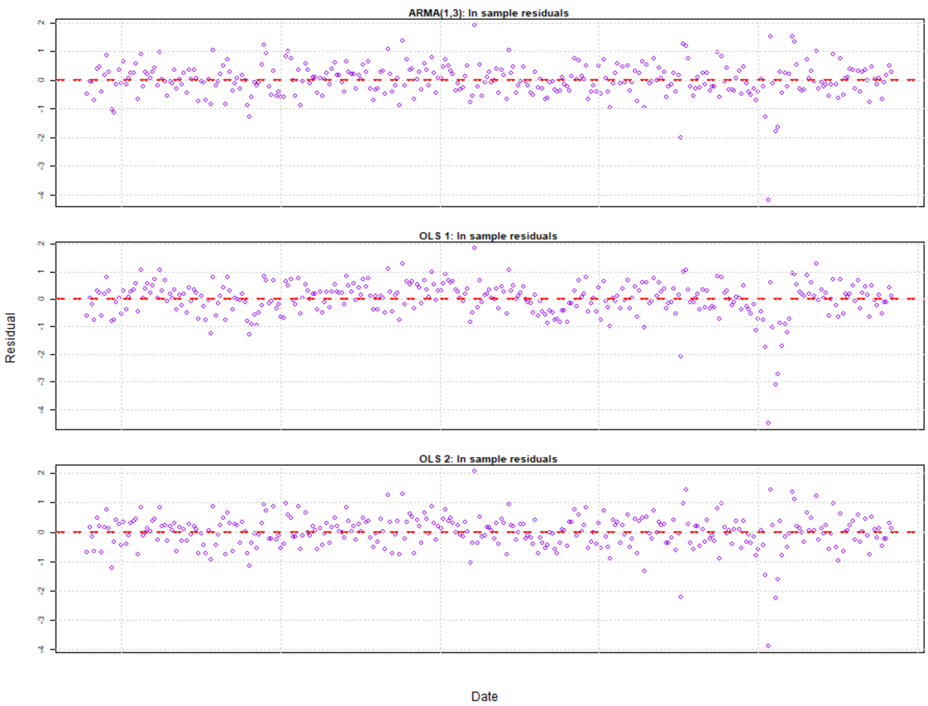

Figure 22: In-sample residuals of Industrial Production Growth for Models (1) - (3)

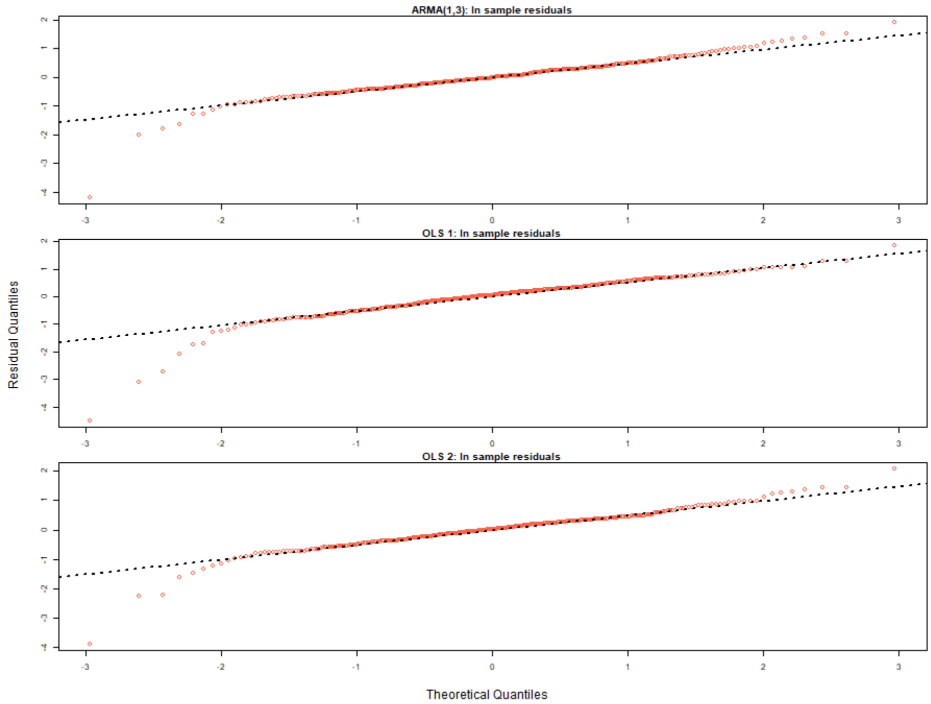

Figure 23: In-sample residual QQ-Plots of Industrial Production Growth for Models (1) - (3)

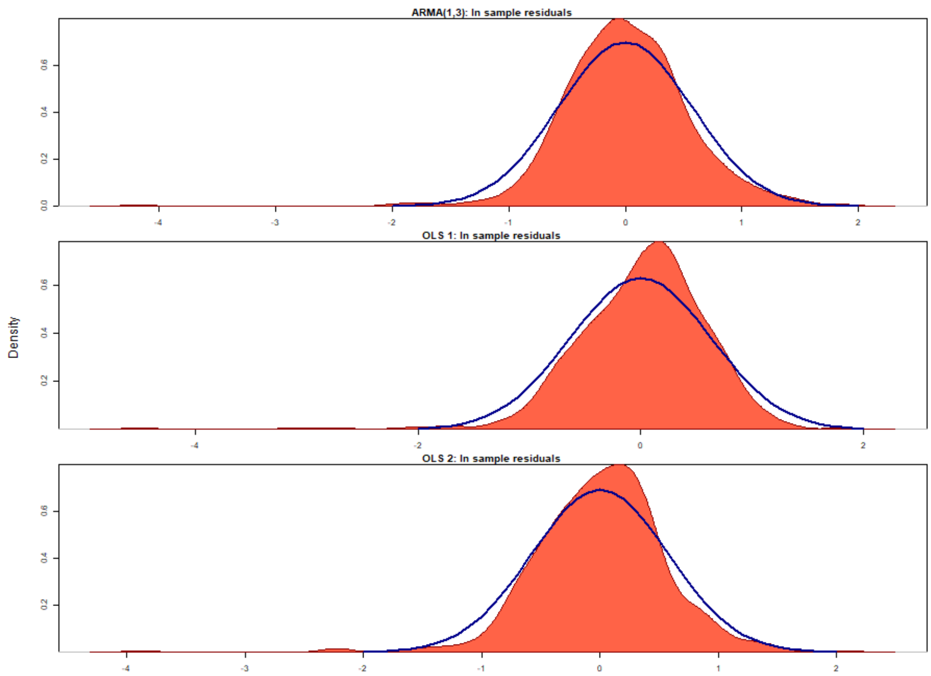

Figure 24: In-sample residual kernel density plots of Industrial Production Growth for Models (1) - (3)

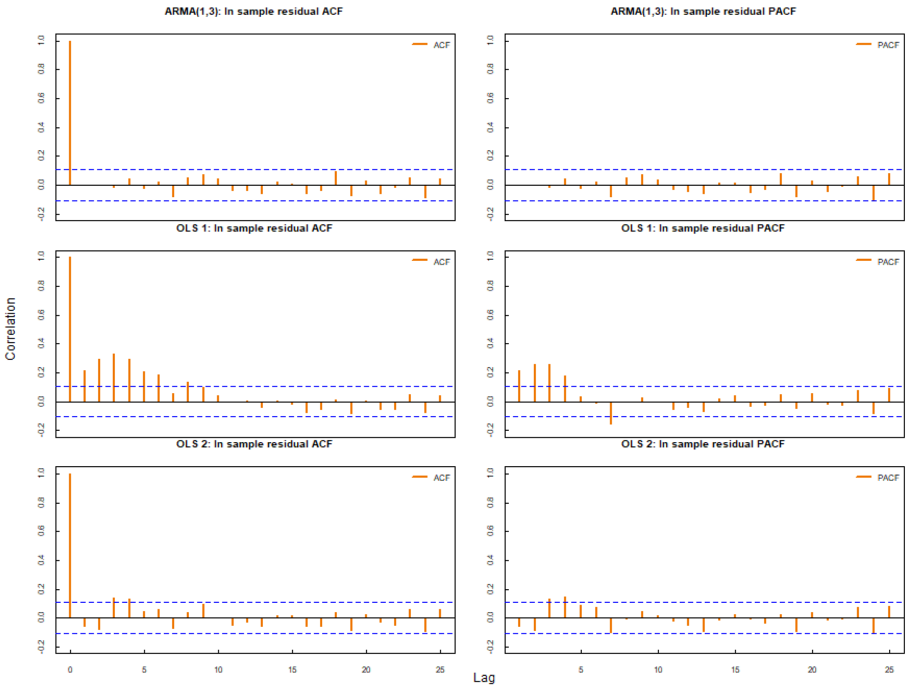

Figure 25: In-sample residual ACF and PACF of Industrial Production Growth for Models (1) - (3)

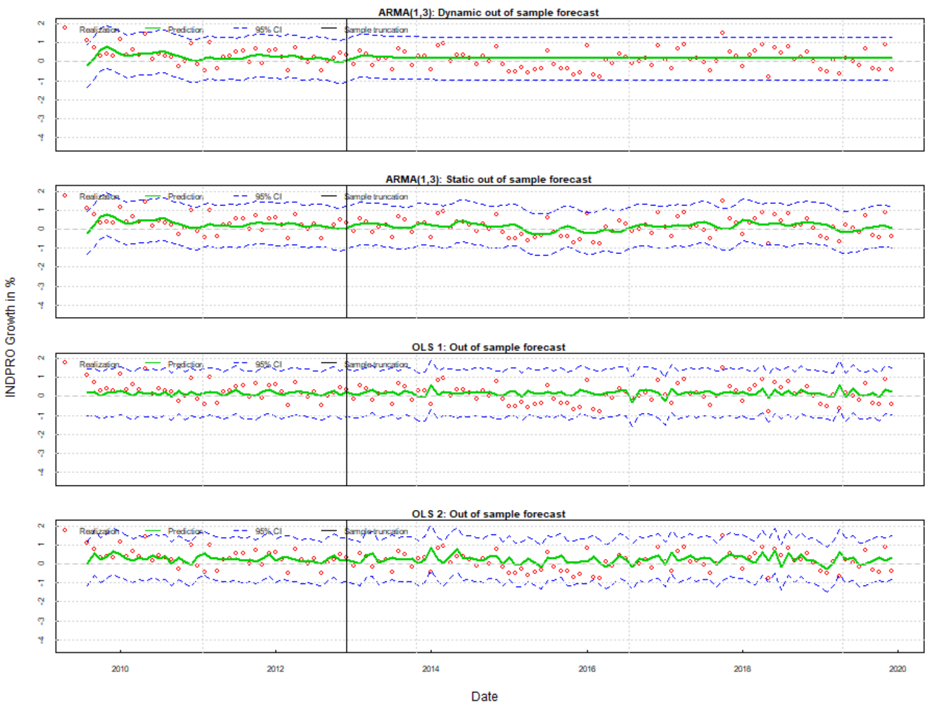

Figure 26: Out-of-sample forecast of industrial production growth

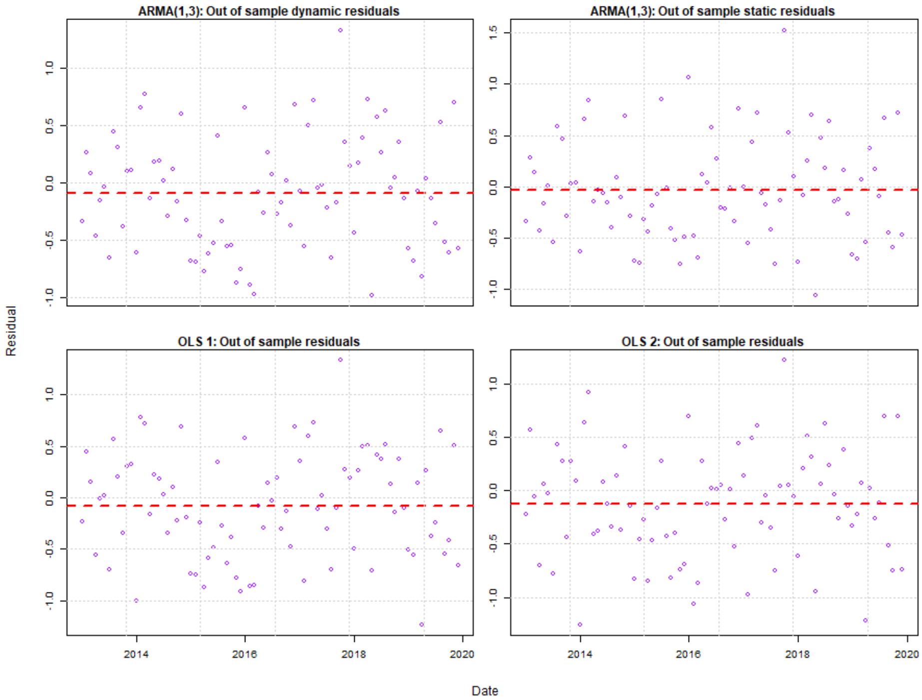

Figure 27: Out-of-sample residuals of industrial production growth

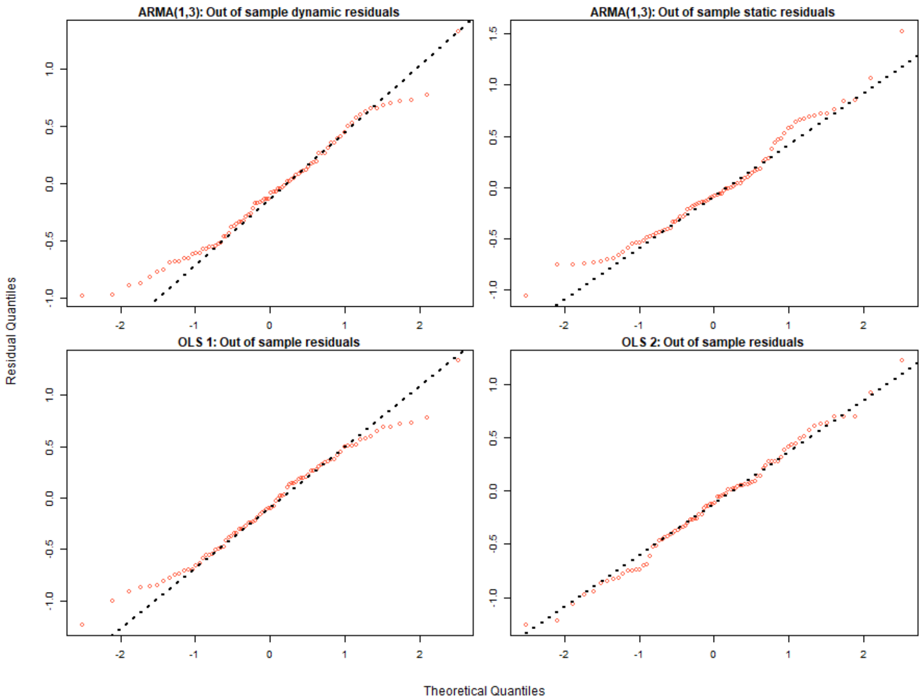

Figure 28: Out-of-sample residual QQ-plots of industrial production growth

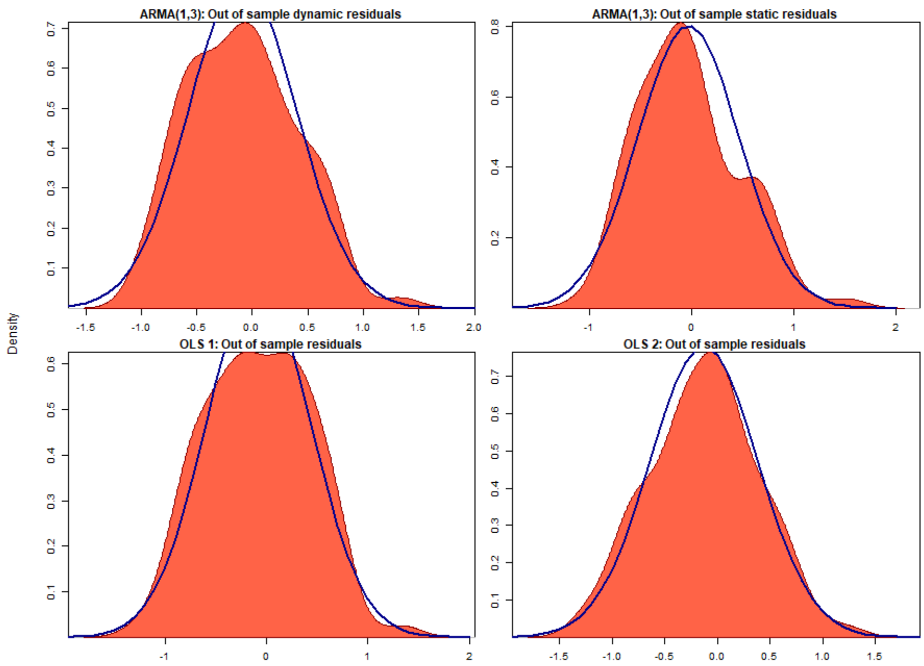

Figure 29: Out-of-sample residual kernel density plots of industrial production growth

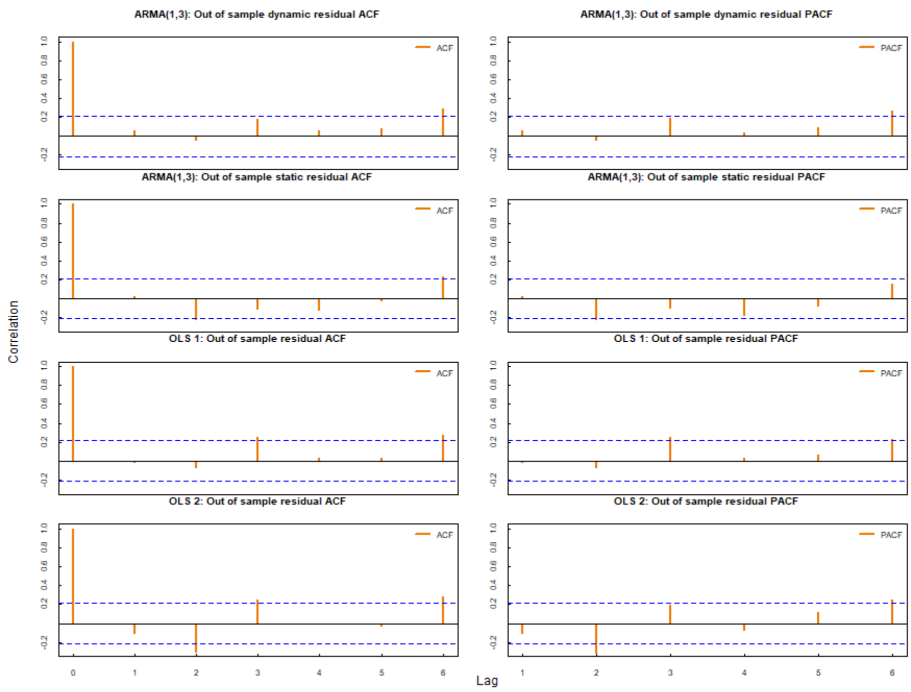

Figure 30: Out-of-sample residual ACF and PACF plots of industrial production growth

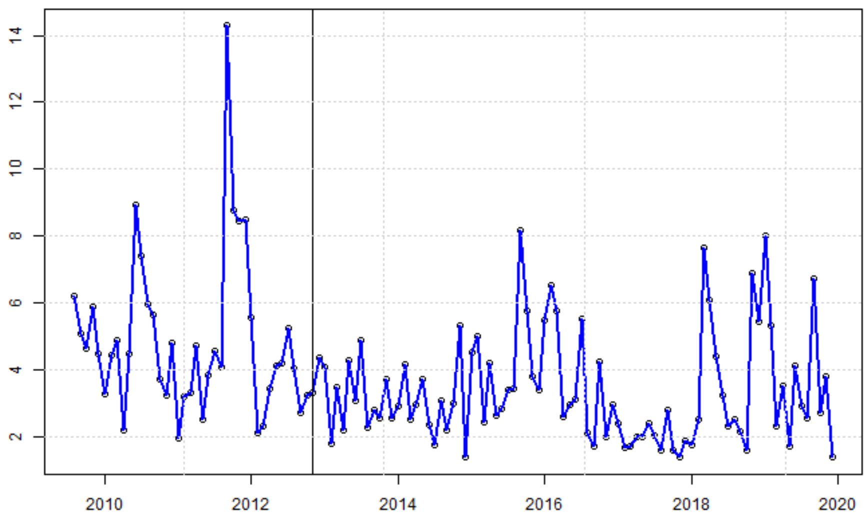

Figure 31: S&P 500 Monthly Volatility (subsample of the data used is shown for better visibility)

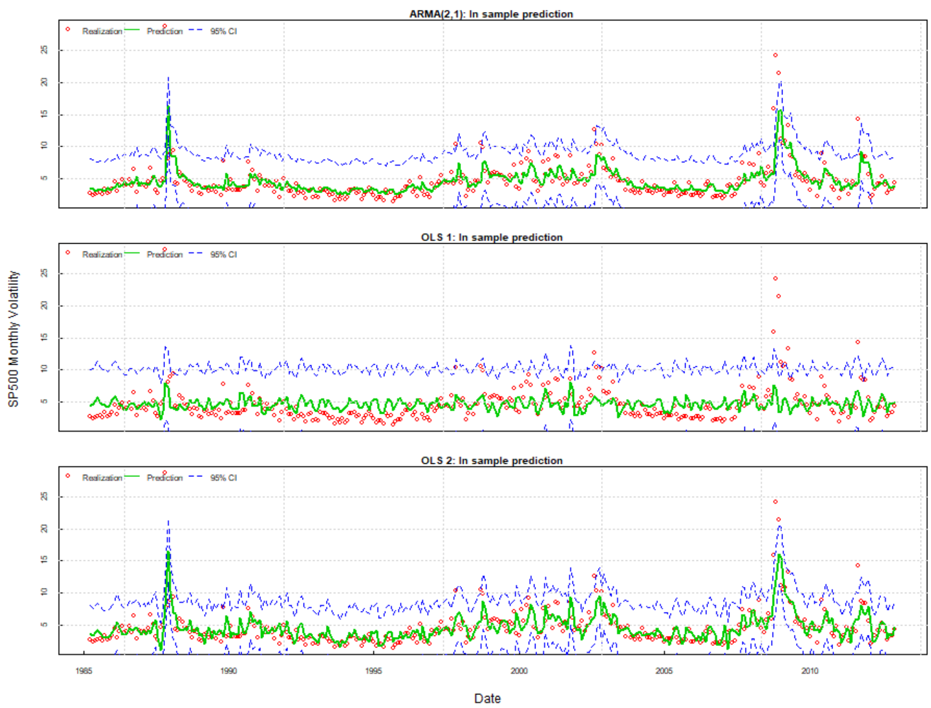

Figure 32: S&P 500 monthly volatility in-sample forecasts

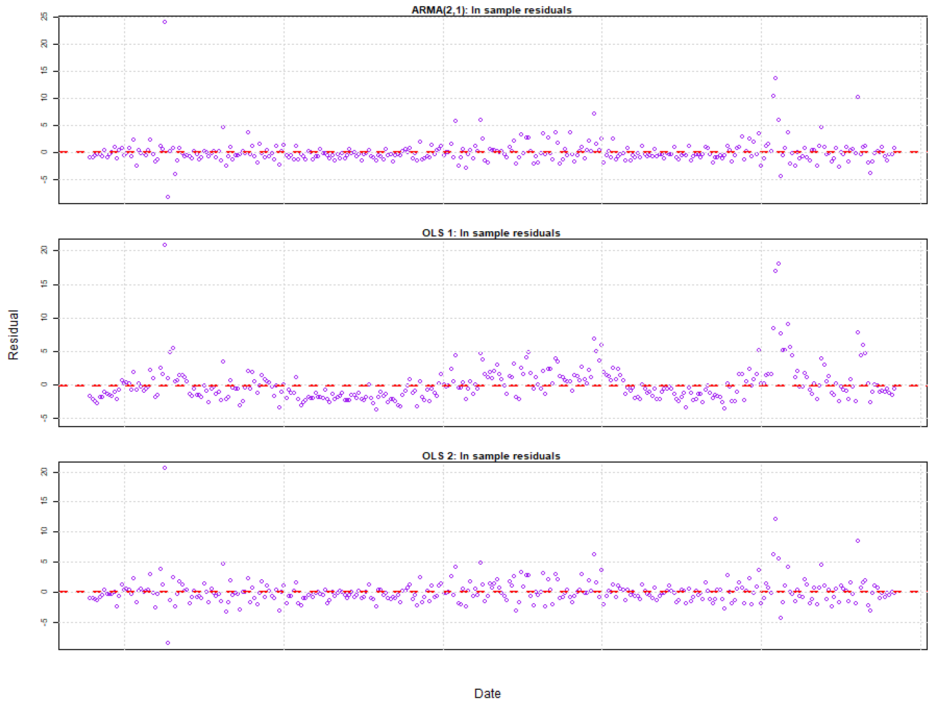

Figure 33: S&P 500 monthly volatility in-sample residual plots

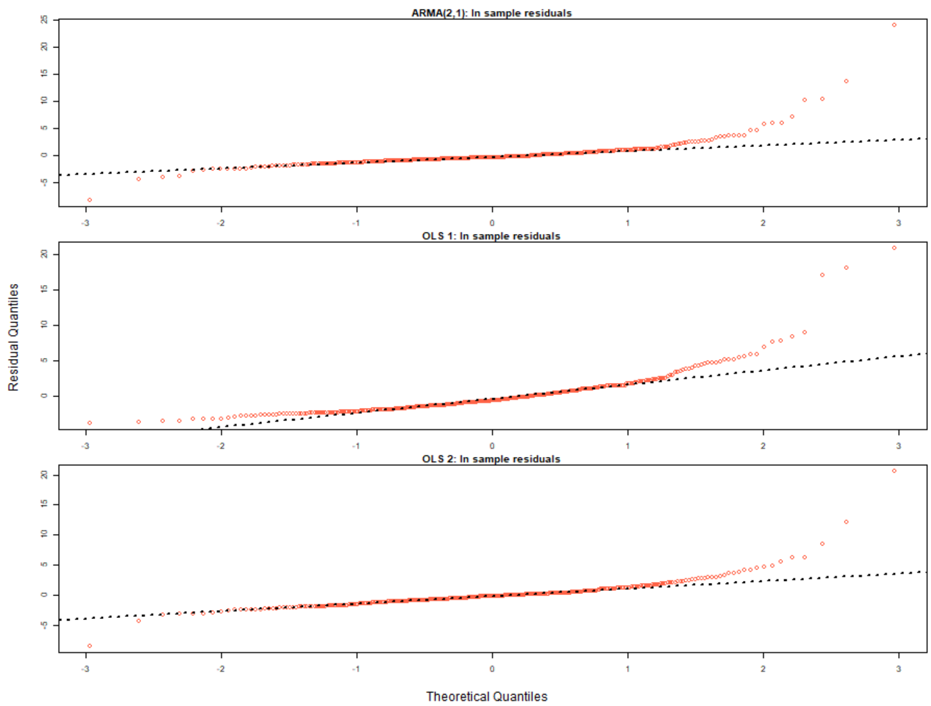

Figure 34: S&P 500 monthly volatility in-sample residual QQ-plots

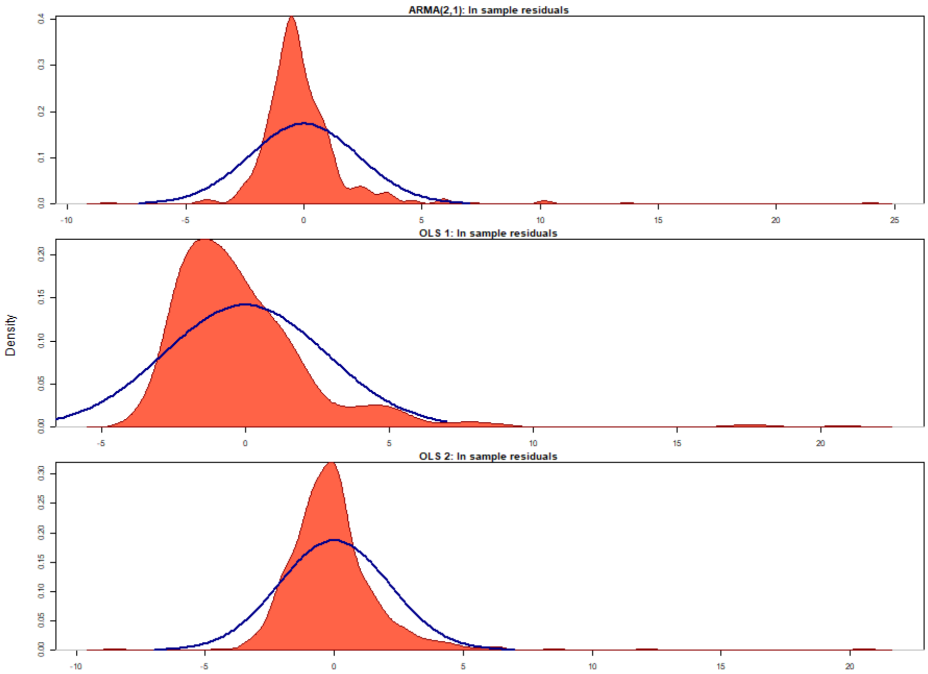

Figure 35: S&P 500 monthly volatility in-sample residual kernel density plots

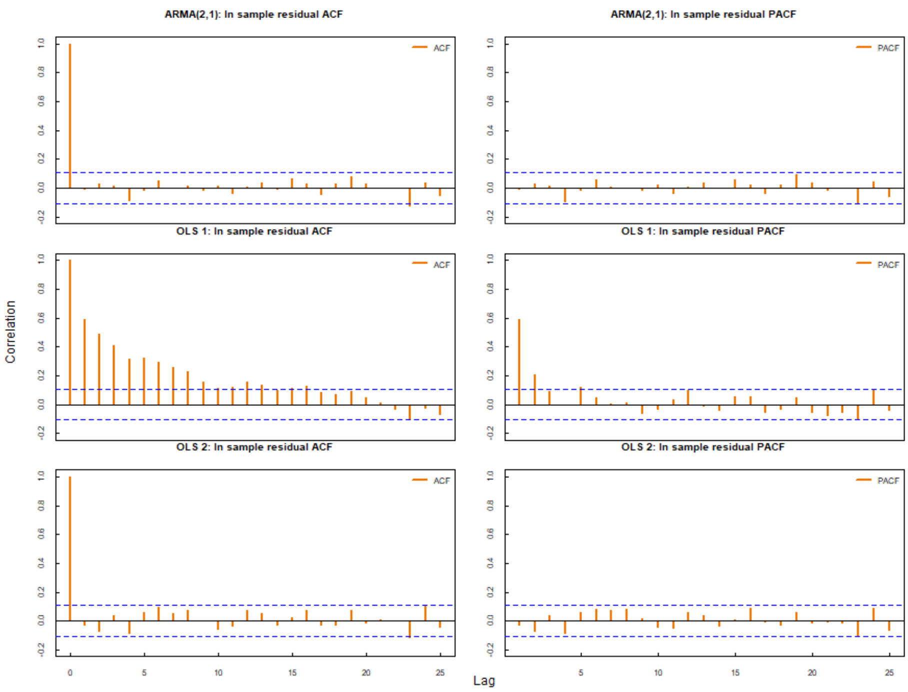

Figure 36: S&P 500 monthly volatility in-sample residual ACF and PACF plots

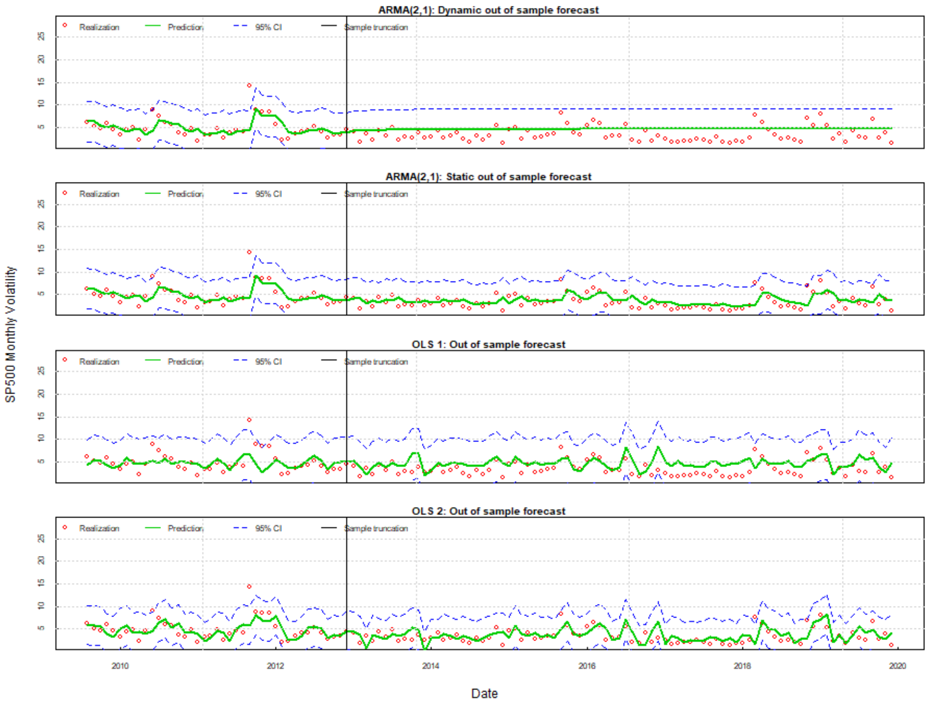

Figure 37: Out-of-sample forecasts of S&P 500 Volatility

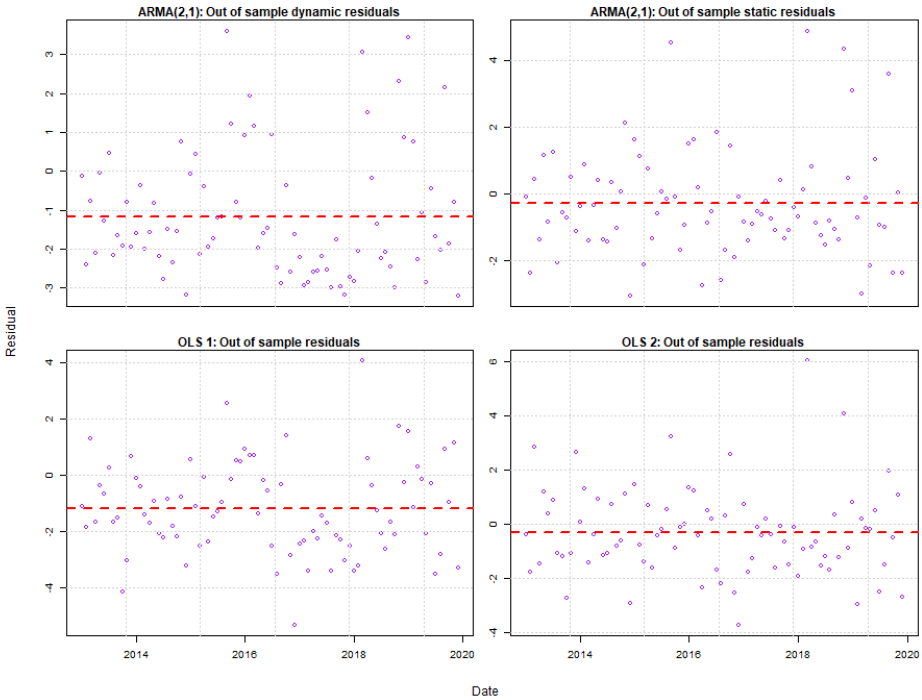

Figure 38: out-of-sample residuals of S&P 500 Volatility

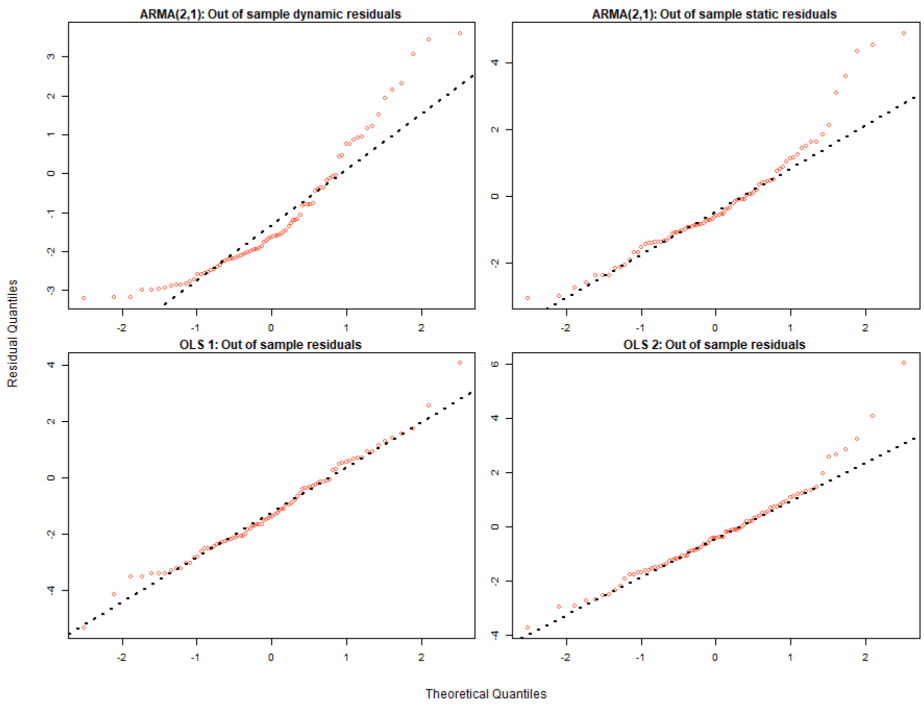

Figure 39: Out-of-sample residual QQ-plots of S&P 500 Volatility

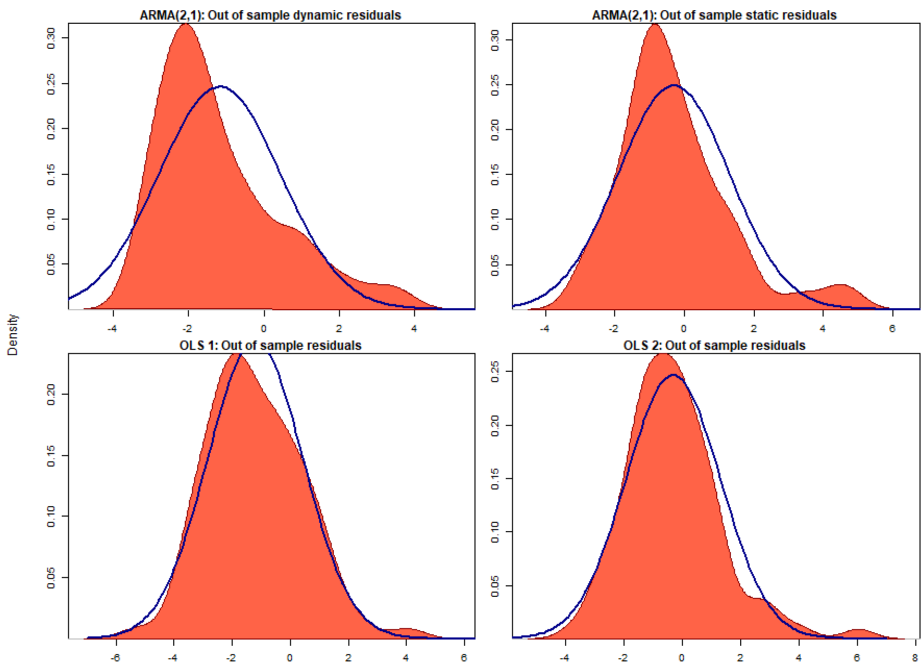

Figure 40: Out-of-sample residual kernel density plots of S&P 500 Volatility

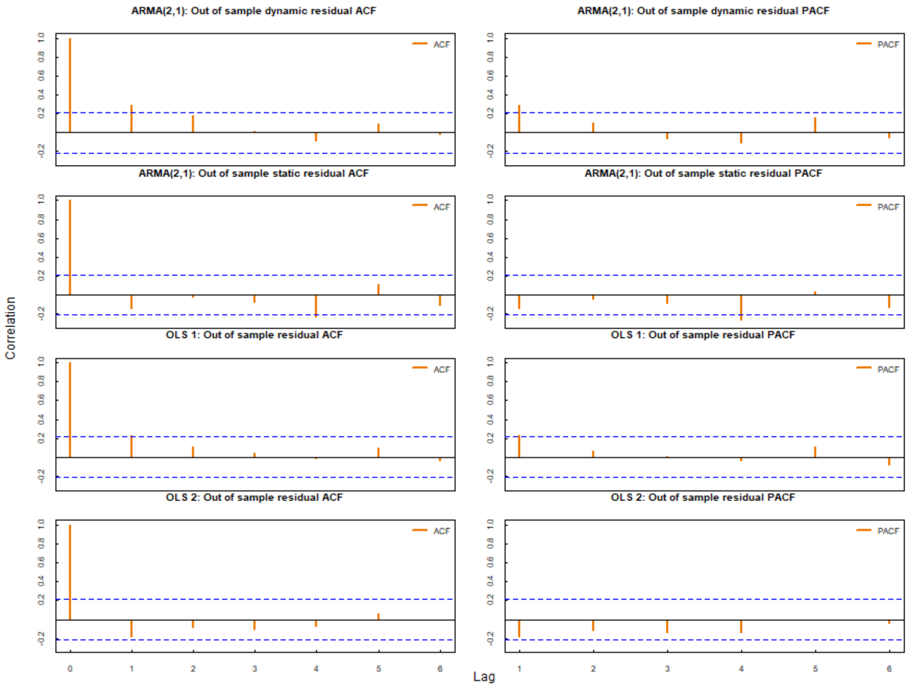

Figure 41: Out-of-sample residual ACF and PACF of S&P 500 Volatility

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Tables

Summary Statistics: Full sample

	uncertainty_growth	Unemployment	CPI Diff.	INDPRO growth	Monthly Vol.
Min	-64.303	3.500	-2.586	-4.434	1.380
25% Quant.	-10.345	4.700	-0.205	-0.170	2.735
Mean	0.030	5.892	-0.003	0.160	4.356
Median	-0.970	5.600	-0.005	0.203	3.752
75% Quant.	-10.345	4.700	-0.205	-0.170	2.735
Max	80.251	10.000	2.021	2.032	28.690
Skewness	0.508	0.826	-0.623	-1.555	3.768
Kurtosis	5.933	3.126	10.909	12.048	26.383
Variance	282.702	2.296	0.141	0.374	7.693
Number Obs.	419				

Table 1: Summary Statistics: Full sample

Summary Statistics: In-sample

	uncertainty_growth	Unemployment	CPI Diff.	INDPRO growth	Monthly Vol.
Min	-42.176	3.800	-2.586	-4.434	1.380
25% Quant.	-9.716	5.200	-0.205	-0.147	2.735
Mean	0.070	6.122	-0.007	0.169	4.356
Median	-0.866	5.700	-0.006	0.216	3.752
75% Quant.	-9.716	5.200	-0.205	-0.147	2.735
Max	80.251	10.000	2.021	2.032	28.690
Skewness	0.854	0.829	-0.534	-1.573	3.768
Kurtosis	6.200	3.280	10.308	11.832	26.383
Variance	228.429	1.943	0.147	0.380	7.693
Number Obs.	335				

Table 2: Summary Statistics: In-sample data

Summary Statistics: Out of sample

	uncertainty_growth	Unemployment	CPI Diff.	INDPRO growth	Monthly Vol.
Min	-64.303	3.500	-0.846	-0.796	1.380
25% Quant.	-12.464	4.000	-0.199	-0.341	2.735
Mean	-0.381	5.085	0.006	0.098	4.356
Median	-1.147	4.900	0.046	0.105	3.752
75% Quant.	-12.464	4.000	-0.199	-0.341	2.735
Max	68.425	8.000	0.644	1.506	28.690
Skewness	-0.017	0.684	-0.371	0.269	3.768
Kurtosis	4.263	2.387	2.784	2.502	26.383
Variance	493.568	1.539	0.078	0.239	7.693
Number Obs.	84				

Table 3: Summary Statistics: Out of sample data

Tests: Full sample properties

	T-Test		Jarque-Bera Test		Ljung-Box Test		ADF Test	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
uncertainty_growth	-0.351	0.726	27.885	0.000	39.188	0.00	-9.630	0.01
Unemployment	83.890	0.000	39.265	0.000	358.691	0.00	-4.078	0.01
CPI Diff.	0.434	0.665	10.423	0.005	25.956	0.00	-8.416	0.01
INDPRO growth	4.120	0.000	9.385	0.009	1.880	0.17	-4.989	0.01
Monthly Vol.	32.151	0.000	10537.205	0.000	150.237	0.00	-4.450	0.01
Number Obs.	419							

Table 4: Properties tests: Full sample

Regression Results: Growth in Economic Policy Uncertainty

	OLS1		OLS2		OLS3		ARMA(1,1)		ARMA(4,1)	
Variable	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Intercept	2.651	2.86192	2.89114	3.58204	2.10354	3.34802	0.1161	0.2593	0.1179	0.2675
uncertainty_growth$_{t-1}$	-0.23264***	0.05570	-0.23749***	0.05560	-0.23546***	0.05545	0.5720***	0.0712	0.5544***	0.0900
uncertainty_growth$_{t-2}$	-0.19551***	0.05625	-0.18684***	0.05577	-0.18507***	0.05565			-0.0084	0.0651
uncertainty_growth$_{t-3}$	-0.21356***	0.05698	-0.21081***	0.05683	-0.20915***	0.05672			-0.0732	0.0643
uncertainty_growth$_{t-4}$	-0.10859*	0.05639	-0.11908*	0.05574	-0.11934*	0.05569			0.0195	0.0632
UNRATE$_{t-1}$	1.63803	5.78415	-0.25643	0.53370	-0.26838	0.53285				
UNRATE$_{t-2}$	-1.88669	5.78845								
cpi_diff$_{t-1}$	-2.46500	2.26623	-0.82829	2.05862	-0.79814	2.05610				
cpi_diff$_{t-2}$	3.94141*	2.29053								
INDPRO_growth$_{t-1}$	-1.51971	1.41911	-1.32722	1.30325	-1.28548	1.30029				
INDPRO_growth$_{t-2}$	0.34568	1.34791								
DIFF$_{t-1}$	-0.02930	0.05934	-0.03677	0.05907						
ε_{t-1}							-0.8599***	0.0419	-0.8278***	0.0712
Observations	331		331		331		334		331	
R^2	0.186		0.190		0.185		0.181		0.186	
Adjusted R^2	0.158		0.169		0.168		0.176		0.173	
MSE	206.487		208.506		208.757		204.178		203.207	

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ (Newey-West standard errors reported for OLS)

Table 5: Regression results: Growth in Economic Policy Uncertainty (EPU).

mean	0
sd	14.47
skew	0.78
kurt	5.71

Table 6: Moments of the residuals of the third OLS model

	Residual Diagnostics: Test Statistics						
	Jarque-Bera Test (6)		Ljung-Box Test		ADF Test		MSE
Model	Statistic	P-Value	Statistic	P-Value	Statistic	P-Value	
OLS 1: In-sample	133.13	0.000	9.735	0.136	-9.644	0.010	206.486
OLS 1: Out of sample	1.842	0.400	8.020	0.237	-5.388	0.010	399.886
OLS 2: In-sample	133.72	0.000	8.984	0.175	-9.584	0.010	208.506
OLS 2: Out of sample	2.667	0.263	7.613	0.268	-5.429	0.010	398.353
OLS 3: In-sample	134.83	0.000	9.076	0.169	-9.611	0.010	208.757
OLS 3: Out of sample	3.144	0.208	7.322	0.292	-5.356	0.010	400.427
ARMA(1,1): In-sample	202.050	0.000	1.760	0.940	-7.687	0.010	204.178
ARMA(1,1): Dynamic OOS	5.972	0.051	15.263	0.018	-6.523	0.010	488.660
ARMA(1,1): Static OOS	4.233	0.120	8.411	0.210	-4.716	0.010	402.519
ARMA(4,1): In-sample	182.450	0.000	0.600	0.996	-7.576	0.010	203.207
ARMA(4,1): Dynamic OOS	5.982	0.050	15.273	0.018	-6.527	0.010	488.441
ARMA(4,1): Static OOS	5.641	0.060	8.150	0.227	-4.832	0.010	400.262

Table 7: Residual Diagnostics: Economic Policy Uncertainty

	ARMA(1,3)	OLS (2 EPU lags)	OLS (extended
	(1)	(2)	(3)
$INDPRO\_growth_{t-1}$	0.771^{***}		0.078
	(0.080)		(0.058)
$INDPRO\_growth_{t-2}$			0.179^{***}
			(0.056)
$uncertainty\_growth_{t-1}$		0.001	0.001
		(0.002)	(0.002)
$uncertainty\_growth_{t-2}$		-0.006^{***}	-0.005^{***}
		(0.002)	(0.002)
$cpidiff_{t-1}$			0.219^{**}
			(0.090)
$cpidiff_{t-2}$			-0.020
			(0.091)
$unemployment\_growth_{t-1}$			-0.048^{***}
			(0.014)
$unemployment\_growth_{t-2}$			-0.020
			(0.014)
ε_{t-1}	-0.723^{***}		
	(0.092)		
ε_{t-2}	0.155^{**}		
	(0.065)		
ε_{t-3}	0.136^{**}		
	(0.061)		
$Intercept$	0.178^{**}	0.175^{***}	0.133^{***}
	(0.077)	(0.035)	(0.035)
Observations	335	333	333
Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ (Newey-West standard errors reported for OLS)			

Table 8: Estimation Results: Growth of Industrial Production

Statistic (p-value)	ARMA(1,3) (dynamic)	ARMA(1,3) (static)	OLS (2 EPU lags)	OLS (extended)
	(1)	(1)	(2)	(3)
$t-test$	-1.678	-0.631	-1.424	-2.292
	(0.097)	(0.530)	(0.158)	(0.024)
$JB-test$	2.025	4.158	1.115	0.347
	(0.363)	(0.125)	(0.573)	(0.841)
$ADF-test(4)$	-2.975	-5.290	-3.006	-3.583
	(0.176)	(0.010)	(0.163)	(0.040)
$LB-test$	0.274	0.034	0.016	0.886
	(0.601)	(0.853)	(0.898)	(0.347)
MSE	0.246	0.245	0.266	0.275

Table 9: Out-Of-Sample INDPRO Test Statistics and Information Criteria

Table 10: Results: Predicting Volatility of the S&P 500

	OLS 1	*OLS 2*	*ARMA(2,1)*
Monthly Vol.$_{t-1}$		0.435***	1.072***
		(0.058)	(0.335)
Monthly Vol.$_{t-2}$		0.211***	−0.184***
		(0.053)	(0.232)
cpidiff$_{t-1}$		-0.727*	
		(0.335)	
cpidiff$_{t-2}$		0.538	
		(0.337)	
unemployment_growth$_{t-1}$		0.057	
		(0.047)	
unemployment_growth$_{t-2}$		0.060	
		(0.047)	
uncertainty_growth$_{t-1}$	0.051***	0.055***	
	(0.010)	(0.008)	
uncertainty_growth$_{t-2}$	0.036***	0.016*	
	(0.010)	(0.008)	
ε_{t-1}			-0.583*
			(0.317)
Constant	4.600***	1.613***	4.576**
	(0.154)	(0.258)	(0.459)
Observations	333	333	333
R^2	0.089	0.477	
Adjusted R^2	0.084	0.463	
Residual Std. Error	2.823 (df = 330)	2.16 (df = 324)	
Note:	*p<0.1; **p<0.05; ***p<0.01 (Newey-West standard errors reported for OLS)		

Statistic (p-value)	ARMA(2,1) (dynamic)	ARMA(2,1) (static)	OLS (2 EPU lags)	OLS extended
	(1)	(1)	(2)	(3)
$t-test$	-6.647	-1.731	-6.731	-1.732
	(0.000)	(0.087)	(0.000)	(0.087)
$JB-test$	18.463	26.229	2.487	28.65
	(0.000)	(0.000)	(0.288)	(0.000)
$ADF-test(4)$	-3.170	-4.780	-3.164	-4.901
	(0.098)	(0.010)	(0.099)	(0.010)
$LB-test$	7.207	1.688	4.434	2.839
	(0.007)	(0.194)	(0.035)	(0.092)
MSE	2.631	3.987	4.094	2.676

Table 11: Out-Of-Sample S&P 500 Test Statistics and Information Criteria