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DOES ECONOMIC POLICY UNCERTAINTY IMPACT INFLATION?

Abstract

Using the monthly economic policy uncertainty (EPU) index of Baker et al. (2016), we examine its impact on inflation rate in the UK over the period from 1998 to 2020. We adopt a vector autoregressive (VAR) model and generate impulse response functions. To ensure that the identified shocks will be uncorrelated, based on economic theoretical considerations, we employed Cholesky restrictions. The results show that a positive innovation in EPU index leads to a weakening of the real exchange rate and unemployment rate and at the same time a rise in inflation rate. The broad implication of the present research is that under economic policy uncertainty shocks, inflation and unemployment rate respond in accordance with the effects described by the economic theory and the Phillips curve, which emphasizes that there is a trade-off between inflation and unemployment.

Keywords: Economic Policy Uncertainty Index, inflation rate, real exchange rate

JEL Codes: C52, E50, F55

1. Introduction

In the last two decades economic policy uncertainty (EPU) and its impact on economic and financial outcomes have gradually become core research topic among researchers and policymakers. Economic policy uncertainty has been shown to be an important driver of investment activities (Gulen and Ion, 2016), interest rates, inflation, and risk premiums (Pastor and Veronesi, 2013), asset prices (Dong et al., 2019), economic growth (Bloom, 2009), exchange rate volatility (Bartsch, 2019), real exchange rate (Moldovan et al., 2021), real economic activity (Istiak and Serletis, 2018), unemployment (Caggiano et al., 2017), bank credit growth (Nguyen et al., 2020), foreign direct investment (Canh et al., 2020), oil prices (Shahbaz et al., 2021), stocks (Wang et al., 2021), corporate fraud (Hou et al., 2021). Gulen (2016) states that economic policy uncertainty refers to the inability of market participants to accurately predict whether a government will change economic policies or introduce new policies. Despite the large number of studies on the economic policy uncertainty, few analyse inflation.

Therefore, this paper hypothesizes that economic policy uncertainty influences inflation rate. To be specific, the importance of examining this hypothesis derives from the key role played by the policy makers which might be confronted to a choose between prioritising inflation or unemployment in any attempt of stabilising the economy due to uncertainty shocks. We consider that one link is especially relevant for the theories of inflation, namely the correlation between the Phillips curve and economic policy uncertainty. Using a sample of the UK indicators from 1998 to 2020 and the UK economic policy uncertainty index of Baker et al. (2016), we examine the impact of economic policy uncertainty on inflation rate. We estimate an inflation, unemployment, economic policy uncertainty and real exchange rate, by applying one model that is useful to capture and describe dynamics between economic times series and which is available to draw conclusion for variables integrated of the same order, the VAR model. Two facts are put forward to support the research undertaken in this study and its contribution to the literature. First, there has been less previous evidence about the relationship between inflation and economic policy uncertainty in developed markets. Second, to the best of our knowledge, there is no

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published study that investigates a combination of inflation, unemployment, real exchange rate and economic policy uncertainty for a developed economy.

The rest of the paper proceeds as follows. Section 2 presents a short review of the literature regarding inflation and economic policy uncertainty. Section 3 outlines the model and data and Section 4 presents the main findings. The impulse response analysis is conducted throughout Section 5, while Section 6 provides concluding remarks.

2. 2. Economic Policy Uncertainty and Inflation: A Literature Review

The Phillips curve is a durable concept in economics which posits a simple relationship between wage growth and unemployment. Phillips (1958) showed, using British data, that annual wage inflation and unemployment rates for the period 1861 to 1957 demonstrates a consistent inverse relationship as when unemployment was high, wages increased slowly or decreased, and the years of low unemployment rates were years of fast rising wages. This trade-off relationship became known as the Phillips curve hypothesis formulated as follows: rate of change of nominal wage rates can be explained by the level of unemployment and the rate of change of unemployment.

The hypothesis is likely to hold if monetary policy is set with the goal of minimising welfare losses and the Central Bank seeks to increase inflation when output is below potential. The relationship between inflation and unemployment is probably one of the most important ones that is explored in macroeconomics studies, and in the literature we can find different theoretical and empirical methods of studying this relationship. Although the policymakers want to deliver both low unemployment and low inflation, according to the Phillips curve, the economy operates in such a way that when unemployment falls, inflation tends to go up and when inflation roses, unemployment goes down. The policymakers might be confronted to a choice between prioritising inflation or unemployment. Beggs (2015) states that the remedy for inflation is symmetrical to the remedy for unemployment.

However, the empirical models explaining inflation in the Phillips curve literature generally fail to account economic policy uncertainty. One reason it could be that the economic policy uncertainty is considered as a variable that is quite hard to measure in a way which can be used in econometric work.

The perspective we offer about the link between economic policy uncertainty and inflation is based on the notion that uncertainty brings both demand and supply effects. Economic policy uncertainty shock affecting the economic activity can be seen as a negative shock on inflation because more uncertainty will be harmful to the economic performance. Indeed, on the demand side, if an uncertainty shock occurs, we can expect a decline in inflation, a rise in unemployment, and at the same time, consumption will contract since the uncertainty will trigger savings.

Higher policy uncertainty reduces inflation expectations (Liu et al., 2019), thus leading to lower inflation. Leduc and Liu (2016) studying the channel through which uncertainty affects aggregate economic activity conclude that and increases in uncertainty are seen as an aggregate demand shock because it increases unemployment and lowers inflation. While Easterly and Fischer (2001) state that from an economic perspective, the periods of price stability are always marked by order and harmony into a country, Bloom (2014) finds that high uncertainty leads to a decline in economic activity. Our basic intuition is that if economic policy uncertainty occurs uncertainty accumulates. In the supply side, we would expect a reduced output and from the Phillips Curve perspective more inflation and higher unemployment. Political uncertainty may difficult the production process and increase the cost of production, thus leading to higher inflation. Economic feasible outcomes could be limited by the economic policy uncertainty shocks.

Aisen and Veiga (2006) argue that politically unstable countries are often susceptible to political shocks, which lead to discontinuous monetary and fiscal policies and high inflation volatility. It has been suggested that political instability increases policy uncertainty, which has negative effects on productive economic decisions and that the impact of political instability on inflation is much stronger for high inflation economies than for moderate and low inflation ones.

Colombo (2013) investigating the effects of the US economic policy uncertainty indicator on the consumer price index using Structural VAR finds a decline in production and a deflationary phase after uncertainty shock. Jones and Olson (2013) estimating monthly data by using dynamic conditional correlation (DCC) GARCH model analyse the correlation between macroeconomic uncertainty, inflation, and output. They found that the correlation between inflation and uncertainty turns from negative to positive during the late 1990s and early 2000s. Istrefi and Piloiu (2014) estimate a structural Bayesian VAR to study the link between economic policy uncertainty and inflation expectations for the US and for the euro area. Their result highlights that a shock in policy uncertainty decreases the short-run inflation expectation while will increase long-run inflation.

Liu et al. (2019) using a mixed-frequency VAR (MF-VAR) approach when studying the impact of economic policy uncertainty shocks on inflation expectations in China found that inflation expectations are sensitive to policy-related uncertainty shocks. Their study concluded that uncertainty shocks generate rise in the inflation expectations in China. A recent study of Ghosh et al.(2020) analyses the macroeconomic factors such as output, monetary policy, and exchange rate, among the economic policy uncertainty in the determination of inflation expectation in India. By using a Bayesian structural with exogenous variables (VAR-X) model concluded that an economic policy uncertainty shock leads to an increase in inflation expectations.

Selmi et al. (2020) studying the effects of the US EPU index on inflation prior to and post Trump's win based on a flexible copula-based with Markov-switching regime approach, find that economic policy uncertainties seem important for the observed changes in inflation. They showed that the period post Trump's inauguration displayed more inflation in comparison to the period prior to Trump's win.

Caggiano et al. (2017) analyse the effect of the US EPU on unemployment in recessions and expansions using Smooth Transition VAR model. They found that the response of unemployment to EPU is higher in contraction periods than in expansionary periods.

Erer and Erer (2020) using a threshold VAR in analysing the effects of the US EPU on macroeconomic variables such as industrial production index, inflation, interbank rate and exchange rate for Turkey and BRICS economies, found that inflation and real effective exchange rate in Turkey, Russia and China respond more significantly to a shock in US EPU.

Together, the previous findings confirm that there is a link between economic policy uncertainty and inflation, but the extent to which it is possible to generalize about the increase or the decrease of inflation rate due to economic policy uncertainty shocks are unknown.

3. Methodology and Data

3.1. Model

VAR model is useful for predicting multiple time series using a single model to analyse the response of the variables when one deviation shock is applied. VAR model pioneered by Sims (1980) have acquired a permanent place in the toolkit of applied macroeconomists both to summarise information contained in the data and to conduct certain types of policy experiments. A simple VAR(p) model of k variables is given by the equation:

$$y_t = A + \sum_{i=1}^{p} B_i \; y_{t-1} \; + u_t \qquad (1)$$

where y_t is a k dimensional vector of variables, A is a vector of constant, B_i are matrices of estimated coefficients ($k \times k$). By assumption u_t are white noise error terms or uncorrelated innovation shocks. The VAR model can be estimated via the ordinary least squares (OLS) method where all the variables entering the model must be stationary. In trying to decide whether the economic data under investigation is stationary or not it would be useful to perform unit root tests, e.g., the ADF test (Dickey and Fuller, 1979), and the PP test (Phillips and Perron, 1988) as well as stationarity tests such as the KPSS test (Kwiatkowski, Phillips, Schmidt and Shin, 1992). The most emphasised caution in performing the ADF and PP unit root tests have to do with the lack of power in situations where the unit root is very close to the nonstationary threshold, which may act as an incentive to not reject the null hypothesis when it should be rejected. This is the main motive for running both, unit root and stationarity tests in targeting robust conclusions with respect to the time series stationarity.

According to Stock and Watson (2007), choosing the order p of a VAR model requires balancing the marginal benefit of including more lags against the marginal cost of additional estimation uncertainty. The most commonly applied selection criteria are Akaike Information Criterion (Akaike, 1974), $AIC = \ln(\hat{\sigma}_{\varepsilon}^2) + \frac{2k}{T}$ and the Schwarz Information Criterion (Schwarz, 1978), $SIC = \ln(\hat{\sigma}_{\varepsilon}^2) + \frac{k}{T}\ \ln(T)$, where $\sigma_{\varepsilon}{}^2$ is the sum of squared residuals, k is the number of the estimated VAR parameters and T is the number of observations used for estimation. Both criteria are based on the estimated variance plus a penalty adjustment depending on the number of estimated parameters. It is in the extent of this penalty that these criteria differ. The penalty proposed by SIC is larger than AIC's if T is large. In practice both criteria are examined - the AIC is widely used in practice. In general, the model with the number of lags corresponding to the smallest AIC is used for further analysis.

3.2. Data

The purpose of this study is to test the hypothesis that economic policy uncertainty affects the inflation rate. We use VAR model to capture the existing dynamic relationship between economic policy uncertainty and economic activity. In the VAR model, we include four variables: inflation rate (INF), economic policy uncertainty index (LNEPU), unemployment rate (UN) and real effective exchange rate (LNREER). The inclusion of these four variables in the model is due to the fact that they are assumed to significantly affect inflation. In these specifications, whereas the economic policy uncertainty index and the exchange rate are expressed in levels and logarithms, the inflation rate and the unemployment rate are expressed in percentage. All the variables entering model are transformed using first differences due to their nonstationarity as we will see below. The data considered in the VAR model under analysis comprises the time interval between January 1998 to September 2020 with monthly frequency. The choice of this period was determined by the availability of EPU index.

Economic policy uncertainty index: *LNEPU*

The main indicator used to represent the UK economic policy uncertainty, the EPU index is presented by Baker et al. (2016). For the UK, EPU requires three components to quantify policy-related economic uncertainty, such as uncertain or uncertainty, economic or economy, and policy relevant terms. The policy relevant terms include the words ”tax”, ”spending”, ”regulation”, ”Bank of England”, ”budget”, and ”deficit”. The 11 UK newspapers entering the UK EPU construction are: The FT, The Times and Sunday Times, The Telegraph, The Daily Mail, The Daily Express, The Guardian, The Mirror, The Northern Echo, The Evening Standard, and The Sun. The UK EPU index,was retrieved from the Economic Policy Uncertainty webpage (www.policyuncertainty.com), is expressed in logarithms and

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begins in January 1998, which is the starting point of the empirical analysis. Backer et al. (2016) shows that an increase in EPU index is generally associated with a decline in economic performance, thus we would also expect that an increase in EPU to increase inflation rate (this is the main hypothesis to test).

Inflation rate:*INF*

Musarat et al.(2021) state that the inflation is one of the leading components that has a major impact on the economy. The UK rate of inflation derived from the UK consumer price index, records the change in the price of a weighted basket of goods and services purchased by an average household, and is obtained from the Office for National Statistics. The time series expresses the inflation as percentage change relative to 2015, when the index is given a value of 100.

Unemployment rate: *UN*

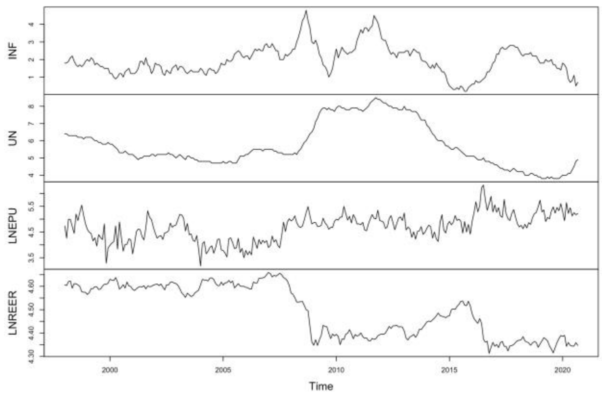
The UK employment rate obtained from the Office for National Statistics, is the proportion of people aged between 16 and 64 years who are in paid work. In the UK, unemployment measures the number of people without a job who have been actively seeking work within the last four weeks and are available to start work within the next two weeks. It is the proportion of the economically active population (those in work plus those seeking and available to work) who are unemployed. It is expressed in percent.

Real effective exchange rate:*LNREER*

LNREER is used as the control variable expressed in logarithms, is based on the nominal exchange rate and a multilateral consumer price index. The variable was retrieved from the Bank of England. REER is the weighted averages of bilateral exchange rates adjusted by relative consumer prices, and it calculates the number of units of foreign goods that will pay for 100 units of equivalent domestic goods, with a weighting pattern time varying, an increase in REER is a currency real appreciation. Is expected that high economic policy uncertainty leads to currency depreciation.

The graphs of the four variables in levels are presented in Figure 1.

Figure 1. Plot of the Variables in Levels



Source: Authors.

4. Empirical Results

4.1. Unit Root and Stationarity Tests

The first step in order to carry out our analysis is to test for stationarity in the four time series. For the VAR model to be feasible, all variables need to be stationary (I (0)) or first difference stationary (I (1)). To examine the nonstationarity of the variables, both ADF and PP unit root tests are conducted, while for the stationary we conducted the KPSS test. Results from unit root and stationarity tests for the levels and the first differences of the variables are shown in Tables 1 and 2.

Table 1. Test Statistic Representation of the ADF and PP Unit Root Tests

	ADF unit root test		PP unit root test	
Variable	Level	Δ	Level	Δ
	Intercept Trend and Intercept None	Intercept Trend and Intercept None	Intercept Trend and Intercept None	Intercept Trend and Intercept None
INF	-2.4161 -2.3801 -1.1616	-13.7592*** -13.7517*** -13.7812***	-2.5217 -2.4845 -1.1946	-13.8564*** -13.8487*** -13.8782***
LNREER	-0.9787 -2.1148 -1.0457	-14.6356*** -14.6120*** -14.6127***	-1.1495 -2.4001 -0.9466	-14.6356*** -14.6121*** -14.6140***
LNEPU	-3.0802*** -4.7524*** -0.1890	-16.2096*** -16.1858*** -16.2391***	-4.6758*** -6.4059*** -0.0450	-29.6739*** -29.6573*** -29.7039***
UN	-1.1939 -1.2018 -0.5759	-6.9324*** -6.9166*** -6.9408***	-1.1907 -1.2068 -0.7267	-12.7221*** -12.7044*** -12.7229***

Source: Authors.
Note: The ADF, PP critical value at 5% significance level is -2.872 for the model with an intercept. The ADF, PP critical value at 5% significance level is -3.426 model with both intercept and trend. The ADF, PP critical value at 5% significance level is -1.941 for
the model without intercept and trend. The ADF test lag lengths were selected automatically based on the SIC criteria. * denotes the
rejection of the null hypothesis at the 10% significance level. ** denotes the rejection of the null hypothesis at the 5% significance level.
*** denotes the rejection of the null hypothesis at the 1% significance level.

Table 2. Test Statistic of the KPSS Stationarity Test

	Level		Critical values	Δ	
	Intercept Trend and Intercept	Stationary decision		Intercept Trend and Intercept	Stationary decision
INF	0.2117* 0.2100	Yes No	0.463 0.146	0.0673* 0.0366*	Yes Yes
LNREER	1.4539 0.1075*	No Yes	0.463 0.146	0.0558* 0.0513*	Yes Yes
LNEPU	1.0374 0.1234*	No Yes	0.463 0.146	0.0614* 0.0427*	Yes Yes
UN	0.2967* 0.2999	Yes No	0.463 0.146	0.1751* 0.1705*	Yes Yes

Source: Authors.
Note: The KPSS critical value at 5% significance level is 0.463 for the model with an intercept. The KPSS critical value at 5%
significance level is 0. 146 with trend and intercept. * denotes the not rejection at 5% significance level of the stationarity hypothesis.
The critical values according to Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

The ADF, PP and KPSS test results reveal that three out of four variables under analysis, INF, UN and LNREER are nonstationary in levels. For INF the ADF and PP test showed that the variable is nonstationary at levels for all three possible test cases, only trend, trend and intercept, none; but the KPSS points to the stationarity of the variable in the case of the inclusion of the trend. Based on the three tests, we can conclude that, when we include both trend and intercept, the variable expressed in levels is nonstationary. Based on the ADF and the PP test, both variable, LNREER and UN are nonstationary in levels in all three cases. The KPSS assigns stationarity in their value when in the LNREER analysis we consider trend and intercept and when in the UN we consider only intercept. On behalf of these tests results, we can conclude that LNREER and UN are nonstationary when expressed in level. When counting for trend and intercept, in the unit root and stationarity analysis, of EPU we can conclude that the variable is stationary in levels.

As the estimation of a VAR model requires stationarity, all the variables are converted into growth rates. According to the ADF test, the PP test and KPSS test, all growth series were found to be stationary, and then they were fit into the four-variable VAR model.

4.2. VAR Model

To study our question of interest we fit a VAR model to the UK monthly data from 1998M01 to 2020M09. Although the EPU is stationary in levels, when including both trend and intercept, for coherence with the other variables, we have used all the variables in their first differences. The VAR model also includes a constant.

Lag length determination

VAR models were estimated to include the number of lags from 1 until 12. Since the lag-length *p* is not derived from theory, we need to determine it by comparing different specifications. We compute selection order criteria, summarized in Table 3 to gauge whether we have included sufficient lags in VAR estimation. Introducing too many lags wastes degrees of freedom, while fewer lags are likely to cause autocorrelation in the residuals and to drive to misspecification of the model. A VAR with autocorrelated residuals it might suggest that is there was some information which was not accounted by the model.

Table 3. Lag Length Selection in VAR Model

Lag	LogL	LR	FPE	AIC	SC
0	900.4098	NA	1.19e-08	-6.895460	-6.840681
1	949.3456	95.98938	9.23e-09	-7.148812	-6.874914*
2	973.8356	47.28458	8.65e-09*	-7.214120*	-6.721103
3	985.6697	22.48479	8.94e-09	-7.182075	-6.469939
4	995.9368	19.19149	9.34e-09	-7.137975	-6.206720
5	1005.958	18.42274	9.79e-09	-7.091981	-5.941607
6	1016.195	18.50587	1.02e-08	-7.047652	-5.678159
7	1029.731	24.05321	1.05e-08	-7.028702	-5.440090
8	1042.291	21.93207	1.08e-08	-7.002242	-5.194511
9	1047.278	8.553684	1.17e-08	-6.917522	-4.890673
10	1056.256	15.12522	1.24e-08	-6.863510	-4.617542
11	1061.480	8.639877	1.35e-08	-6.780619	-4.315532
12	1086.553	40.69470*	1.27e-08	-6.850408	-4.166202

Source: Authors.
* indicates lag order selected by the criterion (each test at 5% level) LR: sequential modified LR test statistic, FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion

The Schwarz information criterion (SIC) indicates a lag structure of p = 1. However, the Akaike information criterion (AIC) and the final prediction error (FPE) indicate a structure of lag where p = 2 and the sequential modified LR test statistic indicates a lag p = 12. The optimal number of lags, two suggested by the AIC criterion will be consider further considered in VAR estimation.

4.2.1. Residuals Analysis

Once we estimate the VAR model with two lags, the next step is to determine if the selected model provides an adequate description of the data by examining the model residuals assumptions such as: autocorrelation, normality and heteroskedasticity.

Autocorrelation among the residuals test results

The Lagrange Multiplier (LM) test is used to check residual autocorrelation in the estimated VAR model. The null hypothesis of no residuals autocorrelation up to lag two is tested against of the alternative of autocorrelated residuals. Table 4 reports the results in terms of chi-square critical values (right-tail).When compared to the table values (chi-square (16) = 26.30) we do not reject the null of no residuals autocorrelation and we conclude that the residuals are independent.

Table 4: Autocorrelation LM test for VAR (2) residuals
VAR Residual Serial Correlation LM Tests
Sample: 1998M01 2020M09
Included observations: 270

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	24.21180	16	0.0850	1.523129	(16, 776.6)	0.0850
2	21.51536	16	0.1595	1.351162	(16, 776.6)	0.1596

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	24.21180	16	0.0850	1.523129	(16, 776.6)	0.0850
2	41.88285	32	0.1134	1.317090	(32, 923.5)	0.1135

Source: Authors.

Normality of the residuals test results

Two commonly used shape statistics are the skewness and the kurtosis. Skewness as a measure of the symmetry of distribution (skewness less than zero, means left tail and skewness more than zero means right tail) and kurtosis as the representation of outliers (distributions with kurtosis larger than 3 tend to have heavy tails indicating more variability due to extreme deviations, a larger number of outliers, whereas a smaller kurtosis coefficient indicates broader thinner tails). The symmetry is tested against the alternative of an asymmetric distribution and the kurtosis of 3 is tested against the alternative of a father/thinner tails distribution. The Jarque-Bera tests jointly consider both implication of skewness and kurtosis under the null hypothesis of normality against the alternative of non-normality of the residuals.

Table 5. Normality test of the VAR (2) residuals
VAR Residual Normality Tests Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Sample: 1998M01 2020M09
Included observations: 270

Component	Skewness	Chi-sq	df	Prob.*
1	-0.255286	2.932687	1	0.0868
2	-0.021533	0.020864	1	0.8851
3	-0.061515	0.170287	1	0.6799
4	-0.647760	18.88166	1	0.0000
Joint		22.00550	4	0.0002

Component	Kurtosis	Chi-sq	df	Prob.
1	3.410631	1.896954	1	0.1684
2	3.311522	1.091767	1	0.2961
3	3.859209	8.305198	1	0.0040
4	4.842499	38.19151	1	0.0000
Joint		49.48543	4	0.0000

Component	Jarque-Bera	df	Prob.
1	4.829640	2	0.0894
2	1.112631	2	0.5733
3	8.475485	2	0.0144
4	57.07317	2	0.0000
Joint	71.49092	8	0.0000

Source: Authors.
*Approximate p-values do not account for coefficient estimation

Table 5 relates the normality test of Jarque-Bera for the VAR residuals based on the skewness statistic, kurtosis statistics and the joint test statistics. Based on skewness and kurtosis values, the VAR Residual Normality Test rejects the normality distribution of the residuals. The Jarque-Bera test, as a joint test of both, also fails to accept the null hypothesis of normality of the residuals.

There are few consequences associated with a violation of the normality assumption, as it does not contribute to bias or inefficiency in regression models. It is only important for the calculation of *p*-values for significance testing, but this is only a consideration when the sample size is very small. When the sample size is sufficiently large (>200), the normality assumption is not needed at all as the Central Limit Theorem ensures that the distribution of disturbance term will approximate normality.

Heteroskedasticity test results

The ARCH LM heteroskedasticity test is applied testing the null hypothesis of constant variance against the alternative of not constant variance. The result of the test is presented in Table 6 in terms of the chi-sq and *p*-value.

Table 6: Heteroskedasticity Test VAR (2) Residuals

ARCH (multivariate)

data: Residuals of VAR

Chi-squared = 2408.7, df = 2400, p-value = 0.4465

Source: Authors.

In the heteroskedasticity test, the result reveals that the null hypothesis cannot be rejected, we conclude that the residuals have constant variance. Therefore, based on the lag length selection and residuals tests we proceed with the analysis of the VAR(2) model with all the variables expressed in their first differences. The outcome of the estimated VAR (2) model is fully represented in Table 7.

Table 7: VAR (2) estimation model
Vector Autoregression Estimates
Sample (adjusted): 1998M04 2020M09
Included observations: 270 after adjustments Standard errors in ( ) & t-statistics in [ ]

	D(INF)	D(UN)	D(LNEPU)	D(LNREER)
D (INF (-1))	0.166990	0.035711	0.065595	0.005729
	(0.06180)	(0.02498)	(0.08487)	(0.00419)
	[2.70219]	[1.42968]	[0.77285]	[1.36686]
D (INF (-2))	0.055963	-0.001543	0.063718	-0.011569
	(0.06281)	(0.02539)	(0.08626)	(0.00426)
	[0.89102]	[-0.06079]	[0.73867]	[-2.71555]
D (UN (-1))	-0.102735	0.258333	0.120528	-0.029908
	(0.14493)	(0.05858)	(0.19905)	(0.00983)
	[-0.70885]	[4.40986]	[0.60551]	[-3.04228]
D (UN (-2))	0.026151	0.271043	0.007377	0.019787
	(0.14910)	(0.06027)	(0.20478)	(0.01011)
	[0.17539]	[4.49742]	[0.03602]	[1.95644]
D (LNEPU (-1))	0.027974	-0.023767	-0.368481	-0.000444
	(0.04391)	(0.01775)	(0.06031)	(0.00298)
	[0.63702]	[-1.33899]	[-6.10960]	[-0.14893]
D (LNEPU (-2))	-0.007140	-0.026569	-0.192662	-0.006688
	(0.04367)	(0.01765)	(0.05998)	(0.00296)
	[-0.16350]	[-1.50524]	[-3.21228]	[-2.25799]
D (LNREER (-1))	0.187181	0.144828	0.404832	0.126647
	(0.88543)	(0.35789)	(1.21606)	(0.06006)
	[0.21140]	[0.40467]	[0.33291]	[2.10874]
D (LNREER (-2))	-1.752793	-0.932403	0.921534	0.007307
	(0.87793)	(0.35485)	(1.20575)	(0.05955)
	[-2.09651]	[-2.62757]	[0.76428]	[0.12271]
C	-0.005264	-0.002226	0.004926	-0.000917
	(0.01345)	(0.00544)	(0.01847)	(0.00091)
	[-0.39134]	[-0.40945]	[0.26665]	[-1.00501]
R-squared	0.050832	0.221764	0.138979	0.093802
Adj. R-squared	0.021739	0.197910	0.112587	0.066026
Sum sq. resids	12.54122	2.048894	23.65580	0.057700
S.E. equation	0.219205	0.088601	0.301057	0.014868

F-statistic	1.747205	9.296729	5.266057	3.377086
Log likelihood	31.25571	275.8381	-54.41354	757.7612
Akaike AIC	-0.164857	-1.976578	0.469730	-5.546380
Schwarz SC	-0.044910	-1.856631	0.589677	-5.426432
Mean dependent	-0.004166	-0.005185	0.000815	-0.001011
S.D. dependent	0.221627	0.098930	0.319585	0.015385
Determinant resid covariance (dof adj.)		7.45E-09		
Determinant resid covariance		6.51E-09		
Log likelihood		1012.335		
Akaike information criterion		-7.232113		
Schwarz criterion		-6.752323		
Number of coefficients		36		

Source: Authors.

Determining cointegration in the VAR model

We want to check if there exists cointegration relationship in our model and therefore perform Johansen Test, approach proposed by Johansen (1988). The Johansen cointegration test contains the variables in their levels. Its results exposed in Table 8 reveal that there is no cointegration among variables under analysis.

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Table 8. Information Criteria by Rank and Model in the Johansen Cointegration test
Sample: 1998M01 2020M09
Included observations: 270
Series: INF UN LNREER
Lags interval: 1 to 2

Selected (0.05 level*) Number of Cointegrating Rela by Model

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	0	0	0	0	0
Max-Eig	0	0	0	0	0

*Critical values based on MacKinnon-Haug-Michelis (1999)

Information Criteria by Rank and Model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or	No Intercept	Intercept	Intercept	Intercept	Intercept
No. of CEs	No Trend	No Trend	No Trend	Trend	Trend
Log Likelihood by Rank (rows) and Model (columns)					
0	1059.256	1059.256	1059.981	1059.981	1060.125
1	1066.592	1066.593	1067.317	1067.612	1067.714
2	1067.600	1068.124	1068.619	1071.676	1071.747
3	1068.352	1069.071	1069.071	1072.699	1072.699
Akaike Information Criteria by Rank (rows) and Model (columns)					
0	-7.713006	-7.713006	-7.696152	-7.696152	-7.675000
1	-7.722901*	-7.715502	-7.706054	-7.700830	-7.686767
2	-7.685924	-7.674992	-7.671252	-7.679084	-7.672199
3	-7.647049	-7.630155	-7.630155	-7.634808	-7.634808
Schwarz Criteria by Rank (rows) and Model (columns)					
0	-7.473111*	-7.473111*	-7.416275	-7.416275	-7.355140
1	-7.403041	-7.382315	-7.346212	-7.327660	-7.286943
2	-7.286100	-7.248513	-7.231445	-7.212622	-7.192409

Source: Authors.

4.3. Granger Causality

The Granger-causality test is conducted to observe how the system is linked.VAR model describes the joint generation process of the variables over time and Granger causality is investigating relationships between the set of variables under analysis. However, Granger causality cannot be interpreted as a real causal relationship but merely, shows that one variable can help to predict the other. Bose et al. (2017) claim that Granger causality states that if the prediction of one time series is improved by incorporating the knowledge of a second time series, then the latter is said to have a causal influence on the first.

Therefore, the null hypothesis to be tested by Granger causality test is that: one variable has no explanatory power on the other variable against the alternative hypothesis of causality relationship.

In the following we provide the results of the Granger causality tests that we have carried out for detecting causality both, using the VAR model with all variables in first differences (the VAR model we studied up to this point) and using a VAR model for each pair of variables in levels.

Table 9: Granger Causality Test Results

Dependent variable	Independent	χ^2	*p* value	Result variable
	Δ(UN)	0.522837	0.7700	UN does not Granger causes INF
Δ(INF)	Δ(LNEPU)	0.629823	0.7299	LNEPU does not Granger causes INF
	Δ(LNREER)	3.409563	0.1818	LNREER does not Granger causes INF

Source: Authors.

Table 9 summarizes the Granger causality (exogeneity test) results when the inflation is the dependent variable and appoints that no causal relationship is established between variables.

Table 10. Pairwise Granger Causality Test Results

Null Hypothesis	Obs	F-Statistic	Prob.
LNREER does not Granger Cause LNEPU	271	3.40958	0.0345**
LNEPU does not Granger Cause LNREER		9.25071	0.0001*
UN does not Granger Cause LNEPU	271	0.39366	0.6750
LNEPU does not Granger Cause UN		0.57012	0.5661
INF does not Granger Cause LNEPU	271	0.36983	0.6912
LNEPU does not Granger Cause INF		0.25443	0.7755
UN does not Granger Cause LNREER	271	3.90807	0.0212**
LNREER does not Granger Cause UN		0.48048	0.6190
INF does not Granger Cause LNREER	271	0.95718	0.3853
LNREER does not Granger Cause INF		0.00681	0.9932
INF does not Granger Cause UN	271	7.16978	0.0009*
UN does not Granger Cause INF		0.04307	0.9579

Source: Authors.
Note: * denotes the rejection at 1% significance level. **denotes the rejection at 5% significance level. *** denotes the rejection at 10% significance level.

The results of the Pairwise Granger causality test are presented in Table 10 and show that we cannot account for any bidirectional causality between INF and LNEPU. The results also indicate that INF Granger causes UN, which could show that the regulation of inflation has implication for the control of unemployment (usually controlling inflation increases unemployment), but the unemployment does not Granger causes inflation, LNREER is Granger caused by LNEPU as we could find in the Granger causality using the complete VAR model of this study.

Based on the Granger causality tests that were carried out to show causal relationship among the variables, we can conclude that LNEPU does not Granger causes INF, no causal relationship could be established between these two time series, nor inside VAR model, neither outside VAR model.

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Christiano (2012) states that the impulse response functions are useful to explain the structure of the economy. Therefore, in order to get an idea about the impact of EPU on inflation rate, unemployment rate and real effective exchange rate, we presented in the next section the impulse response analysis.

5. Impulse Response Analysis

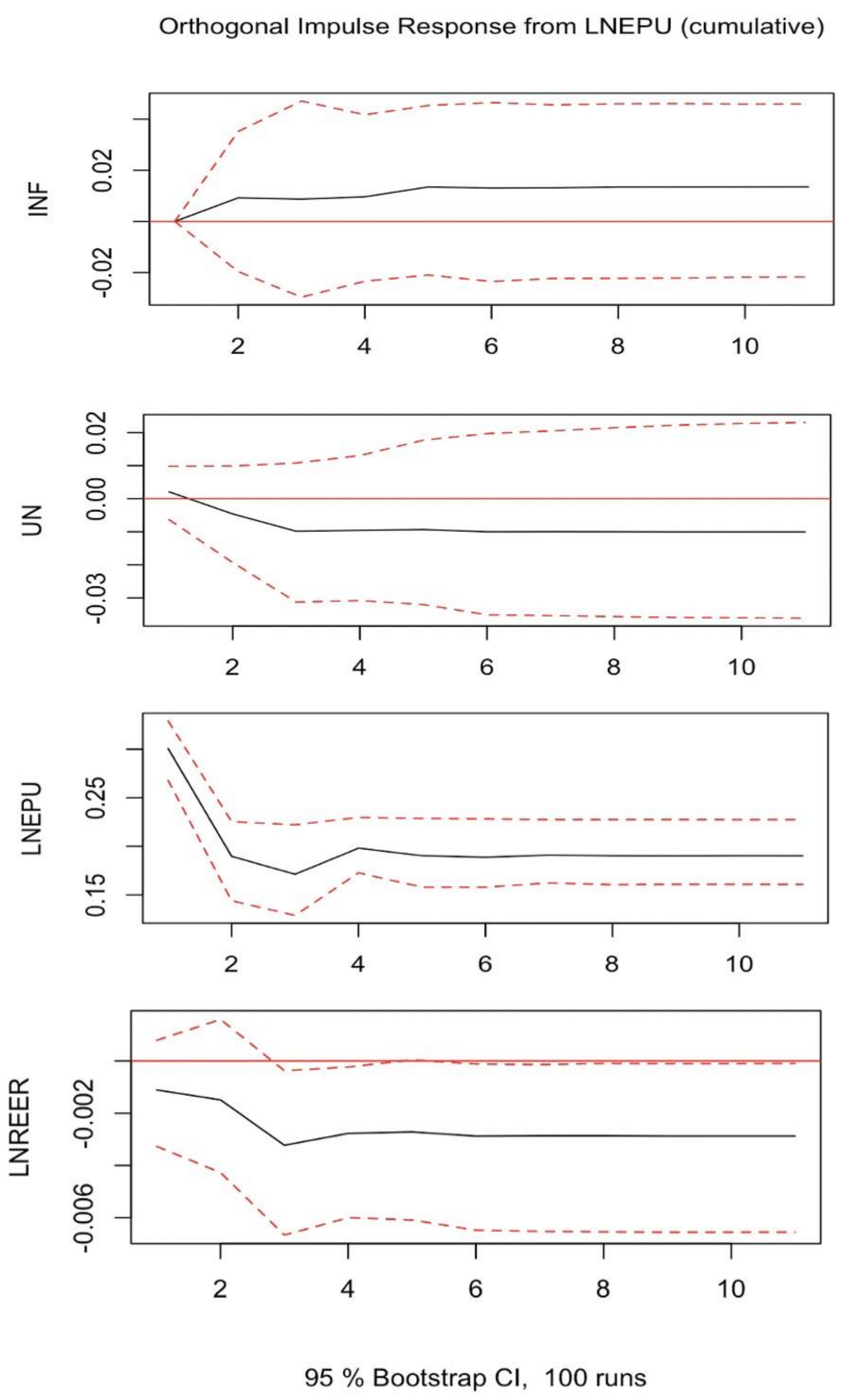
The Impulse Response Function (IRF) traces the effect of one-standard deviation shock on one variable to current and future values of all variables. Thus, a perturbation in one innovation in the VAR system sets up a chain reaction over time in all variables. There are three principal procedures cited in most literature to obtain the confidence intervals: asymptotic, bootstrap and Monte Carlo. The confidence intervals based on the asymptotic normal distribution and on Monte Carlo cannot be applied in this model since we could not rely on the normality of the VAR residuals. Thus, the bootstrap method in generating confidence intervals of the impulse response functions of VAR is used.

The link between variables is analysed with the Cholesky decomposition which imposes an ordering of variables in the VAR system and attributes all of the effect of any common component to the variable that comes first in the VAR system. Ordering means placing all variables under analysis in the decreasing order of exogeneity. As ordering is somewhat arbitrary, our choice is based on prior findings in literature. Lopez and Mitchener (2020) found that increased uncertainty caused a rise in inflation contemporaneously and for a few months afterword in Germany, Austria, Poland and Hungary, but this effect was absent or much more limited for other European countries.

Thus, the order imposed in the Cholesky decomposition is as follows: inflation (INF), unemployment (UN), economic policy uncertainty (LNEPU) and real effective exchange rate (LNREER). We based this ordering criteria on the speed of reaction of the variables toward a shock. When considering the Cholesky ordering, the question is whether the variables under analysis react in the same period to one uncertainty shock. Economic theory advises us that, due to price rigidities, inflation is slow responsive to external shocks and unemployment also reacts slowly to the economic cycle. The economic policy uncertainty can be considered an intermediate variable in terms of reaction time upon a shock while the real exchange rate, which is a market variable, may have immediate response to shocks, as it depends on the nominal exchange rate. In the literature it was also acknowledged that political institutions react more slowly upon a shock than financial markets, which are considered more sensitive to policy shocks.

Hence, we bootstrap the confidence intervals of the IRFs and evaluate their performance, where the two dashed lines in each panel depict the 95% confidence bands and the impulse responses are plotted over a 10-month horizon. The general pattern supports the hypothesis that an increase in economic policy uncertainty corresponds to an increase in inflation (not statistically significant), a decline in unemployment and a drop-in real effective exchange rate (the latter being statistically significant). On the link between the variables under analysis, we can agree that the economy is stimulated because under a policy uncertainty shock, the exchange rate depreciates (the demand for goods increases) while the unemployment decreases (there is a need of more jobs creation). The responses of macroeconomic variables in the UK to a shock in the UK EPU are represented in Figure 2.

Figure 2. IRFs of Inflation Rate, Unemployment Rate and Real Effective Exchange Rate to the UK EPU Shocks



Source: Authors.

Thus, our empirical results support the view that economic policy uncertainty shocks lead to an increase in inflation in the contemporary month and in the following months the response of the inflation rate to a one-unit shock in the EPU index, increases for the first seven periods (months). Although, the inflation increases slowly, its response to EPU shock is mostly insignificant. Besides, a shock in EPU index, though also statistically insignificant, has decreasing effects on unemployment rate for about 3 months. These findings are in line with the theory about the Phillips curve, which trades off an increase in inflation rates for a decrease in unemployment rate. The results also suggest that the VAR model identifies that economic policy uncertainty shock results in a depreciation of the real effective exchange rate.

6. Conclusion

Theory suggests that economic policy uncertainty suggests that uncertainty may dampen economic activity. In this paper, we hypothesised that EPU influences inflation rate. We test this hypothesis between EPU index and a set of three macroeconomic variables, inflation rate, unemployment rate and real exchange rate, for the UK over the period of January 1998 to September 2020 using a VAR approach. The baseline VAR specification includes two lags of all variables; by applying the Johansen cointegration approach, no cointegration among data was founded. We use Cholesky decomposition with the following order: inflation, unemployment, economic policy uncertainty and real effective exchange rate to recover orthogonal shocks and impulse response functions to trace the effect of one-standard deviation shock on EPU to current and future values of analysed variables.

We found that EPU leads to an increase in inflation rate, a one standard deviation increase in EPU leads to a decrease in unemployment rate and real exchange rate. Our finding has economic interpretations, namely, the broad implication is that under economic policy uncertainty shock, the inflation and unemployment rate respond in accordance with the effects described by the economic theory and the Phillips curve, which emphasizes that there is a trade-off between inflation and unemployment. Although in the IRF analysis the responses of inflation and unemployment to a shock in economic policy uncertainty are statistically insignificant, their dynamics seems to indicate some role of economic policy uncertainty in explaining their variations. Such variations were also previously acknowledged by studies of Caggiano et al. (2017), Selmi et al. (2020) and Ghosh et al. (2020).

Our main contribution is that we provide empirical evidence of the impact of EPU on real activity in the UK economy by calculating impulse response functions. It turns out that the impulse responses vary for inflation rate, real exchange rate and unemployment rate in accordance with our prior expectations. Moreover, our findings may provide important implications for policymakers, which could improve the implementation of economic policies to prevent large fluctuations in inflation rate and in foreign exchange markets in the periods of high economic policy uncertainties.

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