Coláiste na Tríonóide, Baile Átha Cliath
Trinity College Dublin
Ollscoil Átha Cliath | The University of Dublin

School of Social Sciences and Philosophy
Assignment Submission Form

Student Name:	**Robert Mulligan**
Student ID Number:	**21363861**
Programme Title:	**BESS**
Module Title:	**Advanced Econometrics**
Assessment Title:	**Forecast macroeconomic variables (Q10)**
Lecturer (s):	**Dr. Martyna Marczak**
Date Submitted	**22/11/24**

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Signed: **_____RM_____**

Date: **_____22/11/24_____**

Title: A Forecast Analysis: Can the UK's Labour Party Hit Their Macroeconomic Targets?

Introduction:

Following the first success of the UK's Labour Party in 19 years, this paper aims to assess whether Labour will hit the macroeconomic targets in its manifesto (Pickard, 2024). This paper will utilise a Vector Autoregressive Model (VAR) to compute out-of-sample forecasts for three macroeconomic variables: Real GDP, CPI, and the Unemployment Rate. Moreover, it will include a Labour Party dummy variable (LPD) to account for the differences in economic policies enacted by the differing governments. By utilising forecast intervals, this paper aims to determine the likelihood that the new Labour government will hit a 2% inflation rate, a 2.5% GDP growth rate, and a decrease in unemployment (Labour, 2024).

Motivation:

The motivation for this analysis stems from the unfavourable economic conditions plaguing the UK since Covid-19, which the Labour Party now must deal with. Domestically, they have a sluggish GDP growth rate, a CPI rate above 2% since 2021, and an increasing Unemployment Rate (House of Commons Library, 2024a; Rye and Jackson, 2020). Moreover, with the Ukraine and Palestine conflicts, the UK has had multiple shocks to its energy and defence spending (Sokhanvar et al., 2023; House of Commons Library, 2024b). Given these domestic and international challenges, it calls to examine the likelihood that the Labour Party can still hit their macroeconomic targets.

Empirical Approach:

To conduct this forecast analysis, this paper employs a VAR model to compute the out-of-sample forecasts. A VAR model allows for N time series regressions in which the lagged values of the N time series are used as regressors to predict future values of those variables. This model is chosen over autoregressive and autoregressive-distributed-lag models because it allows for a multivariate analysis required to include all of the macroeconomic variables and the LPD. The coefficients of the variables are estimated via OLS and are consistent in large samples (Stock & Watson, 2020).

For this paper, a VAR is run on the GDP growth rate, inflation rate, unemployment rate, and the LPD and 4 of each of the macro variables' lagged values. The optimal lag length was selected using the Akaike information criterion. The LPD variable is included to take account of the

different policies enacted by either a Labour majority or a Conservative majority government. The effect of these policies must be considered as they are likely to cause a trend in the variables. The LPD variable is included directly in the VAR framework (as opposed to an exogenous variable) due to political parties not being completely independent of the macroeconomic environment (Lewis-Beck 1986; Hibbs 2010).

After the initial regression, the out-of-sample forecasts must be computed.

The model:

$$\begin{bmatrix} Y_t \\ \pi_t \\ U_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \delta_{11} & \varphi_{11} \\ \beta_{21} & \delta_{21} & \varphi_{21} \\ \beta_{31} & \delta_{31} & \varphi_{31} \end{bmatrix} \begin{bmatrix} Y_{t-1} \\ \pi_{t-1} \\ U_{t-1} \end{bmatrix} + \begin{bmatrix} LP_1 \\ LP_2 \\ LP_3 \end{bmatrix} D_t \text{ °°° } + \begin{bmatrix} \beta_{14} & \delta_{14} & \varphi_{14} \\ \beta_{24} & \delta_{24} & \varphi_{24} \\ \beta_{34} & \delta_{34} & \varphi_{34} \end{bmatrix} \begin{bmatrix} Y_{t-4} \\ \pi_{t-4} \\ U_{t-4} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}$$

$$y_t = \mathrm{A}_0 + \mathrm{B}_1 y_{t-1} + B_2 y_{t-2} + B_3 y_{t-3} + B_4 y_{t-4} + LPD_t + V_t$$

Where:

- $\Rightarrow$ Y_t is the real GDP growth rate.
- $\Rightarrow$ π_t is the inflation growth rate.
- $\Rightarrow$ U_t is the unemployment growth rate.
- $\Rightarrow$ B_i is the vector of estimated coefficients at time lag i.
- $\Rightarrow$ y_{t-p} is the vector of explanatory variables at lag t-p.
- $\Rightarrow$ LPD_t is a dummy variable which = 1 if majority Labour government at time t, = 0 otherwise.
- $\Rightarrow$ V_t is the vector of error terms assumed to be white noise processes.

Out-of-Sample Forecasting

Forecasts for GDP growth, inflation, and the unemployment rate are generated for the next 20 quarters (5 years). The model computes these forecasts using an iterated multi-period forecast process. This recursive process begins by substituting the observed values of the variables for the first forecasted quarter (t+1) into the VAR equations. Forecasts for the subsequent periods (t+2, t+3, ... t+20) are then generated using the previously forecasted values as lagged inputs. This approach uses an iterated forecast over a direct forecast process due to its consistency with the VAR framework.

The forecasting process can be represented as follows:

$$\hat{y}_{t+h} = A_0 + \sum_{i=1}^{p} B_i \hat{y}_{t+h-i} + LPD_t + u_{t+h}$$

where:

- A_0 is the constant.
- h is the forecast horizon = (1, 2, …, 20).
- i is represents the lags = (1, 2, 3, 4).
- $\hat{y}_{t+h}$: the forecasted vector of variables (GDP growth, inflation, unemployment) at time t + h.
- B_i: matrices of estimated coefficients for lag i.

The Data and Data Transformations:

The data for this paper's empirical approach has been collected from the Federal Reserve of Economic Data (FRED). The data is constructed as a quarterly time series covering the period 1971q1 – 2023q4. The dataset contains information on Real GDP (in millions of pounds), the CPI, and the Unemployment rate.

Due to the stability assumption, the data must be transformed so that each series is stationary. Specifically, this approach requires the first difference of each time series to be logged. This produces the percentage change per quarter. In this form, the data is stationary. This is confirmed by running an ADF tests on each series, which all returned p-values < 0.01 Each time series is graphed in the appendix.

Table 1: Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
CPI	212	.013	.014	-.006	.095
Real GDP (in millions of pounds)	212	374902.65	117791.39	195942	569076
Unemployment rate	212	.068	.024	.034	.12
Inflation Rate (% per quarter)	177	-.01	1.009	-2.642	2.538
Real GDPGR (% per quarter)	211	.503	2.161	-22.718	15.508
Unemployment Rate (% per quarter)	211	.012	4.089	-9.515	16.344
Forecasted Inflation	21	.043	.687	-1.107	1.088
Forecasted GDP Growth Rate	21	.728	.741	-.312	3.506
Forecasted Unemployment Rate	21	-2.203	2.587	-7.553	-.121

The Empirical Approach:

Step 1: Initial VAR Results

Inflation:

The results show that all four lags of inflation are statistically significant at the 1% level. This result highlights a strong persistence of previous values on future inflation. None of the other variables had a significant effect on inflation except the first lag of unemployment. This lag had a small negative impact on inflation at the 5% significance level.

GDP Growth Rate (GDPGR):

The first two lags of the GDPGR are significant at the 1% level, but the next two are statistically insignificant. This result shows a low persistence of previous period shocks. All other variables return insignificant results except the first lag of unemployment, which has a sizeable negative association with GDP at the 1% level.

The Unemployment Rate:

Similar to GDPGR, only the first two lags of the unemployment rate are significant at the 1% level. Importantly, the magnitude of the respective coefficients is large being 1.2 and 0.8 of a standard deviation. These results show that while the persistence is short, the effect of previous unemployment values is strong. All other variables had statistically insignificant effects.

The Labour Party Dummy:

The effect of the LPD on all variables across all lags is insignificant. According to this model, it is not significant whether the Labour Party or the Conservative Party are currently in power as the change in government has no meaningful effect on these macro variables.

Step 2: VAR Forecast Results

Inflation:

According to their manifesto, the Labour Party set a goal to maintain an annualised inflation rate of 2%. Forecasted inflation must average 0.5% to reach this goal. If it does not consistently average at that rate, the annual inflation rate will likely exceed 2%. In Figure 1. the red forecasted inflation line is frequently below the 0.5% target. Specifically, this line is below target in 11 of the 20 forecasted quarters.

GDP Growth Rate:

The Labour manifesto also includes a goal of an annualised 2.5% GDP growth rate. To attain this, the forecasted GDPGR must average approximately 0.6%. Any average below this will result in a failure for the Labour Party. Figure 2. shows that the forecast line begins higher than the 0.6% target and then persistently hovers around it.

The Unemployment Rate:

Finally, the Labour manifesto does not have a specific target for the unemployment rate. Instead, it speaks to a general promise to decrease unemployment. To achieve this, the unemployment growth rate must stay below zero. From Figure 3. the forecasted unemployment rate stays below 0 for the entire forecast period, albeit the rate of decrease slows over time. From this result, the Labour Party will likely hit their unemployment goal.

Figure 1.

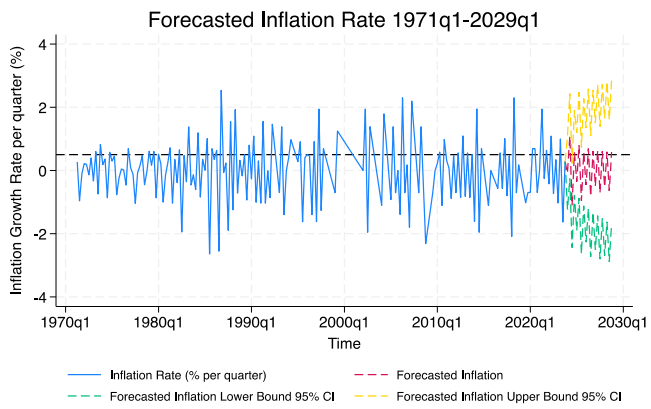


Figure 2.

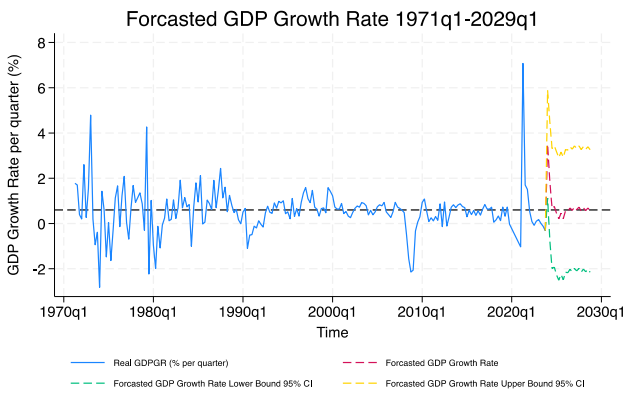
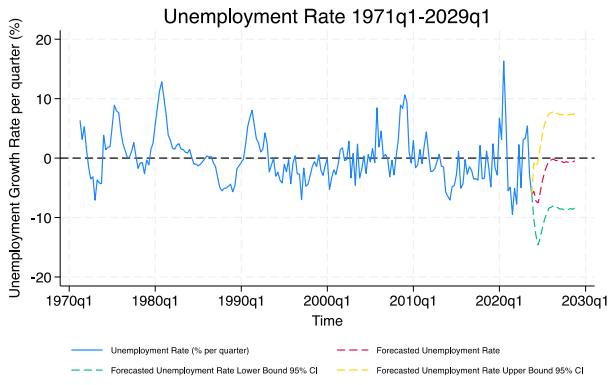


Figure 3.



Step 3: Assessing Forecast Accuracy:

To assess forecast accuracy, both observed and predicted values are needed. However, this approach is not used because this model is predicting out-out-sample to years with no data (e.g., 2025). Instead, this paper takes a pseudo-out-of-sample approach. The data is split into a training and testing set. The cut-off was 20215q1. Values for each of the variables were predicted from 2015q1 onwards. These predictions are then compared against the observed values. The root mean squared forecast error (RMSFE) for each variable is shown below:

Variable	RMSFE	Interpretation	Accurate or Not
Inflation	.81	On average, the model's forecast for inflation deviates from the actual value by 0.81 percentage points per quarter	Given the standard deviation of 1%, and a RMSFE of 0.8%, this means any forecast is 4/5 of a standard deviation away from the actual value. Meaning it is not an accurate measure
GDP growth rate	.28	On average, the model's forecast for GDP growth rate deviates from the actual value by 0.28 percentage points per quarter	Given the standard deviation of 2%, a RMSFE of 0.28% means that the GDP forecasting is accurate.
Unemployment rate	2.77	On average, the model's difference in the forecast for the unemployment rate's actual and predicted values was 2.77 percentage points.	Given the standard deviation of 4%, this means that the forecasted value on average, is over half a standard deviation away from the actual value. This is not an accurate forecast

Moreover, with such wide forecast intervals and the inability of the model to incorporate future shocks, all predicted values should be regarded with caution. Furthermore, VAR models commonly suffer from end-point bias. Meaning that the last predictions are usually the most inaccurate (Enders, 2014).

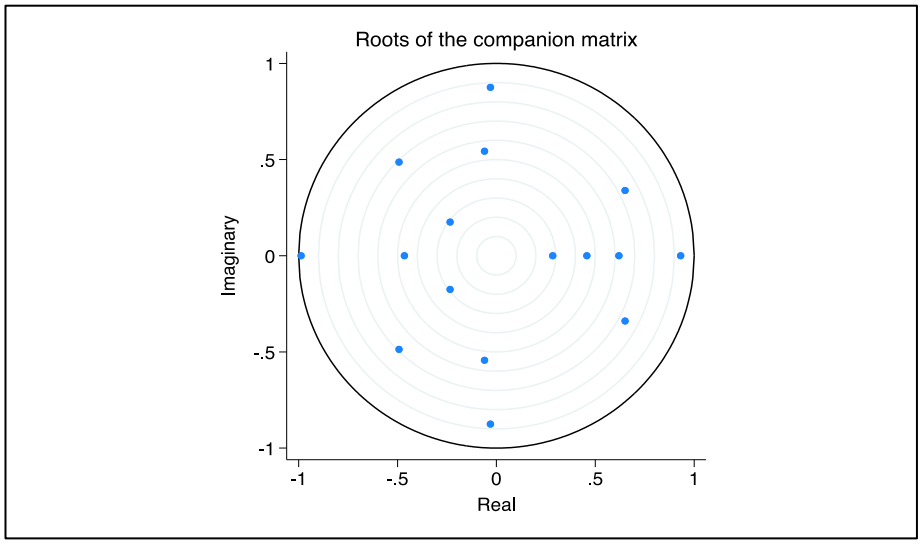
Robustness checks:

The VAR framework hinges on two important assumptions. Firstly, that the model is stable i.e., all the time series included are stationary. Secondly, that there is no autocorrelation. This is a serial dependence on past error terms.

Stability:

To ensure stability of the model, the eigenvalues are computed. If all the eigenvalues are below 1 in absolute values, the VAR is stable. This is shown graphically in Figure 4. Since all the eigenvalues lie within the circle, stability is achieved.

Figure 4.



Autocorrelation:

Autocorrelation must be avoided in time series. If not, our results will be heavily biased. To test for autocorrelation a Lagrange Multiplier test is ran on the model. The null hypothesis for this test, is that there is no autocorrelation at lag order p. The test resulted in there being autocorrelation at all 4 lags. This result means that the results are biased. This result is in spite of using HAC robust standard errors during estimation.

Table 2: Lagrange-multiplier test

lag	chi2	df	Prob>Chi2
1	280.470	16	0.000***
2	139.558	16	0.000***
3	74.366	16	0.000***
4	32.205	16	0.009**

H0: no autocorrelation at lag order

Conclusion:

This paper aimed to assess the likelihood that the Labour Party would hit their macroeconomic targets for three key variables. The empirical approach used a VAR to compute out-of-sample forecasts until the next general election in 2029. The results were graphed showing the 95% confidence interval. All their goals were within the forecast interval, but the results were serially correlated. The accuracy of this forecast was assessed by examining the RMSFE of each variable. Only the inflation forecast was considered economically significantly inaccurate. The model was robust against the stability condition. The Labour Party dummy had no significant impact on any variable.

[1620 words total]

References:

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13. Stock, J.H. and Watson, M.W., 2020. *Introduction to econometrics*. Pearson.

Appendix:

Graphs displaying logged-first differences time series:

Figure 5.

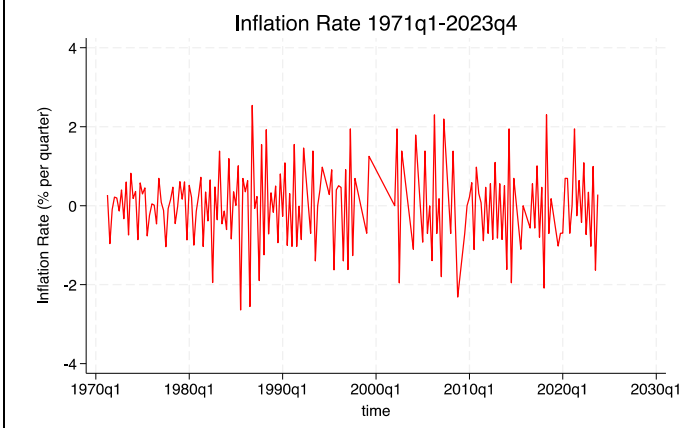


Figure 6.

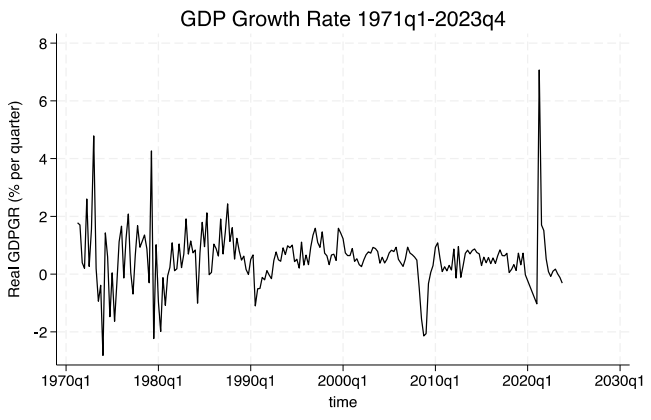
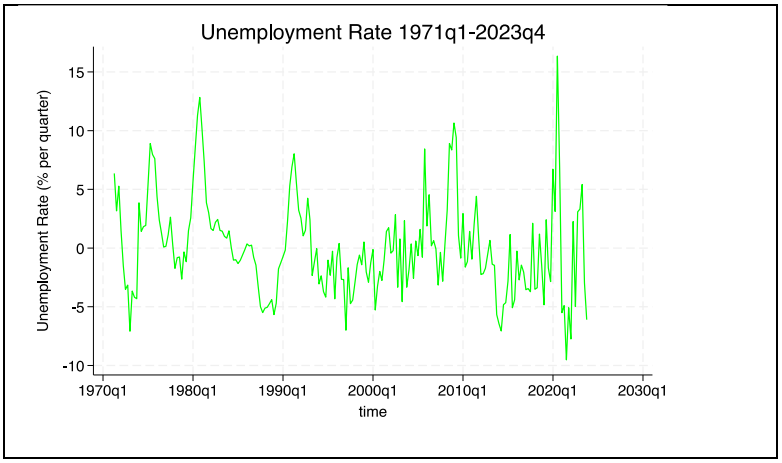


Figure 7.



Full Regression Results

Vector autoregression

Sample: 1972q2 thru 2023q4, but with gaps Number of obs = 135

Equation	Parms	RMSE	R-sq	chi2	P>chi2
Inflation:	17	.595441	0.6929	305.978	0.0000
GDPGR:	17	1.22329	0.5555	50.82114	0.0000
Unemployment:	17	2.43164	0.7259	436.4805	0.0000
Labour Party Dummy:	17	.154746	0.8789	14961.07	0.0000

	Coefficient	Robust std. err.	Z	P>z
Inflation				
infl				
L1.	-0.531	0.089	-5.980	0.000
L2.	-0.286	0.088	-3.230	0.001
L3.	-0.320	0.086	-3.730	0.000
L4.	0.389	0.094	4.150	0.000
GDPGR				
L1.	-0.018	0.025	-0.730	0.466
L2.	-0.023	0.029	-0.810	0.418
L3.	-0.007	0.029	-0.240	0.810
L4.	-0.024	0.027	-0.900	0.370
unemp				
L1.	-0.054	0.022	-2.470	0.014
L2.	0.018	0.021	0.830	0.405
L3.	-0.000	0.020	-0.010	0.994
L4.	0.008	0.019	0.420	0.675
LabourPartyDummy				
L1.	0.250	0.187	1.340	0.181
L2.	-0.294	0.358	-0.820	0.412
L3.	-0.141	0.348	-0.410	0.685
L4.	0.258	0.179	1.440	0.150
_cons	0.013	0.069	0.190	0.849
GDPGR				

infl				
L1.	0.147	0.169	0.870	0.386
L2.	0.038	0.171	0.220	0.827
L3.	-0.008	0.168	-0.050	0.960
L4.	-0.017	0.161	-0.110	0.913
GDPGR				
L1.	-0.478	0.125	-3.820	0.000
L2.	-0.381	0.106	-3.580	0.000
L3.	-0.147	0.090	-1.630	0.103
L4.	-0.202	0.085	-2.380	0.017
unemp				
L1.	-0.207	0.055	-3.740	0.000
L2.	-0.067	0.045	-1.500	0.133
L3.	0.028	0.049	0.570	0.569
L4.	0.136	0.046	2.950	0.003
LabourPartyDummy				
L1.	-1.260	0.852	-1.480	0.139
L2.	1.799	0.897	2.000	0.045
L3.	-0.635	0.623	-1.020	0.309
L4.	0.229	0.530	0.430	0.665
_cons	1.298	0.219	5.940	0.000
Unemployment				
infl				
L1.	0.298	0.323	0.920	0.357
L2.	0.548	0.359	1.530	0.127
L3.	0.439	0.364	1.210	0.227
L4.	0.352	0.370	0.950	0.342
GDPGR				
L1.	-0.589	0.082	-7.210	0.000
L2.	-0.359	0.102	-3.530	0.000
L3.	0.185	0.132	1.410	0.160
L4.	0.233	0.127	1.840	0.066
unemp				
L1.	0.532	0.108	4.910	0.000
L2.	0.348	0.108	3.230	0.001
L3.	-0.114	0.104	-1.090	0.274
L4.	-0.080	0.102	-0.780	0.434
LabourPartyDummy				
L1.	1.199	1.483	0.810	0.419
L2.	-2.223	1.646	-1.350	0.177
L3.	-0.033	1.211	-0.030	0.978
L4.	1.601	0.936	1.710	0.087
_cons	0.023	0.256	0.090	0.928
LabourPartyDummy				
infl				
L1.	0.012	0.009	1.310	0.190
L2.	-0.003	0.012	-0.220	0.828
L3.	0.009	0.013	0.740	0.461
L4.	0.017	0.017	0.960	0.339
GDPGR				
L1.	-0.004	0.004	-1.000	0.315
L2.	-0.006	0.005	-1.120	0.265
L3.	-0.007	0.005	-1.270	0.205

L4.	0.004	0.007	0.520	0.600
unemp				
L1.	-0.005	0.007	-0.700	0.484
L2.	-0.002	0.004	-0.380	0.706
L3.	0.006	0.006	1.100	0.270
L4.	-0.003	0.006	-0.540	0.592
LabourPartyDummy				
L1.	0.985	0.022	44.310	0.000
L2.	-0.022	0.018	-1.220	0.221
L3.	0.014	0.021	0.680	0.500
L4.	-0.030	0.031	-0.960	0.336
_cons	0.026	0.017	1.540	0.125

Do File

```
**********************************************
*          ADVANCED ECONOMETRICS
*
*            Project
*
* Start Date: 23.10.2024
* Title: A Forecast Analysis: Can the UK's Labour Party Hit Their Macroeconomic Targets?
**********************************************

** Set working directory:
clear all
cd "/Users/robmulligan/Desktop/ADV - Econometrics Project/Everything Stata

** Import Data:
use "/Users/robmulligan/Desktop/ADV - Econometrics Project/Everything Stata/FINALDATAUSE.dta"
br
drop in 213/214

** Gen a quarterly time variable **
gen time = qofd(Datequarterly)
```

```
format time %tq
tsset time

** Graphing to check stochastic trends/order of integration

tsline RealGDPinmillionsofpounds
tsline CPI
tsline Unemploymentrate

** Applying Transformations to make the data stationary + graphs

gen infl = (ln(CPI) - ln(L.CPI))
label variable infl "Inflation Rate (% per quarter)"
tsline infl, title("Inflation Rate 1971q1-2023q4") lcolor(red)

gen unemp = 100 * (ln(Unemploymentrate) - ln(L.Unemploymentrate))
label variable unemp "Unemployment Rate (% per quarter)"
tsline unemp, title("Unemployment Rate 1971q1-2023q4") lcolor(lime)


gen GDPGR = 100 *(ln(RealGDPinmillionsofpounds) -
ln(L.RealGDPinmillionsofpounds))
label variable GDPGR "Real GDPGR (% per quarter)"
tsline GDPGR if time < tq(2020q1) | time > tq(2020q4), title("GDP Growth Rate
1971q1-2023q4") lcolor(black)

** Testing for Optimal lag length:

varsoc infl unemp GDPGR LabourPartyDummy

** ADF Tests to ensure stationarity:

dfuller infl,lags(4) trend
```

** p-value = 0 i.e., stationary

dfuller unemp,lags(4) trend

** p-value = 0 i.e., stationary

dfuller GDPGR,lags(4) trend

** p-value = 0 i.e., stationary

** Testing for cointegration (if cointegrated we must use a VEC)

vecrank RealGDPinmillionsofpounds CPI Unemploymentrate, lags(4)

*** test results say 0 integrating factors so VAR it is

** first regression

var infl GDPGR unemp LabourPartyDummy, lags(1/4) vce(robust)

** => i) Stability Checks + ii) Autocorrelation tests

*** i)

varstable, graph

** Results

** All the eigenvalues lie inside the unit circle.

** VAR satisfies stability condition.

*** ii)

asdoc varlmar, mlag(4) save(myLMdoc) replace

** Results

** There is autocorrelation at all lags

vargranger

** Results

** again, GDP and Unemploymentrate seem to cause each other

** Neither cause inflation, and inflation does cause them

** Out of Sample Forecasts:

asdoc fcast compute f_, step(20) dyn(tq(2024q1)) save(my_forecast_values)

replace LabourPartyDummy = 1 if tin(2024q1, 2029q4)

** loop in case I mess up**

```
foreach var of varlist f_* {
   drop `var'
}
```

*** renaming variables

label variable f_infl "Forecasted Inflation"
label variable f_infl_lb "Forecasted Inflation Lower Bound 95% CI"
label variable f_infl_ub "Forecasted Inflation Upper Bound 95% CI"

label variable f_GDPGR "Forcasted GDP Growth Rate"
label variable f_GDPGR_lb "Forcasted GDP Growth Rate Lower Bound 95% CI"
label variable f_GDPGR_ub "Forcasted GDP Growth Rate Upper Bound 95% CI"

label variable f_unemp "Forecasted Unemployment Rate"
label variable f_unemp_lb "Forecasted Unemployment Rate Lower Bound 95% CI"
label variable f_unemp_ub "Forecasted Unemployment Rate Upper Bound 95% CI"

```
        // Generate indicator variables for inflation being below or above 0.5%
gen below_target = f_infl < 0.5
gen above_target = f_infl >= 0.5

count if below_target == 1
count if above_target == 1

// Display the actual quarters where the condition is met
list f_infl if below_target == 1
list f_infl if above_target == 1



tsline GDPGR f_GDPGR f_GDPGR_lb f_GDPGR_ub if time < tq(2020q1) | time >
tq(2020q4), ///
   legend(size(*0.6)) lpatt(solid dash dash dash) ///
        title("Forcasted GDP Growth Rate 1971q1-2029q1") ytitle("GDP Growth Rate
per quarter (%)") xtitle("Time") yline(0.6)

tsline unemp f_unemp f_unemp_lb f_unemp_ub, ///
        legend(size(*0.6)) lpatt(solid dash dash dash) ///
        title("Unemployment Rate 1971q1-2029q1") ytitle("Unemployment Growth
Rate per quarter (%)") xtitle("Time") yline(0)



** Outputting results:

asdoc var infl GDPGR unemp LabourPartyDummy, lags(1/4) vce(robust)
save(myVARDOC) label replace title(Full Regression Results)

** Sum stats **
```

```
asdoc sum CPI RealGDPinmillionsofpounds Unemploymentrate infl GDPGR unemp f_infl
f_GDPGR f_unemp, save(SUMSTATS) label replace

** assessing accuracy **

gen test = time >= tq(2015q1) // define a test sample
var GDPGR infl unemp LabourPartyDummy if test == 0, lags(1/4)
fcast compute mymodel, step(20)
gen infl_error = infl - mymodelinfl
gen GDPGR_error = GDPGR - mymodelGDPGR
gen unemp_error = unemp - mymodelunemp

gen infl_errorsq = infl_error^2
gen GDPGR_errorsq = GDPGR_error^2
gen unemp_errorsq = unemp_error^2

egen rmse_infl = mean(infl_errorsq)
di "RMSFE for inflation:" sqrt(rmse_infl)
RMSFE for inflation:.80525491 ** when sample was 2015q1
** on average the inflation forecast is .8% off the actual value

egen rmse_GDPGR = mean(GDPGR_errorsq)
di "RMSFE for GDPGR:" sqrt(rmse_GDPGR)
RMSFE for GDPGR:.27630574 ** when sample was 2015q1
** on average the GDP forecast is .27% off the actual value

egen rmse_unemp = mean(unemp_errorsq)
di "RMSFE for unemp:" sqrt(rmse_unemp)
RMSFE for unemp:2.7656691 ** when sample was 2015q1
** on average the unemployment forecast is 2.77% off the actual value

end
```