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Stock Market Returns and Economic Policy Uncertainty- An Indian Perspective

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Abstract

The proposed paper attempts to investigate the impact of economic policy uncertainty (EPU) on stock market returns. Policy uncertainty can hamper economic growth by slowing down the inflow of investments. Investors are reluctant to take investment decisions when they perceive uncertainty related to government policy. Vector Auto-Regression (VAR) analysis is used to show how the stock market returns respond to EPU shocks. An Impulse Response Function (IRF) is estimated that traces out the response of the dependent variable (stock market returns) to shocks in the error terms. The stock market returns are estimated from the values of the BSE SENSEX and policy uncertainty values from the EPU Index (Baker, Bloom and Davies 2012)[2]. The data spans from April 2004 until March 2016. This paper seeks to contribute to understand the role of policy uncertainty in the capital market from the Indian perspective and would be relevant to the practitioners in forecasting equity returns.

Keywords: Correlation, Causality, Co-Integration, Economic Policy Uncertainty, Forecasting, Impulse Analysis, Stock Returns, Vector Auto Regression

1. Introduction

Investors are reluctant to take investment decisions when they perceive uncertainty related to government policy. Bernanke[3] argues that in cases where investment is irreversible, it is sensible to defer commitment of scarce resources and rather wait for new information relating policy. Therefore perception of uncertainty about government policy can hamper economic recovery and growth. This paper seeks to study the impact of policy uncertainty on stock market returns which is a critical barometer of economic growth.

Ozoguz[7] reports a negative relationship between stock prices and levels of investor uncertainty. Pastor and Veronesi[8] conclude that a fall in stock prices would be larger when there is higher uncertainty about state policy. Bansal and Yaron[1] show that increased economic uncertainty lowers asset prices. Economic policy uncertainty can be linked to stock market performance citing the literature mentioned above.

The literature above is not from the Indian perspective. The stock market in India has shown to not consistently follow the markets in the west. One instance is of the mortgage crisis of 2007 in the states, when the US markets were on the decline and the Indian markets were not greatly impacted. This paper has the objective of examining the impact of Economic Policy Uncertainty (EPU) on stock market returns from the Indian markets perspective. Vector Auto-Regression is used to construct a model that enables forecasting the stock market returns using the EPU index values with data from April 2004 until March 2016.

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The findings of this paper would be useful to investors and policy makers alike. Policy makers can influence the stock market positively by allaying the fear of investors related to policy uncertainty. Investors can use the available information on policy uncertainty to assess the future stock market performance.

2. Methodology and Data

Vector Auto-Regression (VAR) analysis is used to show how the stock market returns respond to EPU shocks. A VAR model is a generalisation of the univariate autoregressive model for forecasting a collection of variables; that is, a vector of time series. It comprises one equation per variable considered in the system. The right hand side of each equation includes a constant and lags of all the variables in the system. A two dimensional VAR(1) would be:

$$y_{1,t} = c_1 + \phi_{11,}1y_{1,t} - 1 + \phi_{12,}1y_{2,}t - 1 + e_{1,t}$$
$$y_{2,t} = c_2 + \phi_{21},1y_{1,t} - 1 + \phi_{22},1y_2,t - 1 + e_{2,t}$$

where $e_{1,t}$ and $e_{2,t}$ are white noise processes that may be contemporaneously correlated. Coefficient $\phi_{ii,\ell}$ captures the influence of the ℓth lag of variable y_i on itself, while coefficient $\phi_{ij,\ell}$ captures the influence of the ℓth lag of variable y_j on y_i.

The stock market returns would be estimated from the values of the BSE SENSEX and policy uncertainty values from the EPU Index (Baker, Bloom and Davies 2012)[2]. The data would span from April 2004 until March 2016.

The first step is to check for co-integration that indicates a long-term equilibrium relationship between the variables. The Johansen test is used to test for co-integration. If the variables are found to be co-integrated, then the Vector Error Correction Mechanism (VECM) would be used to correct for short run disequilibrium. If not, then the standard VAR procedure is used.

Thereafter, diagnostic tests are carried out to test for serial correlation, heteroscedasticity and stability of the VAR model. We then use the Granger Causality test to test for causality between the variables. Later we proceed to forecast the SENSEX values from April 2016 until January 2017 using our VAR model.

An Impulse Reponse Analysis is carried out where Sensex returns is the response variable and first differenced values of EPU Index is the impulse variable. Impulse Response Function (IRF) analysis traces out the response of the dependent variable (stock market returns) to shocks in the EPU index values.

3. Analysis and Interpretation

The R program is used to carry out the analysis.
Using the values of SENSEX and EPU Index:
The test statistics of various criteria for optimal lag selection for VAR:

AIC(n)	HQ(n)	SC(n)	FPE(n)
4	4	1	4

The AIC criterion gives 4 lags and SC gives 1 lag. To check if there is co-integration between the two variables, a Johansen test is conducted with 2 lags, 3 lags and 4 lags. Results inAppendix A.

Co-integration indicates a long term, equilibrium relationship between the variables. In the short run though, there may be disequilibrium.

Since there is no strong evidence to believe that the variables are co-integrated, we can proceed to carry out the standard VAR procedure. If the variables were found to be co-integrated, then the Vector Error Correction Mechanism (VECM) would be used to correct for short run disequilibrium, and the function vec2var() would convert the VECM specified estimation into its standard VAR representation. For the standard VAR procedure, the returnson the SENSEX values by using ln (t value/t-1 value) and the first differenced values of EPU Index are used. Both the variables are stationary as seen in Appendix B from the results of the **ADF Unit Root test** conducted in R.

For the test, H0 = There is a unit root i.e., the time series is non-stationary

The plots of the ACF (Auto-Correlation function) below also show that the two variables are stationary.

To proceed to estimate a VAR, first the optimal lag order needs to be determined as seen below.

AIC(n)	HQ(n)	SC(n)	FPE(n)
3	2	2	3

As per the above results, the SC (Schwarz Criterion) gives an optimal lag order of 2. The AIC would not be used preferably as it tends to chose large number of lags. For VAR models, the preferred criterion is SC as it is conservative.

The VAR of order 2 (meaning lag 2) is estimated using the VAR( ) function as seen in Appendix C.

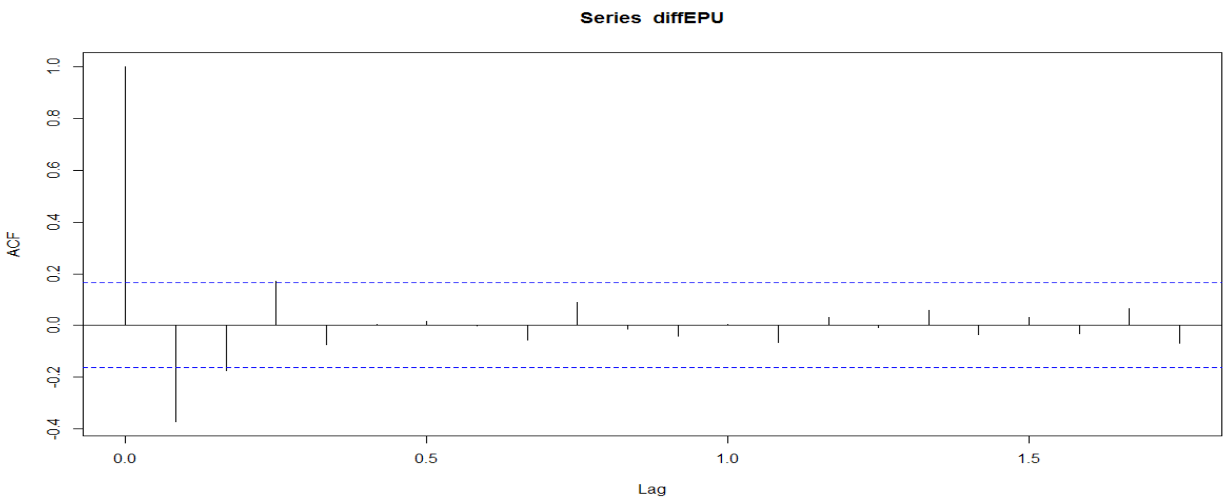

Figure 1. ACF of diffEPU

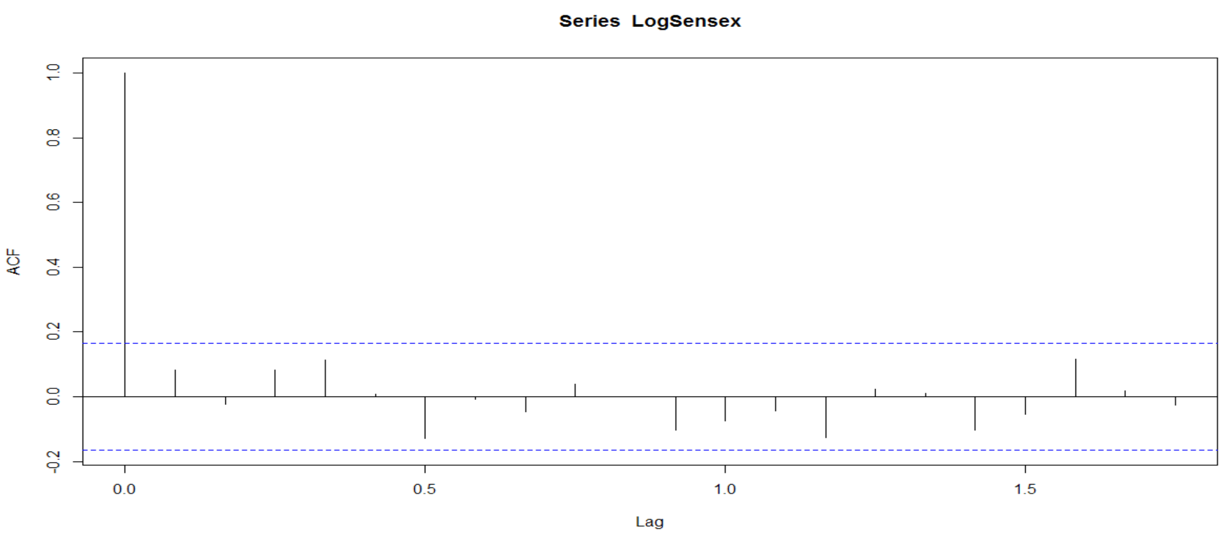

Figure 2. ACF of LogSensex

We observe that not all the lagged endogenous variables enter significantly into the equation of the VAR of order 2 as seen by the large Pr(>|t|) values. Hence there is a need to proceed with the estimation of a restricted VAR model.

The function restrict( ) helps to estimate the **restricted VAR model** which is given in Appendix D.

3.1 Diagnostic Tests

To test for **serial correlation** in the residuals, the Portmanteau test is conducted and the results are below:

Portmanteau Test (asymptotic)
data: Residuals of VAR object restrict_var
Chi-squared = 72.087, df = 56, p-value = 0.07262

From the above, the null hypothesis stating that there is no serial correlation cannot be rejected at the 5% level of significance since the p-value is 0.07262.

To test for **heteroscedasticity**, the ARCH test is conducted with the below result for the residuals of the LogSensex equation which would be used to forecast the SENSEX returns.

$LogSensex
ARCH test (univariate)
data: Residual of LogSensex equation
Chi-squared = 36.143, df = 16, p-value = 0.002764

As seen above, the null hypothesis of homoscedasticity cannot be rejected.

To test **stability**, the OLS-CUSUM test is conducted. As seen in Figure 3, the cumulative sums are within the bands, the residuals are stable.

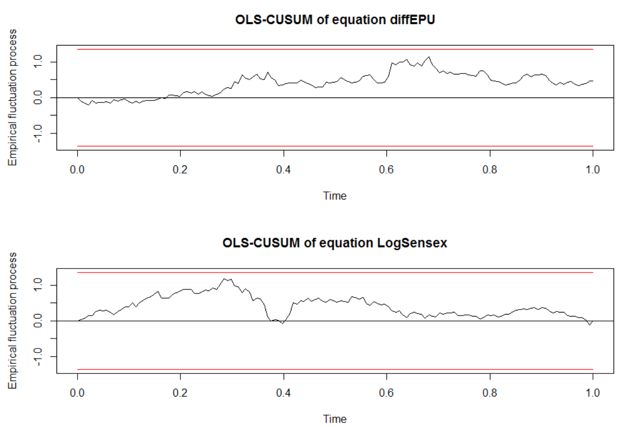

Figure 3. CUSUM test graphs

3.2 Causality

Next, **Granger causality test** is carried out with the following result:

Granger causality H0: diffEPU do not Granger-cause LogSensex
data: VAR object restrict_var
F-Test = 1.817, df1 = 2, df2 = 272, p-value = 0.1645

With a p-value of 0.1645, the H0 may be rejected at 17% significance level which means that there is evidence to show that EPU influences the SENSEX returns. However, to accept this blindly would not be sensible and impulse response analysis would confirm a causal relationship.

3.3 Forecasting

Using the Restricted VAR model in Appendix D, the next 10 months returnson SENSEX values are estimated below with upper and lower bands.

$LogSensex
fcst lower upper CI
[1,] 0.017261364 -0.1160553 0.1505780 0.1333166
[2,] 0.010491154 -0.1228255 0.1438078 0.1333166
[3,] 0.008267926 -0.1255566 0.1420925 0.1338245
[4,] 0.013625173 -0.1203211 0.1475714 0.1339463
[5,] 0.011926286 -0.1220392 0.1458918 0.1339655
[6,] 0.010919971 -0.1230657 0.1449056 0.1339857
[7,] 0.011892947 -0.1220948 0.1458807 0.1339877
[8,] 0.011808728 -0.1221803 0.1457977 0.1339890
[9,] 0.011529322 -0.1224603 0.1455189 0.1339896
[10,] 0.011674304 -0.1223153 0.1456639 0.1339896

Using the fcst (forecasted) column values, below are the computed values of SENSEX:

Table 1. Forecasted SENSEX values

Date	Forecasted SENSEX	Actual SENSEX
2016-04	25779.30	25,606.62
2016-05	26049.75	26,667.96
2016-06	26265.13	26,999.72
2016-07	26622.99	28,051.86
2016-08	26940.51	28,452.17
2016-09	27234.70	27,865.96
2016-10	27558.60	27,930.21
2016-11	27884.03	26,652.81
2016-12	28205.51	26,626.46
2017-01	28534.79	27,655.96

3.4 Forecast Accuracy

The forecast accuracy of the above estimations was evaluated and returned a Root Mean Squared Error (RMSE) of 1029.4 which is 3.77% of the mean of actual SENSEX values i.e., 27250.97. We see that the predicted values deviate by about 3.77% on an average from the actual values.

The SENSEX values forecasted by the restricted VAR model are quite close to the actual closing SENSEX values. There is a large deviation seen in the months of July and August as SENSEX has spiked in these months from the levels seen in June. The deviation observed in November and December where the actual SENSEX values fell, though not substantially, can be most likely attributed to the demonetization announcement that was not expected by investors.

Table 2. Lower and Upper bands of IRF Analysis

		Lower Band, CI= 0.95	Upper Band, CI= 0.95		
$diffEPU		$diffEPU		$diffEPU	
LogSensex		LogSensex		LogSensex	
[1,]	-0.019824	[1,]	-0.03387	[1,]	-0.00660
[2,]	0.005042	[2,]	-0.00517	[2,]	0.01225
[3,]	0.006152	[3,]	-0.00307	[3,]	0.01328
[4,]	-0.004069	[4,]	-0.00795	[4,]	0.00000
[5,]	-0.000512	[5,]	-0.00291	[5,]	0.00230
[6,]	0.001545	[6,]	-0.00033	[6,]	0.00386
[7,]	-0.000379	[7,]	-0.00164	[7,]	0.00075
[8,]	-0.000384	[8,]	-0.00145	[8,]	0.00041
[9,]	0.000267	[9,]	-0.00016	[9,]	0.00095
[10,]	0.000033	[10,]	-0.00038	[10,]	0.00053
[11,]	-0.000102	[11,]	-0.00059	[11,]	0.00005

3.5 Impulse Response Analysis

Below are the impulse response co-efficients for 10 months ahead, where LogSensex is the response variable and diffEPU is the impulse variable.

Figure 4 below shows the plot of Orhogonal Impulse Response. It is orthogonalised since the underlying shocks are less likely to occur in isolation but rather as contemporaneous correlation between the components of the error process of the variables involved. It shows the impact on LogSensex (i.e., SENSEX returns) of a unit change (i.e., one standard deviation) in diffEPU (first differenced EPU). The largest impact on SENSEX returns peaks in the following three months (after a shock in EPU) and thereafter it tapers off gradually. This plot strengthens the causality argument between the two variables.

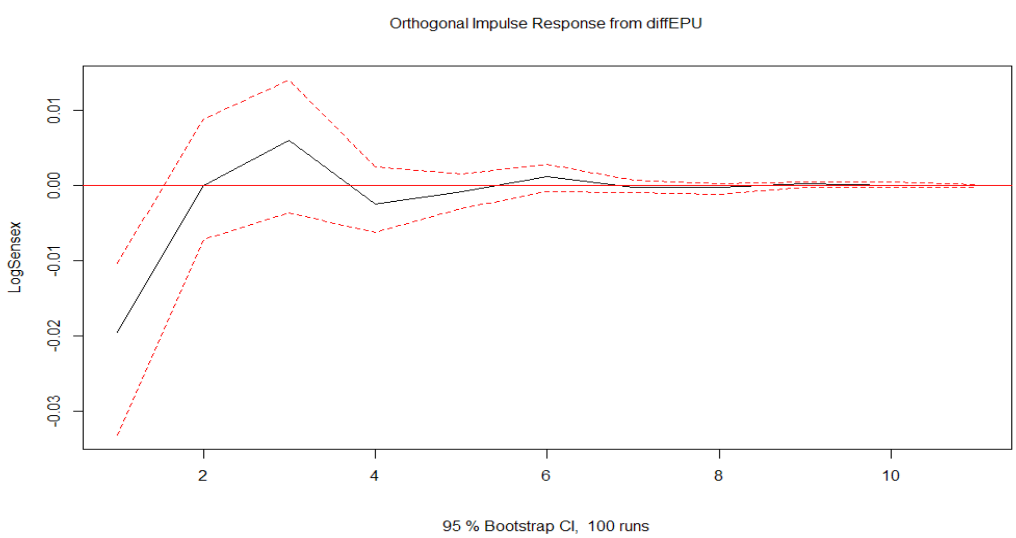

Figure 4. Orthogonal Impulse Responses from diffEPU

4. Conclusion

From the analysis, it is evident that EPU has an impact on SENSEX returns as the VAR model shows robustness in estimating the values of SENSEX ten months into the future. In the VAR approach all the variables are treated on an equal footing. They are modeled as if they influence each other equally.

The Impulse Response Analysis shows the response of SENSEX returns that peak after 3 months following a shock in EPU index. This result gives credence to the results of the Granger Causality test that shows the influence of EPU on the index returns.

This paper presents useful insights to investors and policy makers alike. Policy makers can influence the stock market positively by allaying the fear of investors related to policy uncertainty. Investors can use the available information on policy uncertainty to assess the future stock market performance.

5. References

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Appendix A

Johansen Procedure

2 lags

Eigenvalues (lambda):

[1] 1.257904e-01 5.813663e-02 -2.775558e-17

Values of teststatistic and critical values of test:

		test	10pct	5pct	1pct
r	<= 1	8.51	10.49	12.25	16.26
r	= 0	27.59	22.76	25.32	30.45

Interpretation: The calculated value is 27.59 for r=0 and the test statistic is 30.45 at 1% level of significance. Therefore the H0 cannot be rejected and we may assume at 99% confidence level that there is 0 co-integrating vector i.e. no co-integration relationship between the two variables.

3 lags

Eigenvalues (lambda):

[1] 0.07600022 0.05143660 0.00000000

Values of teststatistic and critical values of test:

		test	10pct	5pct	1pct
r	<= 1	7.45	10.49	12.25	16.26
r	= 0	18.59	22.76	25.32	30.45

Interpretation: The calculated value is 18.59 for r=0 and the test statistic is 30.45 at 1% level of significance. Therefore the H0 cannot be rejected and at 99% confidence level there is 0 co-integrating vector i.e. no co-integration relationship between the two variables.

4 lags

Eigenvalues (lambda):

[1] 1.072152e-01 3.376639e-02 -5.551115e-17

Values of teststatistic and critical values of test:

		test	10pct	5pct	1pct
r	<= 1	4.81	10.49	12.25	16.26
r	= 0	20.69	22.76	25.32	30.45

Interpretation: The calculated test value is 20.69 for r=0 and the test statistic is 30.45 at 1% level of significance. H0 cannot be rejected i.e. there is no co-integration relationship.

Appendix B

Augmented Dickey-Fuller Test Unit Root Test
For **diffEPU (first differenced values of EPU Index)** the results were as follows:
Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
z.lag.1	-1.78478	0.1332	-13.4	< 2e-16	***
z.diff.lag	0.35429	0.08211	4.315	3.14E-05	***

Value of test-statistic is: -13.3997
Critical values for test statistics:
1pct 5pct 10pct
tau1 -2.58 -1.95 -1.62

Interpretation:
The t value of z.lag.1 (i.e. the first lagged value) is -13.3997 and the tau statistic is -2.58 at 1% level of significance. As the tau statistic is greater than the computed t value, therefore the null hypothesis may be rejected and alternative hypothesis accepted i.e., the variable is stationary.

Similarly, **for LogSensex (variable of returns on the SENSEX values)**
Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
z.lag.1	-0.69394	0.15779	-4.398	2.28E-05	***
z.diff.lag1	-0.21594	0.14251	-1.515	0.1322	
z.diff.lag2	-0.23788	0.11819	-2.013	0.0462	*
z.diff.lag3	-0.14393	0.08838	-1.629	0.1059	

Value of test-statistic is: -4.3978
Critical values for test statistics:
1pct 5pct 10pct
tau1 -2.58 -1.95 -1.62

Interpretation:

The **t value** of z.lag.1 (i.e. the first lagged value) is -4.3978 and the tau statistic is -2.58 at 1% level of significance. As the **tau statistic** is greater than the computed t value, therefore the null hypothesis may be rejected and alternative hypothesis accepted i.e. the variable is stationary.

Appendix C

VAR Estimation Results:

===

Endogenous variables: diffEPU, LogSensex
Call:
VAR(y = dx1, p = 2, type = "const")
Coefficients for equation diffEPU:

===

diffEPU = diffEPU.l1 + LogSensex.l1 + diffEPU.l2 + LogSensex.l2 + const

	Estimate	Std. Error	t value	Pr(>|t|)	
diffEPU.l_1	-0.4818	0.07758	-6.21	6.01E-09	***
LogSensex.l_1	-131.423	41.49954	-3.167	0.0019	**
diffEPU.l_2	-0.31638	0.07499	-4.219	4.46E-05	***
LogSensex.l_2	57.96153	41.56373	1.395	0.1654	
const	0.71617	2.7217	0.263	0.7928	

Residual standard error: 31.54 on 136 degrees of freedom
Multiple R-Squared: 0.2764, Adjusted R-squared: 0.2551
F-statistic: 12.98 on 4 and 136 DF, p-value: 5.544e-09

Coefficients for equation LogSensex:

===

LogSensex = diffEPU.l1 + LogSensex.l1 + diffEPU.l2 + LogSensex.l2 + const

	Estimate	Std. Error	t value	Pr(>|t|)	
diffEPU.l_1	0.000236	0.000167	1.407	0.1616	
LogSensex.l_1	0.120336	0.089529	1.344	0.1812	
diffEPU.l_2	0.000284	0.000162	1.754	0.0817	.
LogSensex.l_2	0.022167	0.089667	0.247	0.8051	
const	0.010455	0.005872	1.781	0.0772	.

Residual standard error: 0.06803 on 136 degrees of freedom
Multiple R-Squared: 0.03413, Adjusted R-squared: 0.005722
F-statistic: 1.201 on 4 and 136 DF, p-value: 0.3131
Covariance matrix of residuals:

	diffEPU	LogSensex
diffEPU	994.5165	-0.62517
LogSensex	-0.6252	0.004629

Correlation matrix of residuals:

	diffEPU	LogSensex
diffEPU	1	-0.2914
LogSensex	-0.2914	1

Appendix D

Restricted VAR Model:

VAR Estimation Results:
=====================================
Endogenous variables: diffEPU, LogSensex
Call:

VAR(y = dx1, p = 2, type = "const")

Coefficients for equation diffEPU:
=====================================
diffEPU = diffEPU.l1 + LogSensex.l1 + diffEPU.l2

	Estimate	Std. Error	t value	Pr(>|t|)	
$diffEPU.l_1$	-0.49363	0.07705	-6.407	2.18E-09	***
$LogSensex.l_1$	-124.211	40.8672	-3.039	0.00284	**
$diffEPU.l_2$	-0.35409	0.06992	-5.064	1.29E-06	***

Residual standard error: 31.55 on 138 degrees of freedom

Multiple R-Squared: 0.2649, Adjusted R-squared: 0.2489

F-statistic: 16.58 on 3 and 138 DF, p-value: 2.967e-09

Coefficients for equation LogSensex:
=======================================

LogSensex = diffEPU.l2 + const

	Estimate	Std. Error	t value	Pr(>|t|)	
$diffEPU.l_2$	0.000188	0.000138	1.365	0.1744	
const	0.011812	0.005728	2.062	0.0411	*

Residual standard error: 0.06802 on 139 degrees of freedom

Multiple R-Squared: 0.04212, Adjusted R-squared: 0.02834

F-statistic: 3.056 on 2 and 139 DF, p-value: 0.05024

Covariance matrix of residuals:

	diffEPU	LogSensex
diffEPU	1008.7815	-0.621192
LogSensex	-0.6212	0.004729

Correlation matrix of residuals:

	diffEPU	LogSensex
diffEPU	1	-0.2844
LogSensex	-0.2844	1