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ΣΧΕΣΗ ΜΕΤΑΞΥ ΤΙΜΩΝ ΠΕΤΡΕΛΑΙΟΥ, ΟΙΚΟΝΟΜΙΚΗΣ ΔΡΑΣΤΗΡΙΟΤΗΤΑΣ, ΧΡΗΜΑΤΙΣΤΗΡΙΑΚΗΣ ΔΡΑΣΤΗΡΙΟΤΗΤΑΣ ΚΑΙ ΑΝΕΡΓΙΑΣ ΣΤΙΣ ΗΠΑ

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RELATIONSHIP BETWEEN OIL PRICES, ECONOMIC ACTIVITY, STOCK MARKET ACTIVITY AND UNEMPLOYMENT IN THE USA

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ΣΧΕΣΗ ΜΕΤΑΞΥ ΤΙΜΩΝ ΠΕΤΡΕΛΑΙΟΥ, ΟΙΚΟΝΟΜΙΚΗΣ ΔΡΑΣΤΗΡΙΟΤΗΤΑΣ, ΧΡΗΜΑΤΙΣΤΗΡΙΑΚΗΣ ΔΡΑΣΤΗΡΙΟΤΗΤΑΣ ΚΑΙ ΑΝΕΡΓΙΑΣ ΣΤΙΣ ΗΠΑ

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Περίληψη

Η εργασία αυτή μελετά τη σχέση μεταξύ των τιμών πετρελαίου, της οικονομικής δραστηριότητας, της ανεργίας και της χρηματιστηριακής δραστηριότητας στις ΗΠΑ την περίοδο από το 1986:1 μέχρι το 2014:12, χρησιμοποιώντας δύο διαφορετικές εμπειρικές προσεγγίσεις. Η εμπειρική σχέση μεταξύ της βιομηχανικής παραγωγής, των τιμών των μετοχών, των τιμών του πετρελαίου και των επιτοκίων θα διερευνηθεί αναπτύσσοντας και εκτιμώντας ένα Διανυσματικό Μοντέλο Διόρθωσης Λαθών τεσσάρων μεταβλητών για τη πρώτη προσέγγιση. Αντικαθιστώντας τη βιομηχανική παραγωγή με το ποσοστό ανεργίας των πολιτών, για τη δεύτερη προσέγγιση, ένα νέο Διανυσματικό Μοντέλο Διόρθωσης Λαθών πολλαπλών μεταβλητών θα δημιουργηθεί και οι δυναμικές αλληλεπιδράσεις τους θα μελετηθούν επίσης.

RELATIONSHIP BETWEEN OIL PRICES, ECONOMIC ACTIVITY, STOCK MARKET ACTIVITY AND UNEMPLOYMENT IN THE USA

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Abstract

The paper studies the relationship between oil prices, economic activity, unemployment and stock market activity in the US during the period 1986:1 to 2014:12, using two different empirical specifications. The empirical relationship between industrial production, stock prices, oil prices and interest rates will be investigated by developing and estimating a four variable Vector Error Correction model for the first specification. By replacing industrial production with civilian unemployment rate, for the second specification, a new multivariate Vector Error Correction model will be created and its dynamic interactions will be also studied.

Contents

1. Introduction and previous studies

Since the 1980s, oil price volatility is more significant in its effect on economic activity than the oil price level. A volatile environment weakens the effect of price level changes since it reduces the "surprise". Increasing volatility creates market uncertainties that induce companies to postpone their investments. There seems to be a negative relationship between oil prices and macroeconomic activity.

According to Hamilton's work (1983), oil price increases are responsible for almost every post WWII US recession. Hamilton states that historic correlation between oil price increases and economic recessions is not a statistical coincidence. By using Granger causality, he examined the impact of oil price shocks and the US economy in 1949 to1972. He found that changes in oil prices Granger caused changes in GNP and unemployment, whereas oil prices were determined exogenously. Oil price increase was followed 4 quarters later by slower output growth with a recovery beginning after 6 quarters. Nominal oil price increase could be expected to lead to a minor output effect during inflationary times than in noninflationary times.

Burbridge and Harrison (1984) using VAR models showed that the 1973-1974 oil embargo explains a substantial part of the behavior of industrial production in USA, Canada, UK, Japan and Germany. Although in their work reached the same conclusions with Hamilton, they found little evidence that the changes in oil prices for the years 1979-1980 had an effect on industrial production.

Gisser and Goodwin (1986) found that oil price shocks affect a set of macro variables. In their work and by using Hamilton's data a relationship between crude oil price and employment was detected. They, also, examined the hypothesis that oil shocks had a different impact on the macro economy before 1973 than after. However, they could not provide support for that hypothesis.

Mork (1989) examined the asymmetric response to oil changes by decomposing oil price changes in real price increases and decreases. The analysis showed for the U.S. economy that the correlation with price decreases is significantly different and perhaps zero.

In his work, Uri (1996), studied the impact of crude oil price changes on the agricultural employment in the USA for the years 1947 to 1995. Using Granger causality an empirical relationship between crude oil price changes and agricultural employment was established.

Ferderer (1996) provided an explanation of the observability of the asymmetry in effects. According to his work volatility and oil price changes have a stronger and more significant impact on economic activity than monetary policy variables, oil price increases are accompanied by greater volatility, oil price volatility and the Federal funds rate dominate the oil price level in terms of explaining fluctuations in industrial production and oil price changes have a significant impact on output growth after about one year.

The common feature of all the studies above is that they focus on the relationship between oil price shocks and macroeconomic variables. Contrary to the previous subject, little work has been done investigating the relationship between oil price shocks and financial market.

Jones and Kaul (1996) were the first to analyze the reaction of international stock markets to oil shocks by current and future changes in real cash flows and/or changes in expected returns. Their study considered stock markets in the US, Canada, UK and Japan. Their results showed that the effects of oil shocks on the US and Canadian stock markets can be explained completely by their effects on current and future real cash flows.

Haung et al. (1996) examined the link between daily oil future returns and daily United States stock returns. The evidence provided by their work suggested that oil futures returns do lead some individual oil company stock returns but oil future returns do not have much impact on general market indices.

Sadorsky (1999) contributed further to the studies of stock markets. Sadorsky's analysis is based on monthly data from 1947 to 1996 - in contrast to quarterly data used in the study of Jones and Kaul. The analysis showed that an oil price shock has a negative and statistically significant initial impact on stock returns. Higher production costs due to higher oil prices will cause earnings to decline. An efficient stock market will react with an immediate decline in stock prices. Thus, individual oil price shocks depress real stock returns. After 1986 there is a change in dynamics rather than a change in the response of the system. Thus, oil price volatility shocks play an important asymmetric role. Asymmetry in effects means that oil price increases have a clear negative impact on economic growth while oil price declines don't affect economic activity significantly.

Finally, Papapetrou (2001) contribute further in both subjects from the empirical analysis of her work for Greece. Oil prices play an important role in affecting economic activity and employment and oil prices shocks explain a significant proportion of the fluctuations in output and employment growth. Also, there is an immediate negative impact on industrial production and employment. Furthermore, the results suggested that a positive oil price shock depresses real stock returns. Stock returns do not rationally signal changes in real activity and employment. Industrial production and employment growth respond negatively to a real stock return shock. Real stock returns respond negatively to interest rate shocks. The relationship between interest rates and growth in industrial production and employment is negative.

To summarize briefly the literature review results: From 1986 and after, there are large price increases and decreases that reflect a substantial rise in the volatility of real oil price. Oil price increases matter substantially more than oil price decreases. Volatility weakens the economic response to oil price changes. When it comes to oil price movements, it is the degree of surprise that matters. Price volatility creates uncertainty in investments. Thus, monetary and fiscal policy measures, e.g. increasing interest rates, and therefore increasing prices only explain a part of the oil price – macro economy relationship. After 1986, oil price rises had a significant and detrimental effect on stock markets. The stock returns are negatively affected by both current and lagged oil price variables. The effects of oil shocks on the US and Canadian stock markets can be completely explained by their effects on contemporaneous and future real cash flows. Higher costs of production due to higher oil prices will cause earnings to decline. Also, increasing oil price volatility has a great impact on the economy and dominates the oil price level. It is has become obvious that oil price increases are considerably more important than oil price decreases. Oil price changes in a volatile market environment are less useful to forecast GDP growth.

In the present article two sections conclude the results. The interaction between oil prices and economic activity are investigated in the first section. Of particular interest are any possible asymmetric effects of oil price shocks in the economic activity. The dynamic interactions among oil prices, stock returns, interest rates and economic activity for USA will be studied, by using industrial production as measure of economic activity to capture the dynamic interactions among the variables.

In the second section, the dynamic interactions among oil prices, stock returns, interest rates, economic activity and unemployment are investigated using a large-sized country(USA).

Following the work of Papapetrou (2001, 2009) and contrary to other studies, in this paper, we use both industrial production and unemployment as alternative measures of economic activity to capture the dynamic interactions among the variables. USA serves as an example and the conclusions drawn on the dynamic interrelations among these variables could be indicative of conditions in other large-sized economies.

2. Data

Seasonally adjusted **monthly data** were used for the **period 1986:1-2014:12**, for the **United States**. The data were extracted from the database of Federal Reserve Economic Data – St. Louis Fed (FRED) and Yahoo Finance. **Interest rates** were measured by using the **3-month T-bill rate**. **Real Oil Prices** were measured by using the **Producer Price Index for Fuels** and the **Consumer Price Index**. The formulas used for the extraction of data can be found on Appendix A.

The natural logarithms of the following variables were taken (The plots shown the evolution of each variable over time can be found in Appendix B):

a. US Industrial Production (IP), a measure of output, denoted as **ip**, natural logarithm: **lnip,**
b. interest rates, denoted as **r**, natural logarithm: **lnr**,
c. real oil prices, denoted as **rop**, natural logarithm: **lnrop,**
d. Real Stock Returns, denoted as **rsr**, natural logarithm: **lnrsr,**
e. Unemployment index, denoted as **unemp** , natural logarithm: **lnunemp**.

Variables Definitions and their respected Databases:

- Index of industrial production, 2007=100, seasonally adjusted: **ip**. (FRED)
- Three-month T-bill rate, not seasonally adjusted: **3tbill**. (FRED)
- Producer price index of fuels, 2007=100, seasonally adjusted: **ppif**. (FRED)
- S&P 500 Stock Price Index, not seasonally adjusted: **sp500**. (Yahoo Finance)
- Consumer price index, 2007=100, seasonally adjusted: **cpi**. (FRED)
- Real oil prices: **rop**. (Calculation)
- Real stock returns: **rsr**. (Calculation)
- Civilian unemployment rate: **unemp**. (FRED)

3. Presentation of the Model and Methodology

The empirical analysis, for both sections, has been carried out using monthly data for the period 1986:1-2014:12 for United Stated. The output variable is the US industrial production (a measure of output), the interest rate is the 12- month rate, the real oil prices are the producer price index for fuels deflated by the consumer price index, the real stock returns are the difference of the continuously compounded return on the S&P 500 index and the inflation rate and the unemployment variable is the civilian unemployment rate.

Methodology of the first section

In the first section of this study a VECM analysis is performed to investigate fuel price changes and its effects on stock market returns and economic activity. The empirical analysis has been carried out for the period 1986:1-2014:12 for the United States, as was previously stated. This period can be characterized by huge oil price shocks, mostly due to the credit crisis in the end of 2007.

Methodology of the second section

In the second section of this study a VECM analysis is performed to explain oil price changes and their effects on stock market returns and unemployment. This method of analysis allows us to test for endogeneity of all variables in the economy and the responses of stock market returns and unemployment to oil prices shocks in order to capture the short-run dynamics of the variables.

---*The existence of statistical relationship among the variables is tested in three main steps.*

The first main step is to verify the order of integration of the variables since the causality tests are valid if the variables have the same order of integration. Standard tests for the presence of a unit root based on the work of Perron (1988), Phillips (1987) and Phillips and Perron (1988) and Kwiatkowski et al. (1992) are used to investigate the degree of integration of the variables used in the empirical analysis.

The second main step involves testing for co-integration using the Johansen maximum likelihood approach (Johansen 1988; Johansen and Juselius 1990, 1992). The Johansen- Juselius estimation method is based on the error-correction representation of the VAR (p) model with Gaussian errors.

The third main step is divided in two cases:

1. If a long-run relationship does not exist among the four endogenous variables, the third step involves estimation of the VAR model. The Vector Autoregressive Model (VAR) describes about two or more variables operating in a system where the dependent variables are found as lagged ones on the right hand side of the equation. Variables used in VAR are all assumed to be endogenous. But if a VAR is furnished with some exogenous variables together with endogenous, we can call it as VARMAX model
2. If a long-run relationship does exist among the four endogenous variables, the third step involves estimation of the VEC model. In VECM model, the dynamics of both short run and long run adjustment will be made. VECM will also allow us to find out the causal factors that affect our variables.

In this work we follow the VECM route but the VAR model route is presented for studying in the Appendix F.

4. First section of this study

4.1. Univariate Properties of the Series

Table 1 reports results from Phillips and Perron (1988) Unit Root Tests. Because industrial production and fuel prices exhibit positive upward trends, the alternative hypothesis for these two time series is stationarity about a linear time trend. For the interest rate and real stock return series the alternative hypothesis is stationarity in levels. The test results from Table 1 report that, for the variables in levels, only real stock returns are stationary at 5% level of significance. The table also shows that the first difference of each variable is stationary. The results from Table 1 suggest that each series is best described as being stationary in first differences with the exception of real stock returns which are stationary in levels.

Table 1 - Results from Phillips-Perron test for unit root

Variable	*Z(t)*	*Z(rho)*	*p-value*
		In levels	
lnip	-1.450	-1.315	0.5583
lnrop	-1.465	-4.574	0.5508
lnr	-0.331	-0.817	0.9211
lnrsr	-17.462	-370.975	0.0000
		In first differences	
dlnip	-15.952	-361.647	0.0000
dlnrop	-14.694	-260.708	0.0000
dlnr	-15.459	-251.929	0.0000

Table 2 reports results from Dickey Fuller Unit Root Test. It suggests the same results as in Table 1 (PP Test). Hence, the results from Table 2 suggest that each series is best described as being stationary in first differences with the exception of the real stock return variable which is stationary in levels.

Table 2 - Results from Dickey-Fuller test for unit root

Variable	*p - value*
ln levels	
lnip	0.3709
lnrop	0.6799
lnr	0.9214
lnrsr	0.0000
In first differences	
dlnip	0.0000
dlnrop	0.0000
dlnr	0.0000

Table 3 reports results from Augmented Dickey Fuller Unit Root Test. It suggests that variables lnip, lnrop and lnr are integrated of order one, I(1), variable lnrsr is integrated of order zero, I(0) and the first differences of the variables are all stationary. Therefore, the hypothesis that the time series contain an autoregressive unit root is accepted for all variables except for the stock rate of return.

Table 3 - Results from Augmented Dickey-Fuller test for unit root

Variable	*p - value*
ln levels	
lnip	0.5062
lnrop	0.5991
lnr	0.9330

lnrsr	0.0000
In first differences	
dlnip	0.0001
dlnrop	0.0000
dlnr	0.0000

The estimation period for this study covers the somewhat turbulent time of the credit world crisis (2008-today). Consequently, it is important to check the data for structural breaks. This was done by using the test procedure of Zivot and Andrews (1992). In this testing procedure the Null hypothesis is a unit root process without any endogenous structural breaks and the relevant alternative hypothesis is a trend stationary process with possible structural change occurring at an unknown point in time. For each model, the t-stats that maximize rejection of the Null Hypothesis were picked. The results are summarized in Table 4. The null of a unit root is rejected if the minimum t-statistic < critical.

Table 4 - Results from Zivot-Andrews unit root test

Variable	*Minimum t-stat*	*Critical value (5%)*	*At observation*
ln levels			
lnip	-4.321	-4.80	2008m1 (obs 265)
lnrop	-4.488	-4.80	2004m7 (obs 223)
lnr	-5.593	-4.80	2008m9 (obs 273)
lnrsr	-6.198	-4.80	2007m4 (obs 256)
In first differences			
dlnip	-5.596	-4.80	2009m7 (obs 283)
dlnrop	-8.341	-4.80	1999m3 (obs 159)

dlnr	-9.621	-4.80	2007m8 (obs 260)

To decide about the type of model to use, we need to decide about the order of operators (number of lags), the deterministic trends, etc. Industrial Production is the series which is going to be used for the following tests conducted. A model needs to be specified and then conduct tests on its specification, whether it represents the Industrial Production (ip) adequately. The model ARIMA (2,1,2) is chosen because it qualifies for the smaller AIC and the smaller SSR, rather than the other models studied, although BIC is the second smaller.

Table 5 - Results from ARIMA regressions

Model	**AIC**	**BIC**	**SSR**
ln level			
ARIMA(1,0,0)	-2501.815	-2490.258	0.11487594
ARIMA(0,0,1)	-600.098	-588.5414	3.6865618
ARIMA(1,0,1)	-2518.23	-2502.821	0.11495358
ARIMA(2,0,0)	-2528.805	-2513.397	0.11568382
ARIMA(0,0,2)	-1010.873	-995.4644	1.2350852
ARIMA(2,0,2)	-2593.906	-2570.793	0.13494086
In first difference			
ARIMA(1,1,0)	-2547.721	-2536.173	0.01293478
ARIMA(0,1,1)	-2541.82	-2530.272	0.01315562
ARIMA(1,1,1)	-2586.609	-2571.212	0.01149975
ARIMA(2,1,0)	-2572.497	-2557.1	0.01197768
ARIMA(0,1,2)	-2555.065	-2539.668	0.01259151

ARIMA(2,1,1)	-2594.712	-2575.466	0.01117219
ARIMA(1,1,2)	-2599.498	-2580.251	0.01102052
ARIMA(2,1,2)	-2601.223	-2578.127	0.01090168

Note: ip variable

Therefore, the model will be:

$$\Delta lnip_t = \underset{(0.0008808)}{0.0017621} + \underset{(0.1828391)}{1.173991}\, \Delta lnip_{t-1} - \underset{(0.1712668)}{0.3139662}\, \Delta lnip_{t-2} + u_t - \underset{(0.1778086)}{1.134843}\, u_{t-1} + \underset{(0.1286309)}{0.4922667}\, u_{t-2}$$

The analysis continues by performing CUSUM Tests. The CUSUM test takes the cumulative sum of recursive residuals and plots its value against the upper and lower bounds of the 95% confidence interval at each point. Under the Null of perfect parameter stability, the CUSUM statistic should be zero and the CUSUM squared should range from zero at start of period and end at one. In practice both are normally plotted with a 95% confidence bands and the Null is rejected of the plot strays outside this band. CUSUM begins to drift downward and depart from the band at about t=279 (March 2009). The hypothesis of parameter stability is rejected in our case, because the CUSUM-squared strays outside the confidence intervals (Appendix B).

4.2. Co-integration Analysis

The model examines the long-run relationship among interest rates, real oil prices, real stock returns and industrial production. The real stock return variable is treated in the systems as stationary endogenous variable. To determine the lag length of the model, Akaike Information Criterion AIC, Schwarz Bayesian Criterion SBC and a Likelihood Ratio test will be used. As shown in Appendix C, the sequential LR indicates 20 lags, FPE and AIC indicate 6 lags, HQIC indicates 2 lags and SBIC indicates 1 lag. By comparing the different models by LR test statistics, the results show that the model with 20 lags is better than 16 lags model, model with 16 lags is better than model with 12 lags, etc. The best choice for lags in our model should be 6 lags, as more criteria demands, but eventually, the model with 7 lags will be chosen in order to perform a Vector Co-Integration Model (VECM), because in this model there is no-autocorrelation at lag order, as it is shown by performing Lagrange Multiplier Test (LM Test). Furthermore, it is tiring and complex to use the model with 20 lags.

To test for Co-Integration, the Johansen maximum likelihood approach is used employing both the maximum eigenvalue and trace statistic. To use this test, variables must be non-stationary at level but when converted into their first difference they must be stationary. As shown in both Table 6 and Table 7, we reject the null hypothesis of zero rank and no co-integration in both lag 6 and lag 7 model. So, co-integration is detected among the variables. If the variables were not co-integrated, we should employ a VAR model. In our case a Vector Error Correction model will be developed.

Table 6 - Johansen test for co-integration

Max rank	Parameters	LL	Eigenvalue	Trace statistic	Critical Value
0	84	1311.7946	.	52.8622	47.21
1	91	1328.754	0.09468	18.9434*	29.68
2	96	1336.8321	0.04627	2.7873	15.41
3	99	1338.2243	0.00813	0.0029	3.76
4	100	1338.2257	0.00001		

Note: Lag 6 model

Table 7 - Johansen tests for co-integration

Max rank	Parameters	LL	Eigenvalue	Trace statistic	Critical Value
0	100	1322.5116	.	51.8578	47.21
1	107	1337.7015	0.08548	21.4781*	29.68
2	112	1346.9493	0.05295	2.9824	15.41
3	115	1348.4344	0.00870	0.0122	3.76
4	116	1348.4405	0.00004		

Note: Lag 7 model

4.3. Vector Error Correction model

Once the variables included in our model found to be co-integrated, we will use Vector Error Correction Model (VECM). VECM is special type of restricted VAR, is introduced to correct a disequilibrium that may shock the whole system. In VECM model, the dynamics of both short run and long run adjustment will be made.

The VECM residuals are not normally distributed. In all cases the null hypothesis of the VECM Normality Test is rejected. To check for serial correlation problem Lagrange Multiplier Test is used. For the 6 lag VECM the null of no autocorrelation is rejected but for the 7 lag VECM I fail to reject the null hypothesis. This means that the 7 lag model is good (no autocorrelation on residuals). The model which was chosen seems to be an acceptable model.

The results, running the 7 lag VECM, demonstrate if there is long run causality between the independent variables (real oil prices, real stock returns, interest rates) and the dependent variable (industrial production). Also, they demonstrates if there is short run causality between the lags of the independent variables individually and the dependent variable. Error correction term's coefficient not being significant suggests that there is no long rung causality between our dependent and independent variables. Furthermore, there is no short run causality, in most cases, between the lags of the independent variables and the dependent variable individually.

Table 8 - Results from Vector Error Correction Model

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lnip						
_ce1						
L1.	-.0006869	.0003749	-1.83	0.067	-.0014216	.0000478
lnip						
LD.	.0195074	.0557814	0.35	0.727	-.0898221	.1288369
L2D.	.1933326	.0558173	3.46	0.001	.0839327	.3027326
L3D.	.192265	.0573035	3.36	0.001	.0799523	.3045778
L4D.	.1207187	.0591016	2.04	0.041	.0048816	.2365557
L5D.	.030619	.0579903	0.53	0.597	-.08304	.144278
L6D.	.0095224	.0585445	0.16	0.871	-.1052227	.1242675
lnrop						
LD.	.0090232	.005588	1.61	0.106	-.0019291	.0199754
L2D.	-.0011055	.0056009	-0.20	0.844	-.012083	.009872
L3D.	-.0023632	.0054991	-0.43	0.667	-.0131413	.0084149
L4D.	.0030369	.005477	0.55	0.579	-.0076977	.0137715
L5D.	-.0032482	.0054071	-0.60	0.548	-.013846	.0073496
L6D.	-.0102539	.0053077	-1.93	0.053	-.0206568	.0001491
lnr						
LD.	.0026766	.0015095	1.77	0.076	-.000282	.0056352
L2D.	.0004225	.001513	0.28	0.780	-.002543	.0033879
L3D.	.0012879	.0015361	0.84	0.402	-.0017228	.0042986
L4D.	-.0007859	.0015023	-0.52	0.601	-.0037304	.0021587
L5D.	.0005609	.0014545	0.39	0.700	-.0022899	.0034116
L6D.	.0038746	.0014445	2.68	0.007	.0010435	.0067057
lnrsr						
LD.	.0010625	.0005809	1.83	0.067	-.0000761	.0022011
L2D.	.0008796	.0005618	1.57	0.117	-.0002216	.0019807
L3D.	.0006294	.0005222	1.21	0.228	-.000394	.0016528
L4D.	.0006918	.000464	1.49	0.136	-.0002176	.0016011
L5D.	.0003776	.0003926	0.96	0.336	-.0003919	.0011472
L6D.	-.0001906	.0002816	-0.68	0.498	-.0007424	.0003612
_cons	.0009824	.0003618	2.72	0.007	.0002732	.0016915

Using the Granger causality method, we fail to reject the null of no short run causality between the dependent variable and the lags of the independent variables jointly.

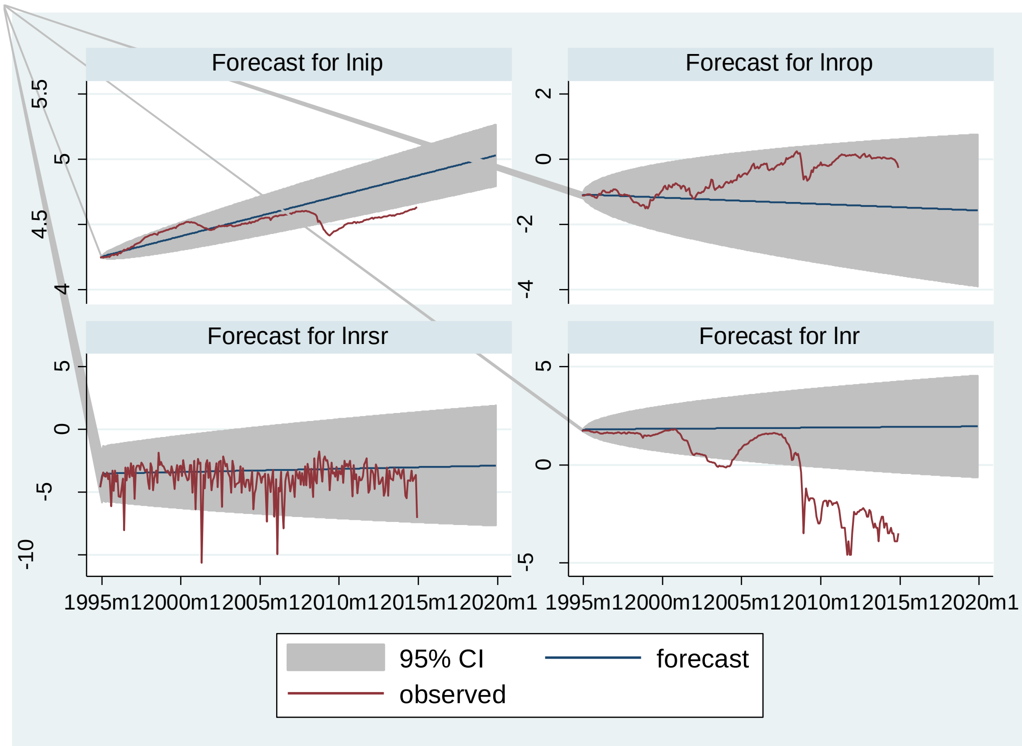
Table 9 - Results from Vector Error Correction Model with restrictions

Real oil prices	Interest rates	Real stock returns
(1) [D_lnip]LD.lnrop = 0	(1) [D_lnip]LD.lnr = 0	(1) [D_lnip]LD.lnrsr = 0
(2) [D_lnip]L2D.lnrop = 0	(2) [D_lnip]L2D.lnr = 0	(2) [D_lnip]L2D.lnrsr = 0
(3) [D_lnip]L3D.lnrop = 0	(3) [D_lnip]L3D.lnr = 0	(3) [D_lnip]L3D.lnrsr = 0
(4) [D_lnip]L4D.lnrop = 0	(4) [D_lnip]L4D.lnr = 0	(4) [D_lnip]L4D.lnrsr = 0
(5) [D_lnip]L5D.lnrop = 0	(5) [D_lnip]L5D.lnr = 0	(5) [D_lnip]L5D.lnrsr = 0
(6) [D_lnip]L6D.lnrop = 0	(6) [D_lnip]L6D.lnr = 0	(6) [D_lnip]L6D.lnrsr = 0
chi2(6) = 8.59	chi2(6) = 11.98	chi2(6) = 7.59
Prob > chi2 = 0.1980	Prob > chi2 = 0.0625	Prob > chi2 = 0.2699

4.4. Forecast

Graphs from Figure 1 show that, our forecasts in industrial production and interest rate appear to not fit with the observations which stray out of the bounds in some point. Forecast in real oil prices also do not fit with the observations very well but they do no stray out of the bounds. In contrast real stock returns appear to fit the data relatively well. Worth to notice, it is from certain points in time between 2005 and 2010 that our data go out of limits or get really close to them. Those results can be justified by the financial crisis of 2007-2009 in the United States.

Figure 1



4.5. Principal Component Analysis and Factor Analysis

The results of the analysis can be found on Appendix E. The eigenvalues are $\lambda_1 = 2.24477$, $\lambda_2 = 1.00493$, $\lambda_3 = 0.477045$, $\lambda_4 = 0.273252$. Only the first two eigenvalues are of interest because they are the only ones larger than one. The first principal (eigenvalue λ_1) explains 56.12% of the total variance in original data and the second principal (eigenvalue λ_2) explains 25.12%. In total the two principals explain the 81.42% of the total variance in original data. The first component is given as $c_1 = (0.5451, 0.5996, -0.0317, -0.5851)$ and the second as $c_2 = (-0.0214, -0.0225, 0.9948, -0.0968)$. We observe that 81.24% of the variation can be explained by the two first components while the average unexplained variance is 18.76%.

For the factor analysis, only two factors are retained because the eigenvalues associated with the remaining factors are negative. We observe that the first factor is given by $f_1 = 0.6734lnip + 0.8229lnrop - 0.0295lnrsr - 0.7905lnr$ and the second by $f_2 = - 0.0343lnip - 0.0238lnrop + 0.1823lnrsr - 0.0608lnr$. The 54.54% of variance in lnip (i.e. uniqueness) cannot be explained by f_1, f_2 and the 45.46% (communality) can be explained by f_1, f_2. Since $0.4546 < 0.6$ (benchmark), the variable lnip is well explained by the factors. Eventually, only one factor is retained because the eigenvalues associated with the remaining factors are smaller than one.

Furthermore, the Kaiser-Meyer-Olkin measure of adequacy is applied to the variables to find if they have enough in common for principal component and factor analysis. The overall value of KMO ($0.6893 > 0.6$) seems to be above the (0.50-0.59) range. With high correlation among the variables, the use of either principal components analysis or factor analysis can be justified.

5. Second Section of this study

5.1. Univariate Properties of the Series

Table 10 reports results from Phillips and Perron (1988) Unit Root Tests. The test results report that, for the variables in levels, only real stock returns are stationary at 5% level of significance. The table also shows that the first difference of each variable is stationary. The results from Table 10 suggest that each series is best described as being stationary in first differences with the exception of real stock returns which are stationary in levels.

Table 10 - Results from Phillips-Perron test for unit root

Variable	*Z(t)*	*Z(rho)*	*p-value*
In levels			
lnunemp	-1.420	-3.935	0.5726
lnrop	-1.465	-4.574	0.5508
lnr	-0.331	-0.817	0.9211
lnrsr	-17.462	-370.975	0.0000
In first differences			
dlnunemp	-18.755	-444.222	0.0000
dlnrop	-14.694	-260.708	0.0000
dlnr	-15.459	-251.929	0.0000

Table 11 reports results from Dickey Fuller Unit Root Test. It suggests the same results as in Table 10 (PP Test). Hence, the results from Table 11 suggest that each series is best described as being stationary in first differences with the exception of the real stock return variable which is stationary in levels.

Table 11 - Results from Dickey-Fuller test for unit root

Variable	*p - value*
ln levels	
lnunemp	0.7156
lnrop	0.6799
lnr	0.9214
lnrsr	0.0000
In first differences	
dlnunemp	0.0000
dlnrop	0.0000
dlnr	0.0000

Table 12 reports results from Augmented Dickey Fuller Unit Root Test. It suggests that variables lnunemp, lnrop and lnr are integrated of order one, I(1), variable lnrsr is integrated of order zero, I(0) and the first differences of the variables are all stationary. Therefore, the hypothesis that the time series contain an autoregressive unit root is accepted for all variables except for the stock rate of return.

Table 12 - Results from Augmented Dickey-Fuller test for unit root

Variable	*p - value*
ln levels	
lnunemp	0.3159
lnrop	0.5991
lnr	0.9330

lnrsr	0.0000
In first differences	
dlnunemp	0.0000
dlnrop	0.0000
dlnr	0.0000

As was also stated in the first section, the estimation period for this study covers the somewhat turbulent time of the credit world crisis (2008-today). Consequently, it is important to check the data for structural breaks. This was done by using the test procedure of Zivot and Andrews (1992). In this testing procedure the Null hypothesis is a unit root process without any endogenous structural breaks and the relevant alternative hypothesis is a trend stationary process with possible structural change occurring at an unknown point in time. For each model, the t-stats that maximize rejection of the Null Hypothesis were picked. The results are summarized in Table 12. The null of a unit root is rejected if the minimum t-statistic < critical.

Table 13 - Results from Zivot-Andrews unit root test

Variable	*Minimum t-stat*	*Critical value (5%)*	*At observation*
		ln levels	
lnunemp	-3.442	-4.80	2008m5 (obs 269)
lnrop	-4.488	-4.80	2004m7 (obs 223)
lnr	-5.593	-4.80	2008m9 (obs 273)
lnrsr	-6.198	-4.80	2007m4 (obs 256)
		In first differences	
dlnunemp	-5.181	-4.80	2009m11 (obs 287)
dlnrop	-8.341	-4.80	1999m3 (obs 159)

dlnr	-9.621	-4.80	2007m8 (obs 260)

To decide about the type of model to use, we need to decide about the order of operators (number of lags), the deterministic trends, etc. Civilian unemployment rate is the series which is going to be used for the following tests conducted. A model needs to be specified and then conduct tests on its specification, whether it represents the Civilian unemployment rate (unemp) adequately. The model ARIMA (2,0,2) is chosen because it qualifies for the smaller AIC and the smaller BIC, rather than the other models studied, although SSR is the fourth smaller.

Table 14 - Results from ARIMA regressions

Model	**AIC**	**BIC**	**SSR**
ln level			
ARIMA(1,0,0)	-1536.845	-1525.289	0.25048429
ARIMA(0,0,1)	-462.2146	-450.658	5.2910523
ARIMA(1,0,1)	-1535.175	-1519.766	0.25044751
ARIMA(2,0,0)	-1535.302	-1519.893	0.25043723
ARIMA(0,0,2)	-744.4187	-729.0099	2.3436708
ARIMA(2,0,2)	-1593.426	-1570.313	0.21818279
In first difference			
ARIMA(1,1,0)	-1535.203	-1523.656	0.2392993
ARIMA(0,1,1)	-1535.104	-1523.556	0.23936588
ARIMA(1,1,1)	-1565.615	-1550.218	0.21831408
ARIMA(2,1,0)	-1545.972	-1530.575	0.23079783
ARIMA(0,1,2)	-1544.822	-1529.425	0.23155273

ARIMA(2,1,1)	-1579.912	-1560.666	0.20848477
ARIMA(1,1,2)	-1584.056	-1564.809	0.20608157
ARIMA(2,1,2)	-1585.227	-1562.131	0.20417899

Note: unemp variable

Therefore, the model will be:

$$lnunemp_t = 1.76707 + 1.950892\ lnunemp_{t-1} - 0.954233\ lnunemp_{t-2} + u_t - 1.102981\ u_{t-1} + 0.2634275\ u_{t-2}$$

(0.0639056) (0.0271317) (0.0267236) (0.0606683) (0.056861)

The analysis continues by performing CUSUM Tests. The CUSUM test takes the cumulative sum of recursive residuals and plots its value against the upper and lower bounds of the 95% confidence interval at each point. Under the Null of perfect parameter stability, the CUSUM statistic should be zero and the CUSUM squared should range from zero at start of period and end at one. In practice both are normally plotted with a 95% confidence bands and the Null is rejected of the plot strays outside this band. The hypothesis of parameter stability is not rejected in our case, because the CUSUM-squared do not strays outside the confidence intervals (Appendix B).

5.2. Co-integration Analysis

The model examines the long-run relationship among interest rates, real oil prices, real stock returns and civilian unemployment rate. The real stock return variable is treated in the systems as stationary endogenous variable. To determine the lag length of the model, Akaike Information Criterion AIC, Schwarz Bayesian Criterion SBC and a Likelihood Ratio test will be used. As shown in Appendix C, the sequential LR indicates 20 lags, FPE and AIC indicate 6 lags, HQIC indicates 2 lags and SBIC indicates 1 lag. By comparing the different models by LR test statistics, the results show that the model with 20 lags is better than 16 lags model, model with 16 lags is better than model with 12 lags, etc. The best choice for lags in our model should be 6 lags, as more criteria demands, in order to perform a Vector Co-Integration Model (VECM). Also in this model there is no-autocorrelation at lag order, as it is shown by performing Lagrange Multiplier Test (LM Test). Furthermore, it is tiring and complex to use the model with 20 lags.

To test for Co-Integration, the Johansen maximum likelihood approach is used employing both the maximum eigenvalue and trace statistic. To use this test, variables must be non-stationary at level but when converted into their first difference they must be stationary. As shown in Table 15, we reject the null hypothesis of zero rank and no co-integration in lag 6. So, co-integration is detected among the variables. If the variables were not co-integrated, we should employ a VAR model. In our case a Vector Error Correction model will be developed.

Table 15 - Johansen test for co-integration

Max rank	Parameters	LL	Eigenvalue	Trace statistic	Critical Value
0	84	801.46181	.	51.5598	47.21
1	91	817.37156	0.08909	19.7403*	29.68
2	96	825.41456	0.04608	3.6543	15.41
3	99	827.08815	0.00977	0.3071	3.76
4	100	827.24171	0.00090		

Note: Lag 6 model

5.3. Vector Error Correction model

Once the variables included in our model found to be co-integrated, we will use Vector Error Correction Model (VECM). VECM is special type of restricted VAR, is introduced to correct a disequilibrium that may shock the whole system. In VECM model, the dynamics of both short run and long run adjustment will be made.

The VECM residuals are not normally distributed. In all cases the null hypothesis of the VECM Normality Test is rejected except for the first differences of unemployment. To check for serial correlation problem Lagrange Multiplier Test is used. For the 6 lag VECM I fail to reject the null of no autocorrelation. This means that the 6 lag model is good (no autocorrelation on residuals). The model which was chosen seems to be an acceptable model.

The results, running the 6 lag VECM, demonstrate if there is long run causality between the independent variables (real oil prices, real stock returns, interest rates) and the dependent variable (civilian unemployment rate). Also, they demonstrates if there is short run causality between the lags of the independent variables individually and the dependent variable. Error correction term's coefficient not being significant suggests that there is no long rung causality between our dependent and independent variables. Furthermore, there is no short run causality, in most cases, between the lags of the independent variables and the dependent variable individually.

Table 16 - Results from Vector Error Correction Model

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lnunemp						
_ce1						
L1.	-.0007667	.000557	-1.38	0.169	-.0018584	.0003249
lnunemp						
LD.	-.0782113	.0550827	-1.42	0.156	-.1861714	.0297487
L2D.	.0886309	.0558492	1.59	0.113	-.0208316	.1980934
L3D.	.1859635	.0554573	3.35	0.001	.0772692	.2946578
L4D.	.0660693	.0560406	1.18	0.238	-.0437682	.1759068
L5D.	.2056126	.0561821	3.66	0.000	.0954977	.3157276
lnrop						
LD.	-.0068614	.0234051	-0.29	0.769	-.0527345	.0390118
L2D.	-.014721	.0235968	-0.62	0.533	-.06097	.0315279
L3D.	.0058034	.0236101	0.25	0.806	-.0404716	.0520783
L4D.	-.0117034	.0232489	-0.50	0.615	-.0572704	.0338636
L5D.	-.0160988	.0226439	-0.71	0.477	-.06048	.0282825
lnr						
LD.	-.0092855	.0062836	-1.48	0.139	-.0216012	.0030302
L2D.	-.0084298	.0063364	-1.33	0.183	-.020849	.0039894
L3D.	-.0039748	.0064492	-0.62	0.538	-.016615	.0086655
L4D.	-.0011077	.0062828	-0.18	0.860	-.0134218	.0112065
L5D.	-.0045344	.0061743	-0.73	0.463	-.0166357	.007567
lnrsr						
LD.	-.0035271	.0024308	-1.45	0.147	-.0082913	.0012371
L2D.	-.001815	.00225	-0.81	0.420	-.0062249	.002595
L3D.	-.0022828	.0019912	-1.15	0.252	-.0061855	.0016199
L4D.	-.0021452	.0016724	-1.28	0.200	-.005423	.0011325
L5D.	-.0011524	.0012145	-0.95	0.343	-.0035329	.001228
_cons	-.0008431	.0013568	-0.62	0.534	-.0035023	.0018161

Using the Granger causality method, we fail to reject the null of no short run causality between the dependent variable and the lags of the independent variables jointly.

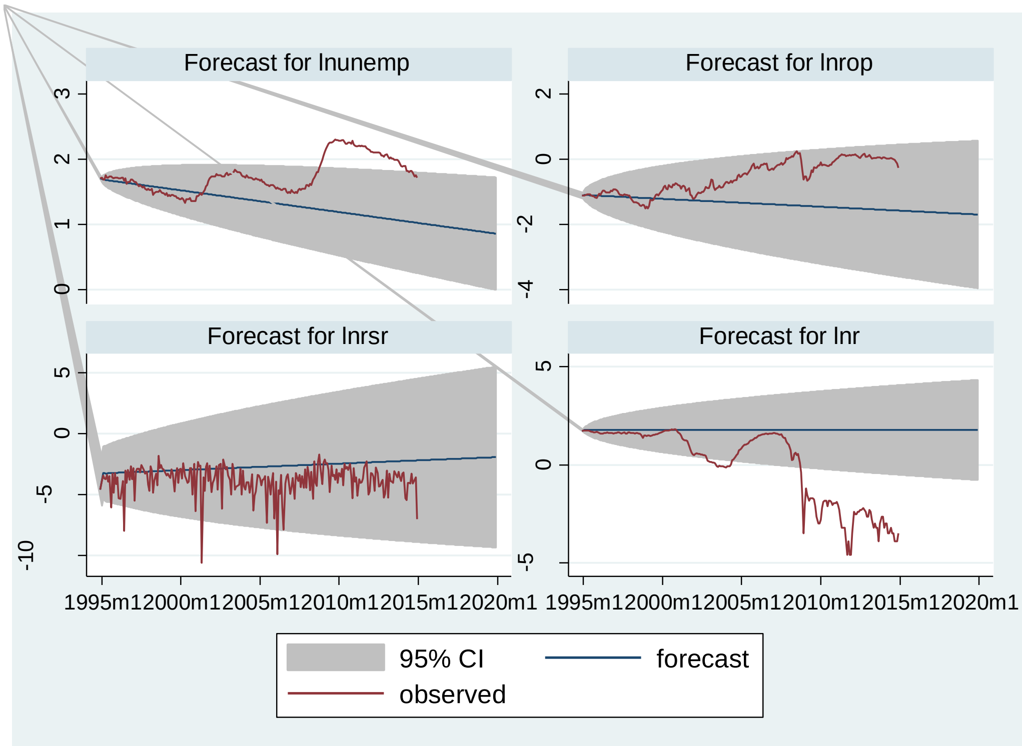
Table 17 - Results from Vector Error Correction Model with restrictions

Real Oil Prices	Interest rates	Real stock returns
(1) [D_lnunemp]LD.lnrop = 0	(1) [D_lnunemp]LD.lnr = 0	(1) [D_lnunemp]LD.lnrsr = 0
(2) [D_lnunemp]L2D.lnrop = 0	(2) [D_lnunemp]L2D.lnr = 0	(2) [D_lnunemp]L2D.lnrsr = 0
(3) [D_lnunemp]L3D.lnrop = 0	(3) [D_lnunemp]L3D.lnr = 0	(3) [D_lnunemp]L3D.lnrsr = 0
(4) [D_lnunemp]L4D.lnrop = 0	(4) [D_lnunemp]L4D.lnr = 0	(4) [D_lnunemp]L4D.lnrsr = 0
(5) [D_lnunemp]L5D.lnrop = 0	(5) [D_lnunemp]L5D.lnr = 0	(5) [D_lnunemp]L5D.lnrsr = 0
chi2(5) = 1.55	chi2(5) = 5.29	chi2(5) = 4.20
Prob > chi2 = 0.9077	Prob > chi2 = 0.3813	Prob > chi2 = 0.5213

5.4. Forecast

Graphs from Figure 2 show that, our forecasts in interest rate and unemployment appear to not fit with the observations very well which stray out of the bounds in some point. Unemployment observations appear to return into the limits in some point after 2014. In contrast real stock returns forecast appear to fit with the observations relatively well. Worth to notice, it is from certain points in time between 2005 and 2010 that our data go out of the limits of get really close to them. Those results can be justified by the financial crisis of 2007-2009 in the United States.

Figure 2



5.5. Principal Component Analysis and Factor Analysis

The results of the analysis can be found on Appendix E. The eigenvalues are λ_1 = 2.20084, λ_2 = 1.01757, λ_3 = 0.57347, λ_4 = 0.208114. Only the first two eigenvalues are of interest because they are the only ones larger than one. The first principal (eigenvalue λ_1) explains 55.02% of the total variance in original data and the second principal (eigenvalue λ_2) explains 25.44%. In total the two principals explain the 80.46% of the total variance in original data. The first component is given as c_1 = (0.5378, 0.5603, 0.0178, -0.6298) and the second as c_2 = (0.1263, -0.1544, 0.9799, -0.0018). We observe that 80.4% of the variation can be explained by the two first components while the average unexplained variance is 19.6%.

For the factor analysis, only two factors are retained because the eigenvalues associated with the remaining factors are negative. We observe that the first factor is given by f_1 = 0.6672lnunemp + 0.7339lnrop + 0.0156lnrsr - 0.8843lnr and the second by f_2 = 0.2087lnunemp - 0.2083lnrop + 0.2185lnrsr - 0.0115lnr. The 51.12% of variance in lnunemp (i.e. uniqueness) cannot be explained by f_1, f_2 and the 48.88% (communality) can be explained by f_1, f_2. Since

0.4888 < 0.6 (benchmark), the variable lnunemp is well explained by the factors. Eventually, only one factor is retained because the eigenvalues associated with the remaining factors are smaller than one.

Furthermore, the Kaiser-Meyer-Olkin measure of adequacy is applied to the variables to find if they have enough in common for principal component and factor analysis. The overall value of KMO (0.5926 < 0.6) seems to be above the (0.50-0.59) range. With high correlation among the variables, the use of either principal components analysis or factor analysis can be justified.

6. Conclusions

This paper analyzed the relationship among interest rates, real oil prices, real stock returns, industrial production and the unemployment rare. Two specifications are estimated, the industrial production specification and unemployment specification. Contrary to previous studies we use both industrial production and employment as alternative measures of economic activity. From the empirical analysis significant conclusions can be drawn about the way in which oil price movements or stock market movements affect industrial production and unemployment. Oil prices play an important role in affecting economic activity.

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Appendix A

- How to calculate the Real Oil Price (rop): $\boldsymbol{rop} = \frac{\boldsymbol{PPIF}}{\boldsymbol{CPI}}$, where PPIF is the Producer Price Index for Fuels.

<u>Note:</u> *the Real Oil Price (rop) is computed by deflating Producer Price Index for Fuels (PPIF) with Consumer Price Index (CPI).*

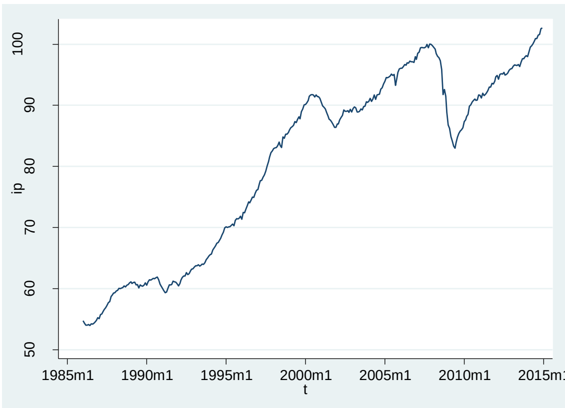
- How to calculate the Real Stock Returns (rsr): $\boldsymbol{rsr = ln(\frac{SP500}{L.SP500}) - \frac{CPI-L.CPI}{L.CPI}}$, **inflation rate** $= \frac{\boldsymbol{CPI-L.CPI}}{\boldsymbol{L.CPI}}$, where SP500 is the S&P 500 Index.

<u>Note:</u> *the Real Stock Returns (rsr) are the difference of the continuously compounded return on the S&P 500 index and the inflation rate.*

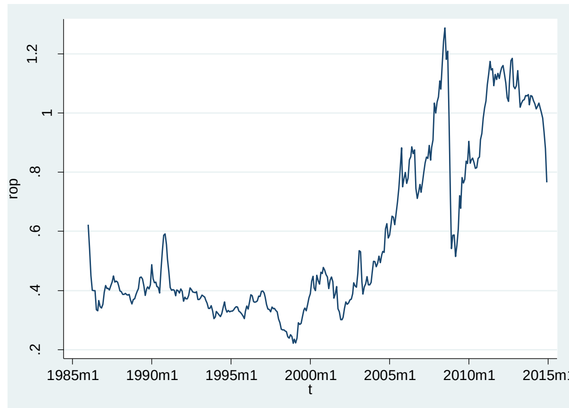
Appendix B

<u>Evolution of each of the variables over time</u>

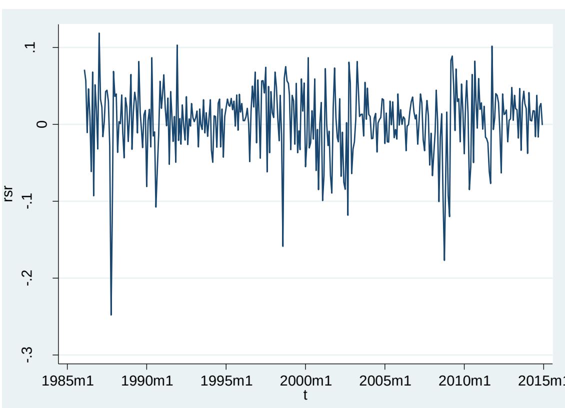
Industrial Production



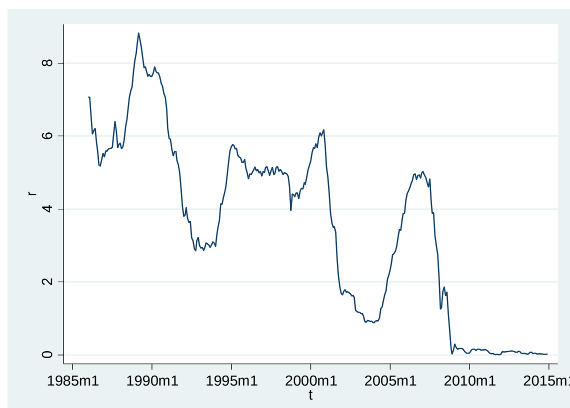
Real Oil Prices



Real Stock Returns

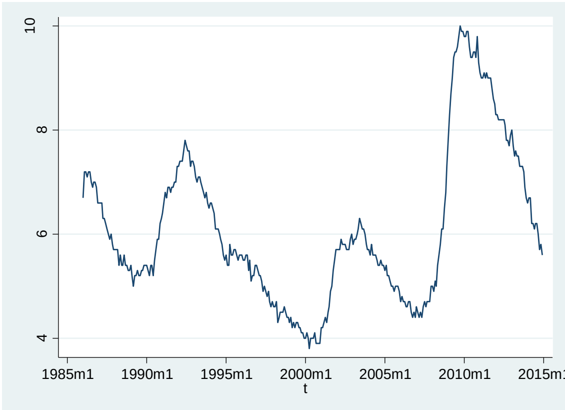


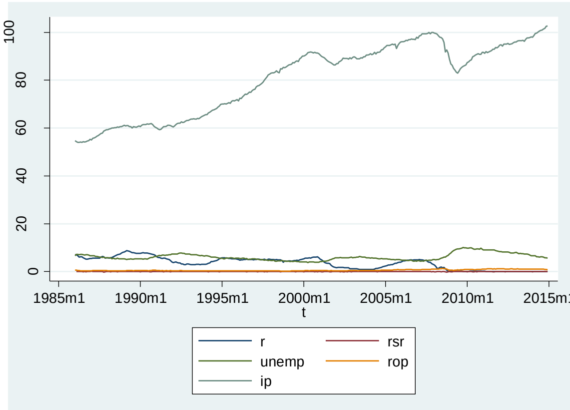
Real Interest Rates



Civilian Unemployment Rate

Co-movement between time series

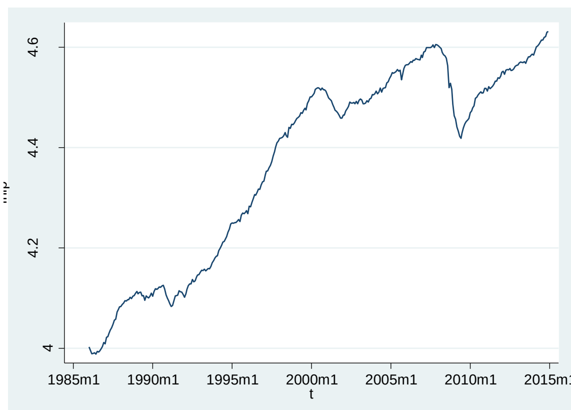


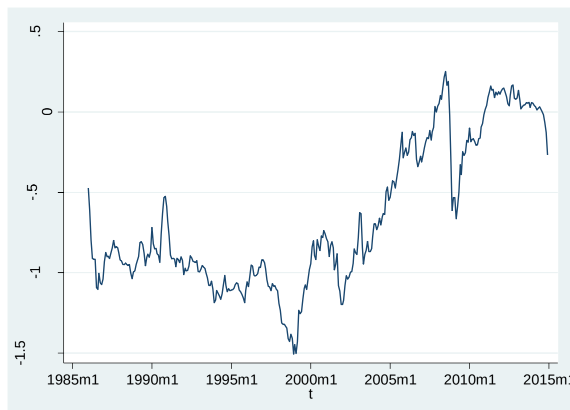


<u>Evolution of the natural logarithms of each of the variables over time</u>

Natural Logarithm of Industrial Production

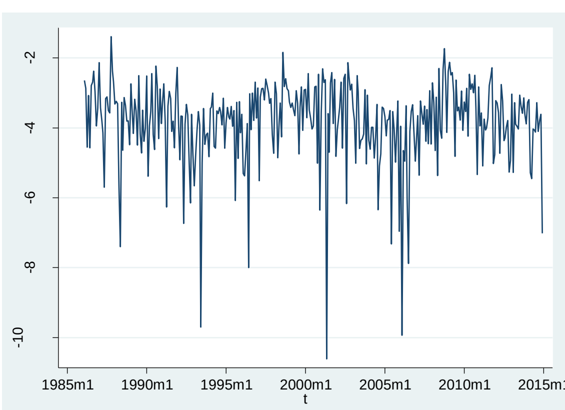
Natural Logarithm of Real Oil Prices

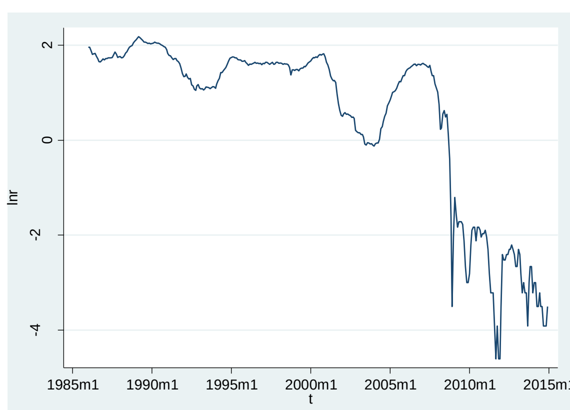




Natural Logarithm of Real Stock Returns

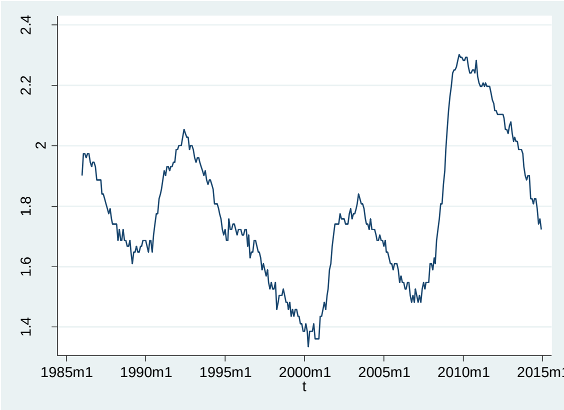
Natural Logarithm of Interest Rates

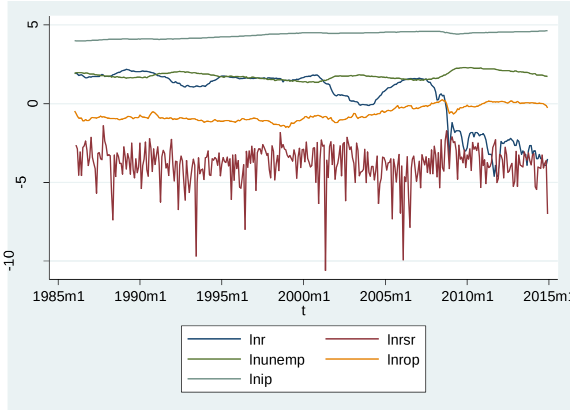




Natural Logarithm of Civilian Unemployment Rate

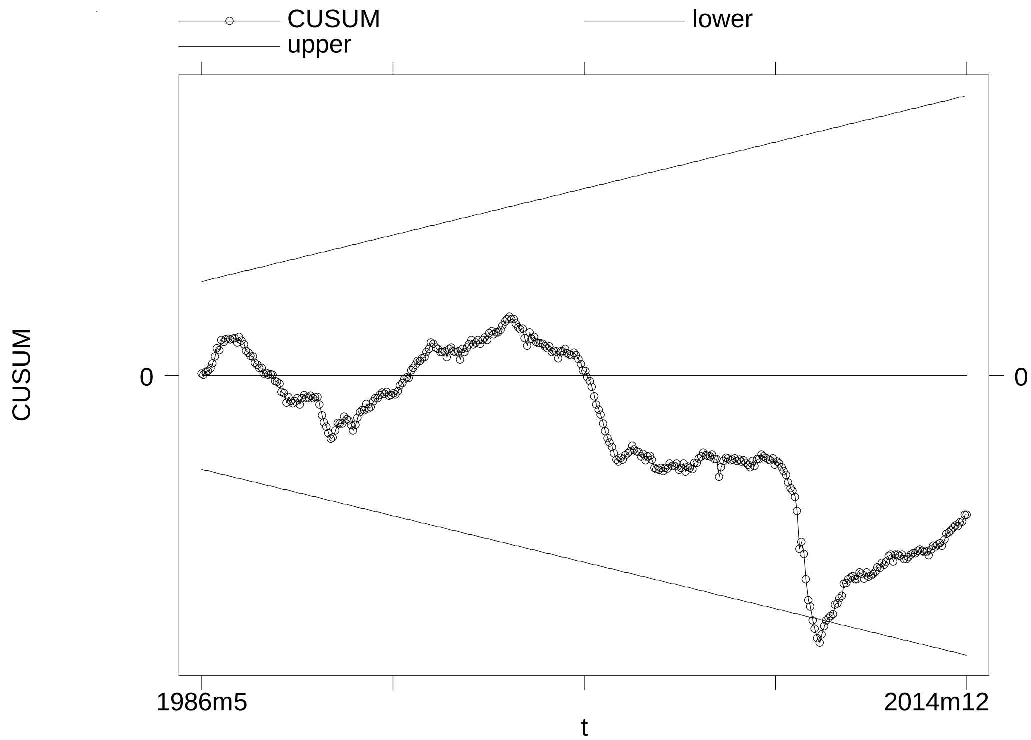
Co-movement between time series

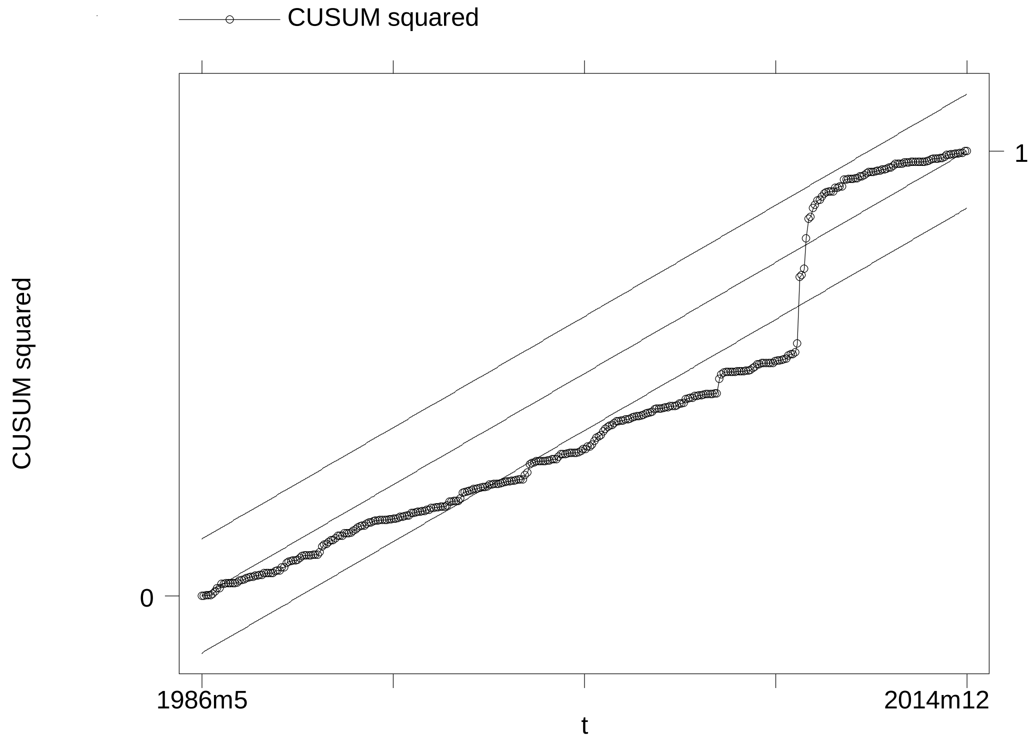




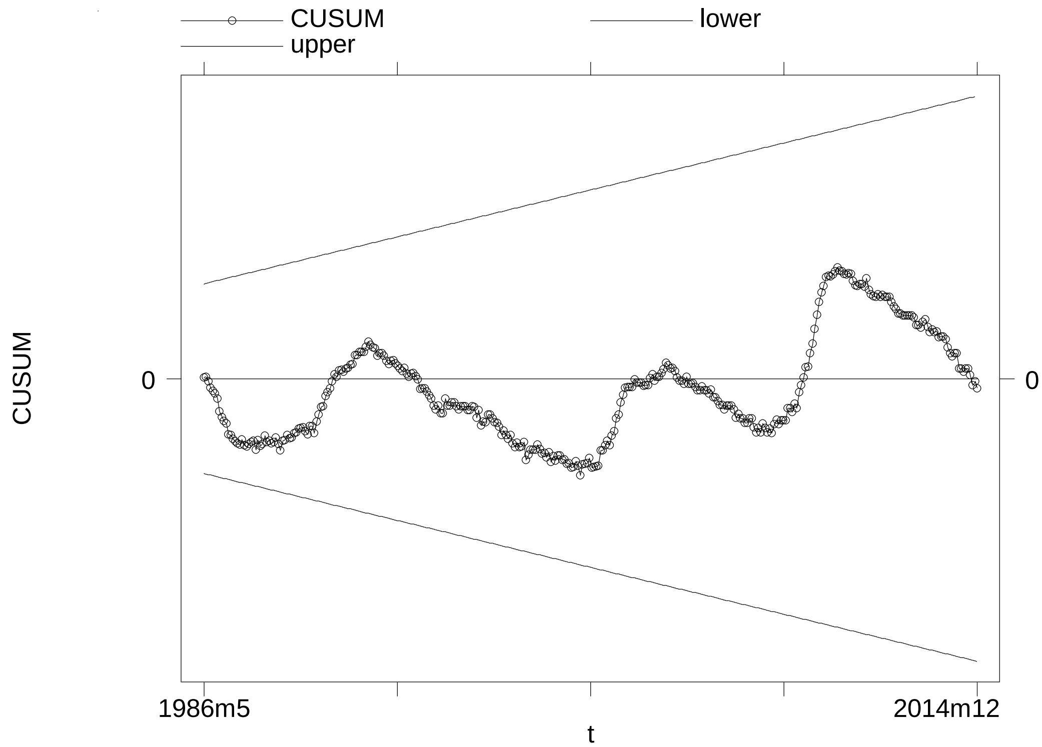
<u>Exogenous Break Test: CUSUM Test</u>

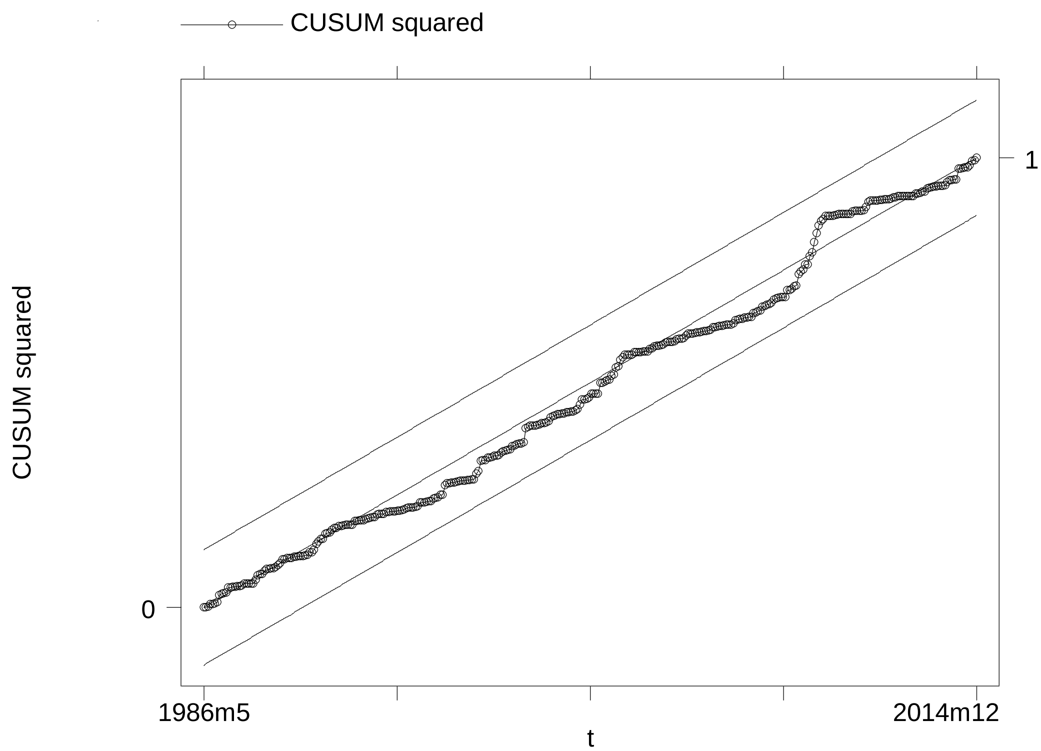
- Industrial Production





- Civilian Unemployment Rate



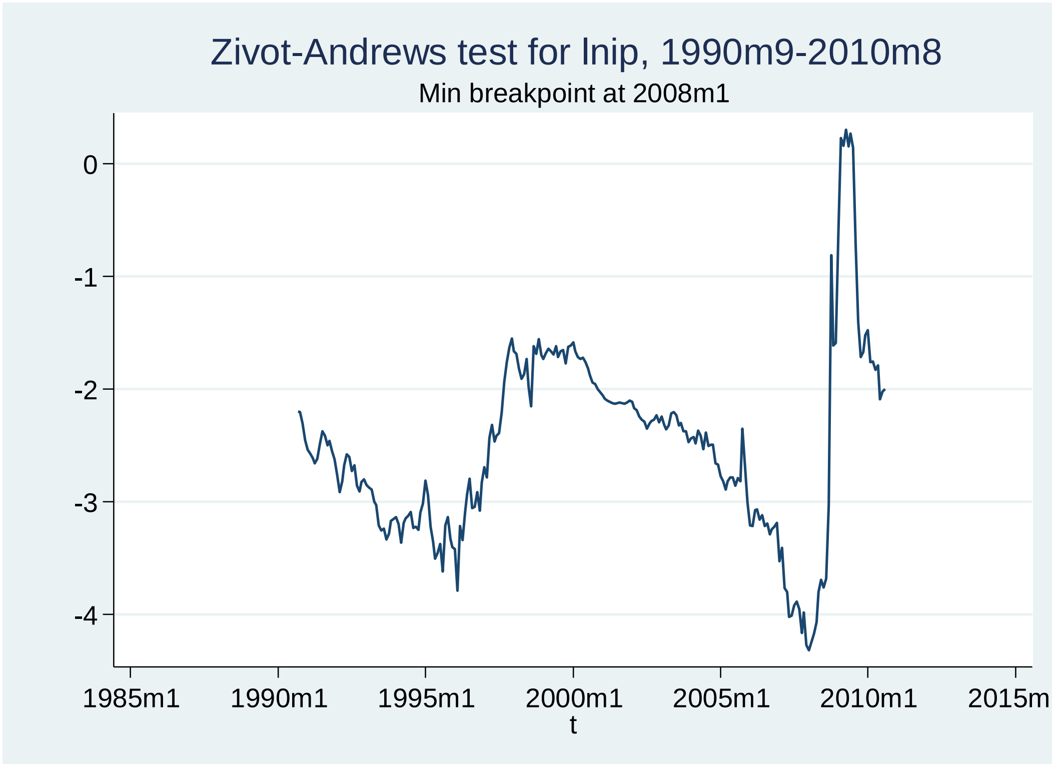


Endogenous Break Test: Zivot-Andrews

- Industrial Production

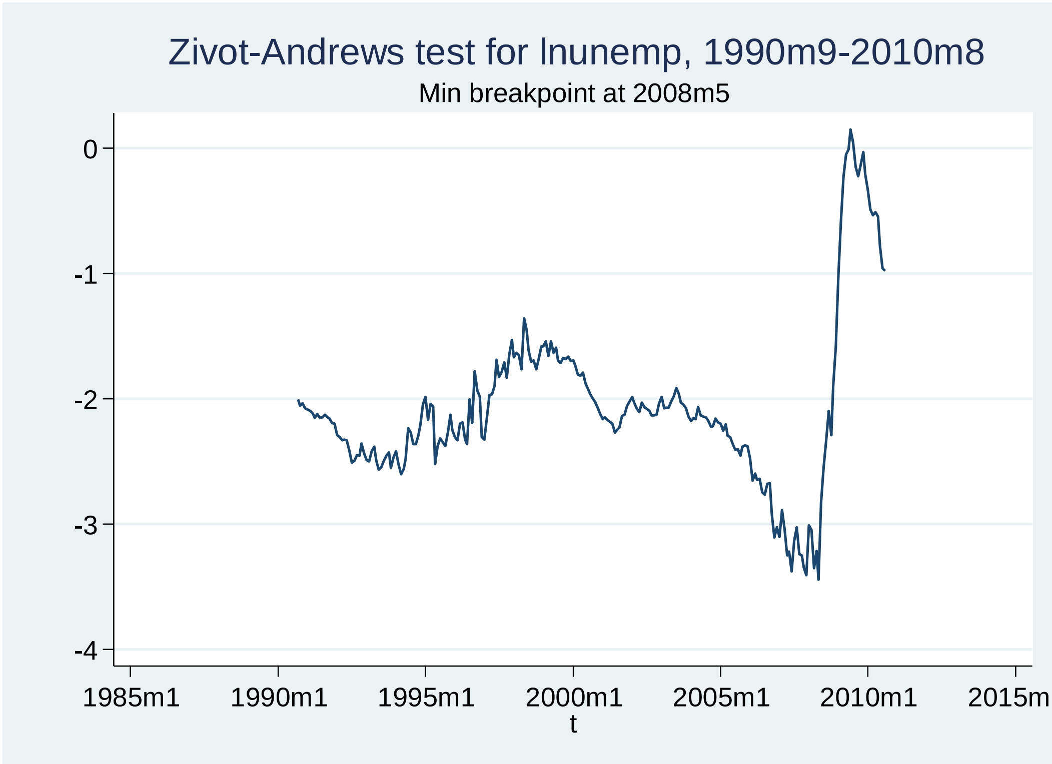
```
. zandrews lnip      /* We fail to reject the null hypothesis of a unit root at 5% Critical Value */

Zivot-Andrews unit root test for  lnip

Allowing for break in intercept

Lag selection via TTest: lags of D.lnip included = 4

Minimum t-statistic -4.321 at 2008m1  (obs 265)

Critical values: 1%: -5.34 5%: -4.80 10%: -4.58
```

```
. zandrews lnip, break(both) trim(0.15)    /* We fail to reject the null hypothesis of a unit root
>  at 5% Critical Value in both intercept and trend */

Zivot-Andrews unit root test for  lnip

Allowing for break in both intercept and trend

Lag selection via TTest: lags of D.lnip included = 4

Minimum t-statistic -4.156 at 1996m2  (obs 122)

Critical values: 1%: -5.57 5%: -5.08 10%: -4.82
```



- Civilian Unemployment Rate

```
. zandrews lnunemp   /* We fail to reject the null hypothesis of a unit root at 5% Critical Value */

Zivot-Andrews unit root test for  lnunemp

Allowing for break in intercept

Lag selection via TTest: lags of D.lnunemp included = 4

Minimum t-statistic -3.442 at 2008m5  (obs 269)

Critical values: 1%: -5.34 5%: -4.80 10%: -4.58

. zandrews lnunemp, break(both) trim(0.15) /* We fail to reject the null hypothesis of a unit root
>  at 5% Critical Value in both intercept and trend */

Zivot-Andrews unit root test for  lnunemp

Allowing for break in both intercept and trend

Lag selection via TTest: lags of D.lnunemp included = 4

Minimum t-statistic -3.820 at 2008m5  (obs 269)

Critical values: 1%: -5.57 5%: -5.08 10%: -4.82
```


Zivot-Andrews test for lnunemp, 1990m9-2010m8
Min breakpoint at 2008m5
0
-1
-2
-3
-4
1985m1
1990m1
1995m1
2000m1
2005m1
2010m1
2015m1
t

Appendix C

Determine the lag length of the model

- Industrial Production

```
. varsoc ip rop r rsr, maxlag(20)                /* 7 lags */

   Selection-order criteria
   Sample:  1987m10 - 2014m12                    Number of obs      =       327
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1390.45				.05944	8.52873	8.54723	8.57509
1	982.586	4746.1	16	0.000	3.3e-08	-5.88737	-5.79488	-5.65557
2	1071.83	178.5	16	0.000	2.1e-08	-6.33537	-6.16888	-5.91813*
3	1107.24	70.805	16	0.000	1.9e-08	-6.45404	-6.21356	-5.85136
4	1140.14	65.818	16	0.000	1.7e-08	-6.55746	-6.24298*	-5.76933
5	1158.45	36.621	16	0.002	1.6e-08	-6.57159	-6.18312	-5.59802
6	1174.35	31.795	16	0.011	1.6e-08	-6.57096	-6.1085	-5.41195
7	1194.09	39.466	16	0.001	1.6e-08*	-6.59379*	-6.05734	-5.24934
8	1205.42	22.671	16	0.123	1.7e-08	-6.56526	-5.95481	-5.03537
9	1214.03	17.213	16	0.372	1.7e-08	-6.52004	-5.8356	-4.80471
10	1226.11	24.163	16	0.086	1.8e-08	-6.49608	-5.73764	-4.5953
11	1239.24	26.26	16	0.050	1.8e-08	-6.47852	-5.64609	-4.3923
12	1246.31	14.145	16	0.588	1.9e-08	-6.42392	-5.51749	-4.15226
13	1258.94	25.261	16	0.065	2.0e-08	-6.40331	-5.42289	-3.94621
14	1271.99	26.097	16	0.053	2.0e-08	-6.38525	-5.33084	-3.74271
15	1282.09	20.205	16	0.211	2.1e-08	-6.34918	-5.22078	-3.5212
16	1291.44	18.691	16	0.285	2.2e-08	-6.30848	-5.10608	-3.29506
17	1305.68	28.49	16	0.028	2.2e-08	-6.29775	-5.02135	-3.09888
18	1324.54	37.71*	16	0.002	2.2e-08	-6.31521	-4.96482	-2.93091
19	1335.44	21.815	16	0.149	2.3e-08	-6.28406	-4.85968	-2.71432
20	1347.18	23.466	16	0.102	2.3e-08	-6.25797	-4.75959	-2.50278

```
   Endogenous:  ip rop r rsr
    Exogenous:  _cons
```

```
. varsoc lnip lnrop lnr lnrsr, maxlag(20)        /* 6 lags */
```

Selection-order criteria
Sample: 1987m10 - 2014m12 Number of obs = 327

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1092.53				.00961	6.70659	6.72509	6.75295
1	1150.48	4486	16	0.000	1.2e-08	-6.91423	-6.82173	-6.68242*
2	1182.5	64.049	16	0.000	1.1e-08	-7.01224	-6.84575*	-6.59499
3	1209.54	54.087	16	0.000	9.9e-09	-7.07978	-6.8393	-6.47709
4	1237.27	55.444	16	0.000	9.2e-09	-7.15147	-6.837	-6.36335
5	1253.96	33.397	16	0.007	9.2e-09	-7.15575	-6.76728	-6.18218
6	1271.45	34.971	16	0.004	9.1e-09*	-7.16483*	-6.70237	-6.00582
7	1286.38	29.867	16	0.019	9.2e-09	-7.15831	-6.62185	-5.81386
8	1300.69	28.605	16	0.027	9.3e-09	-7.14793	-6.53748	-5.61804
9	1310.34	19.304	16	0.253	9.6e-09	-7.1091	-6.42466	-5.39377
10	1321.55	22.427	16	0.130	9.9e-09	-7.07983	-6.32139	-5.17906
11	1334.27	25.439	16	0.062	1.0e-08	-7.05977	-6.22734	-4.97355
12	1342.45	16.351	16	0.429	1.1e-08	-7.01191	-6.10549	-4.74025
13	1358.84	32.78	16	0.008	1.1e-08	-7.0143	-6.03388	-4.5572
14	1370.57	23.465	16	0.102	1.1e-08	-6.9882	-5.93378	-4.34565
15	1379.76	18.389	16	0.302	1.2e-08	-6.94657	-5.81816	-4.11859
16	1394.12	28.704	16	0.026	1.2e-08	-6.93649	-5.73409	-3.92307
17	1400.83	13.425	16	0.641	1.2e-08	-6.87969	-5.60329	-3.68082
18	1413.13	24.603	16	0.077	1.3e-08	-6.85706	-5.50667	-3.47276
19	1421.72	17.19	16	0.373	1.3e-08	-6.81177	-5.38739	-3.24202
20	1445.72	47.981*	16	0.000	1.3e-08	-6.86064	-5.36227	-3.10545

Endogenous: lnip lnrop lnr lnrsr
Exogenous: _cons

- Civilian Unemployment Rate

```
. varsoc unemp rop r rsr, maxlag(20)            /* 2 or 9 lags */

   Selection-order criteria
   Sample:  1987m10 - 2014m12                   Number of obs      =       327

  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 | -694.262                      .000841   4.27072   4.28922   4.31708  |
  |  1 |  1385.76    4160    16  0.000  2.8e-09  -8.35329  -8.26079  -8.12149  |
  |  2 |  1457.55  143.57    16  0.000  2.0e-09  -8.69449    -8.528* -8.27725* |
  |  3 |  1473.33  31.567    16  0.011  2.0e-09  -8.69316  -8.45268  -8.09048  |
  |  4 |  1500.74  54.819    16  0.000  1.8e-09  -8.76295  -8.44847  -7.97482  |
  |  5 |  1515.75  30.018    16  0.018  1.9e-09  -8.75688  -8.36842  -7.78332  |
  |  6 |  1534.19  36.877    16  0.002  1.8e-09   -8.7718  -8.30934  -7.61279  |
  |  7 |  1553.18  37.981    16  0.002  1.8e-09  -8.79009  -8.25364  -7.44564  |
  |  8 |  1566.86   27.37    16  0.038  1.8e-09  -8.77593  -8.16548  -7.24604  |
  |  9 |  1588.43  43.121    16  0.000  1.8e-09* -8.80994*  -8.1255  -7.09461  |
  | 10 |  1604.11  31.368    16  0.012  1.8e-09  -8.80801  -8.04957  -6.90723  |
  | 11 |  1615.69  23.166    16  0.109  1.8e-09  -8.78099  -7.94856  -6.69478  |
  | 12 |  1624.08  16.785    16  0.400  1.9e-09  -8.73446  -7.82804   -6.4628  |
  | 13 |  1638.22  28.268    16  0.029  1.9e-09  -8.72305  -7.74263  -6.26595  |
  | 14 |  1650.59  24.752    16  0.074  2.0e-09  -8.70088  -7.64647  -6.05834  |
  | 15 |  1659.27  17.359    16  0.363  2.1e-09  -8.65611   -7.5277  -5.82813  |
  | 16 |  1670.51  22.474    16  0.129  2.2e-09  -8.62698  -7.42458  -5.61356  |
  | 17 |  1677.81  14.589    16  0.555  2.3e-09  -8.57374  -7.29734  -5.37487  |
  | 18 |  1686.11  16.603    16  0.412  2.4e-09  -8.52665  -7.17626  -5.14234  |
  | 19 |  1699.74  27.266*   16  0.039  2.4e-09  -8.51217  -7.08779  -4.94242  |
  | 20 |  1707.62  15.755    16  0.470  2.6e-09  -8.46249  -6.96412   -4.7073  |
  +---------------------------------------------------------------------------+
   Endogenous:  unemp rop r rsr
    Exogenous:  _cons

. varsoc lnunemp lnrop lnr lnrsr, maxlag(20)      /* 6 lags */

   Selection-order criteria
   Sample:  1987m10 - 2014m12                   Number of obs      =       327

  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 | -1153.21                      .013929   7.07771   7.09621   7.12407  |
  |  1 |  679.574  3665.6    16  0.000  2.1e-07  -4.03409   -3.9416  -3.80229* |
  |  2 |  708.784   58.42    16  0.000  1.9e-07  -4.11489   -3.9484* -3.69764  |
  |  3 |  729.355  41.142    16  0.001  1.9e-07  -4.14284  -3.90236  -3.54016  |
  |  4 |   749.37   40.03    16  0.001  1.8e-07   -4.1674  -3.85293  -3.37927  |
  |  5 |  762.601  26.462    16  0.048  1.9e-07  -4.15046    -3.762   -3.1769  |
  |  6 |  783.049  40.896    16  0.001  1.8e-07* -4.17767* -3.71521  -3.01866  |
  |  7 |  796.344  26.591    16  0.046  1.8e-07  -4.16113  -3.62467  -2.81668  |
  |  8 |  807.015  21.342    16  0.166  1.9e-07  -4.12853  -3.51808  -2.59864  |
  |  9 |  815.703  17.376    16  0.362  2.0e-07  -4.08381  -3.39937  -2.36848  |
  | 10 |  828.163  24.921    16  0.071  2.0e-07  -4.06216  -3.30372  -2.16139  |
  | 11 |  845.049   33.77    16  0.006  2.0e-07  -4.06758  -3.23514  -1.98136  |
  | 12 |  852.135  14.173    16  0.586  2.1e-07  -4.01306  -3.10663   -1.7414  |
  | 13 |  866.252  28.233    16  0.030  2.2e-07  -4.00154  -3.02112  -1.54444  |
  | 14 |  879.016  25.529    16  0.061  2.2e-07  -3.98175  -2.92734  -1.33921  |
  | 15 |  885.206   12.38    16  0.717  2.4e-07  -3.92175  -2.79334  -1.09377  |
  | 16 |  895.256    20.1    16  0.216  2.5e-07  -3.88536  -2.68296  -.871933  |
  | 17 |  901.769  13.025    16  0.671  2.6e-07  -3.82733  -2.55094  -.628465  |
  | 18 |  912.832  22.127    16  0.139  2.7e-07  -3.79714  -2.44675   -.41283  |
  | 19 |  922.489  19.315    16  0.253  2.8e-07  -3.75835  -2.33396  -.188597  |
  | 20 |  946.452  47.925*   16  0.000  2.7e-07  -3.80704  -2.30867  -.051855  |
  +---------------------------------------------------------------------------+
   Endogenous:  lnunemp lnrop lnr lnrsr
    Exogenous:  _cons
```

Rank of Co-integrating Matrix- Johansen maximum likelihood approach

- Industrial Production

```
. vecrank lnip lnrop lnrsr lnr, lag(6) max       /* There is cointegration among
>  the variables */

                       Johansen tests for cointegration
Trend: constant                                         Number of obs =     341
Sample:  1986m8 - 2014m12                                        Lags =       6
-------------------------------------------------------------------------------
                                                         5%
maximum                                      trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0      84      1311.7946           .     52.8622    47.21
    1      91       1328.754     0.09468     18.9434*   29.68
    2      96      1336.8321     0.04627      2.7873    15.41
    3      99      1338.2243     0.00813      0.0029     3.76
    4     100      1338.2257     0.00001
-------------------------------------------------------------------------------
                                                         5%
maximum                                       max     critical
  rank    parms       LL       eigenvalue  statistic    value
    0      84      1311.7946           .     33.9188    27.07
    1      91       1328.754     0.09468     16.1561    20.97
    2      96      1336.8321     0.04627      2.7844    14.07
    3      99      1338.2243     0.00813      0.0029     3.76
    4     100      1338.2257     0.00001
-------------------------------------------------------------------------------

. vecrank lnip lnrop lnrsr lnr, lag(7) max       /* There is cointegration among
> the variables */

                       Johansen tests for cointegration
Trend: constant                                         Number of obs =     340
Sample:  1986m9 - 2014m12                                        Lags =       7
-------------------------------------------------------------------------------
                                                         5%
maximum                                      trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0     100      1322.5116           .     51.8578    47.21
    1     107      1337.7015     0.08548     21.4781*   29.68
    2     112      1346.9493     0.05295      2.9824    15.41
    3     115      1348.4344     0.00870      0.0122     3.76
    4     116      1348.4405     0.00004
-------------------------------------------------------------------------------
                                                         5%
maximum                                       max     critical
  rank    parms       LL       eigenvalue  statistic    value
    0     100      1322.5116           .     30.3798    27.07
    1     107      1337.7015     0.08548     18.4957    20.97
    2     112      1346.9493     0.05295      2.9702    14.07
    3     115      1348.4344     0.00870      0.0122     3.76
    4     116      1348.4405     0.00004
-------------------------------------------------------------------------------
```

- Civilian Unemployment Rate

```
. vecrank lnunemp lnrop lnrsr lnr, lag(6) max    /* There is cointegration among
> the variables */

                       Johansen tests for cointegration
Trend: constant                                         Number of obs =     341
Sample:  1986m8 - 2014m12                                        Lags =       6
-------------------------------------------------------------------------------
                                                         5%
maximum                                      trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0      84      801.46181           .     51.5598    47.21
    1      91      817.37156     0.08909     19.7403*   29.68
    2      96      825.41456     0.04608      3.6543    15.41
    3      99      827.08815     0.00977      0.3071     3.76
    4      100     827.24171     0.00090
-------------------------------------------------------------------------------
                                                         5%
maximum                                       max     critical
  rank    parms       LL       eigenvalue  statistic    value
    0      84      801.46181           .     31.8195    27.07
    1      91      817.37156     0.08909     16.0860    20.97
    2      96      825.41456     0.04608      3.3472    14.07
    3      99      827.08815     0.00977      0.3071     3.76
    4      100     827.24171     0.00090
-------------------------------------------------------------------------------
```

Appendix D

Normality Test

- Industrial Production

```
. vecnorm, jbera    /* We reject the null hypothesis in all cases */

   Jarque-Bera test
```

Equation	chi2	df	Prob > chi2
D_lnip	1041.827	2	0.00000
D_lnrop	16.844	2	0.00022
D_lnr	1723.455	2	0.00000
D_lnrsr	659.553	2	0.00000
ALL	3441.678	8	0.00000

Note: 6 lag VECM

```
. vecnorm, jbera    /* We reject the null hypothesis in all cases */

   Jarque-Bera test
```

Equation	chi2	df	Prob > chi2
D_lnip	787.366	2	0.00000
D_lnrop	13.646	2	0.00109
D_lnr	1848.253	2	0.00000
D_lnrsr	660.728	2	0.00000
ALL	3309.992	8	0.00000

Note: 7 lag VECM

- Civilian Unemployment Rate

```
. vecnorm, jbera    /* We reject the null hypothesis in all cases exc
> ept the first differences of unemployment */

   Jarque-Bera test
```

Equation	chi2	df	Prob > chi2
D_lnunemp	3.112	2	0.21094
D_lnrop	57.484	2	0.00000
D_lnr	3285.366	2	0.00000
D_lnrsr	636.863	2	0.00000
ALL	3982.826	8	0.00000

Note: 6 lag VECM

Lagrange Multiplier Test (LM Test)

- Industrial Production

```
. veclmar     /* We reject the null hypothesis at lag 2 */
```

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	16.0721	16	0.44794
2	30.6518	16	0.01490

H0: no autocorrelation at lag order

Note: 6 lag VECM

```
. veclmar     /* We fail to reject the null hypothesis */
```

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	18.5758	16	0.29127
2	19.1050	16	0.26326

H0: no autocorrelation at lag order

Note: 7 lag VECM

- Civilian Unemployment Rate

```
. veclmar     /* We fail to reject the null hypothesis */
```

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	21.0532	16	0.17648
2	25.3795	16	0.06341

H0: no autocorrelation at lag order

Note: 6 lag VECM

Appendix E

Principal Components Analysis (PCA)

- Industrial Production

```
. correlate lnip lnrop lnrsr lnr
(obs=347)
```

	lnip	lnrop	lnrsr	lnr
lnip	1.0000			
lnrop	0.5950	1.0000		
lnrsr	-0.0400	-0.0572	1.0000	
lnr	-0.5478	-0.7182	-0.0285	1.0000

```
. pca lnip lnrop lnrsr lnr

Principal components/correlation                  Number of obs    =       347
                                                  Number of comp.  =         4
                                                  Trace            =         4
    Rotation: (unrotated = principal)             Rho              =    1.0000
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.24477	1.23984	0.5612	0.5612
Comp2	1.00493	.527887	0.2512	0.8124
Comp3	.477045	.203793	0.1193	0.9317
Comp4	.273252	.	0.0683	1.0000

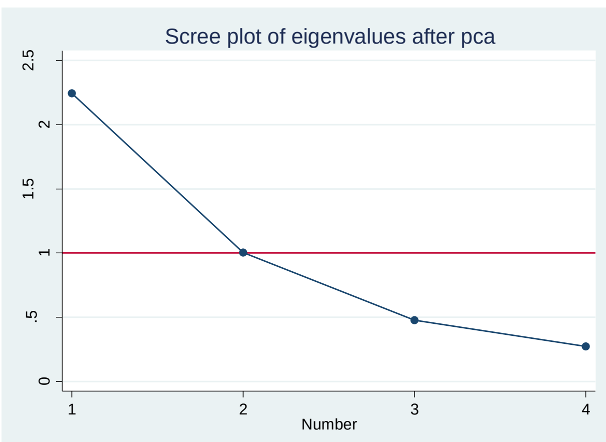
Principal components (eigenvectors)

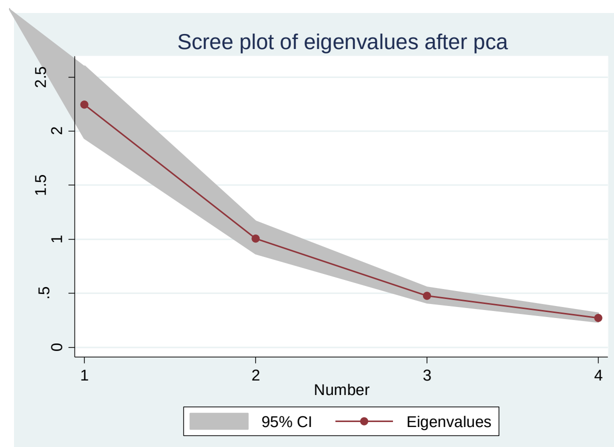
Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
lnip	0.5451	-0.0214	0.8306	-0.1118	0
lnrop	0.5996	-0.0225	-0.2939	0.7441	0
lnrsr	-0.0317	0.9948	0.0570	0.0781	0
lnr	-0.5851	-0.0968	0.4696	0.6540	0

```
. estat kmo                /* We can justify the use of PCA, the correlation is
>  high among variables*/

Kaiser-Meyer-Olkin measure of sampling adequacy
```

Variable	kmo
lnip	0.7991
lnrop	0.6497
lnrsr	0.2152
lnr	0.6695
Overall	0.6893

Scree plots





```
. pca lnip lnrop lnrsr lnr, mineigen(1)

Principal components/correlation                  Number of obs    =       347
                                                  Number of comp.  =         2
                                                  Trace            =         4
    Rotation: (unrotated = principal)             Rho              =    0.8124
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.24477	1.23984	0.5612	0.5612
Comp2	1.00493	.527887	0.2512	0.8124
Comp3	.477045	.203793	0.1193	0.9317
Comp4	.273252	.	0.0683	1.0000

```
Principal components (eigenvectors)
```

Variable	Comp1	Comp2	Unexplained
lnip	0.5451	-0.0214	.3325
lnrop	0.5996	-0.0225	.1925
lnrsr	-0.0317	0.9948	.003214
lnr	-0.5851	-0.0968	.2221

```
. pca lnip lnrop lnrsr lnr, components (1)

Principal components/correlation                  Number of obs    =       347
                                                  Number of comp.  =         1
                                                  Trace            =         4
    Rotation: (unrotated = principal)             Rho              =    0.5612
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.24477	1.23984	0.5612	0.5612
Comp2	1.00493	.527887	0.2512	0.8124
Comp3	.477045	.203793	0.1193	0.9317
Comp4	.273252	.	0.0683	1.0000

```
Principal components (eigenvectors)
```

Variable	Comp1	Unexplained
lnip	0.5451	.333
lnrop	0.5996	.193
lnrsr	-0.0317	.9978
lnr	-0.5851	.2315

- Civilian Unemployment Rate

```
. correlate lnunemp lnrop lnrsr lnr
(obs=347)
```

	lnunemp	lnrop	lnrsr	lnr
lnunemp	1.0000			
lnrop	0.4120	1.0000		
lnrsr	0.0660	-0.0572	1.0000	
lnr	-0.6571	-0.7182	-0.0285	1.0000

```
. pca lnunemp lnrop lnrsr lnr

Principal components/correlation                 Number of obs    =       347
                                                 Number of comp.  =         4
                                                 Trace            =         4
    Rotation: (unrotated = principal)            Rho              =    1.0000
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.20084	1.18327	0.5502	0.5502
Comp2	1.01757	.444105	0.2544	0.8046
Comp3	.57347	.365356	0.1434	0.9480
Comp4	.208114	.	0.0520	1.0000

Principal components (eigenvectors)

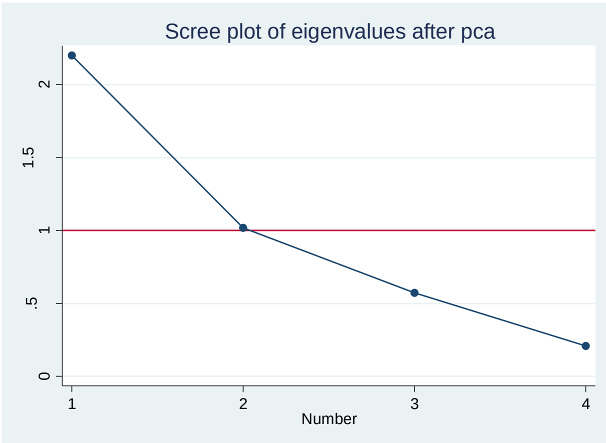
Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
lnunemp	0.5378	0.1263	-0.7448	0.3743	0
lnrop	0.5603	-0.1544	0.6344	0.5097	0
lnrsr	0.0178	0.9799	0.1959	0.0335	0
lnr	-0.6298	-0.0018	-0.0661	0.7740	0

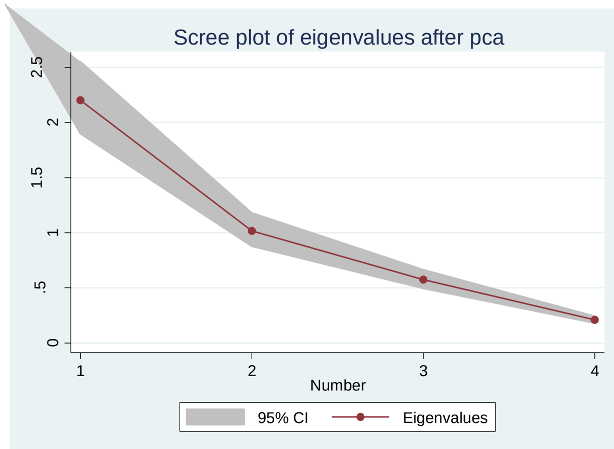
```
. estat kmo                 /* We can justify the use of PCA, the correlation is
>  high among variables*/
```

Kaiser-Meyer-Olkin measure of sampling adequacy

Variable	kmo
lnunemp	0.6447
lnrop	0.6055
lnrsr	0.3372
lnr	0.5589
Overall	0.5926

Scree plots






```
. pca lnunemp lnrop lnrsr lnr, mineigen(1)

Principal components/correlation                 Number of obs    =       347
                                                 Number of comp.  =         2
                                                 Trace            =         4
    Rotation: (unrotated = principal)            Rho              =    0.8046
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.20084	1.18327	0.5502	0.5502
Comp2	1.01757	.444105	0.2544	0.8046
Comp3	.57347	.365356	0.1434	0.9480
Comp4	.208114	.	0.0520	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Unexplained
lnunemp	0.5378	0.1263	.3473
lnrop	0.5603	-0.1544	.2849
lnrsr	0.0178	0.9799	.02224
lnr	-0.6298	-0.0018	.1272

```
. pca lnunemp lnrop lnrsr lnr, components (1)

Principal components/correlation                 Number of obs    =       347
                                                 Number of comp.  =         1
                                                 Trace            =         4
    Rotation: (unrotated = principal)            Rho              =    0.5502
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.20084	1.18327	0.5502	0.5502
Comp2	1.01757	.444105	0.2544	0.8046
Comp3	.57347	.365356	0.1434	0.9480
Comp4	.208114	.	0.0520	1.0000

```
Principal components (eigenvectors)
```

Variable	Comp1	Unexplained
lnunemp	0.5378	.3635
lnrop	0.5603	.3091
lnrsr	0.0178	.9993
lnr	-0.6298	.1272

Factor Analysis

- Industrial Production

```
. factor lnip lnrop lnrsr lnr
(obs=347)

Factor analysis/correlation                      Number of obs    =      347
    Method: principal factors                    Retained factors =        2
    Rotation: (unrotated)                        Number of params =        6
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.75648	1.71781	1.1559	1.1559
Factor2	0.03867	0.13536	0.0254	1.1813
Factor3	-0.09669	0.08213	-0.0636	1.1177
Factor4	-0.17882	.	-0.1177	1.0000

```
    LR test: independent vs. saturated:  chi2(6)  =  422.07 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances
```

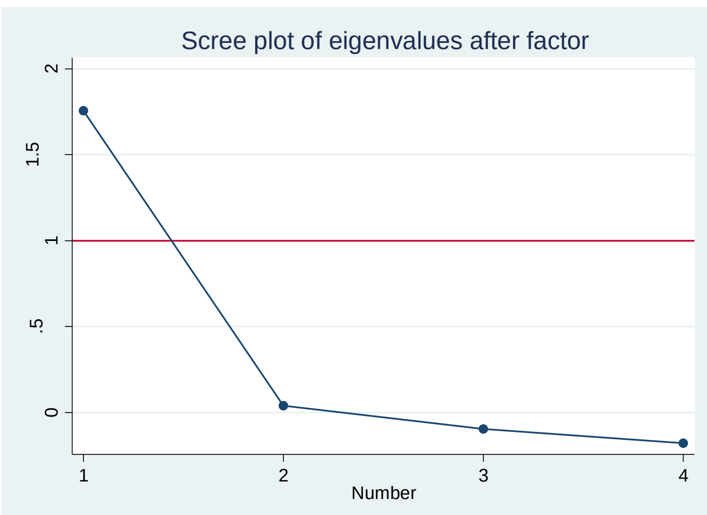
Variable	Factor1	Factor2	Uniqueness
lnip	0.6734	-0.0343	0.5454
lnrop	0.8229	-0.0238	0.3222
lnrsr	-0.0295	0.1823	0.9659
lnr	-0.7905	-0.0608	0.3714

```
. estat kmo                /* We can justify the use of Factor Analysis, the cor
> relation is high among variables*/
```

Kaiser-Meyer-Olkin measure of sampling adequacy

Variable	kmo
lnip	0.7991
lnrop	0.6497
lnrsr	0.2152
lnr	0.6695
Overall	0.6893

Scree plot



```
. factor lnip lnrop lnrsr lnr, mineigen(1)
(obs=347)

Factor analysis/correlation                     Number of obs    =      347
    Method: principal factors                   Retained factors =        1
    Rotation: (unrotated)                       Number of params =        4
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.75648	1.71781	1.1559	1.1559
Factor2	0.03867	0.13536	0.0254	1.1813
Factor3	-0.09669	0.08213	-0.0636	1.1177
Factor4	-0.17882	.	-0.1177	1.0000

```
    LR test: independent vs. saturated:  chi2(6)  =  422.07 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Uniqueness
lnip	0.6734	0.5465
lnrop	0.8229	0.3228
lnrsr	-0.0295	0.9991
lnr	-0.7905	0.3751

- Civilian Unemployment Rate

```
. factor lnunemp lnrop lnrsr lnr
(obs=347)

Factor analysis/correlation                     Number of obs    =      347
    Method: principal factors                   Retained factors =        2
    Rotation: (unrotated)                       Number of params =        6
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.76613	1.63128	1.0654	1.0654
Factor2	0.13485	0.18244	0.0814	1.1468
Factor3	-0.04759	0.14813	-0.0287	1.1181
Factor4	-0.19572	.	-0.1181	1.0000

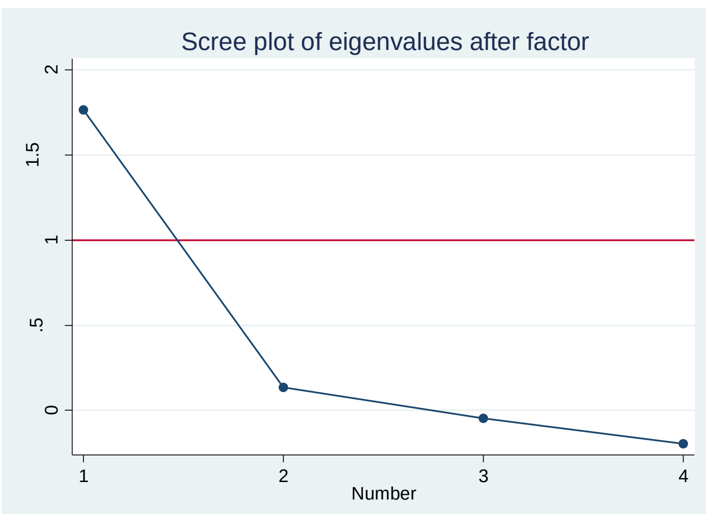
```
    LR test: independent vs. saturated:  chi2(6)  =  454.99 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Uniqueness
lnunemp	0.6672	0.2087	0.5112
lnrop	0.7339	-0.2083	0.4180
lnrsr	0.0156	0.2185	0.9520
lnr	-0.8843	-0.0115	0.2178

```
. estat kmo                 /* We can justify the use of Factor Analysis, the cor
> relation is high among variables*/

Kaiser-Meyer-Olkin measure of sampling adequacy
```

Variable	kmo
lnunemp	0.6447
lnrop	0.6055
lnrsr	0.3372
lnr	0.5589
Overall	0.5926

Scree plot



```
. factor lnunemp lnrop lnrsr lnr, mineigen(1)
(obs=347)

Factor analysis/correlation                        Number of obs    =      347
    Method: principal factors                      Retained factors =        1
    Rotation: (unrotated)                          Number of params =        4
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.76613	1.63128	1.0654	1.0654
Factor2	0.13485	0.18244	0.0814	1.1468
Factor3	-0.04759	0.14813	-0.0287	1.1181
Factor4	-0.19572	.	-0.1181	1.0000

```
    LR test: independent vs. saturated:  chi2(6)  =  454.99 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Uniqueness
lnunemp	0.6672	0.5548
lnrop	0.7339	0.4614
lnrsr	0.0156	0.9998
lnr	-0.8843	0.2179

Appendix F

Stata Code

```
*RELATIONSHIP BETWEEN OIL PRICES, ECONOMIC ACTIVITY, STOCK MARKET ACTIVITY AND UNEMPLOYMENT IN THE USA
*Kimissis Stavros

****************************************************************

*****Set the time frame

generate t=tm(1986m1)+_n-1
format t %tm
sort t
tsset t

****************************************************************

*****Calculate the extra 2 variables needed in my model

*1. Generate the Real Oil Price variable (rop)
generate rop=(ppif/cpi)

*2. Generate the Real Stock Returns Variable (rsr)
generate rsr=ln(sp500/l.sp500)- ((cpi-l.cpi)/l.cpi)

****************************************************************

*****The Real interest rates (r) are measured by the three month t-bill rate (tbill)

generate r=tbill

****************************************************************

*****Generate the natural logarithms of the 5 variables of my model

*1. Natural logarithm of Industrial production (ip)
generate lnip=ln(ip)

*2. Natural logarithm of Real oil prices (rop)
generate lnrop=ln(rop)

*3. Natural logarithm of Real stock returns (rsr)
generate lnrsr=ln(abs(rsr))

*4. Natural logarithm of Real interest rates (r)
generate lnr=ln(r)

*5. Natural logarithm of Civilian unemployment rate (unemp)
generate lnunemp=ln(unemp)

*******************************************************************

*****Generate the first differences of the variables of my model except the Real stock returns (rsr)
```

```
*1. First differences of Industrial  production (ip)
generate dlnip=lnip-l.lnip  /* or generate dlnip=D1.lnip */

*2. First differences of Real oip prices (rop)
generate dlnrop=lnrop-l.lnrop   /* or generate dlnrop=D1.lnrop */

*3. First differences of Real interest rates (r)
generate dlnr=lnr-l.lnr   /* or generate dlnr=D1.lnr */

*4. First differences of Civilian unemployment rate (unemp)
generate dlnunemp=lnunemp-l.lnunemp   /* or generate dlnunemp=D1.lnunemp */

*****************************************************************

*****Genetare the histograms of the variables, their natural logarithms and their first differences (except Real stock returns) of my model

*1. Industrial production (ip) histograms
histogram ip, kdensity normal           /* Does not follow Normal Distribution */
histogram lnip, kdensity normal         /* Does not follow Normal Distribution */
histogram dlnip, kdensity normal        /* Follow Normal Distribution */

*2. Real oil prices (rop) histograms
histogram rop, kdensity normal          /* Does not follow Normal Distribution */
histogram lnrop, kdensity normal        /* Does not follow Normal Distribution */
histogram dlnrop, kdensity normal       /* Follow Normal Distribution */

*3. Real stock returns (rsr) histograms
histogram rsr, kdensity normal          /* Follow Normal Distribution */
histogram lnrsr, kdensity normal        /* Follow Normal Distribution */

*4. Real interest rates (r) histograms
histogram r, kdensity normal            /* Does not follow Normal Distribution */
histogram lnr, kdensity normal          /* Does not follow Normal Distribution */
histogram dlnr, kdensity normal         /* Follow Normal Distribution */

*5. Civilian unemployment rate (unemp) histograms
histogram unemp, kdensity normal        /* Follow Normal Distribution */
histogram lnunemp, kdensity normal      /* Follow Normal Distribution */
histogram dlnunemp, kdensity normal     /* Follow Normal Distribution */

*****************************************************************

*****Genetare the boxplots of the variables, their natural logarithms and their first differences (except Real stock returns) of my model

*1. Industrial production (ip) boxplots
graph box ip                 /* No outliers */
graph box lnip               /* No outliers */
graph box dlnip              /* Lot of outliers */

*2. Real oil prices (rop) boxplots
graph box rop                /* No outliers */
graph box lnrop              /* No outliers */
graph box dlnrop             /* Lot of outliers */
```

```
*3. Real stock returns (rsr) boxplots
graph box rsr                /* Lot of outliers */
graph box lnrsr              /* Lot of outliers */

*4. Real interest rates (r) boxplots
graph box r                  /* No outliers */
graph box lnr                /* Lot of outliers */
graph box dlnr               /* Lot of outliers */

*5. Civilian unemployment rate (unemp) boxplots
graph box unemp              /* No outliers */
graph box lnunemp            /* No outliers */
graph box dlnunemp           /* Lot of outliers */

*******************************************************************

*****Genetare the line graphs of the variables, their natural logarithms and their first differences (except Real stock returns) of my model

*1. Industrial production (ip) line graphs
twoway (line ip t)           /* We can observe a trend */
twoway (line lnip t)         /* We can observe a trend */
twoway (line dlnip t)        /* We cannot observe a trend */

*2. Real oil prices (rop) line graphs
twoway (line rop t)          /* We can observe a trend */
twoway (line lnrop t)        /* We can observe a trend */
twoway (line dlnrop t)       /* We cannot observe a trend */

*3. Real stock returns (rsr) line graphs
twoway (line rsr t)          /* We cannot observe a trend */
twoway (line lnrsr t)        /* We cannot observe a trend */

*4. Real interest rates (r) line graphs
twoway (line r t)            /* We can observe a trend */
twoway (line lnr t)          /* We can observe a trend */
twoway (line dlnr t)         /* We cannot observe a trend */

*5. Civilian unemployment rate (unemp) line graphs
twoway (line unemp t)        /* We cannot observe a trend */
twoway (line lnunemp t)      /* We cannot observe a trend */
twoway (line dlnunemp t)     /* We cannot observe a trend */

*******************************************************************

*****Comovement between time series
twoway (line r rsr unemp rop ip t)
twoway (line lnr lnrsr lnunemp lnrop lnip t)
twoway (line dlnr dlnunemp dlnrop dlnip t)

*******************************************************************

*****Unit Root Tests (Dickey Fuller, Augmented Dickey Fuller, Phillips- Perron)
```

*Dickey Fuller Test (use dfuller command) (Ho: the variable contains a unit root, H1: the variable was generated by a stationary process)

```
dfuller ip          /* We fail to reject the null hypothesis of a unit root */
dfuller rop         /* We fail to reject the null hypothesis of a unit root */
dfuller rsr         /* We reject the null hypothesis of a unit root */
dfuller r           /* We fail to reject the null hypothesis of a unit root */
dfuller unemp       /* We fail to reject the null hypothesis of a unit root */

dfuller lnip        /* We fail to reject the null hypothesis of a unit root */
dfuller lnrop       /* We fail to reject the null hypothesis of a unit root */
dfuller lnrsr       /* We reject the null hypothesis of a unit root */
dfuller lnr         /* We fail to reject the null hypothesis of a unit root */
dfuller lnunemp     /* We fail to reject the null hypothesis of a unit root */

dfuller dlnip       /* We reject the null hypothesis of a unit root */
dfuller dlnrop      /* We reject the null hypothesis of a unit root */
dfuller dlnr        /* We reject the null hypothesis of a unit root */
dfuller dlnunemp    /* We reject the null hypothesis of a unit root */
```

*Augmented Dickey Fuller Test (use dfuller command with lags[.]) (Ho: the variable contains a unit root, H1: the variable was generated by a stationary process)

```
varsoc ip                  /* 4 lags */
dfuller ip, lags(4)        /* We fail to reject the null hypothesis of a unit root */
varsoc rop                 /* 2 lags */
dfuller rop, lags(2)       /* We fail to reject the null hypothesis of a unit root */
varsoc rsr                 /* 1 lag */
dfuller rsr, lags(1)       /* We reject the null hypothesis of a unit root */
varsoc r                   /* 4 lags */
dfuller r, lags(4)         /* We fail to reject the null hypothesis of a unit root */
varsoc unemp               /* 4 lags */
dfuller unemp, lags(4)     /* We fail to reject the null hypothesis of a unit root */

varsoc lnip                /* 4 lags */
dfuller lnip, lags(4)      /* We fail to reject the null hypothesis of a unit root */
varsoc lnrop               /* 2 lags */
dfuller lnrop, lags(2)     /* We fail to reject the null hypothesis of a unit root */
varsoc lnrsr               /* 0 or 4 lags */
dfuller lnrsr              /* We reject the null hypothesis of a unit root */
dfuller lnrsr, lags(4)     /* We reject the null hypothesis of a unit root */
varsoc lnr                 /* 3 lags */
dfuller lnr, lags(3)       /* We fail to reject the null hypothesis of a unit root */
varsoc lnunemp             /* 4 lags */
dfuller lnunemp, lags(4)   /* We fail to reject the null hypothesis of a unit root */

varsoc dlnip               /* 4 lags */
dfuller dlnip, lags(4)     /* We reject the null hypothesis of a unit root */
varsoc dlnrop              /* 1 lag */
dfuller dlnrop, lags(1)    /* We reject the null hypothesis of a unit root */
varsoc dlnr                /* 2 lags */
dfuller dlnr, lags(2)      /* We reject the null hypothesis of a unit root */
varsoc dlnunemp            /* 3 lags */
dfuller dlnunemp, lags(3)  /* We reject the null hypothesis of a unit root */
```

*Phillips-Perron Test (use pperron command) (Ho: the variable contains a unit root, H1: the variable was generated by a stationary process)

pperron ip /* We fail to reject the null hypothesis of a unit root */
pperron rop /* We fail to reject the null hypothesis of a unit root */
pperron rsr /* We reject the null hypothesis of a unit root */
pperron r /* We fail to reject the null hypothesis of a unit root */
pperron unemp /* We fail to reject the null hypothesis of a unit root */

pperron lnip /* We fail to reject the null hypothesis of a unit root */
pperron lnrop /* We fail to reject the null hypothesis of a unit root */
pperron lnrsr /* We reject the null hypothesis of a unit root */
pperron lnr /* We fail to reject the null hypothesis of a unit root */
pperron lnunemp /* We fail to reject the null hypothesis of a unit root */

pperron dlnip /* We reject the null hypothesis of a unit root */
pperron dlnrop /* We reject the null hypothesis of a unit root */
pperron dlnr /* We reject the null hypothesis of a unit root */
pperron dlnunemp /* We reject the null hypothesis of a unit root */

****

*****Zivot Andrews Test_Endogenous Break Test (Installation of zandrews command was needed)

/* zandrews calculates the Zivot-Andrews (JBES 1992) unit root test for a timeseries allowing for one structural break in the series,
which may appear in intercept, trend or both. Various criteria for detecting the structural break are supported,
and the t-statistics calculated for each breakpoint may be graphed. The routine has been modified to work with a single time series from a panel. */

/*(Ho: unit root process without any endogenous structural breaks, H1: trend stationary process with possible structural change occurring at an unknown point in time)*/

/* The test is analogous to a Dickey-Fuller test (dfuller, or the improved version dfgls) in that you are looking to reject the null of a unit root in the process.
In the Z-A test, you allow for a breakpoint in the series (which might mistakenly lead you to conclude that the series is nonstationary,
whereas it could be stationary with a level or trend shift). To reject the null of I(1) you need a large negative t-stat, larger than the critical values
or the null hypothesis of a unit root is rejected if the minimum t-statistic < critical */

zandrews ip /* We reject the null hypothesis of a unit root at 5% Critical Value */ /* Does not follow the other Unit root tests */
zandrews rop /* We reject the null hypothesis of a unit root at 5% Critical Value */ /* Does not follow the other Unit root tests */
zandrews rsr /* We reject the null hypothesis of a unit root at 5% Critical Value */
zandrews r /* We fail to reject the null hypothesis of a unit root at 5% Critical Value */
zandrews unemp /* We fail to reject the null hypothesis of a unit root at 5% Critical Value */

zandrews lnip /* We fail to reject the null hypothesis of a unit root at 5% Critical Value */
zandrews lnrop /* We fail to reject the null hypothesis of a unit root at 5% Critical Value */
zandrews lnrsr /* We reject the null hypothesis of a unit root at 5% Critical Value */
zandrews lnr /* We reject the null hypothesis of a unit root at 5% Critical Value */ /* Does not follow the other Unit root tests */
zandrews lnunemp /* We fail to reject the null hypothesis of a unit root at 5% Critical Value */

zandrews dlnip /* We reject the null hypothesis of a unit root at 5% Critical Value */
zandrews dlnrop /* We reject the null hypothesis of a unit root at 5% Critical Value */
zandrews dlnr /* We reject the null hypothesis of a unit root at 5% Critical Value */
zandrews dlnunemp /* We reject the null hypothesis of a unit root at 5% Critical Value */

zandrews lnip, graph
zandrews lnip, break(both) trim(0.15) /* We fail to reject the null hypothesis of a unit root at 5% Critical Value in both intercept and trend */

zandrews lnunemp, graph
zandrews lnunemp, break(both) trim(0.15) /* We fail to reject the null hypothesis of a unit root at 5% Critical Value in both intercept and trend */

****

*****ARIMA models and model choosing

/* The best ARIMA model is the one that qualifies for the smaller AIC, BIC and SSR or for the most of those criteria */

**Industrial Production

*ARIMA(1,0,0) or AR(1)
arima lnip,arima(1,0,0)
estat ic /* AIC: -2501.815 , BIC: -2490.258 */
predict res_ar100_ip,residuals
gen sr100_ip=(res_ar100_ip)^2
egen sumsr100_ip=sum(sr100_ip)
egen ssr100_ip=rowfirst(sumsr100_ip)
display "SSR="=ssr100_ip /* SSR: 0.11487594 */

*ARIMA(0,0,1) or MA(1)
arima lnip,arima(0,0,1)
estat ic /* AIC: -600.098 , BIC: -588.5414 */
predict res_ar001_ip,residuals
gen sr001_ip=(res_ar001_ip)^2
egen sumsr001_ip=sum(sr001_ip)
egen ssr001_ip=rowfirst(sumsr001_ip)
display "SSR="=ssr001_ip /* SSR: 3.6865618 */

*ARIMA(1,0,1) or AR(1),MA(1)
arima lnip,arima(1,0,1)
estat ic /* AIC: -2518.23 , BIC: -2502.821 */
predict res_ar101_ip,residuals
gen sr101_ip=(res_ar101_ip)^2
egen sumsr101_ip=sum(sr101_ip)
egen ssr101_ip=rowfirst(sumsr101_ip)
display "SSR="=ssr101_ip /* SSR: 0.11495358 */

*ARIMA(2,0,0) or AR(2)
arima lnip,arima(2,0,0)
estat ic /* AIC: -2528.805 , BIC: -2513.397 */
predict res_ar200_ip,residuals
gen sr200_ip=(res_ar200_ip)^2
egen sumsr200_ip=sum(sr200_ip)
egen ssr200_ip=rowfirst(sumsr200_ip)

```
display "SSR="=ssr200_ip                    /* SSR: 0.11568382 */

*ARIMA(0,0,2) or MA(2)
arima lnip,arima(0,0,2)
estat ic                          /* AIC: -1010.873 , BIC: -995.4644 */
predict res_ar002_ip,residuals
gen sr002_ip=(res_ar002_ip)^2
egen sumsr002_ip=sum(sr002_ip)
egen ssr002_ip=rowfirst(sumsr002_ip)
display "SSR="=ssr002_ip                    /* SSR: 1.2350852 */

*ARIMA(2,0,2) or AR(2,MA(2)
arima lnip,arima(2,0,2)
estat ic                          /* AIC: -2593.906 , BIC: -2570.793 */
predict res_ar202_ip,residuals
gen sr202_ip=(res_ar202_ip)^2
egen sumsr202_ip=sum(sr202_ip)
egen ssr202_ip=rowfirst(sumsr202_ip)
display "SSR="=ssr202_ip                    /* SSR: 0.13494086 */

*ARIMA on differenced variable(1,0,0) or AR(1) on differenced variable
*or ARIMA(1,1,0) with lnip
arima dlnip,arima(1,0,0)
estat ic                          /* AIC: -2547.721 , BIC: -2536.173 */
predict res_ar110_ip,residuals
gen sr110_ip=(res_ar110_ip)^2
egen sumsr110_ip=sum(sr110_ip)
egen ssr110_ip=rowfirst(sumsr110_ip)
display "SSR="=ssr110_ip                    /* SSR: 0.01293478 */

*ARIMA on differenced variable(0,0,1) or MA(1) on differenced variable
*or ARIMA(0,1,1) with lnip
arima dlnip,arima(0,0,1)
estat ic                          /* AIC: -2541.82 , BIC: -2530.272 */
predict res_ar011_ip,residuals
gen sr011_ip=(res_ar011_ip)^2
egen sumsr011_ip=sum(sr011_ip)
egen ssr011_ip=rowfirst(sumsr011_ip)
display "SSR="=ssr011_ip                    /* SSR: 0.01315562 */

*ARIMA on differenced variable(1,0,1) or AR(1),MA(1) on differenced variable
*or ARIMA(1,1,1) with lnip
arima dlnip,arima(1,0,1)
estat ic                          /* AIC: -2586.609 , BIC: -2571.212 */
predict res_ar111_ip,residuals
gen sr111_ip=(res_ar111_ip)^2
egen sumsr111_ip=sum(sr111_ip)
egen ssr111_ip=rowfirst(sumsr111_ip)
display "SSR="=ssr111_ip                    /* SSR: 0.01149975 */

*ARIMA on differenced variable(2,0,0) or AR(2) on differenced variable
*or ARIMA(2,1,0) with lnip
arima dlnip,arima(2,0,0)
estat ic                          /* AIC: -2572.497 , BIC: -2557.1 */
predict res_ar210_ip,residuals
gen sr210_ip=(res_ar210_ip)^2
```

```
egen sumsr210_ip=sum(sr210_ip)
egen ssr210_ip=rowfirst(sumsr210_ip)
display "SSR="=ssr210_ip                     /* SSR: 0.01197768 */

*ARIMA on differenced variable(0,0,2) or MA(2) on differenced variable
*or ARIMA(0,1,2) with lnip
arima dlnip,arima(0,0,2)
estat ic                              /* AIC: -2555.065 , BIC: -2539.668 */
predict res_ar012_ip,residuals
gen sr012_ip=(res_ar012_ip)^2
egen sumsr012_ip=sum(sr012_ip)
egen ssr012_ip=rowfirst(sumsr012_ip)
display "SSR="=ssr012_ip                     /* SSR: 0.01259151 */

*ARIMA on differenced variable(2,0,1) or AR(2),MA(1) on differenced variable
*or ARIMA(2,1,1) with lnip
arima dlnip,arima(2,0,1)
estat ic                              /* AIC: -2594.712 , BIC: -2575.466 */
predict res_ar211_ip,residuals
gen sr211_ip=(res_ar211_ip)^2
egen sumsr211_ip=sum(sr211_ip)
egen ssr211_ip=rowfirst(sumsr211_ip)
display "SSR="=ssr211_ip                     /* SSR: 0.01117219 */

*ARIMA on differenced variable(1,0,2) or AR(1),MA(2) on differenced variable
*or ARIMA(1,1,2) with lnip
arima dlnip,arima(1,0,2)
estat ic                              /* AIC: -2599.498 , BIC: -2580.251  */
predict res_ar112_ip,residuals
gen sr112_ip=(res_ar112_ip)^2
egen sumsr112_ip=sum(sr112_ip)
egen ssr112_ip=rowfirst(sumsr112_ip)
display "SSR="=ssr112_ip                    /* SSR: 0.01102052 */

*ARIMA on differenced variable (2,0,2) or AR(2),MA(2) on differenced variable
*or ARIMA(2,1,2) with lnip  (This is the best ARIMA model, it qualifies for the smaller AIC and the smaller SSR,
rather than the other models studied, although BIC is the second smaller)
arima dlnip,arima(2,0,2)
estat ic                             /* AIC: -2601.223 , BIC: -2578.127 */
predict res_ar212_ip,residuals
gen sr212_ip=(res_ar212_ip)^2
egen sumsr212_ip=sum(sr212_ip)
egen ssr212_ip=rowfirst(sumsr212_ip)
display "SSR="=ssr212_ip                    /* SSR: 0.01090168 */

**Civilian Unemployment rate

*ARIMA(1,0,0) or AR(1)
arima lnunemp,arima(1,0,0)
estat ic                             /* AIC: -1536.845 , BIC: -1525.289 */
predict res_ar100_unemp,residuals
gen sr100_unemp=(res_ar100_unemp)^2
egen sumsr100_unemp=sum(sr100_unemp)
egen ssr100_unemp=rowfirst(sumsr100_unemp)
display "SSR="=ssr100_unemp                  /* SSR: 0.25048429 */
```

```
*ARIMA(0,0,1) or MA(1)
arima lnunemp,arima(0,0,1)
estat ic                          /* AIC: -462.2146 , BIC: -450.658 */
predict res_ar001_unemp,residuals
gen sr001_unemp=(res_ar001_unemp)^2
egen sumsr001_unemp=sum(sr001_unemp)
egen ssr001_unemp=rowfirst(sumsr001_unemp)
display "SSR="=ssr001_unemp                 /* SSR: 5.2910523 */

*ARIMA(1,0,1) or AR(1),MA(1)
arima lnunemp,arima(1,0,1)
estat ic                          /* AIC: -1535.175 , BIC: -1519.766 */
predict res_ar101_unemp,residuals
gen sr101_unemp=(res_ar101_unemp)^2
egen sumsr101_unemp=sum(sr101_unemp)
egen ssr101_unemp=rowfirst(sumsr101_unemp)
display "SSR="=ssr101_unemp                 /* SSR: 0.25044751 */

*ARIMA(2,0,0) or AR(2)
arima lnunemp,arima(2,0,0)
estat ic                          /* AIC: -1535.302 , BIC: -1519.893 */
predict res_ar200_unemp,residuals
gen sr200_unemp=(res_ar200_unemp)^2
egen sumsr200_unemp=sum(sr200_unemp)
egen ssr200_unemp=rowfirst(sumsr200_unemp)
display "SSR="=ssr200_unemp                 /* SSR: 0.25043723 */

*ARIMA(0,0,2) or MA(2)
arima lnunemp,arima(0,0,2)
estat ic                          /* AIC: -744.4187 , BIC: -729.0099 */
predict res_ar002_unemp,residuals
gen sr002_unemp=(res_ar002_unemp)^2
egen sumsr002_unemp=sum(sr002_unemp)
egen ssr002_unemp=rowfirst(sumsr002_unemp)
display "SSR="=ssr002_unemp                 /* SSR: 2.3436708 */

*ARIMA(2,0,2) or AR(2,MA(2)  (This is the best ARIMA model, it qualifies for the smaller AIC and the smaller BIC, rather than the other models studied, although SSR is the fourth smaller)
arima lnunemp,arima(2,0,2)
estat ic                          /* AIC: -1593.426 , BIC: -1570.313 */
predict res_ar202_unemp,residuals
gen sr202_unemp=(res_ar202_unemp)^2
egen sumsr202_unemp=sum(sr202_unemp)
egen ssr202_unemp=rowfirst(sumsr202_unemp)
display "SSR="=ssr202_unemp                 /* SSR: 0.21818279 */

*ARIMA on differenced variable(1,0,0) or AR(1) on differenced variable
*or ARIMA(1,1,0) with lnunemp
arima dlnunemp,arima(1,0,0)
estat ic                          /* AIC: -1535.203 , BIC: -1523.656 */
predict res_ar110_unemp,residuals
gen sr110_unemp=(res_ar110_unemp)^2
egen sumsr110_unemp=sum(sr110_unemp)
egen ssr110_unemp=rowfirst(sumsr110_unemp)
display "SSR="=ssr110_unemp                 /* SSR: 0.2392993 */
```

```
*ARIMA on differenced variable(0,0,1) or MA(1) on differenced variable
*or ARIMA(0,1,1) with lnunemp
arima dlnunemp,arima(0,0,1)
estat ic                          /* AIC: -1535.104 , BIC: -1523.556 */
predict res_ar011_unemp,residuals
gen sr011_unemp=(res_ar011_unemp)^2
egen sumsr011_unemp=sum(sr011_unemp)
egen ssr011_unemp=rowfirst(sumsr011_unemp)
display "SSR="=ssr011_unemp                 /* SSR: 0.23936588 */

*ARIMA on differenced variable(1,0,1) or AR(1),MA(1) on differenced variable
*or ARIMA(1,1,1) with lnunemp
arima dlnunemp,arima(1,0,1)
estat ic                          /* AIC: -1565.615 , BIC: -1550.218 */
predict res_ar111_unemp,residuals
gen sr111_unemp=(res_ar111_unemp)^2
egen sumsr111_unemp=sum(sr111_unemp)
egen ssr111_unemp=rowfirst(sumsr111_unemp)
display "SSR="=ssr111_unemp                 /* SSR: 0.21831408 */

*ARIMA on differenced variable(2,0,0) or AR(2) on differenced variable
*or ARIMA(2,1,0) with lnunemp
arima dlnunemp,arima(2,0,0)
estat ic                          /* AIC: -1545.972 , BIC: -1530.575 */
predict res_ar210_unemp,residuals
gen sr210_unemp=(res_ar210_unemp)^2
egen sumsr210_unemp=sum(sr210_unemp)
egen ssr210_unemp=rowfirst(sumsr210_unemp)
display "SSR="=ssr210_unemp                 /* SSR: 0.23079783 */

*ARIMA on differenced variable(0,0,2) or MA(2) on differenced variable
*or ARIMA(0,1,2) with lnunemp
arima dlnunemp,arima(0,0,2)
estat ic                          /* AIC: -1544.822 , BIC: -1529.425 */
predict res_ar012_unemp,residuals
gen sr012_unemp=(res_ar012_unemp)^2
egen sumsr012_unemp=sum(sr012_unemp)
egen ssr012_unemp=rowfirst(sumsr012_unemp)
display "SSR="=ssr012_unemp                 /* SSR: 0.23155273 */

*ARIMA on differenced variable(2,0,1) or AR(2),MA(1) on differenced variable
*or ARIMA(2,1,1) with lnunemp
arima dlnunemp,arima(2,0,1)
estat ic                          /* AIC: -1579.912 , BIC: -1560.666 */
predict res_ar211_unemp,residuals
gen sr211_unemp=(res_ar211_unemp)^2
egen sumsr211_unemp=sum(sr211_unemp)
egen ssr211_unemp=rowfirst(sumsr211_unemp)
display "SSR="=ssr211_unemp                 /* SSR: 0.20848477 */

*ARIMA on differenced variable(1,0,2) or AR(1),MA(2) on differenced variable
*or ARIMA(1,1,2) with lnunemp
arima dlnunemp,arima(1,0,2)
estat ic                          /* AIC: -1584.056 , BIC: -1564.809 */
predict res_ar112_unemp,residuals
gen sr112_unemp=(res_ar112_unemp)^2
```

```
egen sumsr112_unemp=sum(sr112_unemp)
egen ssr112_unemp=rowfirst(sumsr112_unemp)
display "SSR="=ssr112_unemp                    /* SSR: 0.20608157 */

*ARIMA on differenced variable (2,0,2) or AR(2),MA(2) on differenced variable
*or ARIMA(2,1,2) with lnunemp
arima dlnunemp,arima(2,0,2)
estat ic                              /* AIC: -1585.227 , BIC: -1562.131 */
predict res_ar212_unemp,residuals
gen sr212_unemp=(res_ar212_unemp)^2
egen sumsr212_unemp=sum(sr212_unemp)
egen ssr212_unemp=rowfirst(sumsr212_unemp)
display "SSR="=ssr212_unemp                    /* SSR: 0.20417899 */

******************************************************************

*****CUSUM6 Test (Installation of cusum6 command was needed)

*Industrial Production

regress lnip l.lnip
cusum6 lnip l.lnip, cs(cusum) lw(lower) uw(upper)

*Civilian Unemployment Rate

regress lnunemp l.lnunemp
cusum6 lnunemp l.lnunemp, cs(cusum) lw(lower) uw(upper)

******************************************************************

*****Choose the number of lags in our model

*Industrial Production

varsoc ip rop r rsr, maxlag(20)              /* 7 lags */
varsoc lnip lnrop lnr lnrsr, maxlag(20)        /* 6 lags */

*Civilian Unemployment Rate

varsoc unemp rop r rsr, maxlag(20)             /* 2 or 9 lags */
varsoc lnunemp lnrop lnr lnrsr, maxlag(20)      /* 6 lags */

******************************************************************

*****Rank of Cointegrating Matrix- Johansen maximum likelihood approach

/* In Johansen Test of Cointegration variables must be non-stationary at level but when i convert them into first differenced they must be stationary */

/* Ho: We have zero rank and no Cointegration, H1: We have one rank or more and there is Cointegration */

/* If trace stastistics > 5% critical value we reject the null hypothesis */

/* If max statistics > 5% critical value we reject the null hypothesis */

*Industrial Production
```

vecrank lnip lnrop lnrsr lnr, lag(16) max /* There is no cointegration among the variables */
vecrank lnip lnrop lnrsr lnr, lag(12) max /* There is no cointegration among the variables */
vecrank lnip lnrop lnrsr lnr, lag(8) max /* There is no cointegration among the variables */
vecrank lnip lnrop lnrsr lnr, lag(7) max /* There is cointegration among the variables */
vecrank lnip lnrop lnrsr lnr, lag(6) max /* There is cointegration among the variables */
vecrank lnip lnrop lnrsr lnr, lag(4) max /* There is cointegration among the variables */
vecrank lnip lnrop lnrsr lnr, max /* There is cointegration among the variables */

*Civilian Unemployment Rate

vecrank lnunemp lnrop lnrsr lnr, lag(25) max /* There is no cointegration among the variables */
vecrank lnunemp lnrop lnrsr lnr, lag(24) max /* There is cointegration among the variables */
vecrank lnunemp lnrop lnrsr lnr, lag(16) max /* There is cointegration among the variables */
vecrank lnunemp lnrop lnrsr lnr, lag(12) max /* There is cointegration among the variables */
vecrank lnunemp lnrop lnrsr lnr, lag(6) max /* There is cointegration among the variables */
vecrank lnunemp lnrop lnrsr lnr, lag(4) max /* There is cointegration among the variables */
vecrank lnunemp lnrop lnrsr lnr, max /* There is cointegration among the variables */

*Note: If we find that there is no cointegration among the variables we follow a VAR model (Apendix). If we find that there is cointegration among the variables we follow a VEC model.

****

*****VECM
/* If we have negative error correction term (coefficient of cointegrated equation) and P>z less than 5% (or error correction term is signifficant) then we have long run causality.*/

*Industrial Productions

vec lnip lnrop lnr lnrsr,lags(4)
vec lnip lnrop lnr lnrsr,lags(5)
vec lnip lnrop lnr lnrsr,lags(6) /* There is long run causality */
vec lnip lnrop lnr lnrsr,lags(7)

*Civilian Unemployment Rate

vec lnunemp lnrop lnr lnrsr,lags(4)
vec lnunemp lnrop lnr lnrsr,lags(6)
vec lnunemp lnrop lnr lnrsr,lags(7)
vec lnunemp lnrop lnr lnrsr,lags(8) /* There is long run causality */

****

*****VECM with restrictions
/* Ho: There is no long/short run causality from the independent variable to the dependent */

**Industrial Production

vec lnip lnrop lnr lnrsr,lags(4)
test ([D_lnip]: LD.lnrop L2D.lnrop L3D.lnrop) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnip]: LD.lnr L2D.lnr L3D.lnr) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnip]: LD.lnrsr L2D.lnrsr L3D.lnrsr) /* There is no short run causality from the independent variable to the dependent */

vec lnip lnrop lnr lnrsr,lags(5)
test ([D_lnip]: LD.lnrop L2D.lnrop L3D.lnrop L4D.lnrop) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnip]: LD.lnr L2D.lnr L3D.lnr L4D.lnr) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnip]: LD.lnrsr L2D.lnrsr L3D.lnrsr L4D.lnrsr) /* There is no short run causality from the independent variable to the dependent */

vec lnip lnrop lnr lnrsr,lags(6)
test ([D_lnip]: LD.lnrop L2D.lnrop L3D.lnrop L4D.lnrop L5D.lnrop) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnip]: LD.lnr L2D.lnr L3D.lnr L4D.lnr L5D.lnr) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnip]: LD.lnrsr L2D.lnrsr L3D.lnrsr L4D.lnrsr L5D.lnrsr) /* There is no short run causality from the independent variable to the dependent */

vec lnip lnrop lnr lnrsr,lags(7)
test ([D_lnip]: LD.lnrop L2D.lnrop L3D.lnrop L4D.lnrop L5D.lnrop L6D.lnrop) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnip]: LD.lnr L2D.lnr L3D.lnr L4D.lnr L5D.lnr L6D.lnr) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnip]: LD.lnrsr L2D.lnrsr L3D.lnrsr L4D.lnrsr L5D.lnrsr L6D.lnrsr) /* There is no short run causality from the independent variable to the dependent */

**Civilian unemployment rate

vec lnunemp lnrop lnr lnrsr,lags(4)
test ([D_lnunemp]: LD.lnrop L2D.lnrop L3D.lnrop) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnunemp]: LD.lnr L2D.lnr L3D.lnr) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnunemp]: LD.lnrsr L2D.lnrsr L3D.lnrsr) /* There is no short run causality from the independent variable to the dependent */

vec lnunemp lnrop lnr lnrsr,lags(6)
test ([D_lnunemp]: LD.lnrop L2D.lnrop L3D.lnrop L4D.lnrop L5D.lnrop) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnunemp]: LD.lnr L2D.lnr L3D.lnr L4D.lnr L5D.lnr) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnunemp]: LD.lnrsr L2D.lnrsr L3D.lnrsr L4D.lnrsr L5D.lnrsr) /* There is no short run causality from the independent variable to the dependent */

vec lnunemp lnrop lnr lnrsr,lags(7)
test ([D_lnunemp]: LD.lnrop L2D.lnrop L3D.lnrop L4D.lnrop L5D.lnrop L6D.lnrop) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnunemp]: LD.lnr L2D.lnr L3D.lnr L4D.lnr L5D.lnr L6D.lnr) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnunemp]: LD.lnrsr L2D.lnrsr L3D.lnrsr L4D.lnrsr L5D.lnrsr L6D.lnrsr) /* There is no short run causality from the independent variable to the dependent */

vec lnunemp lnrop lnr lnrsr,lags(8)
test ([D_lnunemp]: LD.lnrop L2D.lnrop L3D.lnrop L4D.lnrop L5D.lnrop L6D.lnrop L7D.lnrop) /* There is no short run causality from the independent variable to the dependent */
test ([D_lnunemp]: LD.lnr L2D.lnr L3D.lnr L4D.lnr L5D.lnr L6D.lnr L7D.lnr) /* There is no short run causality from the independent variable to the dependent */

test ([D_lnunemp]: LD.lnrsr L2D.lnrsr L3D.lnrsr L4D.lnrsr L5D.lnrsr L6D.lnrsr L7D.lnrsr)   /* There is no short run causality from the independent variable to the dependent */

****

*****Lagrange Multiplier Test (LM test) (check if there is serial correlation problem or not)
/* Ho: There is no autocorrelation at lag order */

*Industrial Productions

vec lnip lnrop lnr lnrsr,lags(4)
veclmar   /* We reject the null hypothesis at lag 2 */

vec lnip lnrop lnr lnrsr,lags(5)
veclmar   /* We reject the null hypothesis at lag 1 */

vec lnip lnrop lnr lnrsr,lags(6)
veclmar   /* We reject the null hypothesis at lag 2 */

vec lnip lnrop lnr lnrsr,lags(7)
veclmar   /* We fail to reject the null hypothesis */

*Civilian Unemployment Rate

vec lnunemp lnrop lnr lnrsr,lags(4)
veclmar   /* We reject the null hypothesis at lag 2 */

vec lnunemp lnrop lnr lnrsr,lags(5)
veclmar   /* We reject the null hypothesis */

vec lnunemp lnrop lnr lnrsr,lags(6)
veclmar   /* We fail to reject the null hypothesis */

vec lnunemp lnrop lnr lnrsr,lags(7)
veclmar   /* We fail to reject the null hypothesis */

****

*****Normality Test (check if the residuals are normaly distributed or not)
/* Ho: residuals are normaly distributed */

*Industrial Productions

vec lnip lnrop lnr lnrsr,lags(4)
vecnorm, jbera   /* We reject the null hypothesis in all cases */

vec lnip lnrop lnr lnrsr,lags(5)
vecnorm, jbera   /* We reject the null hypothesis in all cases */

vec lnip lnrop lnr lnrsr,lags(6)
vecnorm, jbera   /* We reject the null hypothesis in all cases */

vec lnip lnrop lnr lnrsr,lags(7)
vecnorm, jbera   /* We reject the null hypothesis in all cases */

*Civilian Unemployment Rate

```
vec lnunemp lnrop lnr lnrsr,lags(4)
vecnorm, jbera    /* We reject the null hypothesis in all cases except the first differences of unemployment */

vec lnunemp lnrop lnr lnrsr,lags(5)
vecnorm, jbera    /* We reject the null hypothesis in all cases except the first differences of unemployment */

vec lnunemp lnrop lnr lnrsr,lags(6)
vecnorm, jbera    /* We reject the null hypothesis in all cases except the first differences of unemployment */

vec lnunemp lnrop lnr lnrsr,lags(7)
vecnorm, jbera    /* We reject the null hypothesis in all cases except the first differences of unemployment */

******************************************************************

*****Forecast

*Industrial Production

vec lnip lnrop lnr lnrsr if t<tm(1995m1)
fcast compute y1_, step(300)
fcast graph y1_lnip y1_lnrop y1_lnrsr y1_lnr, observed

*Civilian Unemployment Rate

vec lnunemp lnrop lnr lnrsr if t<tm(1995m1)
fcast compute y2_, step(300)
fcast graph y2_lnunemp y2_lnrop y2_lnrsr y2_lnr, observed

******************************************************************

*****Impulse Responses

*Industrial Production

vec lnip lnrop lnr lnrsr,lags(7)
irf set, clear
irf set results1,replace
irf create asympt_ip, step(20) set(results1)
irf graph irf
irf graph irf, impulse(lnrsr) response(lnip)
irf graph oirf, impulse(lnrsr) response(lnip)
irf table oirf, impulse(lnrsr) response(lnip)

*Civilian Unempoyment Rate

vec lnunemp lnrop lnr lnrsr,lags(6)
irf set, clear
irf set results2,replace
irf create asympt_unemp, step(20) set(results2)
irf graph irf
irf graph oirf, impulse(lnrsr) response(lnunemp)
irf table oirf, impulse(lnrsr) response(lnunemp)

******************************************************************
```

```
*****PCA Analysis

*Industrial Production

correlate lnip lnrop lnrsr lnr
summarize lnip lnrop lnrsr lnr
pca lnip lnrop lnrsr lnr
screeplot
screeplot, yline(1)      /* Only components 1 and 2 has eingenvalue above one */
screeplot, ci

pca lnip lnrop lnrsr lnr, mineigen(1)
pca lnip lnrop lnrsr lnr, components (1)
pca lnip lnrop lnrsr lnr, components (1) blanks(.3)
estat loadings
predict pc1_ip
estat kmo               /* We can justify the use of PCA, the correlation is high among variables*/

*Civilian Unemployment Rate

correlate lnunemp lnrop lnrsr lnr
summarize lnunemp lnrop lnrsr lnr
pca lnunemp lnrop lnrsr lnr
screeplot
screeplot, yline(1)      /* Only component 1 and 2 has eingenvalue above one */
screeplot, ci

pca lnunemp lnrop lnrsr lnr, mineigen(1)
pca lnunemp lnrop lnrsr lnr, components (1)
pca lnunemp lnrop lnrsr lnr, components (1) blanks(.3)
estat loadings
predict pc1_unemp
estat kmo               /* We can justify the use of PCA, the correlation is high among variables*/

****************************************************************

*****Factor Analysis

*Industrial Production

factor lnip lnrop lnrsr lnr
screeplot
screeplot, yline(1)      /* Only factor 1 has eingenvalue above one */

factor lnip lnrop lnrsr lnr, mineigen(1)
factor lnip lnrop lnrsr lnr, factor (1)
factor lnip lnrop lnrsr lnr, factor (1) blanks(.3)
predict factor1_ip
estat kmo              /* We can justify the use of Factor Analysis, the correlation is high among variables*/

*Civilian Unempoyment Rate

factor lnunemp lnrop lnrsr lnr
screeplot
screeplot, yline(1)      /* Only factor 1 has eingenvalue above one */
```

```
factor lnunemp lnrop lnrsr lnr, mineigen(1)
factor lnunemp lnrop lnrsr lnr, factor (1)
factor lnunemp lnrop lnrsr lnr, factor (1) blanks(.3)
predict factor1_unemp
estat kmo		/* We can justify the use of Factor Analysis, the correlation is high among variables*/

*******************************************************************
*******************************************************************
*******************************************************************
*******************************************************************
*******************************************************************

*****Appendix Material*****

*****Genetare the Correlograms of the variables, their natural logarithms and their first differences (except Real stock returns) of my model

corrgram ip, lag(12)
ac ip
pac ip
corrgram rop, lag(12)
ac rop
pac rop
corrgram rsr, lag(12)
ac rsr
pac rsr
corrgram r, lag(12)
ac r
pac r
corrgram unemp, lag(12)
ac unemp
pac unemp

corrgram lnip, lag(12)
ac lnip
pac lnip
corrgram lnrop, lag(12)
ac lnrop
pac lnrop
corrgram lnrsr, lag(12)
ac lnrsr
pac lnrsr
corrgram lnr, lag(12)
ac lnr
pac lnr
corrgram lnunemp, lag(12)
ac lnunemp
pac lnunemp

corrgram dlnip, lag(12)
ac dlnip
pac dlnip
corrgram dlnrop, lag(12)
ac dlnrop
pac dlnrop
corrgram dlnr, lag(12)
```

```
ac dlnr
pac dlnr
corrgram dlnunemp, lag(12)
ac dlnunemp
pac dlnunemp

**********************************************************************

*****HP Filter Decomposition (Installation of hprescott command was needed)

hprescott lnip,stub(ip)
twoway line ip_lnip_1 t, title(" ip - HP Cyclical Component") ytitle("lnip")
twoway line ip_lnip_sm_1 t, title(" ip - HP Trend Component") ytitle("lnip")
twoway line lnip ip_lnip_sm_1 t, title(" ip - HP Trend Component") ytitle("lnip")

hprescott lnrop,stub(rop)
twoway line rop_lnrop_1 t, title(" rop - HP Cyclical Component") ytitle("lnrop")
twoway line rop_lnrop_sm_1 t, title(" rop - HP Trend Component") ytitle("lnrop")
twoway line lnrop rop_lnrop_sm_1 t, title(" rop - HP Trend Component") ytitle("lnrop")

hprescott lnunemp,stub(unemp)
twoway line unemp_lnunemp_1 t, title(" unemp - HP Cyclical Component") ytitle("lnunemp")
twoway line unemp_lnunemp_sm_1 t, title(" unemp - HP Trend Component") ytitle("lnunemp")
twoway line lnunemp unemp_lnunemp_sm_1 t, title(" unemp - HP Trend Component") ytitle("lnunemp")

**********************************************************************

*****BN Decomposition (Beveridge-Nelson Decomposition)

*Generate Cyclical Component
generate cycle=(0.72)*res_ar212
*Generate Trend Component
generate trend=lnip-cycle
twoway line lnip trend t, title("BN TR Component")
twoway line cycle t, title("BN Cyclical Component")
twoway (line cycle trend lnip t), title("BN Decomposition")

**********************************************************************

*****Estimate an Unrestricted VAR & Co-Integration Analysis

*Generate seasonal dummies for each 3-month period of the year

generate dummy1=0
replace dummy1=1 in 1
replace dummy1=1 if (dummy1[_n-4]==1)

generate dummy2=0
replace dummy2=1 in 2
replace dummy2=1 if (dummy2[_n-4]==1)

generate dummy3=0
replace dummy3=1 in 3
replace dummy3=1 if (dummy3[_n-4]==1)

generate dummy4=0
```

```
replace dummy4=1 in 4
replace dummy4=1 if (dummy4[_n-4]==1)

*Test the Lag Length_Model with industrial production

varsoc lnip lnrop lnrsr lnr, exog(dummy1 dummy2 dummy3)                /* 4 lags */
varsoc lnip lnrop lnrsr lnr, maxlag(20) exog(dummy1 dummy2 dummy3)       /* 6 lags */
varsoc lnip lnrop lnrsr lnr, maxlag(20)                                  /* 6 lags */

*Test the Lag Length_Model with unemployment

varsoc lnunemp lnrop lnrsr lnr, exog(dummy1 dummy2 dummy3)               /* 4 lags */
varsoc lnunemp lnrop lnrsr lnr, maxlag(20) exog(dummy1 dummy2 dummy3)    /* 6 lags */
varsoc lnunemp lnrop lnrsr lnr, maxlag(20)                               /* 6 lags */

*Estimate with 6 lags the Unrestricted VAR_Model with industrial production

var lnip lnrop lnrsr lnr, lags(6) exog(dummy2 dummy3 dummy4)

*Estimate with 6 lags the Unrestricted VAR_Model with unemployment

var lnunemp lnrop lnrsr lnr, lags(6) exog(dummy1 dummy2 dummy3)

**********************************************************************

*****Lagrange Multiplier Test (LM test)

*Industrial Production

var lnip lnrop lnrsr lnr, lags(6) exog(dummy1 dummy2 dummy3)
varlmar, mlag(20)

*Civilian Unemployment Rate

var lnunemp lnrop lnrsr lnr, lags(6) exog(dummy1 dummy2 dummy3)
varlmar, mlag(20)

**********************************************************************

*****Normality Test

*Industrial Production

var lnip lnrop lnrsr lnr, lags(6) exog(dummy1 dummy2 dummy3)
varnorm, jbera

*Civilian Unemployment Rate

var lnunemp lnrop lnrsr lnr, lags(6) exog(dummy1 dummy2 dummy3)
varnorm, jbera

**********************************************************************

*****Granger Causality Test (Ho: x does NOT Granger cause y, H1: x does Granger cause y)

*Industrial Production
```

```
var lnip lnrop lnrsr lnr, lags(6) exog(dummy1 dummy2 dummy3)
vargranger

*Civilian Unemployment Rate

var lnunemp lnrop lnrsr lnr, lags(6) exog(dummy1 dummy2 dummy3)
vargranger

******************************************************************

*****VAR Representation

*Industrial Production

var lnip lnrop lnrsr lnr, lags(6) exog(dummy1 dummy2 dummy3)
varlmar, mlag(20)
varnorm, jbera
vargranger

*Civilian Unempoyment Rate
var lnunemp lnrop lnrsr lnr, lags(6) exog(dummy1 dummy2 dummy3)
varlmar, mlag(20)
varnorm, jbera
vargranger

******************************************************************

*****Cointegration

*Industrial Production

var lnip lnrop lnrsr lnr, lags(6) exog(dummy1 dummy2 dummy3)
predict res_id,resid
tsline res_id
twoway (scatter res_id L.res_id)

*Civilian Unempoyment Rate

var lnunemp lnrop lnrsr lnr, lags(6) exog(dummy1 dummy2 dummy3)
predict res_unemp,resid
tsline res_unemp
twoway (scatter res_unemp L.res_unemp)

******************************************************************

*****Engle-Granger Test

*Industrial Production

regress lnip lnrop lnr lnrsr
regress d.res_id l.res_id dl.res_id, noconstant

*Civilian Unempoyment Rate
regress lnunemp lnrop lnr lnrsr
regress d.res_unemp l.res_unemp dl.res_unemp, noconstant
```