Econometrics - sVAR and Co-integration

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Contents

1 Exercise 1 - sIRF

1.1 Structural VAR and structural Impulse Response Function

In the initial stage, as we are dealing with time series data and we have to estimate a sVAR model, it is essential to assess whether the series are stationary, checking for the presence or absence of a unit root. This examination can be performed through both visual inspection and a more precise test, such as the Augmented Dickey Fuller test. In both instances, as there is no evidence of volatility clustering or trend in the graphs(Figure 1), and the Augmented Dickey Fuller test (Figure 2) consistently rejects the null hypothesis, we can reasonably assume that the three series are stationary.
Having established stationarity, the subsequent step involves estimating the Vector Autoregression model. To accomplish this, it is crucial to identify the optimal number of lags by evaluating which number minimizes information criteria (AIC, BIC and HQC), ensuring the correct specification of the model. As depicted in the graph below (Figure 3), the optimal number of lags is one. Therefore, we can proceed with the estimation process.
To assess the validity of the model, I conducted tests to ensure that the residuals of the VAR(1) model exhibit no autocorrelation. In each lag, none of the p-values exceeded conventional alpha levels, indicating a failure to reject the null hypothesis of no autocorrelation. Furthermore, I examined the presence of heteroskedasticity using an ARCH test, and once again, the null hypothesis was not rejected, confirming homoskedasticity. The final test performed aimed to verify if the residuals followed a normal distribution, and the results aligned with previous findings, providing further confirmation of the model's correctness(Figure 4).
Furthermore, I examined whether all the equations estimated by the VAR(1) are statistically significant by assessing if, jointly, all the regressors in each equation significantly differ from zero. The result (Figure 5) indicates that, for each equation, the p-value of the F-Test rejects the null hypothesis, yielding a desirable outcome. Given that the model is correctly specified, the next step is to compute the structural impulse response function. It is worth mentioning that the VAR model has limitations in providing a clear understanding of cause-and-effect relationships between variables, as it primarily focuses on describing how variables move together over time without explicitly addressing the underlying economic mechanisms. To address this limitation, it is recommended to use Structural VARs, which aim to enhance the interpretability of relationships among variables by incorporating economic theories and assumptions.
Once the Structural VAR is estimated and the impulse-response functions are computed, we can delve into the propagation mechanism of oil price shocks (Figure 6, first column) on itself, inflation, and GDP. Regarding the persistence of an oil price shock, which can be considered as the "memory" of the shock, it is observed that before dissipating, the shock persists in the financial time series for approximately seven months. This persistence follows an exponential decay after an immediate peak. Concerning the impact of an oil shock on inflation, the peak of the impact is reached after two months, followed by a gradual decay lasting up to nine months. This aligns with economic theory, as the computation of inflation heavily weights the energy component. Therefore, an oil shock is expected to significantly influence inflation, as seen in recent events following the war in Ukraine.
In contrast, even though at the very beginning it seems to have a positive influence, the impact of an oil shock on GDP is negative. The negative impact reaches its peak after 5 months before gradually diminishing, with reabsorption occurring after the tenth month. This is plausible given the extensive use of oil in industry, being a fundamental component in almost every daily

consumable product. Thus, a shock in oil prices could lead to an economic slowdown.

1.2 ARMA Model vs VAR

Regarding the second part, I decided to analyze the oil time series and compute an ARMA model. An ARMA(p,q) model is a statistical model that combines autoregressive (AR) and moving average (MA) components. The AR part models the relationship between an observation and its lagged values, while the MA part models the relationship between an observation and a linear combination of past error terms.
To estimate our model, similar to what I did previously for the VAR, we need to determine the number of lags, p and q. This can be achieved in two ways: graphically by inspecting the ACF and the PACF (Figure 7) or by checking which model minimizes the information criteria (Figure 8). A gradually geometrically declining ACF and a PACF that is significant for only a few lags indicate an AR process. In this case, the PACF has only one significant lag (the ninth lag goes outside the bands, but we are hyphotizing an alpha at 5%, so we can neglect it) followed by a drop in PACF values, becoming insignificant. Thus, the correlogram suggests that the series follows an AR(1) process, where the lags are determined by the number of significant lags in the PACF.
The result is confirmed even when looking at the models that minimize the information criteria. Although, following this method, the model that minimizes the AIC criteria is an ARMA(3,3), once estimating that model, some of the coefficients are not significant, and, in addition, the model is not so parsimonious. For these reasons and since the model that minimizes the BIC and HQC is an AR(1), this is the model I estimated (Figure 9) . The coefficient associated with the lagged value of oil is significant, the residuals of the model are not autocorrelated, and they follow a normal distribution (Figure 10). Moreover, we also do not reject the null hypothesis of the presence of an ARCH effect, so the model is overall correctly specified.
In a comparison with the equation in the VAR model, some differences can be spotted. The R^2 in the VAR equation is higher, but this could be due to the obvious presence of more regressors. However, even looking at the R^2 adjusted, the final conclusion is the same, so the VAR equation explains more variance of the dependent variable than the AR(1) model. As mentioned, the VAR equation has more regressors. Indeed, it seems that the lagged value of the growth has an explanatory power with respect to oil, which is something that the ARMA model, working only on the dependent variable, can't capture. Moreover, all the information criteria of the VAR equation are lower. Another difference, from a theoretical point of view, is that the VAR model considers contemporaneous relationships among all variables, while the autoregressive model does not.

2 Exercise 2 - Purchasing Power Parity

2.1 Stationarity and Co-Integration

The Purchasing Power Parity (PPP) is an economic concept suggesting that national price levels, once converted to a common currency, should equalize. To investigate the potential relationship of cointegration between the log prices of the product in the first country (denoted as p_a), the log prices of the product in the second country (denoted as p_b), and the log nominal exchange rate (denoted as e_{AB}), we first need to check whether these variables are stationary. This can be done visually or with the ADF test. As illustrated in the appendix, the three time series appear to exhibit a common upward trend (Figure 11), suggesting the presence of a unit root. In a statistical context, the ADF tests (Figure 12, Figure 13) consistently fail to reject the null hypothesis (H0) of non-stationarity, indicating that our series possess a unit root and are integrated of order 1 (I(1)).

With the non-stationarity of our series established, the objective is to identify evidence of a linear combination among these I(1) variables capable of generating I(0) (or stationary) residuals. Given the aim to verify the reaction of the three variables to disequilibria and the intention to estimate a Vector Error Correction Model (VECM), the Johansen Test is employed to check for cointegration and identify the possible number of cointegration equations.

The use of the Johansen Test is preferred as it avoids the issue of choosing a dependent variable and is more suitable for multivariate analysis. It can detect multiple cointegrating vectors and treats every test variable as endogenous variables, making it more appropriate than the Engle-Granger test for multivariate analysis.

The Johansen Co-Integration test is run with the number of lags chosen based on what would be used if estimating a Vector Autoregression (VAR), which, in this case, is one (Figure 14). The trace-statistic in the Johansen table (Figure 15), for the rank 0, rejects the null hypothesis of no cointegration at any alpha level, indicating the presence of cointegration. Further examination for a higher rank of the matrix reveals that the null hypothesis of the presence of more than one cointegration equation is not rejected, leading to the conclusion that the rank of the matrix is one. Thus, only one cointegration relationship is identified.

In the context of a VECM, variables are in their first difference form. Therefore, the number of lags when estimating the VECM is one less than the number of lags in the corresponding VAR. In this case, the number of lags is zero, resulting in each equation in the VECM consisting of a constant term and the Error Correction Term (ECT), with no lagged variables included. This setup implies that the short-run equilibrium cannot be analyzed directly.

The equations derived from the VECM (Figure 16), reveal that only two out of the three variables react to a disequilibrium, namely p_a (ECT1 coefficient $\approx$ -0,304) and p_b (ECT1 coefficient $\approx$ -0,02), although the latter not at a 1% significance level. This implies that if the long-run equilibrium is disturbed, P_a and P_b will adjust, leading to a restoration of the equilibrium. Even in this case, the residuals of the model are not autocorrelated and they're normal. Moreover, there's no evidence of any ARCH effect (Figure 17).

To assess whether the PPP exists in its strong form, linear restrictions are imposed on the coefficients in the cointegrating vector related to p_b and e_{AB}. However, running a restricted VECM (Figure 18) by imposing restrictions such as $b[1] = 1$, $b[2] = -1$, and $b[3] = -1$ leads to the rejection of the null hypothesis that these linear restrictions are respected. In conclusion, the PPP exists, but not in a strong form.

3 Appendix - First Exercise

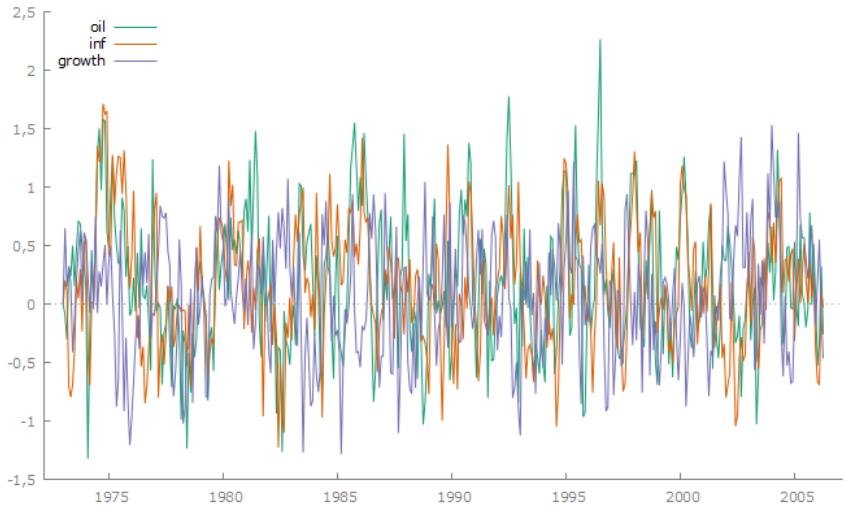


Figure 1: Time Series Plot

```
Test Dickey-Fuller aumentato per oil
test all'indietro da 16 ritardi, criterio AIC
Ampiezza campionaria 399
Ipotesi nulla di radice unitaria: a = 1

  Test con costante
  inclusi 0 ritardi di (1-L)oil
  Modello: (1-L)y = b0 + (a-1)*y(-1) + e
  Valore stimato di (a - 1): -0,426515
  Statistica test: tau_c(1) = -10,364
  p-value asintotico 2,233e-20
  Coefficiente di autocorrelazione del prim'ordine per e: 0,011
```

```
Test Dickey-Fuller aumentato per inf
test all'indietro da 16 ritardi, criterio AIC
Ampiezza campionaria 399
Ipotesi nulla di radice unitaria: a = 1

  Test con costante
  inclusi 0 ritardi di (1-L)inf
  Modello: (1-L)y = b0 + (a-1)*y(-1) + e
  Valore stimato di (a - 1): -0,347793
  Statistica test: tau_c(1) = -9,14088
  p-value asintotico 1,742e-16
  Coefficiente di autocorrelazione del prim'ordine per e: 0,028
```

```
Test Dickey-Fuller aumentato per growth
test all'indietro da 16 ritardi, criterio AIC
Ampiezza campionaria 399
Ipotesi nulla di radice unitaria: a = 1

  Test con costante
  inclusi 0 ritardi di (1-L)growth
  Modello: (1-L)y = b0 + (a-1)*y(-1) + e
  Valore stimato di (a - 1): -0,521735
  Statistica test: tau_c(1) = -11,817
  p-value asintotico 4,126e-25
  Coefficiente di autocorrelazione del prim'ordine per e: 0,021
```

Figure 2: ADF Test for each variable

The VAR Lag Selection of Gretl suggests that the number of lags that minimize all the information criteria is one.

```
Sistema VAR, ordine massimo ritardi 12

Gli asterischi indicano i valori migliori (ossia minimizzati)
dei rispettivi criteri di informazione, AIC = criterio di Akaike,
BIC = criterio bayesiano di Schwartz e HQC = criterio di Hannan-Quinn.
```

ritardi	logver	p(LR)	AIC	BIC	HQC
1	-653,64006		3,431134*	3,553640*	3,479706*
2	-650,55264	0,72230	3,461612	3,675996	3,546612
3	-647,11085	0,64924	3,490262	3,796525	3,611691
4	-641,59519	0,27357	3,508223	3,906365	3,666080
5	-637,24020	0,46446	3,532166	4,022187	3,726452
6	-630,84614	0,17243	3,545599	4,127499	3,776313
7	-626,37609	0,44282	3,568949	4,242728	3,836092
8	-621,40895	0,35583	3,589737	4,355395	3,893309
9	-612,19478	0,03052	3,588633	4,446170	3,928633
10	-608,58294	0,61384	3,616407	4,565823	3,992836
11	-603,48424	0,33474	3,636517	4,677812	4,049374
12	-594,42107	0,03374	3,636191	4,769365	4,085477

Figure 3: VAR Lag Selection

There are the tests to check whether the model is correctly specified or not.

Test per l'autocorrelazione fino all'ordine 12

	Rao F	Approx dist.	p-value
lag 1	0,653	F(9, 949)	0,7515
lag 2	0,665	F(18, 1095)	0,8472
lag 3	0,777	F(27, 1122)	0,7851
lag 4	0,784	F(36, 1126)	0,8169
lag 5	0,862	F(45, 1123)	0,7289
lag 6	0,814	F(54, 1118)	0,8289
lag 7	0,916	F(63, 1111)	0,6618
lag 8	1,079	F(72, 1103)	0,3092
lag 9	1,072	F(81, 1095)	0,3168
lag 10	1,036	F(90, 1087)	0,3929
lag 11	1,143	F(99, 1078)	0,1693
lag 12	1,111	F(108, 1070)	0,2155

Test per ARCH di ordine 12

	LM	df	p-value
lag 1	28,992	36	0,7900
lag 2	77,360	72	0,3116
lag 3	117,663	108	0,2470
lag 4	139,703	144	0,5857
lag 5	179,638	180	0,4936
lag 6	205,669	216	0,6819
lag 7	237,248	252	0,7391
lag 8	272,305	288	0,7384
lag 9	302,408	324	0,8000
lag 10	340,858	360	0,7585
lag 11	377,099	396	0,7450
lag 12	404,741	432	0,8225

Matrice di correlazione dei residui, C (3 x 3)

1,0000	0,28441	-0,016664
0,28441	1,0000	-0,045188
-0,016664	-0,045188	1,0000

Autovalori di C

0,71415
0,994851
1,291

Test di Doornik-Hansen
Chi-quadro(6) = 0,676364 [0,9950]

Figure 4: Validation of the VAR Model

This is the VAR model with one lag. In all the equations the F-Test rejects the null, so at least one coefficient is different from zero.

```
Sistema VAR, ordine ritardi 1
Stime OLS usando le osservazioni 1973:02-2006:04 (T = 399)
Log-verosimiglianza = -669,05555
Determinante della matrice di covarianza = 0,0057418759
AIC = 3,4138
BIC = 3,5338
HQC = 3,4613
Test portmanteau: LB(48) = 496,792, df = 423 [0,0076]

Equazione 1: oil

             coefficiente   errore std.   rapporto t    p-value
  -------------------------------------------------------------
  const        0,0650306      0,0251229      2,589      0,0100    ***
  oil_1        0,536946       0,0473278     11,35       5,15e-026 ***
  inf_1        0,0730337      0,0510778      1,430      0,1535
  growth_1     0,144265       0,0460109      3,135      0,0018    ***

Media var. dipendente   0,187046   SQM var. dipendente     0,576148
Somma quadr. residui    86,38327   E.S. della regressione  0,467645
R-quadro                0,346149   R-quadro corretto       0,341183
F(3, 395)               69,70441   P-value(F)              3,39e-36
rho                     0,019763   Durbin-Watson           1,957488
Note: SQM = scarto quadratico medio; E.S. = errore standard

Test F per zero vincoli:

Tutti i ritardi di oil           F(1, 395) =   128,71 [0,0000]
Tutti i ritardi di inf           F(1, 395) =   2,0445 [0,1535]
Tutti i ritardi di growth        F(1, 395) =   9,8310 [0,0018]
Tutte le variabili, ritardo 1    F(3, 395) =   69,704 [0,0000]

Equazione 2: inf

             coefficiente   errore std.   rapporto t    p-value
  -------------------------------------------------------------
  const        0,0223693      0,0205834      1,087      0,2778
  oil_1        0,286222       0,0387761      7,381      9,35e-013 ***
  inf_1        0,501980       0,0418484     12,00       1,76e-028 ***
  growth_1     0,0279317      0,0376971      0,7410     0,4592

Media var. dipendente   0,156672   SQM var. dipendente     0,538433
Somma quadr. residui    57,98613   E.S. della regressione  0,383145
R-quadro                0,497452   R-quadro corretto       0,493635
F(3, 395)               130,3316   P-value(F)              1,08e-58
rho                     0,049019   Durbin-Watson           1,900789
Note: SQM = scarto quadratico medio; E.S. = errore standard

Test F per zero vincoli:

Tutti i ritardi di oil           F(1, 395) =   54,485 [0,0000]
Tutti i ritardi di inf           F(1, 395) =   143,88 [0,0000]
Tutti i ritardi di growth        F(1, 395) =  0,54901 [0,4592]
Tutte le variabili, ritardo 1    F(3, 395) =   130,33 [0,0000]

Equazione 3: growth

             coefficiente   errore std.   rapporto t    p-value
  -------------------------------------------------------------
  const         0,0547284     0,0240839      2,272      0,0236    **
  oil_1         0,0504742     0,0453706      1,112      0,2666
  inf_1        -0,179873      0,0489655     -3,673      0,0003    ***
  growth_1      0,451900      0,0441081     10,25       5,32e-022 ***

Media var. dipendente   0,066655   SQM var. dipendente     0,517453
Somma quadr. residui    79,38628   E.S. della regressione  0,448306
R-quadro                0,255061   R-quadro corretto       0,249403
F(3, 395)               45,08150   P-value(F)              4,48e-25
rho                     0,021554   Durbin-Watson           1,949737
Note: SQM = scarto quadratico medio; E.S. = errore standard

Test F per zero vincoli:

Tutti i ritardi di oil           F(1, 395) =   1,2376 [0,2666]
Tutti i ritardi di inf           F(1, 395) =   13,494 [0,0003]
Tutti i ritardi di growth        F(1, 395) =   104,97 [0,0000]
Tutte le variabili, ritardo 1    F(3, 395) =   45,082 [0,0000]
```

Figure 5: Vector Autoregressive Model

Below, the structural Impulse Response Functions. We must focus on the oil shocks, so the first column.

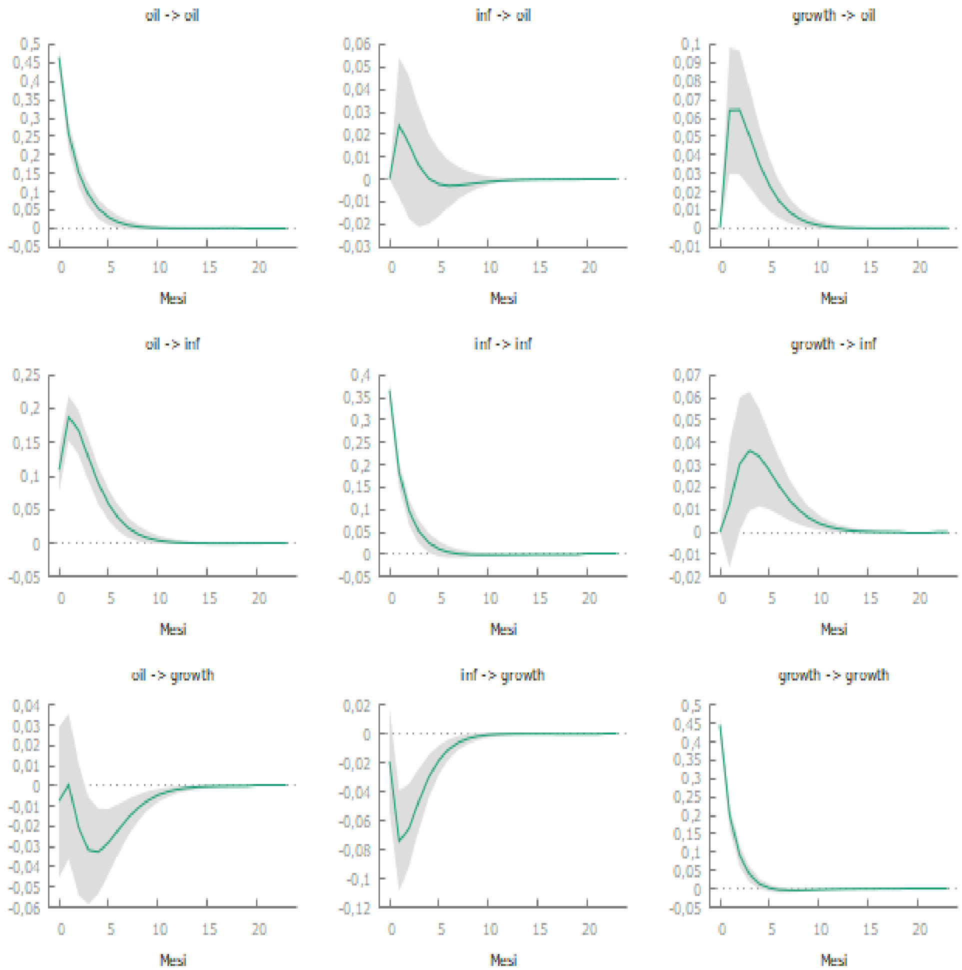


Figure 6: Impulse Response Function

3.1 ARMA Model - Oil prices

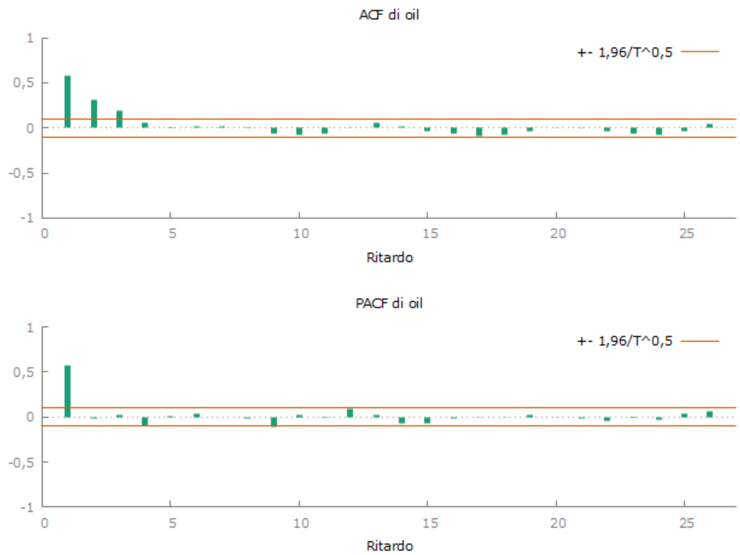


Figure 7: ACF - PACF

Stimato usando AS 197 (MV esatta)
Dependent variable oil, T = 400
Criteria for ARMA(p, q) specifications

p, q	AIC	BIC	HQC	loglik
0, 0	696,1386	704,1215	699,3000	-346,0693
0, 1	569,3741	581,3485	574,1161	-281,6870
0, 2	554,5525	570,5184	560,8752	-273,2763
0, 3	541,9689	561,9262	549,8723	-265,9845
1, 0	539,2531	551,2275*	543,9951*	-266,6265
1, 1	541,0723	557,0381	547,3950	-266,5361
1, 2	542,6668	562,6241	550,5701	-266,3334
1, 3	541,2283	565,1770	550,7123	-264,6141
2, 0	541,0931	557,0589	547,4158	-266,5465
2, 1	542,1191	562,0765	550,0225	-266,0596
2, 2	543,6708	567,6196	553,1548	-265,8354
2, 3	541,5614	569,5016	552,6261	-263,7807
3, 0	542,7394	562,6968	550,6428	-266,3697
3, 1	543,4716	567,4204	552,9556	-265,7358
3, 2	539,3918	567,3321	550,4565	-262,6959
3, 3	538,3418*	570,2735	550,9871	-261,1709

Figure 8: ARMA Lag Selection

Modello 7: ARMA, usando le osservazioni 1973:01-2006:04 (T = 400)
Stimato usando AS 197 (MV esatta)
Variabile dipendente: oil
Errori standard basati sull'Hessiana

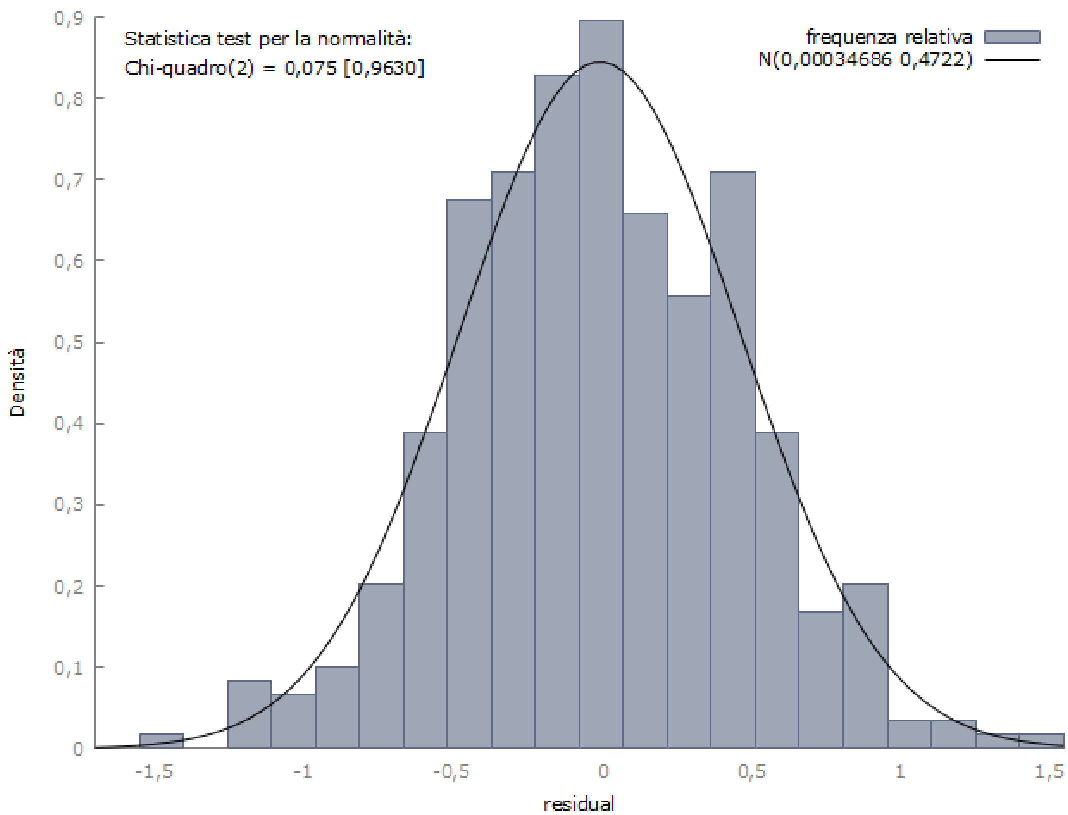
	coefficiente	errore std.	z	p-value	
const	0,184476	0,0548699	3,362	0,0008	***
phi_1	0,572210	0,0409091	13,99	1,86e-044	***

Media var. dipendente	0,186578	SQM var. dipendente	0,575501
Media innovazioni	0,000347	SQM innovazioni	0,471014
R-quadro	0,328478	R-quadro corretto	0,328478
Log-verosimiglianza	-266,6265	Criterio di Akaike	539,2531
Criterio di Schwarz	551,2275	Hannan-Quinn	543,9951

Note: SQM = scarto quadratico medio; E.S. = errore standard

Figure 9: AR(1) Model

Below, the test for the normality of the residual and the test for the presence of autocorrelation.




```
Test per l'autocorrelazione fino all'ordine 12

Ljung-Box Q' = 10,9984,
con p-value = P(Chi-quadro(11) > 10,9984) = 0,4434
```

Figure 10: Residuals distribution and Autocorrelation Test

4 Appendix - Second Exercise

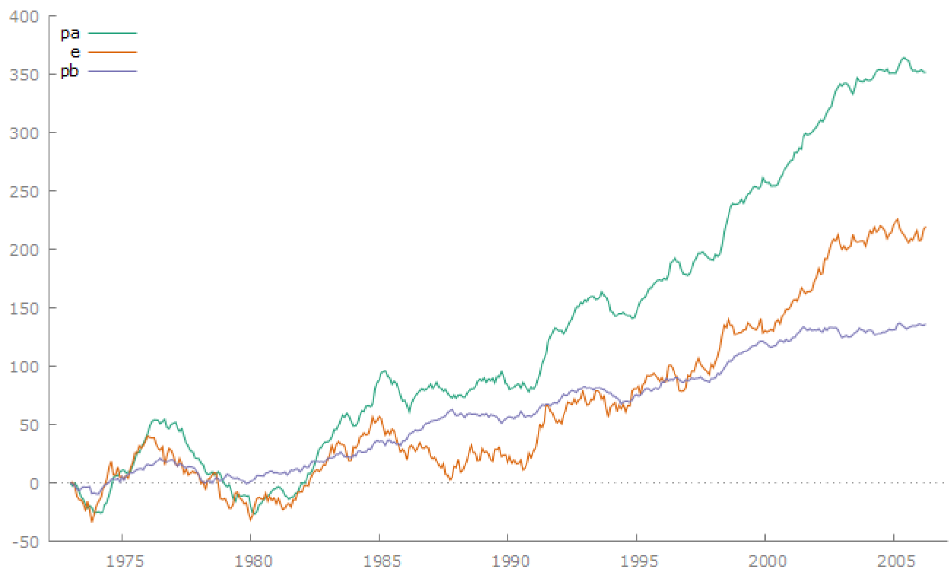


Figure 11: Time Series Plot

```
Test Dickey-Fuller aumentato per pa
test all'indietro da 16 ritardi, criterio AIC
Ampiezza campionaria 391
Ipotesi nulla di radice unitaria: a = 1

  Test con costante
  inclusi 8 ritardi di (1-L)pa
  Modello: (1-L)y = b0 + (a-1)*y(-1) + ... + e
  Valore stimato di (a - 1): 0,000260122
  Statistica test: tau_c(1) = 0,184954
  p-value asintotico 0,9717
  Coefficiente di autocorrelazione del prim'ordine per e: -0,002
  differenze ritardate: F(8, 381) = 10,935 [0,0000]

  Con costante e trend
  inclusi 8 ritardi di (1-L)pa
  Modello: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  Valore stimato di (a - 1): -0,00768343
  Statistica test: tau_ct(1) = -1,75197
  p-value asintotico 0,728
  Coefficiente di autocorrelazione del prim'ordine per e: -0,003
  differenze ritardate: F(8, 380) = 11,115 [0,0000]
```

Figure 12: ADF Pa

```
Test Dickey-Fuller aumentato per e
test all'indietro da 16 ritardi, criterio AIC
Ampiezza campionaria 399
Ipotesi nulla di radice unitaria: a = 1

  Test con costante
  inclusi 0 ritardi di (1-L)e
  Modello: (1-L)y = b0 + (a-1)*y(-1) + e
  Valore stimato di (a - 1): 0,00218475
  Statistica test: tau_c(1) = 0,615708
  p-value asintotico 0,9902
  Coefficiente di autocorrelazione del prim'ordine per e: -0,002

  Con costante e trend
  inclusi 0 ritardi di (1-L)e
  Modello: (1-L)y = b0 + b1*t + (a-1)*y(-1) + e
  Valore stimato di (a - 1): -0,0138472
  Statistica test: tau_ct(1) = -1,6944
  p-value asintotico 0,7541
  Coefficiente di autocorrelazione del prim'ordine per e: 0,002
```

```
Test Dickey-Fuller aumentato per pb
test all'indietro da 16 ritardi, criterio AIC
Ampiezza campionaria 399
Ipotesi nulla di radice unitaria: a = 1

  Test con costante
  inclusi 0 ritardi di (1-L)pb
  Modello: (1-L)y = b0 + (a-1)*y(-1) + e
  Valore stimato di (a - 1): 0,000534501
  Statistica test: tau_c(1) = 0,281572
  p-value asintotico 0,9774
  Coefficiente di autocorrelazione del prim'ordine per e: 0,051

  Con costante e trend
  inclusi 0 ritardi di (1-L)pb
  Modello: (1-L)y = b0 + b1*t + (a-1)*y(-1) + e
  Valore stimato di (a - 1): -0,0223825
  Statistica test: tau_ct(1) = -2,36121
  p-value asintotico 0,4001
  Coefficiente di autocorrelazione del prim'ordine per e: 0,059
```

Figure 13: ADF Test for E and Pb

```
Sistema VAR, ordine massimo ritardi 6

Gli asterischi indicano i valori migliori (ossia minimizzati)
dei rispettivi criteri di informazione, AIC = criterio di Akaike,
BIC = criterio bayesiano di Schwartz e HQC = criterio di Hannan-Quinn.

ritardi     logver    p(LR)       AIC          BIC          HQC

   1   -2774,27176             14,143511*   14,264619*   14,191500*
   2   -2772,02898  0,87665   14,177812    14,389750    14,261792
   3   -2769,56934  0,84129   14,211012    14,513780    14,330983
   4   -2765,57607  0,53550   14,236427    14,630025    14,392389
   5   -2761,00653  0,42454   14,258916    14,743345    14,450870
   6   -2753,25806  0,07816   14,265269    14,840528    14,493214
```

Figure 14: Lag Selection for Johansen test and VECM

```
Caso 3: costante non vincolata

Log-verosimiglianza = -1675,55 (termine costante incluso: -2807,86)

Rango Autovalore Test traccia  p-value   Test Lmax  p-value
   0    0,67348     450,90 [0,0000]     446,59 [0,0000]
   1   0,010719     4,3111 [0,8717]     4,3000 [0,8218]
   22,7941e-005   0,011149 [0,9159]   0,011149 [0,9159]

Corretto per ampiezza campionaria (df = 395)
Rango Test traccia p-value
   0      450,90 [0,0000]
   1      4,3111 [0,8727]
   2    0,011149 [0,9165]
```

Figure 15: Johansen Test

```
Sistema VECM, ordine ritardi 1
Stime Massima verosimiglianza usando le osservazioni 1973:02-2006:04 (T = 399)
Rango di cointegrazione = 1
Caso 3: costante non vincolata

beta (vettori di cointegrazione, errori standard tra parentesi)

pa       1,0000
       (0,00000)
e      -0,99082
      (0,012463)
pb      -1,0691
      (0,019550)

alpha (vettori di aggiustamento)

pa     -0,30454
e     -0,014125
pb    -0,019888

Log-verosimiglianza = -2810,0181
Determinante della matrice di covarianza = 262,87335
AIC = 14,1455
BIC = 14,2654
HQC = 14,1930

Equazione 1: d_pa

             coefficiente   errore std.   rapporto t    p-value
  -------------------------------------------------------------
  const        0,262149      0,100961        2,597     0,0098    ***
  EC1         -0,304539      0,0107420     -28,35      1,90e-097 ***

Media var. dipendente   0,881044   SQM var. dipendente     3,419977
Somma quadr. residui    1539,117   E.S. della regressione  1,968977
R-quadro                0,669370   R-quadro corretto       0,668537
rho                     0,028894   Durbin-Watson           1,932139
Note: SQM = scarto quadratico medio; E.S. = errore standard

Equazione 2: d_e

             coefficiente   errore std.   rapporto t   p-value
  -----------------------------------------------------------
  const        0,520731      0,259683       2,005      0,0456  **
  EC1         -0,0141254     0,0276298     -0,5112     0,6095

Media var. dipendente   0,549437   SQM var. dipendente     5,059747
Somma quadr. residui    10182,51   E.S. della regressione  5,064448
R-quadro                0,000658   R-quadro corretto      -0,001859
rho                    -0,015444   Durbin-Watson           2,030526
Note: SQM = scarto quadratico medio; E.S. = errore standard

Equazione 3: d_pb

             coefficiente   errore std.   rapporto t   p-value
  -----------------------------------------------------------
  const        0,300510     0,0880630        3,412     0,0007  ***
  EC1         -0,0198877    0,00936974      -2,123     0,0344  **

Media var. dipendente   0,340926   SQM var. dipendente     1,724990
Somma quadr. residui    1170,996   E.S. della regressione  1,717444
R-quadro                0,011221   R-quadro corretto       0,008730
rho                     0,006996   Durbin-Watson           1,984176
Note: SQM = scarto quadratico medio; E.S. = errore standard
```


Figure 16: VECM Cointegration Vector and Pa equation

Test per l'autocorrelazione fino all'ordine 12

	Rao F	Approx dist.	p-value
lag 1	0,486	F(9, 956)	0,8845
lag 2	0,525	F(18, 1103)	0,9474
lag 3	0,651	F(27, 1130)	0,9143
lag 4	0,729	F(36, 1135)	0,8814
lag 5	0,901	F(45, 1132)	0,6587
lag 6	0,972	F(54, 1127)	0,5342
lag 7	0,897	F(63, 1120)	0,7020
lag 8	0,884	F(72, 1112)	0,7426
lag 9	0,824	F(81, 1104)	0,8655
lag 10	0,828	F(90, 1096)	0,8736
lag 11	0,775	F(99, 1087)	0,9468
lag 12	0,866	F(108, 1079)	0,8296

Test per ARCH di ordine 12

	LM	df	p-value
lag 1	40,266	36	0,2870
lag 2	73,748	72	0,4208
lag 3	120,657	108	0,1909
lag 4	154,864	144	0,2534
lag 5	194,946	180	0,2113
lag 6	223,229	216	0,3535
lag 7	255,763	252	0,4221
lag 8	307,563	288	0,2047
lag 9	339,773	324	0,2624
lag 10	382,136	360	0,2023
lag 11	419,043	396	0,2041
lag 12	445,301	432	0,3190

Matrice di correlazione dei residui, C (3 x 3)

1,0000	-0,077449	-0,046608
-0,077449	1,0000	0,28990
-0,046608	0,28990	1,0000

Autovalori di C

0,708388
0,977175
1,31444

Test di Doornik-Hansen
Chi-quadro(6) = 3,83493 [0,6990]

Figure 17: ARCH Effects

```
Insieme di vincoli
 1: b[1] = 1
 2: b[2] = -1
 3: b[3] = -1
Rango dello Jacobiano = 5, numero di parametri liberi = 3
Il modello è pienamente identificato
Basato sullo Jacobiano, df = 0
Log-verosimiglianza non vincolata (lu) = -2810,0181
Log-verosimiglianza vincolata (lr) = -2838,8329
2 * (lu - lr) = 57,6297
P(Chi-quadro(2) > 57,6297) = 3,06103e-013

Vettori di cointegrazione

pa        1,0000
e        -1,0000
pb       -1,0000

Alfa (vettori di aggiustamento) (errori standard tra parentesi)

pa      -0,29446
       (0,011580)
e    -0,0034977
       (0,027777)
pb     -0,019391
      (0,0094199)
```

Figure 18: Restricted VECM