

AQM Assignment One

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a. ARIMA Models

*Identify, estimate and diagnostic check ARIMA models for each of the following variables: *ln_inv*, *ln_inc*, and *ln_consump*.*

To identify an ARIMA model we must check for stationarity, correct for stationarity and examine the graphs for the autocorrelations and partial autocorrelations.¹

a.i. ARIMA model for *ln_inv*

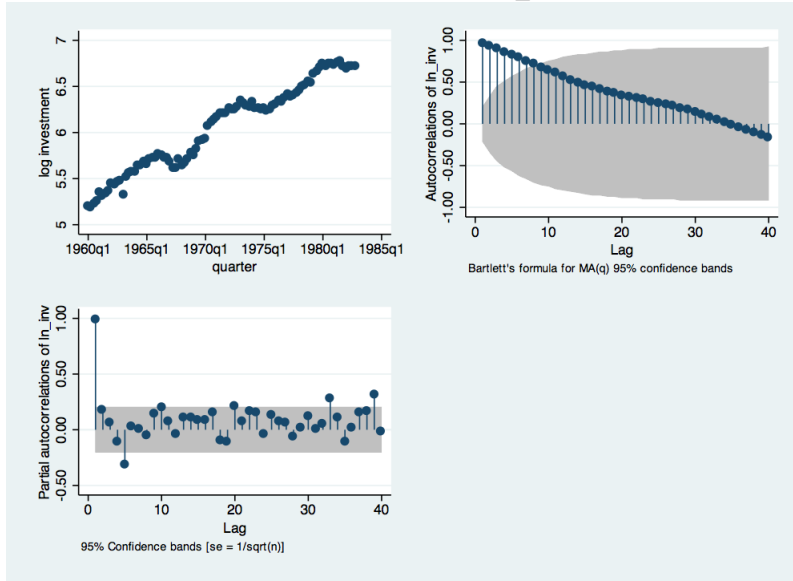
As can be seen in figure 1 on the following page, the ACF decays monotonically. That the ACF decays slowly indicates that the data is non-stationary, i.e. that we have a non-stationary mean.² Stationarity is when we have a flat looking series without trend.³ The scatterplot in figure 1 on the next page also indicates

¹<http://www.polsci.wvu.edu/duval/ps791c/Notes/Stata/arimaident.html>

²<http://www.polsci.wvu.edu/duval/ps791c/Notes/Stata/arimaident.html>

³<http://www.itl.nist.gov/div898/handbook/pmc/section4/pmc442.htm>

Figure 1: Graphs for \ln_inv



that the series is non-stationary as we can see a clear trend. The PACF cuts off after one lag (see figure 1), so we probably have an AR(1) process. However, because of non-stationarity we first attempt to correct for this by taking the first difference.

Now in figure 2 on the next page we see that the scatterplot is flatter, portraying stationarity. The ACF decays in an alternating or oscillating fashion, probably portraying some sort of MA as it seems to cut off (becomes zero) after four values or after zero values ($q = 0$). The PACF never seems to cut off ($p = 0$), although it can be seen as decaying. Thus, we have evidence of an ARIMA(0,1,0) model:

```
. arima ln_inv, arima(0,1,0)

(setting optimization to BHHH)
Iteration 0:  log likelihood = 154.00497
Iteration 1:  log likelihood = 154.00497

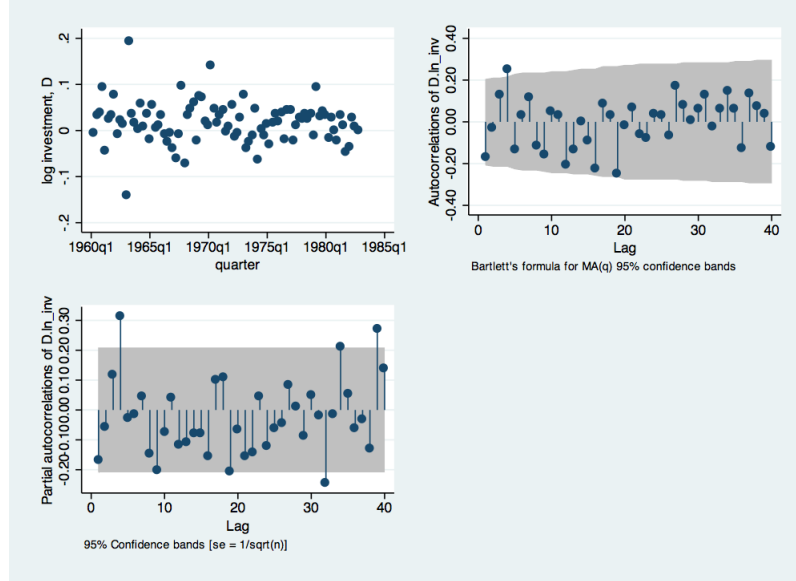
ARIMA regression

Sample: 1960q2 - 1982q4                Number of obs   =          91
                                         Wald chi2(.)     =          .
Log likelihood = 154.005                 Prob > chi2      =          .

-----+-----
          |               OPG
D.ln_inv |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
ln_inv   |

```

Figure 2: Graphs for \ln_inv after correcting for stationarity



_cons		.0167964	.0047276	3.55	0.000	.0075304	.0260623

/sigma		.044543	.0020718	21.50	0.000	.0404823	.0486037

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at z

It does not make sense to do an `armaroot` test as we have no AR or MA parameters in the model.

Another way of interpreting the graphs in figure 2 is that we have an ARIMA(4,1,4) model, the results of which are:

```
. arima ln_inv, arima(4,1,4)

(setting optimization to BHHH)
Iteration 0:  log likelihood = 151.19416
Iteration 1:  log likelihood = 153.8349
Iteration 2:  log likelihood = 155.72441
Iteration 3:  log likelihood = 158.06115
Iteration 4:  log likelihood = 158.78522
(switching optimization to BFGS)
Iteration 5:  log likelihood = 160.42741
Iteration 6:  log likelihood = 161.31532
Iteration 7:  log likelihood = 161.57824
Iteration 8:  log likelihood = 162.63005
Iteration 9:  log likelihood = 162.99665
Iteration 10: log likelihood = 163.47528
Iteration 11: log likelihood = 163.81731
Iteration 12: log likelihood = 164.09801
Iteration 13: log likelihood = 164.17117
```

```

Iteration 14: log likelihood = 164.23693
(switching optimization to BHHH)
Iteration 15: log likelihood = 164.28633
Iteration 16: log likelihood = 164.28633 (backed up)
Iteration 17: log likelihood = 164.28633 (not concave)
Iteration 18: log likelihood = 164.29517
Iteration 19: log likelihood = 164.29517 (backed up)
(switching optimization to BFGS)
Iteration 20: log likelihood = 164.29519 (backed up)
Iteration 21: log likelihood = 164.29682
Iteration 22: log likelihood = 164.30153
Iteration 23: log likelihood = 164.30185
Iteration 24: log likelihood = 164.3047
Iteration 25: log likelihood = 164.30508
Iteration 26: log likelihood = 164.30518
Iteration 27: log likelihood = 164.30518

```

ARIMA regression

```

Sample: 1960q2 - 1982q4
Log likelihood = 164.3052
Number of obs = 91
Wald chi2(7) = 361.32
Prob > chi2 = 0.0000

```

D.ln_inv	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	

ln_inv						
_cons	.0170483	.0066675	2.56	0.011	.0039803	.0301164

ARMA						
ar						
L1.	.250352	.3175816	0.79	0.431	-.3720964	.8728004
L2.	-.6410894	.3055835	-2.10	0.036	-1.240022	-.0421568
L3.	.6959524	.2326489	2.99	0.003	.2399689	1.151936
L4.	-.1234277	.371418	-0.33	0.740	-.8513935	.6045381
ma						
L1.	-.4332859	.3581174	-1.21	0.226	-1.135183	.2686114
L2.	.7828925	.3674864	2.13	0.033	.0626323	1.503153
L3.	-.7487543
L4.	.5336774	.347815	1.53	0.125	-.1480275	1.215382

/sigma	.0387658	.0050688	7.65	0.000	.0288311	.0487004

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at z

To test for stationarity we use the `-armaroots-` command to know whether the absolute value of the roots of the characteristic equation are smaller than one, which is required for stationarity. As we can see in the following table all the roots are smaller than one in absolute value:

```
. armaroots
```

```
Characteristic roots of AR-polynomial
```

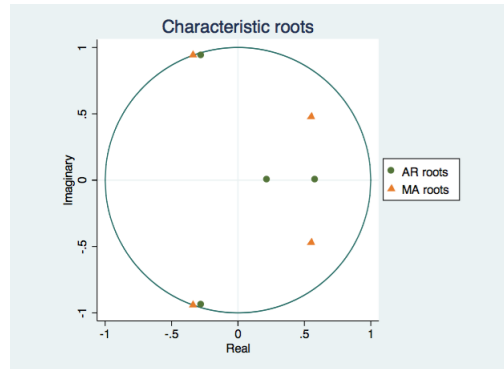
```
+-----+
```

Characteristic roots	Modulus	Period
$-.2762973 + .9377075i$.977566	3.38
$-.2762973 - .9377075i$.977566	3.38
.5804232	.580423	
.2225233	.222523	

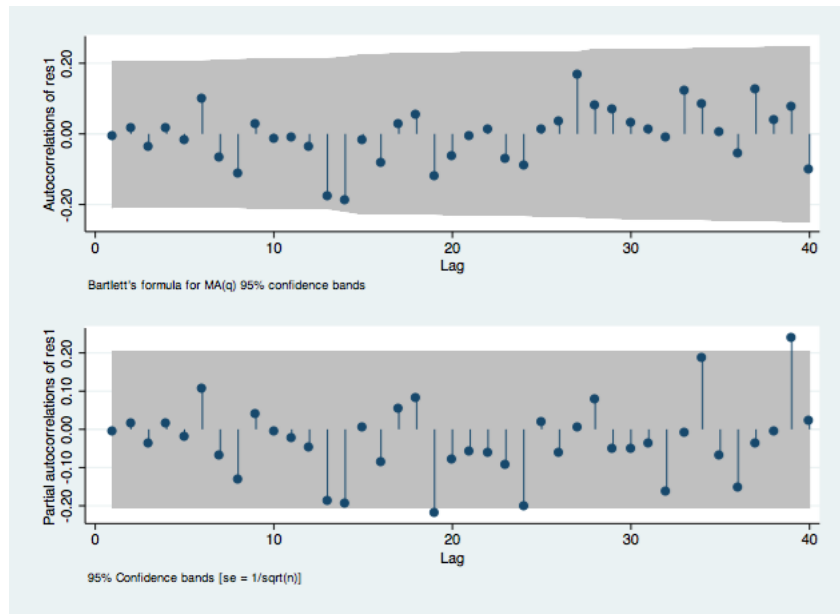
Characteristic roots of MA-polynomial

Characteristic roots	Modulus	Period
$-.3382539 + .941054i$.999999	3.28
$-.3382539 - .941054i$.999999	3.28
.5548968 + .4751503i	.730533	8.87
.5548968 - .4751503i	.730533	8.87

Graphically we can also confirm that none of the roots are larger than one in absolute value:



We now turn to the ACF and the PACF for the residuals to confirm that these have no distinct pattern:



The graph above indeed seems to confirm that the residuals are white noise. The Portmanteau statistics confirms this by yielding:

```
. wntestq res1

Portmanteau test for white noise
-----
Portmanteau (Q) statistic =    30.0852
Prob > chi2(40)          =    0.8728
```

a.ii. ARIMA model for \ln_inc

We now turn to the variable \ln_inc . The graphs shown in 3 on the next page again demonstrate that we probably have non-stationary data, so we do a first difference transformation again.

The results of this first difference transformation can be seen in figure 4 on the following page. Now the data does not portray a non-stationary mean, so we decide that $d = 1$. Again the case is more ambiguous for the ACF and PACF. We could again conclude that the ACF never cuts off, so we have a $MA(0)$, where $q = 0$, and the PACF never cuts off (becomes zero), so $p = 0$.

Estimating an $ARIMA(0,1,0)$ model gives the results shown in figure 5 on page 8.

The Portmanteau statistics yield...

Figure 3: Graphs for \ln_inc

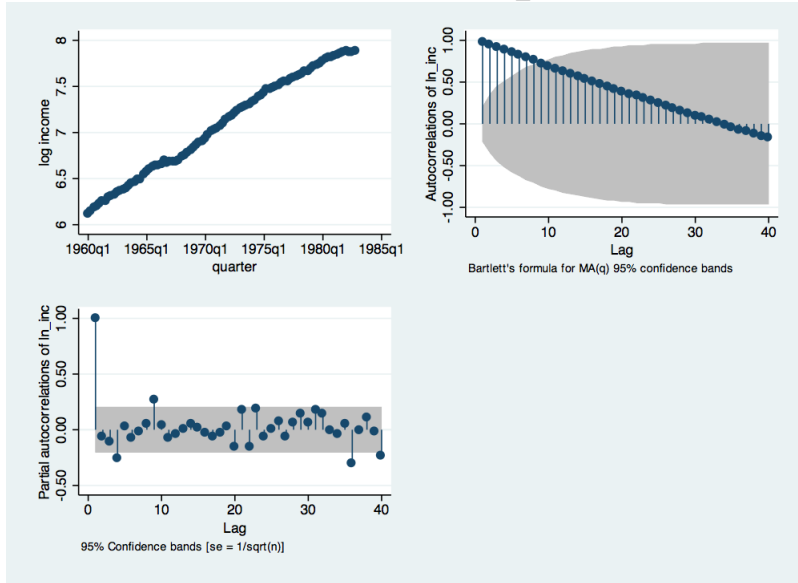


Figure 4: Graphs of \ln_inc after first differencing

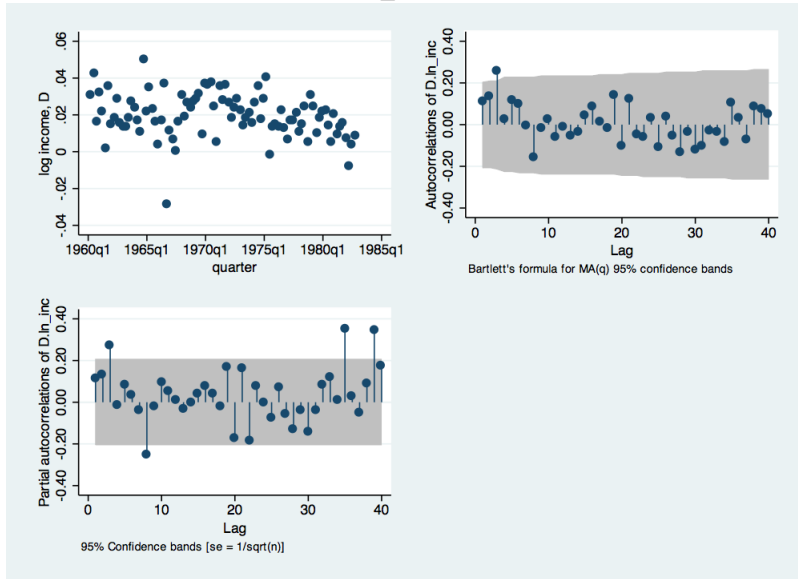


Figure 5: Results from ARIMA(0,1,0) of \ln_inc

	(1)	(2)
VARIABLES	\ln_inc	sigma
Constant	0.0195*** (0.00129)	0.0119*** (0.000645)
Observations	91	91
Standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

a.iii. ARIMA model for $\ln_consump$

Identifying an ARIMA model for the variable $\ln_consump$ we again first look at some graphs in figure 6 on the following page. Again we have to take the first difference to correct for stationarity. After this is done we see in the lower pane that we have a stationary mean.

Estimating an ARIMA(?,1,?) gives...

b. Dynamic Linear Model

Formulate and estimate a dynamic linear model with four lags for $\ln_consump$ with \ln_inc and \ln_inv as explanatory variables.

The model can be written as

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + a_3 y_{t-3} + a_4 y_{t-4} + b_0 \ln_inc_t + c_0 \ln_inv_t + u_t, \quad (1)$$

where y is $\ln_consump$.⁴

In figure 7 on page 11 we see the results of a dynamic linear model with four lags for $\ln_consump$. Mis-specification tests are:

Ramsey RESET test using powers of the fitted values of $\ln_consump$

Ho: model has no omitted variables
 $F(3, 78) = 6.02$
 $\text{Prob} > F = 0.0010$

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance
 Variables: fitted values of $\ln_consump$

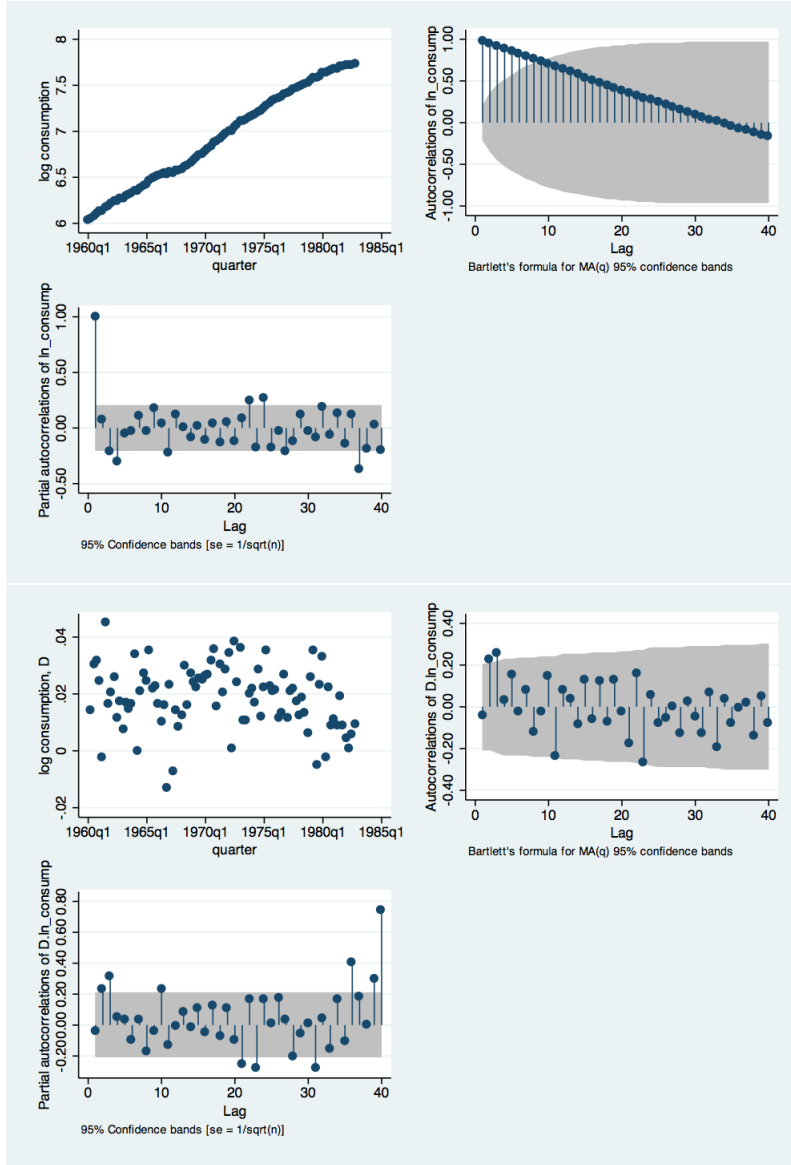
$\text{chi2}(1) = 1.10$
 $\text{Prob} > \text{chi2} = 0.2944$

White's test for Ho: homoskedasticity

against Ha: unrestricted heteroskedasticity

⁴See AQM lecture notes chapter 3, p. 18.

Figure 6: Graphs for $\ln_consump$



```

chi2(27)      =    30.03
Prob > chi2   =    0.3130

```

Cameron & Trivedi's decomposition of IM-test

Source	chi2	df	p
Heteroskedasticity	30.03	27	0.3130
Skewness	6.37	6	0.3831
Kurtosis	4.75	1	0.0294
Total	41.14	34	0.1863

(n = 88)	D-H	P-value	asy.	P-value
Residuals	6.1568	0.0460	3.6067	0.1647

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	2.096	1	0.1476

H0: no serial correlation

LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(p)	chi2	df	Prob > chi2
1	1.558	1	0.2120

H0: no ARCH effects vs. H1: ARCH(p) disturbance

c. Error Correction Model

Reformulate the model in b. as an error correction model; store the log-likelihood value using the command `-estimates store llu-`; and subject the model to mis-specification testing.

Writing equation 1 on page 8 as an error correction model yields:

$$\Delta y_t = a_0 + \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-2} + \alpha_3 \Delta y_{t-3} + \beta_0 \Delta \ln_inc_t + \gamma_0 \Delta \ln_inv_t + \alpha y_{t-1} + u_t,$$

again where y is $\ln_consump$.⁵ Running the regression gives:

⁵See answer to assignment 4, IQM, p. 13.

Figure 7: Dynamic linear model with four lags

(1)	
VARIABLES	ln_consump
L.ln_consump	0.405*** (0.106)
L2.ln_consump	0.278** (0.113)
L3.ln_consump	0.118 (0.111)
L4.ln_consump	-0.154* (0.0871)
ln_inc	0.333*** (0.0490)
ln_inv	0.00970 (0.0121)
Constant	0.0493*** (0.0135)
Observations	88
R-squared	1.000
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Source	SS	df	MS	Number of obs = 88		
Model	.004719858	6	.000786643	F(6, 81)	=	11.06
Residual	.005759951	81	.000071111	Prob > F	=	0.0000
				R-squared	=	0.4504
				Adj R-squared	=	0.4097
Total	.010479809	87	.000120458	Root MSE	=	.00843

dln_consump	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dln_consump						
L1.	-.2673194	.087738	-3.05	0.003	-.4418905	-.0927483
L2.	.1660194	.0843342	1.97	0.052	-.0017792	.333818
L3.	.2591583	.0865452	2.99	0.004	.0869605	.4313562
dln_inc	.4554999	.0815985	5.58	0.000	.2931446	.6178553
dln_inv	.062451	.0202667	3.08	0.003	.0221265	.1027754
ln_consump						
L1.	-.0004039	.0018446	-0.22	0.827	-.0040741	.0032664
_cons	.008395	.0138116	0.61	0.545	-.0190858	.0358757

The results of mis-specification tests are:

Ramsey RESET test using powers of the fitted values of dln_consump

Ho: model has no omitted variables
F(3, 78) = 1.19
Prob > F = 0.3193

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance
Variables: fitted values of dln_consump

chi2(1) = 0.47
Prob > chi2 = 0.4911

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance
Variables: L.dln_consump L2.dln_consump L3.dln_consump dln_inc dln_inv L.ln_consump

chi2(6) = 7.60
Prob > chi2 = 0.2686

White's test for Ho: homoskedasticity

against Ha: unrestricted heteroskedasticity

chi2(27) = 38.39
Prob > chi2 = 0.0719

Cameron & Trivedi's decomposition of IM-test

Source	chi2	df	p
--------	------	----	---

Heteroskedasticity		38.39	27	0.0719
Skewness		9.38	6	0.1532
Kurtosis		0.65	1	0.4218
Total		48.42	34	0.0519

(n = 88)		D-H	P-value	asy.	P-value
Residuals		2.5948	0.2732	2.4639	0.2917

Breusch-Godfrey LM test for autocorrelation

lags(p)		chi2	df	Prob > chi2
1		4.266	1	0.0389
2		8.164	2	0.0169
3		9.789	3	0.0205
4		10.731	4	0.0298

H0: no serial correlation

LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(p)		chi2	df	Prob > chi2
1		3.184	1	0.0743
2		8.175	2	0.0168
3		1.331	3	0.7217
4		0.949	4	0.9175

H0: no ARCH effects vs. H1: ARCH(p) disturbance

The Ramsey RESET test and the two Breusch-Pagan tests for heteroskedasticity do not reveal any problems as we have p-values comfortably above, say, a 10% significance level. However, the White's test for homoskedasticity is rejected at a 10% significance level. Moreover, the Breusch-Godfrey LM test for autocorrelation shows some problems as the null hypothesis of no serial correlation is rejected for all the lags at the 5% significance level.

d. Model Specification

Reduce the model in successive steps by dropping insignificant variables (subjecting each step to mis-specification testing) in order to obtain a parsimonious model.

We now drop the first lag of $\ln_consump$ in the error correction model above. This gives us the following result:

Source	SS	df	MS	Number of obs = 88		
Model	.004716449	5	.00094329	F(5, 82)	=	13.42
Residual	.005763359	82	.000070285	Prob > F	=	0.0000
				R-squared	=	0.4501
				Adj R-squared	=	0.4165
Total	.010479809	87	.000120458	Root MSE	=	.00838

dln_consump	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dln_consump						
L1.	-.2657825	.0869475	-3.06	0.003	-.4387488	-.0928161
L2.	.1683854	.083152	2.03	0.046	.0029696	.3338012
L3.	.2603634	.0858671	3.03	0.003	.0895463	.4311805
dln_inc	.4581345	.0802364	5.71	0.000	.2985187	.6177503
dln_inv	.0626535	.0201277	3.11	0.003	.022613	.102694
_cons	.0054381	.0028747	1.89	0.062	-.0002807	.0111569

Now we see that we do not have insignificant variables.

The mis-specification tests of this model are:

Ramsey RESET test using powers of the fitted values of dln_consump

Ho: model has no omitted variables

F(3, 79) = 1.20

Prob > F = 0.3151

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: fitted values of dln_consump

chi2(1) = 0.57

Prob > chi2 = 0.4492

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: L.dln_consump L2.dln_consump L3.dln_consump dln_inc dln_inv

chi2(5) = 4.26

Prob > chi2 = 0.5122

White's test for Ho: homoskedasticity

against Ha: unrestricted heteroskedasticity

chi2(20) = 25.95

Prob > chi2 = 0.1675

Cameron & Trivedi's decomposition of IM-test

Source	chi2	df	p
Heteroskedasticity	25.95	20	0.1675
Skewness	9.69	5	0.0846

Kurtosis		0.62	1	0.4322
-----+				
Total		36.25	26	0.0871

(n = 88)		D-H	P-value	asy.	P-value
-----+					
Residuals		2.7414	0.2539	2.6979	0.2595

Breusch-Godfrey LM test for autocorrelation

lags(p)		chi2	df	Prob > chi2
-----+				
1		4.309	1	0.0379
2		8.027	2	0.0181
3		9.487	3	0.0235
4		10.267	4	0.0362

H0: no serial correlation

LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(p)		chi2	df	Prob > chi2
-----+				
1		3.173	1	0.0748
2		8.125	2	0.0172
3		1.381	3	0.7100
4		0.998	4	0.9101

H0: no ARCH effects vs. H1: ARCH(p) disturbance

We now test whether we can exclude the last lag, but the `-testparm-` command does lead to rejection, so we keep the third lag.

```
( 1)  L3.dln_consump = 0
      F( 1, 82) = 9.19
      Prob > F = 0.0032
```

e. Comparison of Models

Save the log-likelihood value of the parsimonious model (-estimates store llr-) and perform a likelihood ratio test comparing the model in c. with the model in d. (-lrtest llu llr). You may wish to save the log-likelihood value at each step of the reduction using different names with the estimates command at each step.

```
. lrtest llu1 llu2
```

Likelihood-ratio test

LR chi2(1) = 0.05

(Assumption: llu2 nested in llu1)

Prob > chi2 = 0.8195

f. VAR(4) Model

Estimate a VAR(4) for the three variables dln_consump, dln_inc, and dln_inv, that is, for the first difference of ln_inv, ln_inc, and ln_consump. Then determine the minimum number of lags required for the VAR, and subject it to mis-specification testing.

We determine the lag structure by starting with three lags:

```
. var dln_consump dln_inc dln_inv, lags(1/3) dfk
```

Vector autoregression

Sample:	1961q1 - 1982q4	No. of obs	=	88
Log likelihood =	737.5558	AIC	=	-16.08081
FPE	= 2.09e-11	HQIC	=	-15.74057
Det(Sigma_ml)	= 1.05e-11	SBIC	=	-15.23627

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dln_consump	10	.00973	0.2953	32.68978	0.0002
dln_inc	10	.011309	0.1800	17.12733	0.0468
dln_inv	10	.045251	0.1096	9.599902	0.3838

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
dln_consump						
dln_consump						
	L1.	-.3930788	.1385722	-2.84	0.005	-.6646753 -.1214823
	L2.	-.1281016	.1441055	-0.89	0.374	-.4105431 .15434
	L3.	.1015717	.1278624	0.79	0.427	-.149034 .3521773
dln_inc						
	L1.	.2940007	.1174905	2.50	0.012	.0637236 .5242778
	L2.	.3438497	.1205479	2.85	0.004	.1075802 .5801192
	L3.	.1810283	.1187276	1.52	0.127	-.0516734 .4137301
dln_inv						
	L1.	.0034602	.0256856	0.13	0.893	-.0468826 .0538031
	L2.	.0437956	.0264529	1.66	0.098	-.0080512 .0956423
	L3.	.0168297	.0263789	0.64	0.523	-.034872 .0685314
_cons		.0091472	.0034369	2.66	0.008	.0024111 .0158833
dln_inc						
dln_consump						
	L1.	.1923453	.161054	1.19	0.232	-.1233148 .5080055
	L2.	-.0339177	.167485	-0.20	0.840	-.3621824 .294347
	L3.	-.0434862	.1486067	-0.29	0.770	-.33475 .2477776


```

      dln_inc |
      L1. | -.0815851 .136552 -0.60 0.550 -.3492222 .186052
      L2. | .0624807 .1401055 0.45 0.656 -.212121 .3370824
      L3. | .1984851 .1379898 1.44 0.150 -.07197 .4689402
      |
      dln_inv |
      L1. | .0476297 .0298528 1.60 0.111 -.0108808 .1061401
      L2. | .0598946 .0307446 1.95 0.051 -.0003637 .1201529
      L3. | .0155151 .0306586 0.51 0.613 -.0445747 .0756048
      |
      _cons | .011234 .0039945 2.81 0.005 .003405 .019063
-----+-----
dln_inv
dln_consump |
      L1. | .4585587 .644436 0.71 0.477 -.8045127 1.72163
      L2. | .4443132 .6701688 0.66 0.507 -.8691936 1.75782
      L3. | -.199181 .5946297 -0.33 0.738 -1.364634 .9662718
      |
      dln_inc |
      L1. | .3711541 .5463946 0.68 0.497 -.6997597 1.442068
      L2. | .2534399 .5606132 0.45 0.651 -.8453418 1.352222
      L3. | .3569366 .5521478 0.65 0.518 -.7252532 1.439126
      |
      dln_inv |
      L1. | -.2598316 .1194521 -2.18 0.030 -.4939533 -.0257098
      L2. | -.1253296 .1230204 -1.02 0.308 -.3664451 .115786
      L3. | .0466697 .1226763 0.38 0.704 -.1937714 .2871107
      |
      _cons | -.0100135 .0159833 -0.63 0.531 -.0413401 .0213131
-----+-----
. varsoc

Selection-order criteria
Sample: 1961q1 - 1982q4 Number of obs = 88
-----+-----
|lag | LL LR df p FPE AIC HQIC SBIC |
|-----+-----|
| 0 | 703.801 2.4e-11 -15.9273 -15.8933 -15.8428* |
| 1 | 719.587 31.572 9 0.000 2.1e-11 -16.0815 -15.9454* -15.7437 |
| 2 | 732.981 26.787* 9 0.002 1.9e-11* -16.1814* -15.9432 -15.5902 |
| 3 | 737.556 9.1506 9 0.423 2.1e-11 -16.0808 -15.7406 -15.2363 |
-----+-----
Endogenous: dln_consump dln_inc dln_inv
Exogenous: _cons

```

The -varsoc- command shows us that we can drop the third lag, so we try with two lags:

```

. dln_consump dln_inc dln_inv, lags(1/2) dfk

Vector autoregression

Sample: 1960q4 - 1982q4 No. of obs = 89
Log likelihood = 742.2131 AIC = -16.20704
FPE = 1.84e-11 HQIC = -15.97035
Det(Sigma_ml) = 1.15e-11 SBIC = -15.61983

```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dln_consump	7	.009938	0.2400	25.88962	0.0002
dln_inc	7	.011224	0.1514	14.62996	0.0233
dln_inv	7	.044295	0.1051	9.633771	0.1409

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
dln_consump						
dln_consump						
L1.	-.2845172	.1274068	-2.23	0.026	-.5342299	-.0348044
L2.	-.1159776	.1270233	-0.91	0.361	-.3649386	.1329834
dln_inc						
L1.	.2893204	.112313	2.58	0.010	.069191	.5094497
L2.	.3664341	.1089872	3.36	0.001	.1528231	.5800451
dln_inv						
L1.	.0027381	.0255556	0.11	0.915	-.0473499	.0528261
L2.	.0497402	.025462	1.95	0.051	-.0001644	.0996447
_cons	.0123795	.0029602	4.18	0.000	.0065776	.0181813
dln_inc						
dln_consump						
L1.	.3050571	.1438994	2.12	0.034	.0230195	.5870947
L2.	.0490208	.1434662	0.34	0.733	-.2321677	.3302094
dln_inc						
L1.	-.1232543	.1268517	-0.97	0.331	-.371879	.1253704
L2.	.0209769	.1230954	0.17	0.865	-.2202857	.2622394
dln_inv						
L1.	.0433473	.0288637	1.50	0.133	-.0132244	.0999191
L2.	.0616319	.028758	2.14	0.032	.0052673	.1179965
_cons	.0125949	.0033434	3.77	0.000	.006042	.0191478
dln_inv						
dln_consump						
L1.	.6520473	.5678885	1.15	0.251	-.4609936	1.765088
L2.	.5980687	.566179	1.06	0.291	-.5116217	1.707759
dln_inc						
L1.	.3374819	.5006109	0.67	0.500	-.6436975	1.318661
L2.	.1827302	.4857871	0.38	0.707	-.7693951	1.134855
dln_inv						
L1.	-.2725654	.1139085	-2.39	0.017	-.4958218	-.0493089
L2.	-.1340503	.1134912	-1.18	0.238	-.3564891	.0883884
_cons	-.0099191	.0131944	-0.75	0.452	-.0357798	.0159415
. varsoc						

```

Selection-order criteria
Sample: 1960q4 - 1982q4                                Number of obs   =      89
+-----+-----+-----+-----+-----+-----+-----+-----+
|lag |   LL   LR    df    p    FPE      AIC    HQIC    SBIC   |
+-----+-----+-----+-----+-----+-----+-----+-----+
| 0 | 712.092                2.4e-11 -15.9346 -15.9008 -15.8508* |
| 1 | 728.167   32.15    9 0.000 2.1e-11 -16.0936 -15.9584 -15.7581 |
| 2 | 742.213  28.092*   9 0.001 1.8e-11* -16.207* -15.9704* -15.6198 |
+-----+-----+-----+-----+-----+-----+-----+-----+
Endogenous:  dln_consump dln_inc dln_inv
Exogenous:   _cons

```

g. Final Model

Finally, drop individual variables from each of the three equations until you end up with a parsimonious model.

We now drop individual variables from each equation until we end up with the following parsimonious model with eight constraints:

```

. var dln_consump dln_inc dln_inv, lags(1/2) dfk constraint (1 2 3 4 5 6 7 8)
Estimating VAR coefficients

```

```

Iteration 1:  tolerance = .08076175
Iteration 2:  tolerance = .00197295
Iteration 3:  tolerance = .0000493
Iteration 4:  tolerance = 1.529e-06
Iteration 5:  tolerance = 5.099e-08

```

Vector autoregression

```

Sample: 1960q4 - 1982q4                                No. of obs   =      89
Log likelihood = 739.5869                                AIC          = -16.14802
FPE           = 2.18e-15                                HQIC         = -15.91133
Det(Sigma_ml) = 1.63e-15                                SBIC         = -15.56081

```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
dln_consump	5	.009606	0.2292	37.83738	0.0000
dln_inc	4	.01085	0.1394	15.67358	0.0013
dln_inv	4	.042994	0.0849	9.673415	0.0216

```

( 1) [dln_consump]L.dln_inv = 0
( 2) [dln_inc]L2.dln_inc = 0
( 3) [dln_inv]L2.dln_inc = 0
( 4) [dln_inc]L2.dln_consump = 0
( 5) [dln_inv]L.dln_inc = 0
( 6) [dln_inc]L.dln_inc = 0
( 7) [dln_inv]L2.dln_inv = 0
( 8) [dln_consump]L2.dln_consump = 0

```

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	

dln_consump							
dln_consump							
	L1.	-.2560975	.1075375	-2.38	0.017	-.4668671	-.0453279
	L2.	2.70e-18	1.79e-17	0.15	0.880	-3.24e-17	3.78e-17
dln_inc							
	L1.	.2899923	.0825004	3.52	0.000	.1282945	.4516901
	L2.	.286996	.0723422	3.97	0.000	.1452079	.4287841
dln_inv							
	L1.	1.12e-19	5.57e-18	0.02	0.984	-1.08e-17	1.10e-17
	L2.	.0515305	.0226578	2.27	0.023	.0071221	.095939
_cons		.0112223	.0024842	4.52	0.000	.0063534	.0160913

dln_inc							
dln_consump							
	L1.	.235463	.1110663	2.12	0.034	.0177771	.4531489
	L2.	-3.32e-17	2.73e-17	-1.22	0.224	-8.67e-17	2.03e-17
dln_inc							
	L1.	-3.35e-17	2.71e-17	-1.24	0.215	-8.66e-17	1.95e-17
	L2.	-1.73e-17	1.61e-17	-1.07	0.282	-4.88e-17	1.42e-17
dln_inv							
	L1.	.0472669	.0230169	2.05	0.040	.0021546	.0923791
	L2.	.0629894	.0263325	2.39	0.017	.0113786	.1146003
_cons		.0127585	.0024014	5.31	0.000	.0080519	.0174651

dln_inv							
dln_consump							
	L1.	.8894705	.4463473	1.99	0.046	.0146459	1.764295
	L2.	.7532321	.4187462	1.80	0.072	-.0674953	1.573959
dln_inc							
	L1.	-8.84e-17	1.10e-16	-0.80	0.421	-3.04e-16	1.27e-16
	L2.	-8.48e-17	2.14e-16	-0.40	0.692	-5.05e-16	3.35e-16
dln_inv							
	L1.	-.25624	.1045915	-2.45	0.014	-.4612356	-.0512443
	L2.	-2.63e-17	2.54e-17	-1.04	0.300	-7.62e-17	2.35e-17
_cons		-.0097218	.0125614	-0.77	0.439	-.0343416	.014898

. varlmar							
Lagrange-multiplier test							
+-----+							
lag		chi2	df	Prob > chi2			
+-----+							
1		-7.1e+02	9	1.00000			
2		-7.2e+02	9	1.00000			
+-----+							
H0: no autocorrelation at lag order							

```
. varnorm
```

Jarque-Bera test

Equation	chi2	df	Prob > chi2
dln_consump	11.036	2	0.00401
dln_inc	0.869	2	0.64764
dln_inv	12.553	2	0.00188
ALL	24.457	6	0.00043

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
dln_consump	-.74579	8.250	1	0.00407
dln_inc	-.17547	0.457	1	0.49915
dln_inv	.42156	2.636	1	0.10446
ALL		11.343	3	0.01001

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
dln_consump	3.8666	2.785	1	0.09514
dln_inc	2.6666	0.412	1	0.52091
dln_inv	4.6353	9.917	1	0.00164
ALL		13.114	3	0.00440

dfk estimator used in computations