

Assignment 1

COURSE: FSSS23 - Analytical Methods for Economic and Financial Analysis

PROGRAMME: International Financial Analysis

AUTHOR: Sophie Dick (25.12.1999), Enrique Höner (03.11.1997)

TUTOR: Pär Henrik Sjölander

Q.1.1

<u>Y1:</u>

1. Model identification

Correlogram of Y1							
Date: 02/09/22 Time: 15:24 Sample: 3 1450 Included observations: 1448							
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob	
1	ı	1	0.917	0.917	1219.8	0.000	
	l III	2	0.841	-0.000	2245.8	0.000	
	l ili	3	0.770	-0.007	3106.2	0.000	
ı	l i	4	0.708	0.019	3834.0	0.000	
ı	l i	5	0.656	0.036	4460.7	0.000	
1	l III	6	0.609	0.003	5000.8	0.000	
1	ψ	7	0.564	-0.009	5464.1	0.000	
·	III	8	0.525	0.021	5866.1	0.000	
·	ψ	9	0.486	-0.019	6210.2	0.000	
· -	I	10	0.452	0.019	6508.9	0.000	
·	l ij	11	0.429	0.052	6778.2	0.000	
· 	(+	12	0.400	-0.042	7012.6	0.000	
· -	ψ	13	0.370	-0.024	7212.5	0.000	
· !	l III	14	0.341	-0.000	7382.6	0.000	
· !	ψ	15	0.312	-0.014	7524.9	0.000	
· =	(+	16	0.282	-0.026	7641.3	0.000	
	(+	17	0.250	-0.029	7733.3	0.000	
-	ψ	18	0.219	-0.021	7803.5	0.000	
-	l III	19	0.192	0.007	7857.9	0.000	
-	(20	0.164	-0.028	7897.6	0.000	
-	1)	21	0.145	0.035	7928.6	0.000	
 	l ili	22	0.128	-0.006	7952.7	0.000	
,		23	0.111	-0.013	7970.8	0.000	
巾	l ilji	24	0.098	0.017	7984.9	0.000	

The correlogram shows a spike at lag 1 for the SPAC and a decay for the SAC. This suggest that an autoregressive model with one lag (AR(1)) should be used.

2. Parameter estimation

Dependent Variable: Y1

Method: ARMA Maximum Likelihood (BFGS)

Date: 02/09/22 Time: 15:28

Sample: 3 1450

Included observations: 1448

Convergence achieved after 3 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C AR(1) SIGMASQ	0.409359 0.919036 1.009878	0.326445 0.010528 0.037521	0.2100 0.0000 0.0000	
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.843231 0.843014 1.005969 1462.303 -2062.670 3886.183 0.000000	Mean depende S.D. depende Akaike info cri Schwarz crite Hannan-Quin Durbin-Watso	0.455027 2.538949 2.853136 2.864071 2.857217 2.005232	
Inverted AR Roots	.92			

From this follows that estimated AR(1) model has the following form:

$$Y_t^1 = 0.409359 + 0.919036 * Y_{t-1}^1$$

3. Diagnostic testing

i) Checking for autocorrelation in the residuals

The hypotheses for this first test are as follows:

$$H_0$$
: ρ_1 = ρ_2 =... = ρ_K =0 (no autocorrelation)

$$H_1: \rho_{(1, \dots, k)} \neq 0$$
 (autocorrelation)

Correlogram of Residuals Date: 02/09/22 Time: 15:38 Sample: 3 1450 Q-statistic probabilities adjusted for 1 ARMA term Autocorrelation Partial Correlation Q-Stat AC PAC Prob 1 -0.003 -0.003 0.0102 0.006 0.006 0.0712 0.790 -0.021 -0.0210.7218 -0.031 -0.031 2.1429 0.009 0.009 0.016 0.017 2.6459 0.754 -0.009 -0.010 2.7578 0.028 0.027 3.8759 -0.016 -0.014 4.2284 -0.037-0.0376.2434 0.052 0.053 10.204 0.024 0.026 11.066 0.007 0.003 11.137 0.019 0.018 11.661 12.109 15 0.017 0.024 0.026 0.027 13.096 0.595

It becomes apparent that none of the values exceed the confidence bound. Since all p-values are greater than 0.05 we can reject H_0 and assume that there is no autocorrelation in the residuals. Therefore, we can assume that the residuals are white noise.

0.013

18 -0 016 -0 013

17

0.012

13.341

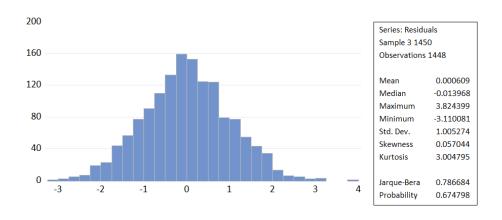
13 733

0.648

ii) Jarque-Bera test

 H_0 : Normal distribution

 H_1 : Non-normal distribution



Since the Jarque-Bera statistic is 0.786 with a p-value of 0.67 > 0.05 we cannot reject H_0 . There is no indication against normality, which leads us to assume a normal distribution.

<u>Y2:</u>

1. Model identification

Correlogram of Y2

Date: 02/09/22 Time: 15:49

Sample: 3 1450

Included observations: 1448

Autocorrelation	Partial Correlation	AC		PAC	Q-Stat	Prob
- I	i iii				283.21	
111					283.78 283.86	
ď					284.75	
ιþ	Q i	5 0.0	018	-0.053	285.24	0.000
<u>"</u>	1				285.71	
q'	"!"	7 -0.0	026	-0.021	286.71	0.000

The correlogram shows a spike at lag 1 for the SAC and a decay for the SPAC. This suggest that an moving average model with one lag (MA(1)) should be used.

2. Parameter Estimation

Dependent Variable: Y2

Method: ARMA Maximum Likelihood (BFGS)

Date: 02/09/22 Time: 15:51

Sample: 3 1450

Included observations: 1448

Convergence achieved after 4 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error t-Statistic		Prob.
C MA(1) SIGMASQ	0.017256 -0.577106 1.012539	0.011202 0.021856 0.037672	0.1237 0.0000 0.0000	
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.253450 0.252417 1.007294 1466.156 -2063.847 245.2857 0.000000	Mean depend S.D. depende Akaike info cri Schwarz critei Hannan-Quin Durbin-Watso	0.017762 1.165002 2.854761 2.865696 2.858842 2.009779	
Inverted MA Roots	.58			

From this follows that the estimated MA(1) model has the following form:

$$Y_t^2 = 0.017256 - 0.577106 * e_{t-1}$$

3. Diagnostic testing

i) Checking for autocorrelation in the residuals

 H_0 : ρ_1 = ρ_2 =... = ρ_K =0 (no autocorrelation)

 $H_1: \rho_{(1, \dots, k)} \neq 0$ (autocorrelation)

Correlogram of Residuals

Date: 02/09/22 Time: 15:52

Sample: 3 1450

Q-statistic probabilities adjusted for 1 ARMA term

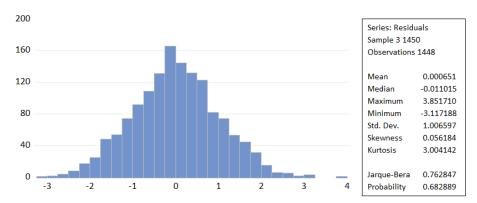
	Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
_	ф		1	-0.005	-0.005	0.0424	
	ı j ı		2	0.013	0.013	0.2839	0.594
	10		3	-0.011	-0.010	0.4452	0.800
	ψ.		4	-0.020	-0.020	1.0137	0.798
	ıþι	III	5	0.022	0.022	1.7308	0.785
	ıþ	1	6	0.029	0.030	2.9507	0.708
	ı ı	1	7	0.003	0.002	2.9635	0.813
	ψ	1	8	0.039	0.038	5.1435	0.642
	ılı	1	9	-0.005	-0.003	5.1738	0.739
	q ı	(1	10	-0.028	-0.029	6.3540	0.704
	ıþ	1	11	0.061	0.061	11.784	0.300
	ı)ı	1	12	0.030	0.032	13.093	0.287
	ı j ı		13	0.012	0.008	13.295	0.348
	ıþι	1 1	14	0.024	0.022	14.125	0.365
	ıβι	1	15	0.022	0.027	14.837	0.389
	ı)ı	1	16	0.030	0.029	16.173	0.371
	ıþι	III	17	0.017	0.014	16.603	0.412
	ψ.		18	-0.013	-0.012	16.848	0.465
	ıþι	·	19	0.021	0.015	17.469	0.491
	al.	۱ ام		0.007	0.040	40 507	0.400

It becomes apparent that none of the values exceed the confidence bound. Since all p-values are greater than 0.05 we can reject H_0 and assume that there is no autocorrelation in the residuals. Therefore, we can assume that the residuals are white noise.

ii) Jarque-Bera test

 H_0 : Normal distribution

 H_1 : non-normal distribution



Since the Jarque-Bera statistic is 0.763 with a p-value of 0.68 > 0.05 we cannot reject H_0 . There is no indication against normality, which leads us to assume a normal distribution.

<u>Y3:</u>

1. Model identification

	Correlogram of Y3							
Date: 02/09/22 Tim Sample: 3 1450 Included observation Autocorrelation			AC	PAC	Q-Stat	Prob		
	l	1	-0.561	-0.561	457.12	0.000		
ı		2	0.537	0.324	876.13	0.000		
· ·	1 1	3	-0.380	0.010	1085.5	0.000		
ı	1 1	4	0.307	-0.015	1222.5	0.000		
□ I	1 1	5	-0.228	0.008	1298.3	0.000		
· =	·	6	0.203	0.041	1358.6	0.000		
<u>d</u> i	l ili	7	-0.145	0.015	1389.3	0.000		
ı		8	0.129	0.006	1413.5	0.000		
dı	1)	9	-0.077	0.033	1422.2	0.000		
ı	(1	10	0.045	-0.033	1425.2	0.000		
ı ı	· ·	11	-0.007	0.030	1425.3	0.000		
ıþ	·	12	0.035	0.064	1427.0	0.000		
ılı	ı j ı	13	-0.004	0.010	1427.0	0.000		
ı	1 1	14	0.021	0.006	1427.7	0.000		
ı	h	15	0.011	0.034	1427.9	0.000		
ı[ı	1 1	16	0.006	0.016	1427.9	0.000		
1	1 1	17	0.025	0.024	1428.8	0.000		

The correlogram shows a decay for the SAC and two spikes at lag 1 and 2 for the SPAC. This suggest that an autoregressive model with two lags (AR(2)) should be used.

2. Parameter Estimation

Dependent Variable: Y2

Method: ARMA Maximum Likelihood (BFGS)

Date: 02/09/22 Time: 15:51

Sample: 3 1450

Included observations: 1448

Convergence achieved after 4 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	Prob.	
C MA(1) SIGMASQ	0.017256 -0.577106 1.012539	0.011202 0.021856 0.037672	0.1237 0.0000 0.0000	
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.253450 0.252417 1.007294 1466.156 -2063.847 245.2857 0.000000	Mean depend S.D. depende Akaike info cr Schwarz crite Hannan-Quin Durbin-Watso	0.017762 1.165002 2.854761 2.865696 2.858842 2.009779	
Inverted MA Roots	.58			

From this follows that the estimated AR(2) model has the following form:

$$Y_t^3 = 0.038942 - 0.378933 * Y_{t-1}^3 + 0.324412 * Y_{t-2}^3$$

3. Diagnostic testing

i) Checking for autocorrelation in the residuals

$$H_0$$
: ρ_1 = ρ_2 =... = ρ_K =0 (no autocorrelation)

 $H_1: \rho_{(1, \dots, k)} \neq 0$ (autocorrelation)

Correlogram of Residuals

Date: 02/09/22 Time: 15:59

Sample: 3 1450

Q-statistic probabilities adjusted for 2 ARMA terms

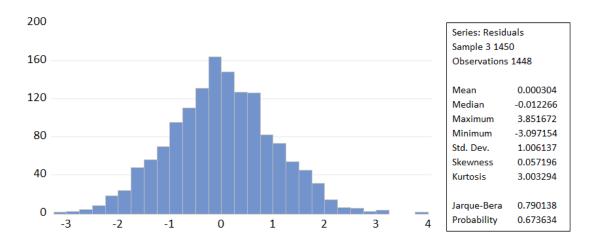
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
ılı		1	-0.003	-0.003	0.0161	
ıþı	m	2	0.010	0.010	0.1609	
ıþι	1	3	-0.003	-0.003	0.1761	0.675
ųli		4	-0.020	-0.020	0.7700	0.680
ıþ	1	5	0.026	0.026	1.7668	0.622
ıþ	1	6	0.028	0.029	2.9012	0.574
ψ		7	0.005	0.004	2.9329	0.710
ıþ	1	8	0.038	0.038	5.0773	0.534
ψ		9	-0.004	-0.002	5.0964	0.648
(I	•	10	-0.029	-0.029	6.3047	0.613
ıþ	· i	11	0.062	0.061	11.890	0.220
ıþ	1	12	0.030	0.032	13.242	0.210
ı j ı	1 1	13	0.013	0.009	13.474	0.263
ı j ı	III	14	0.024	0.021	14.342	0.279
ı j ı	1)	15	0.022	0.027	15.078	0.302
ıþ	1)	16	0.031	0.029	16.458	0.286
ıþι	• •	17	0.017	0.014	16.895	0.325
ı l ı		18	-0.012	-0.012	17.122	0.378
ıþı	·	19	0.021	0.015	17.762	0.404
al.	ا. ا			~ ~	** ***	~ ~

It becomes apparent that none of the values exceed the confidence bound. Since all p-values are greater than 0.05 we can reject H_0 and assume that there is no autocorrelation in the residuals. Therefore, we can assume that the residuals are white noise.

ii) Jarque-Bera test

 H_0 : Normal distribution

 H_1 : non-normal distribution



Since the Jarque-Bera statistic is 0.79 with a p-value of 0.67 > 0.05 we cannot reject H_0 . There is no indication against normality, which leads us to assume a normal distribution.

<u>Y4:</u>

1. Model identification

	Correlog	ram of \	Y4						
Date: 02/09/22 Time: 16:02 Sample: 3 1450 Included observations: 1448 Autocorrelation Partial Correlation AC PAC Q-Stat Prob									
ı	ı	1 -0.	773	-0.773	868.12	0.000			
ı	l 🖃	2 0.	478	-0.300	1199.4	0.000			
- I	 -	3 -0.	322	-0.202	1350.1	0.000			
–	d	4 0.	228	-0.089	1425.6	0.000			
□ i	1 1	5 -0.	146	-0.007	1456.7	0.000			
ıþ	(t	6 0.	076	-0.038	1465.2	0.000			
(i	1 1	7 -0.	.031	-0.007	1466.6	0.000			
ı j ı	1)	8 0.	021	0.030	1467.2	0.000			
(I	10	9 -0.	.027	-0.010	1468.3	0.000			
· III	(t	10 0.	019	-0.027	1468.8	0.000			
ı ı	10	11 -0.	.007	-0.010	1468.9	0.000			
ı j ı	1	12 0.	.009	0.014	1469.0	0.000			
ψ.	1 1	13 -0.	.018	-0.006	1469.5	0.000			
ı) ı	1	14 0.	.035	0.042	1471.3	0.000			
<u>!</u> !	l <u>«</u> !	15 -0.	062	-0.036	1476.8	0.000			

This suggest that an ARMA(1,1) model should be used. Since there is an exponential decay in both the SPAC and SAC.

2. Parameter Estimation

Dependent Variable: Y4

Method: ARMA Maximum Likelihood (BFGS)

Date: 02/09/22 Time: 16:03

Sample: 3 1450

Included observations: 1448

Convergence achieved after 6 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1) MA(1) SIGMASQ	-0.597455 -0.501792 0.995786	0.024793 0.025793 0.037350	0.0000 0.0000 0.0000	
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood Durbin-Watson stat	0.652537 0.652056 0.998926 1441.899 -2052.194 1.977742	Mean depend S.D. depende Akaike info cr Schwarz crite Hannan-Quin	0.003664 1.693474 2.838666 2.849601 2.842746	
Inverted AR Roots Inverted MA Roots	60 .50			

From this follows that the estimated ARMA(1,1) model has the following form:

$$Y_t^4 = 0.002971 - 0.597404 * Y_{t-1}^4 - 0.501962 * e_{t-1}$$

3. Diagnostic testing

i) Checking for autocorrelation in the residuals

The hypotheses for this first test are as follows:

$$H_0$$
: ρ_1 = ρ_2 =... = ρ_K =0 (no autocorrelation)

 $H_1: \rho_{(1, \dots, k)} \neq 0$ (autocorrelation)

Date: 02/09/22 Time: 16:07

Sample: 3 1450

Q-statistic probabilities adjusted for 2 ARMA terms

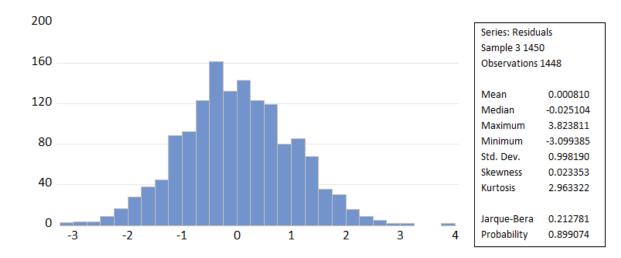
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
ı j ı	1)	1	0.010	0.010	0.1473	
ų l		2	-0.019	-0.019	0.6846	
ı l ı		3	-0.023	-0.022	1.4395	0.230
ıþ	1	4	0.051	0.051	5.2529	0.072
ųli		5	-0.020	-0.022	5.8170	0.121
ф	1	6	-0.003	-0.001	5.8271	0.212
ıþ	1	7	0.029	0.031	7.0927	0.214
		8	-0.017	-0.022	7.5157	0.276
q i	•	9	-0.034	-0.031	9.2060	0.238
ф		10	0.006	0.008	9.2658	0.320
· III	• • • • • • • • • • • • • • • • • • •	11	0.022	0.017	9.9744	0.353
ф		12	0.005	0.007	10.013	0.439
ф	• • • • • • • • • • • • • • • • • • •	13	0.005	0.009	10.051	0.526
ψ		14	-0.005	-0.007	10.082	0.609
		15	-0.020	-0.020	10.660	0.639
ıþ	•	16	0.035	0.038	12.463	0.569

It becomes apparent that none of the values exceed the confidence bound. Since all p-values are greater than 0.05 we can reject H_0 and assume that there is no autocorrelation in the residuals. Therefore, we can assume that the residuals are white noise.

ii) Jarque-Bera test

 H_0 : Normal distribution

 H_1 : non-normal distribution



Since the Jarque-Bera statistic is 0.21 with a p-value of 0.899 > 0.05 we cannot reject H_0 . There is no indication against normality, which leads us to assume a normal distribution.

Q.1.2

As shown in Q.1.1 for Y1 the optimal model is an AR(1). However, when using a MA(1) model we get the following results:

Dependent Variable: Y1

Method: ARMA Maximum Likelihood (BFGS)

Date: 02/09/22 Time: 16:12

Sample: 3 1450

Included observations: 1448

Convergence achieved after 7 iterations

Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	Prob.	
C MA(1) SIGMASQ	0.453473 0.756033 2.723890	0.076207 0.016991 0.093864	0.0000 0.0000 0.0000	
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.577154 0.576569 1.652134 3944.193 -2780.539 986.1615 0.000000	Mean depend S.D. depende Akaike info cri Schwarz criter Hannan-Quin Durbin-Watso	0.455027 2.538949 3.844667 3.855602 3.848748 0.947520	
Inverted MA Roots	76			

Therefore, the estimated MA(1) model has the following form:

$$Y_t^1 = 0.453473 + 0.756033 * e_{t-1}$$

Diagnostic testing:

i) Testing for autocorrelation in the residuals

 H_0 : $\rho_{\rm 1}$ = $\rho_{\rm 2}$ =... = $\rho_{\rm K}$ =0 (no autocorrelation)

 $H_1: \rho_{(1, \dots, k)} \neq 0$ (autocorrelation)

Date: 02/09/22 Time: 16:17

Sample: 3 1450

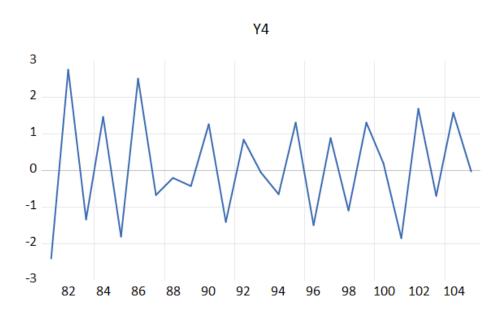
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.525	0.525	400.42	
ı	ı	2	0.780	0.696	1282.8	0.000
ı	1	3	0.488	-0.007	1628.3	0.000
ı	1	4	0.618	-0.005	2183.5	0.000
ı	1	5	0.445	0.026	2472.2	0.000
ı	1	6	0.513	0.034	2855.8	0.000
1	1	7	0.397	-0.007	3084.9	0.000
ı	1	8	0.430	0.000	3354.2	0.000
ı	·	9	0.355	0.018	3538.5	0.000
ı	(1	10	0.353	-0.028	3720.7	0.000
ı <u> </u>	· b	11	0.328	0.046	3878.0	0.000
ı <u> </u>	1	12	0.310	0.026	4018.5	0.000
ı 	(+	13	0.283	-0.039	4135.3	0.000
–		14	0.262	-0.020	4236.2	0.000
· =		15	0.241	0.002	4321.4	0.000
· 		16	0.214	-0.023	4388.5	0.000

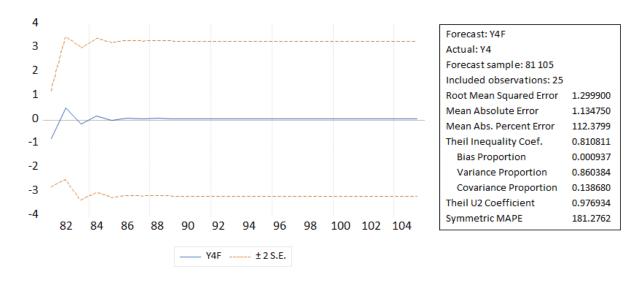
The output shows statistically relevant (because all p-values are <0.05) autocorrelation in the residuals. We must therefore reject H_0 . This leads to biased results.

Q.1.3 (Dynamic out of sample forecasting for Y4)

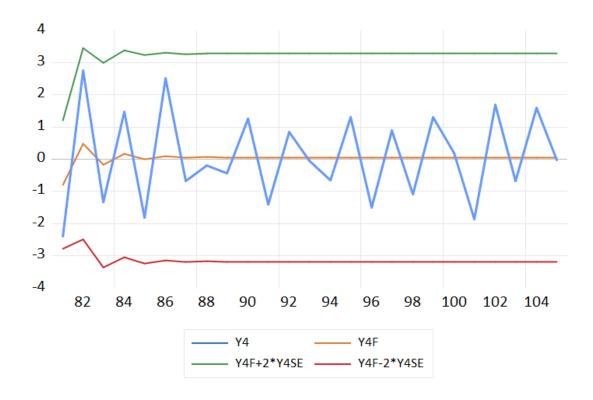
Plot of the real outcomes of Y4 for the period 81 to 105:



Forecast of Y4 for the period 81 to 105 using only the data from period 2 to 80:



Comparison between the dynamic out of sample forecast and reality:



Dependent Variable: SMOKER

Method: Least Squares Date: 02/09/22 Time: 17:01

Sample: 1 1196

Included observations: 1196

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C AGE EDUC INCOME PCIGS79	1.123089 -0.004726 -0.020613 1.03E-06 -0.005132	0.188356 0.000829 0.004616 1.63E-06 0.002852	5.962575 -5.700952 -4.465272 0.628522 -1.799076	0.0000 0.0000 0.0000 0.5298 0.0723
R-squared Adjusted R-squared S.E. of regression Sum squared resid Log likelihood F-statistic Prob(F-statistic)	0.038770 0.035541 0.476988 270.9729 -809.1885 12.00927 0.000000	Mean depende S.D. depende Akaike info cr Schwarz crite Hannan-Quin Durbin-Watso	ent var iterion rion in criter.	0.380435 0.485697 1.361519 1.382785 1.369531 1.943548

If the years of education of the average person increase by 1, the probability of being a smoker decreases by 0.020613=2.06%

Logit Model:

Since in the linear probability model very high cigarette prices could lead to a negative probability of smoking the Logit model uses odds ratios:

 $Odds = \frac{P_i}{1 - P_i}$ where $\frac{P_i}{1 - P_i} \in [0, \infty]$ with a midpoint at 1 (which can be seen by inserting 0.5 for P_i .

However, a distribution over a range of $[0, \infty]$ is heavily skewed. Furthermore, a lower bound of 0 does not exclude negative probabilities.

To work around this problem the natural logarithm of the odds ratio is taken:

 $\ln\left(\frac{P_i}{1-P_i}\right)$ where $\ln\left(\frac{P_i}{1-P_i}\right) \in [-\infty, \infty]$ with a midpoint at 0 (which can be seen by inserting 0.5 for P_i .

Therefore, a simple Logit model takes the following form:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_1 + \beta_2 * X_i = Z_i$$

Solving for P_i :

$$\begin{split} &\frac{P_i}{1-P_i} = e^{Z_i} \\ &\to P_i = (1-P_i) * e^{Z_i} = e^{Z_i} - e^{Z_i} * P_i \\ &\to P_i + e^{Z_i} * P_i = P_i * (1+e^{Z_i}) = e^{Z_i} \\ &\to P_i = \frac{e^{Z_i}}{1+e^{Z_i}} = \frac{e^{Z_i}}{(1+e^{-Z_i}) * e^{Z_i}} = \frac{1}{1+e^{-Z_i}} = \frac{1}{1+e^{-(\beta_1 + \beta_2 * X_i)}} \end{split}$$

When solving for $1 - P_i$ we get through the same transformation the following:

$$1 - P_i = \frac{1}{1 + e^{Z_i}} = \frac{1}{1 + e^{\beta_1 + \beta_2 * X_i}}$$

Going back to the odds ratio we now get:

$$\frac{P_i}{1 - P_i} = \frac{\frac{e^{Z_i}}{1 + e^{Z_i}}}{\frac{1}{1 + e^{Z_i}}} = e^{Z_i}$$

When taking the natural logarithm, we get:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \ln(e^{Z_i}) = Z_i = \beta_1 + \beta_2 * X_i$$

The estimated Logit model from the assignment has the following form:

Dependent Variable: SMOKER Method: ML - Binary Logit (Newton-Raphson / Marquardt steps) Date: 02/09/22 Time: 17:23 Sample: 1 1196

Included observations: 1196

Convergence achieved after 2 iterations

Coefficient covariance computed using the Huber-White method

Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	2.745082	0.821766	3.340466	0.0008
AGE	-0.020853	0.003613	-5.772377	0.0000
EDUC	-0.090973	0.020548	-4.427426	0.0000
INCOME	4.72E-06	7.27E-06	0.649033	0.5163
PCIGS79	-0.022319	0.012388	-1.801631	0.0716
McFadden R-squared	0.029748	Mean depend	dent var	0.380435
S.D. dependent var	0.485697	S.E. of regression		0.477407
Akaike info criterion	1.297393	Sum squared resid		271.4495
Schwarz criterion	1.318658	Log likelihood		-770.8409
Hannan-Quinn criter.	1.305405	Deviance		1541.682
Restr. deviance	1588.950	Restr. log like	elihood	-794.4748
LR statistic	47.26785	Avg. log likelil	hood	-0.644516
Prob(LR statistic)	0.000000			
Obs with Dep=0	741	Total obs	·	1196
Obs with Dep=1	455			

With these estimated coefficients we can now calculate the probability that an individual is a smoker, considering their specific data.

$$P_i = \frac{1}{1 + e^{-Z_i}} = \frac{1}{1 + e^{-(\beta_1 + \beta_2 * AGE_i + \beta_3 * Education_i + \beta_4 * Income_i + \beta_5 * Price_i)}}$$

If we assume the following information about an individual: Age= 30, Education= 20, Income= 15000 and Price (of cigarettes)=80 we get the following probability:

$$P_i = \frac{1}{1 + e^{-Z_i}} = \frac{1}{1 + e^{-(2.745082 - 0.020853 * 30 - 0.090973 * 20 + 0.00000472 * 15000 - 0.022319 * 80)}}$$

$$= 0.195496 \sim 19.5\%$$

Therefore, we can assume that a person with these characteristics has a probability of about 19.5% to be a smoker.

The marginal effect on the probability of smoking on age is given by the following formula:

$$\hat{\beta}_4 * \bar{Y} * (1 - \bar{Y}) = -0.020853 * 0.38 * 0.62 = -0.0049129668$$

(Where \overline{Y} gives the percentage of smokers in the considered sample)

This could be interpreted in the following way: An increase in age by 1 unit (years) causes on average a decrease of probability of being a smoker by 0.5%.

View Proc Object | Print Name Freeze | Estimate Forecast Stats Resids

Dependent Variable: SMOKER

Method: ML - Binary Probit (Newton-Raphson / Marquardt steps)

Date: 02/10/22 Time: 11:14

Sample: 1 1196

Included observations: 1196

Convergence achieved after 2 iterations

Coefficient covariance computed using the Huber-White method

Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	1.701906	0.506635	3.359234	0.0008
AGE	-0.012965	0.002226	-5.824174	0.0000
EDUC	-0.056230	0.012554	-4.479040	0.0000
INCOME	2.72E-06	4.45E-06	0.611796	0.5407
PCIGS79	-0.013794	0.007653	-1.802412	0.0715
McFadden R-squared	0.030066	Mean dependent var		0.380435
S.D. dependent var	0.485697	S.E. of regression		0.477328
Akaike info criterion	1.296970	Sum squared resid		271.3598
Schwarz criterion	1.318236	Log likelihood		-770.5881
Hannan-Quinn criter.	1.304982	Deviance		1541.176
Restr. deviance	1588.950	Restr. log likelihood		-794.4748
LR statistic	47.77335	Avg. log likelil	nood	-0.644304
Prob(LR statistic)	0.000000			
Obs with Dep=0	741	Total obs		1196
Obs with Dep=1	455			

In the Probit model all variables, except the income variable, are significant at the 10% level.

To calculate the marginal effect, the coefficient of the variable is multiplied with the value of the normal density function evaluated for all the X values for that individual.

If we multiply the Probit coefficient by approximately 1.81 we will get the Logit coefficient.

Age: -0.012965*1.81= -0.0235

This is about the same result we get from the Logit age coefficient.

Marginal effect of education:

$$\bar{Y} = \frac{455}{1196} = 0.38$$

$$\hat{\beta}_2 * \overline{Y} * (1 - \overline{Y}) = -0.056230 * 0.38 * 0.62 = -0.013247788$$

Marginal effect on probability of smoking of education: An increase of 1 unit (year) in education decreases the probability on the average person by $\sim 0.1\%$.

Q.1.4.7

Uncensored data:

Dependent Variable: HOURS Method: Least Squares Date: 02/10/22 Time: 12:00 Sample: 1 753

Included observations: 753

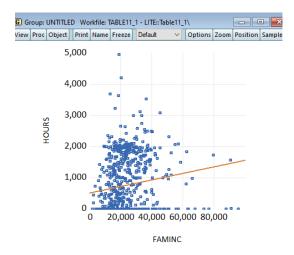
Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	1298.293	231.9451	5.597413	0.0000
AGE	-29.55452	3.864413	-7.647869	0.0000
EDUC	5.064135	12.55700	0.403292	0.6868
EXPER	68.52186	9.398942	7.290380	0.0000
EXPERSQ	-0.779211	0.308540	-2.525480	0.0118
FAMINC	0.028993	0.003201	9.056627	0.0000
KIDSL6	-395.5547	55.63591	-7.109701	0.0000
HWAGE	-70.51493	9.024624	-7.813615	0.0000
R-squared	0.338537	Mean depend	lent var	740.5764
Adjusted R-squared	0.332322	S.D. dependent var		871.3142
S.E. of regression	711.9647	Akaike info criterion		15.98450
Sum squared resid	3.78E+08	Schwarz criterion		16.03363
Log likelihood	-6010.165	Hannan-Quinn criter.		16.00343
F-statistic	54.47011	Durbin-Watson stat		1.482101
Prob(F-statistic)	0.000000			

The results out of this output are interpreted in the framework of the standard linear regression model. That means each of the slope coefficients above gives the marginal effect of that variable on the mean of the dependent variable, ceteris paribus.

For instance, if husband's wages go up by one-dollar, average hours worked by a married women decline by about 71 hours, ceteris paribus.

All coefficients, except education are statistically significant.

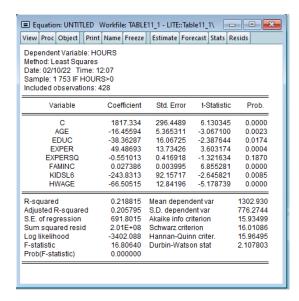
Now a plot, that shows two variables, namely FAMINC and HOURS simultaneously.



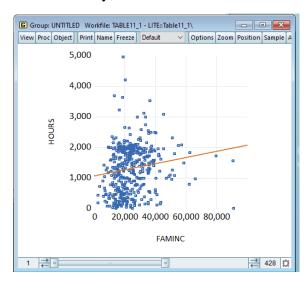
In this case, caution should be given towards the fact, that in the sample 325 women had 0 hours of work. In the plot above it is visible that the regression line is pressed down by all the zeros (that are the women with 0 working hours), leading to biased and inconsistent results.

Now the output of data with only women that have working hours:

Censored data:



We will again plot a relationship between the two variables FAMINC and HOURS simultaneously, but for this case where women have working hours.

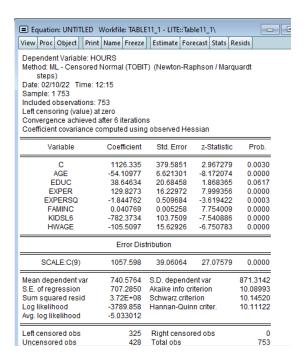


If we now compare the results, it is noticeable that the variable education in the regression of women that work now is statistically significant with a negative sign.

Still the results from the first and the second regression are biased and inconsistent, since we have an OLS estimate of censored regression models. In censored regression models the conditional mean of the error term is nonzero and the error is correlated with the regressors, which leads to the fact that the OLS estimators are biased and inconsistent.

If we now compare the plots, we can see that in the figure with the whole sample size, the zeroes (women that don't work) bias the regression down to the zeroes. In the other plot (where we included only women that work) no observation lies on the horizontal axis, since we excluded that data. But the results will again be misleading since we don't use information about the entire population. Therefore, the slope coefficients of the regression lines will be different.

Q.1.4.8



This is a Tobit regression estimated by maximum likelihood. It uses the maximum likelihood method to estimate a model where some observations on the regressand are censored.

The signs of the different regressors are the same for both OLS-regressions above.

The education variable is only significant in the OLS sample where we disregard all the zeroes (only working women in the sample), but with a negative sign. Instead in the Tobit regression the education variable has a positive sign because the model is suitable for this type of censored data.

The issue is that we cannot interpret the Tobit coefficient of a regressor as giving the marginal impact of that regressor on the mean value of the observed regressand.

The reason for that is, that the Tobit regression models a unit change in the value of a regressor has two effects. First, the effect on the mean value of the observed regressand and second, the effect on the probability that Yi* is observed.

We have for example the coefficient for age, which is about -54 (Tobit regression), ceteris paribus. If age increases by one unit, the hours of work per year will decrease by about 54 hours per year and additionally the probability of a married woman entering the labour force also decreases. We are not able to compute the aggregate impact of an increase in age on the hours worked unless we know the probability to multiply with -54.

The probability Y* must lie between zero and one, meaning the product of each slope coefficient will be smaller than the coefficient itself. Therefore, the sign of the marginal impact will depend on the sign of the slope coefficient, for the probability of observing Yi* is always positive.

Important to note is, that all coefficients are statistically significant at the 10% level of significance.

We want to determine the influence of R&D, industry category and the two countries on the mean or average number of patents received by the 181 firms.

Dependent Variable: P90 Method: Least Squares Date: 02/10/22 Time: 12:50 Sample: 1 181 Included observations: 181

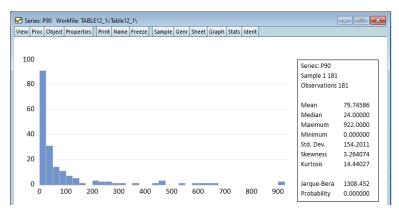
Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	-250.8386	55.43486	-4.524925	0.0000
LR90	73.17202	7.970758	9.180058	0.0000
AEROSP	-44.16199	35.64544	-1.238924	0.2171
CHEMIST	47.08123	26.54182	1.773851	0.0779
COMPUTER	33.85645	27.76933	1.219203	0.2244
MACHINES	34.37942	27.81328	1.236079	0.2181
VEHICLES	-191.7903	36.70362	-5.225378	0.0000
JAPAN	26.23853	40.91987	0.641217	0.5222
US	-76.85387	28.64897	-2.682605	0.0080
R-squared	0.472911	Mean depend	lent var	79.74586
Adjusted R-squared	0.448396	S.D. depende	nt var	154.2011
S.E. of regression	114.5253	Akaike info cri	iterion	12.36791
Sum squared resid	2255959.	Schwarz criterion		12.52695
Log likelihood	-1110.296	Hannan-Quinn criter.		12.43239
F-statistic	19.29011	Durbin-Watson stat		1.946344
Prob(F-statistic)	0.000000			

The p-value is zero for the variable LR90, indicating a positive relationship between the number of patents received and R&D expenditure.

The R&D variable is in the logarithmic form and the patent variable is in the linear form, so the interpretation would be, if you increase R&D expenditure by 1 %, the average number of patents received will increase by about 0.73, ceteris paribus.

From the other variables only chemistry, vehicles and US are statistically significant.

From interpretation, it can be said that average level of patents granted in the chemistry industry is higher by 47 patents and the average level of patents granted in the vehicle industry is lower by 192. On average US firms received 77 fewer patents than the base group.



View Proc Obj	T 1	- T T	eeze Sample	e Gen
[VIEW] FIOC OD	ect Properties	[Finit] Name [11	ccze J Sampi	COCI
	atistics for P90			
	values of P90			
Date: 02/10/22				
Sample: 1 181 Included obse				
	IValions. 101			
P90	Mean	Std. Dev.	Obs.	
[0, 10)	2.809524	2.728920	63	
[10, 20)	13.76190	3.048028	21	
[20, 30)	24.69231 35.86667	2.897833 2.559762	13 15	
[30, 40) [40, 50)	43.30000	2.406011	10	
[50, 60)	52.75000	1.281740	8	
[60, 70)	65.50000	1.914854	4	
[70, 80)	75.33333	3.669696	6	
[80, 90)	85.50000	4.041452	4	
[90, 100)	95.33333	4.041452	3	
[100, 110)	105.7500	3.774917	4	
[110, 120)	111.0000	NA	1	
[120, 130)	123.0000	0.000000	2	
[130, 140)	137.3333	0.577350	3	
[140, 150)	146.0000	1.414214	2	
[160, 170)	165.0000	NA	1	
[200, 210)	207.0000	NA	1	
[210, 220)	213.5000	2.121320	2	
[230, 240)	235.0000	NA	1	
[240, 250)	246.0000	NA	1	
[250, 260)	257.0000	NA	1	
[260, 270)	260.0000 279.0000	NA NA	1 1	
[270, 280) [310, 320)	313.0000	NA NA	1	
[350, 360)	353.0000	NA NA	1	
[420, 430)	428.0000	NA NA	1	
[450, 460)	458.0000	NA NA	i	
[470, 480)	470.0000	0.000000	2	
[530, 540)	533.0000	NA	1	
[570, 580)	577.0000	NA	1	
[620, 630)	621.0000	NA	1	
[640, 650)	640.0000	NA	1	
[660, 670)	667.0000	NA	1	
[900, 910)	900.0000	NA	1	
[920, 930)	922.0000	NA	1	
All	79.74586	154.2011	181	

Most patents are in the interval of 0 to 30 patents.

The Jarque-Bera test confirms that the null hypothesis of normality can be rejected. But the assumption that the error term is normally distributed cannot hold for a simple LPM when the dependent variable is asymmetric. This indicates that LPM is not a suitable model for this data set since the dependent variable is Poisson distributed. A Poisson regression is more suitable.

Now a Poisson model will be estimated:

View Proc Object Prin	t Name Freez	e Estimate	Forecast	Stats	Resids	
Dependent Variable: Ps	90					
Method: ML/QML - Pois		ewton-Raph	ison / Mai	quard	lt steps)
Date: 02/10/22 Time: 15:42						
Sample: 1 181	404					
Included observations: 181 Convergence achieved after 7 iterations						
Coefficient covariance			r-White m	ethod		
Variable	Coefficient	Std. En	or z-S	Statisti	C F	rob.
С	-0.745849	0.6691	33 -1.	11456	7 0	.2650
LR90	0.865149	0.0847	25 10	.2113	2 0	.0000
AEROSP	-0.796538			12353		.0154
CHEMIST	0.774752			3503		.0003
COMPUTER	0.468894			77910		.0752
MACHINES	0.646383			55682		.0976
VEHICLES	-1.505641			9948		.0000
JAPAN	-0.003893			1194		.9905
US	-0.418938	0.2418	99 -1.7	73187	3 0	.0833
R-squared	0.675516	Mean dep	endent v	ar	79.7	74586
Adjusted R-squared	0.660424	S.D. depe	endent va	r	154	.2011
S.E. of regression	89.85789	Akaike inf	o criterio	n	56.2	24675
Sum squared resid	1388804.					10579
Log likelihood	-5081.331		Quinn crit	er.	56.3	31123
Restr. log likelihood -15822.38 LR statistic		214	82.10			
Avg. log likelihood	-28.07365	Prob(LR:				00000

In nonlinear models the R2 is not meaningful. Instead, the LR (likelihood ratio) is important. Here we have a significant LR statistic of 21282, which suggests that the explanatory variables are collectively important in explaining the conditional mean of patents, which is λ_i

This can also be stated by comparing the restricted log-likelihood with the unrestricted log-likelihood function.

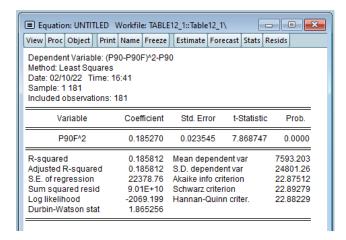
Interpretation: The LR90 coefficient (which is expressed in logarithmic form) is about 0.86, indicating that an increase in R&D expenditure by 1%, will increase the average number of patents given a firm by about 0.86%, ceteris paribus.

The dummy variable of the machines is in a semi-log model. The coefficient is 0.6464 and the average number of patents in the machines industry is higher by 90.86% compared to the comparison category. The coefficient of US variable is -0.4189 and the average number of patents is lower by -34.23%.

The Japan variable is statistically not significant.

The Poisson distribution has the feature that the mean and the variance of a Poisson-distributed variable are the same. This is called equidispersion.

If the variance is higher than the mean there is overdispersion. In this case the solution would be to use the negative binomial regression method instead of the Poisson method.



In six steps we estimated the dispersion test to see if there is overdispersion or not.

Attention should be paid to the regression coefficient. If this one is positive and statistically significant, there is overdispersion and if it is negative, then there is under-dispersion.

We reject the Poisson model if the coefficient is statistically significant and don't reject it when its statistically insignificant.

As seen above the p-value is 0 and the coefficient is positive we can reject the assumption of equidispersion and conclude that there is overdispersion.

In this case the Poisson regression cannot be used since the standard errors are misleading. Therefore, the negative binomial regression model is more suitable for this type of data set.

Dependent Variable: P90
Method: QML - Negative Binomial Count (Newton-Raphson / Marquardt steps)
Date: 02/10/22 Time: 16:43
Sample: 1 181
Included observations: 181
QML parameter used in estimation: 1
Convergence achieved after 5 iterations
Coefficient covariance computed using the Huber-White method

Coefficient covaria	ince computed using the	Huber-White method							

Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	-0.406826	0.641560	-0.634119	0.5260
LR90	0.866808	0.072283	11.99182	0.0000
AEROSP	-0.873849	0.411650	-2.122797	0.0338
CHEMIST	0.665741	0.204927	3.248675	0.0012
COMPUTER	-0.129847	0.263131	-0.493470	0.6217
MACHINES	0.011432	0.272389	0.041970	0.9665
VEHICLES	-1.516676	0.364282	-4.163466	0.0000
JAPAN	0.122250	0.383324	0.318922	0.7498
US	-0.689748	0.365911	-1.885018	0.0594
R-squared	0.442121	Mean depend	lent var	79.74586
Adjusted R-squared	0.416173	S.D. depende	nt var	154.2011
S.E. of regression	117.8229	Akaike info cr	iterion	9.363858
Sum squared resid	2387745.	Schwarz criterion		9.522899
Log likelihood	-838.4291	Hannan-Quin	n criter.	9.428336
Restr. log likelihood	-974.7010	LR statistic		272.5439
Avg. log likelihood	-4.632205	Prob(LR stati	stic)	0.000000

The results out of the negative binomial regression model are interpreted in the same way as above for the Poisson model.

If LR90 increases by 1% the average number of patents increases by $\sim 0.867\%$