TIME SERIES FOR FINANCE AND ECONOMICS – TEAM ASSIGNMENT

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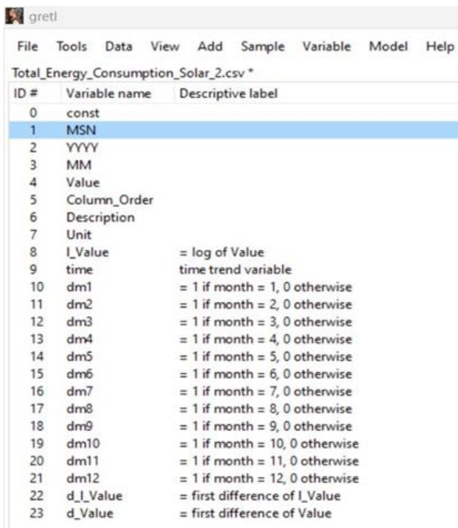
Problem 1 – Forecasting energy variables

1. This is the dataset and the plot of the variable Value, which consists in Small-Scale Solar Energy Consumption



gretl

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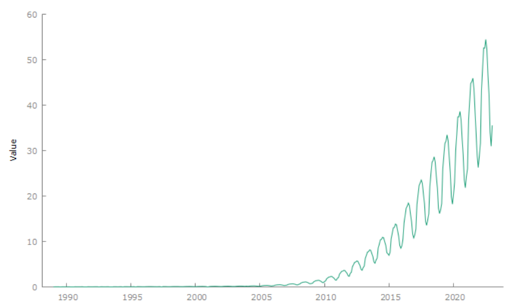
Total_Energy_Consumption_Solar_2.csv *

ID #	Variable name	Descriptive label
0	const	
1	MSN	
2	YYYY	
3	MM	
4	Value	
5	Column_Order	
6	Description	
7	Unit	
8	l_Value	= log of Value
9	time	time trend variable
10	dm1	= 1 if month = 1, 0 otherwise
11	dm2	= 1 if month = 2, 0 otherwise
12	dm3	= 1 if month = 3, 0 otherwise
13	dm4	= 1 if month = 4, 0 otherwise
14	dm5	= 1 if month = 5, 0 otherwise
15	dm6	= 1 if month = 6, 0 otherwise
16	dm7	= 1 if month = 7, 0 otherwise
17	dm8	= 1 if month = 8, 0 otherwise
18	dm9	= 1 if month = 9, 0 otherwise
19	dm10	= 1 if month = 10, 0 otherwise
20	dm11	= 1 if month = 11, 0 otherwise
21	dm12	= 1 if month = 12, 0 otherwise
22	d_l_Value	= first difference of l_Value
23	d_Value	= first difference of Value



2. We decided to adopt a log transformation of the Value. We observed that to have an acceptable correlogram we needed to use a Seasonal Arima. We observed that we had two possible unit roots, one in the AR and the other in the seasonal AR. So, to preserve stability, we added a I(1) in both. We observed that the best BIC (-1603) was achieved with a SARIMA (2,1,0) (2,1,0). The R squared is high, we can explain 99,99 percent of the variance. We can observe that the only three coefficients with a good p_value are phi_1 (ar not seasonal), Phi_1 (seasonal) and dm1. We can observe that the remaining modulus of the roots are far away from 1.

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Convergence achieved after 55 iterations

Model 11: ARMAX, using observations 1992:04-2023:01 (T = 370)
Estimated using least squares (conditional ML)
Dependent variable: (1-L)(1-Ls) l_Value

              coefficient    std. error      z         p-value
  -----------------------------------------------------------------
  const        0.00185234    0.00523615    0.3538     0.7235
  phi_1       -0.125491      0.0536071    -2.341      0.0192     **
  phi_2       -0.0284460     0.0533520    -0.5332     0.5939
  Phi_1       -0.472380      0.0535522    -8.821      1.14e-018 ***
  Phi_2       -0.0344457     0.0538378    -0.6398     0.5223
  dm1          0.0114681     0.00632401    1.813      0.0698     *
  dm2          0.00455829    0.00637504    0.7150     0.4746
  dm3          0.00114542    0.00637287    0.1797     0.8574
  dm4          0.00120902    0.00629750    0.1920     0.8478
  dm5          0.00147213    0.00629728    0.2338     0.8152
  dm6          0.00138691    0.00629625    0.2203     0.8257
  dm7          6.02846e-05   0.00629575    0.009575   0.9924
  dm8         -0.00101821    0.00629569   -0.1617     0.8715
  dm9          0.000557748   0.00629582    0.08859    0.9294
  dm10         0.000519324   0.00629567    0.08249    0.9343
  dm11         0.000496101   0.00629727    0.07878    0.9372
  time        -1.41731e-05   1.21283e-05  -1.169      0.2426

Mean dependent var    0.000402   S.D. dependent var    0.027605
Mean of innovations   0.000000   S.D. of innovations   0.024784
R-squared             0.999904   Adjusted R-squared    0.999900
Log-likelihood        851.7953   Akaike criterion     -1669.591
Schwarz criterion    -1603.061   Hannan-Quinn         -1643.164

                        Real  Imaginary    Modulus  Frequency
  -----------------------------------------------------------
  AR
    Root  1          -2.2058    -5.5035     5.9291    -0.3107
    Root  2          -2.2058     5.5035     5.9291     0.3107
  AR (seasonal)
    Root  1          -2.6159     0.0000     2.6159     0.5000
    Root  2         -11.0978     0.0000    11.0978     0.5000
  -----------------------------------------------------------
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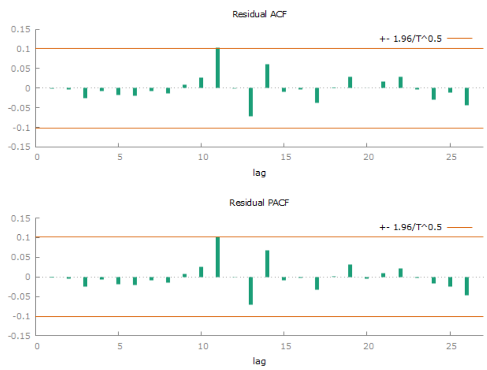
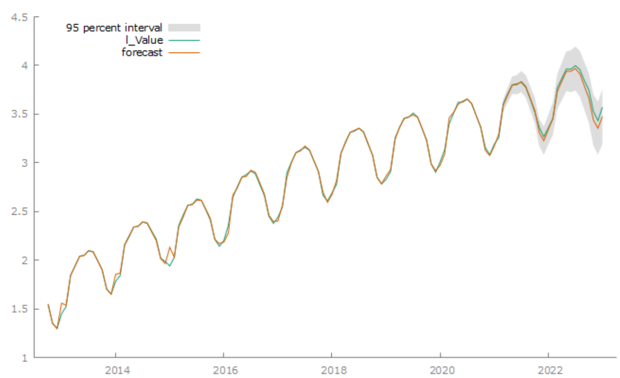
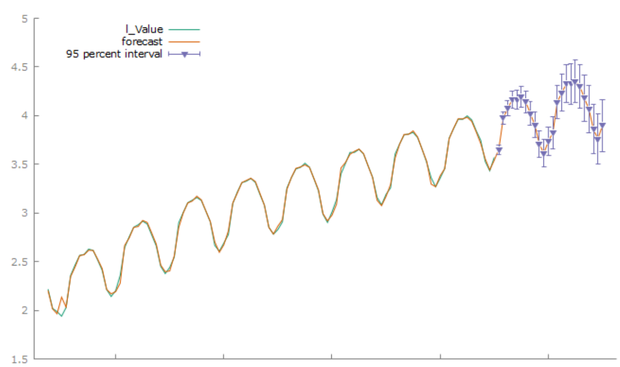


3. This is the forecast using the last two months as a test. We can observe the more we try to forecast in the future the more our confidence interval becomes bigger and bigger. This is because the standard errors are being added along the way. We can also observe that the forecasts for the first months are really accurate.



4. This is the forecast 24 months in the future:



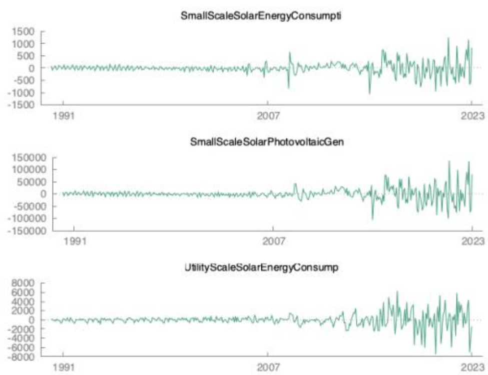
5. Small-Scale Solar Photovoltaic Generation Total Net Generation and Utility-Scale Solar Energy Consumption: Total were the two other time series chosen to analyse.

VAR system, maximum lag order 26

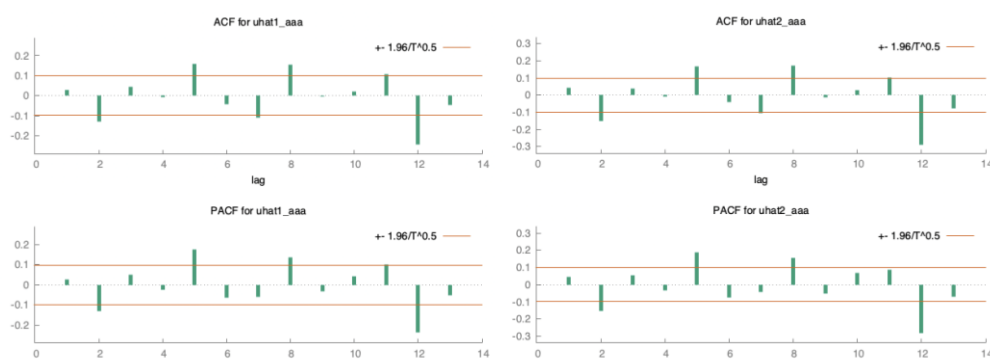
The asterisks below indicate the best (that is, minimized) values of the respective information criteria, AIC = Akaike criterion, BIC = Schwarz Bayesian criterion and HQC = Hannan-Quinn criterion.

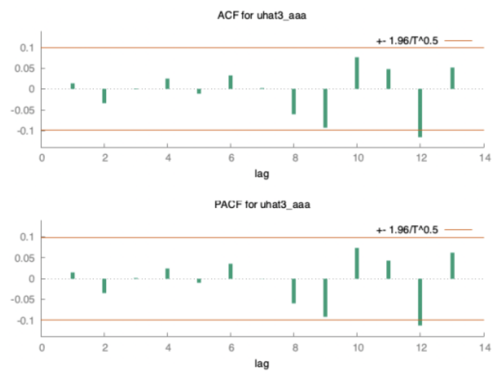
lags	loglik	p(LR)	AIC	BIC	HQC
1	-10850.39023		56.910654	57.405447	57.106930
2	-10685.95067	0.00000	56.098959	56.686526	56.332037
3	-10655.79360	0.00000	55.988478	56.668819	56.258358
4	-10590.31195	0.00000	55.693535	56.466649	56.000217
5	-10540.53335	0.00000	55.480592	56.346479	55.824076
6	-10512.08517	0.00000	55.379035	56.337696	55.759320
7	-10476.61563	0.00000	55.240813	56.292248	55.657900
8	-10428.04554	0.00000	55.034180	56.178389	55.488069
9	-10348.79019	0.00000	54.667312	55.904294	55.158003
10	-10217.55236	0.00000	54.028994	55.358750	54.556487
11	-10190.57192	0.00000	53.935101	55.357631	54.499396
12	-9993.39929	0.00000	52.952477	54.467780	53.553573
13	-9906.77084	0.00000	52.547106	54.155183*	53.185004
14	-9893.92034	0.00229	52.526999	54.227850	53.201699
15	-9884.73772	0.03116	52.526046	54.319670	53.237547
16	-9856.61143	0.00000	52.426169	54.312567	53.174473
17	-9833.02290	0.00000	52.349989	54.329161	53.135095
18	-9814.08143	0.00002	52.298075	54.370021	53.119983
19	-9798.36589	0.00025	52.263007	54.427726	53.121716
20	-9773.62617	0.00000	52.180816	54.438308	53.076326
21	-9756.59470	0.00009	52.138876	54.489142	53.071188
22	-9742.83649	0.00115	52.114029	54.557069	53.083143
23	-9704.69906	0.00000	51.961875	54.497689	52.967791
24	-9660.65485	0.00000	51.778876	54.407464	52.821595
25	-9590.75769	0.00000	51.460876	54.182237	52.540396*
26	-9576.50179	0.00078	51.433430*	54.247564	52.549752

6. Lags 26, 13, and 25 exhibit significant autocorrelation. However, lag 13 generally has higher ACF and PACF values, indicating a stronger correlation and the best fit.



- The log-likelihood of -10224.73 suggests a good fit
- The high determinant of 5.3649611e+18 indicates significant linear dependence
- The p-value of 0.0000 indicates strong evidence of residual autocorrelation
- A high R-squared value of 0.999594 explains the large portion of the dependent variable's variance

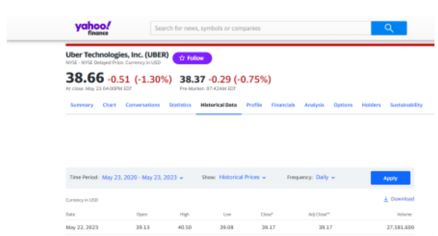




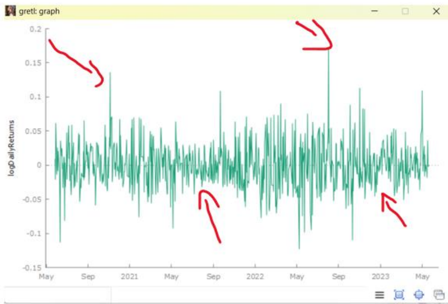
- All ACF tables show consistent high levels for autocorrelation coefficients
- When comparing the VAR forecasts with the univariate ARIMA forecasts, we find:
    - The ARIMA model provides accurate short-term forecasts but has larger confidence intervals for longer-term forecasts
    - Regarding autocorrelation lags, lag 13 has the strongest correlation
    - Comparing the ACF results of the residuals, uhat3_aaa exhibits weaker autocorrelation with smaller magnitudes and fewer significant coefficients
    - The lag order and Q-statistic analysis indicate that uhat3_aaa has a weaker overall autocorrelation structure compared to uhat1_aaa and uhat2_aaa
- The univariate ARIMA model performs well for short-term forecasts, while the VAR model may capture specific autocorrelation patterns

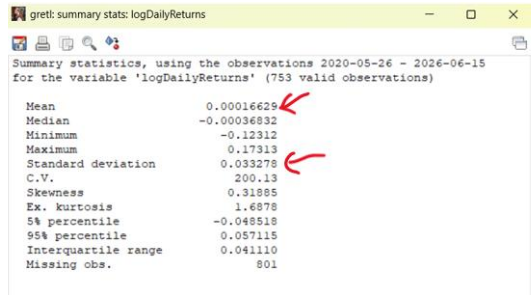
Problem 2 – Modelling volatility

1. Uber was chosen as our stock with a 3-year span of Historical Data



2. Then we created a new variable called daily returns and logDaily returns and perfomed a timeseries plot on the latter. The shape indicates volatility. Moreover, summary statistics indicate a mean close to 0 and a high standard deviation.





gretl: summary stats: logDailyReturns

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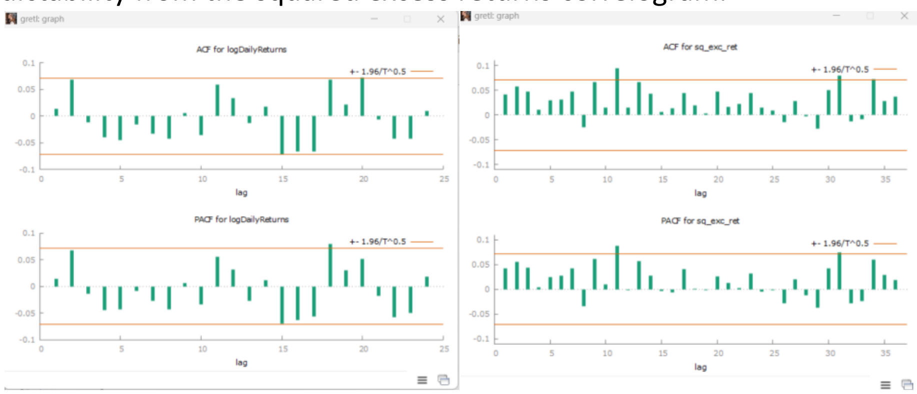
Summary statistics, using the observations 2020-05-26 - 2026-06-15
for the variable 'logDailyReturns' (753 valid observations)

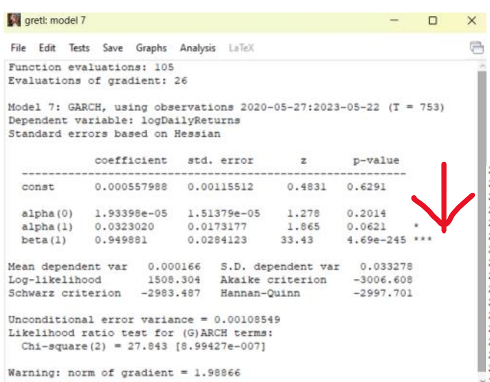
  Mean                      0.00016629
  Median                   -0.00036832
  Minimum                     -0.12312
  Maximum                      0.17313
  Standard deviation          0.033278
  C.V.                          200.13
  Skewness                     0.31885
  Ex. kurtosis                  1.6878
  5% percentile              -0.048518
  95% percentile              0.057115
  Interquartile range         0.041110
  Missing obs.                     801
```

3. There is almost total uncorrelation according to the correlogram. There's a hint of predictability from the squared excess returns correlogram.



4. In exploring values of GARCH p and ARCH q, we find the best model is the following:
    - Garch 1 arch 1 including variable
        - **Unconditional st error** of 0.03294

   The forecasted values are very close to the unconditional st error



gretl: model 7

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Function evaluations: 105
Evaluations of gradient: 26

Model 7: GARCH, using observations 2020-05-27:2023-05-22 (T = 753)
Dependent variable: logDailyReturns
Standard errors based on Hessian

             coefficient    std. error      z         p-value
  ---------------------------------------------------------------
  const      0.000557988   0.00115512     0.4831    0.6291

  alpha(0)   1.93398e-05   1.51379e-05    1.278     0.2014
  alpha(1)   0.0323020     0.0173177      1.865     0.0621     *
  beta(1)    0.949881      0.0284123     33.43      4.69e-245 ***

Mean dependent var   0.000166   S.D. dependent var   0.033278
Log-likelihood       1508.304   Akaike criterion    -3006.608
Schwarz criterion   -2983.487   Hannan-Quinn        -2997.701

Unconditional error variance = 0.00108549
Likelihood ratio test for (G)ARCH terms:
  Chi-square(2) = 27.843 [8.99427e-007]

Warning: norm of gradient = 1.98866
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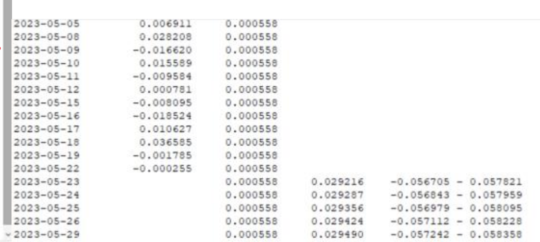
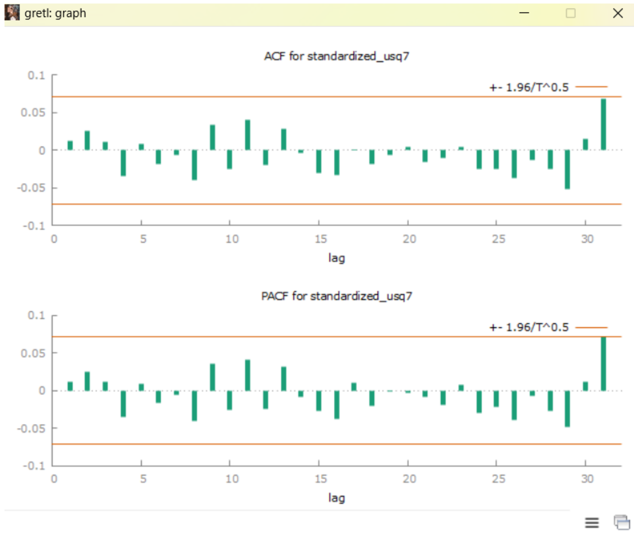


2023-05-05	0.006911	0.000558		
2023-05-08	0.028208	0.000558		
2023-05-09	-0.016620	0.000558		
2023-05-10	0.015589	0.000558		
2023-05-11	-0.009584	0.000558		
2023-05-12	0.000781	0.000558		
2023-05-15	-0.008095	0.000558		
2023-05-16	-0.018524	0.000558		
2023-05-17	0.010627	0.000558		
2023-05-18	0.036585	0.000558		
2023-05-19	-0.001785	0.000558		
2023-05-22	-0.000255	0.000558		
2023-05-23		0.000558	0.029216	-0.056705 - 0.057821
2023-05-24		0.000558	0.029287	-0.056843 - 0.057959
2023-05-25		0.000558	0.029356	-0.056979 - 0.058095
2023-05-26		0.000558	0.029424	-0.057112 - 0.058228
2023-05-29		0.000558	0.029490	-0.057242 - 0.058358

5. Standardized square residual are uncorrelated:


gretl: graph
ACF for standardized_usq7
+- 1.96/T^0.5
lag
PACF for standardized_usq7
+- 1.96/T^0.5
lag