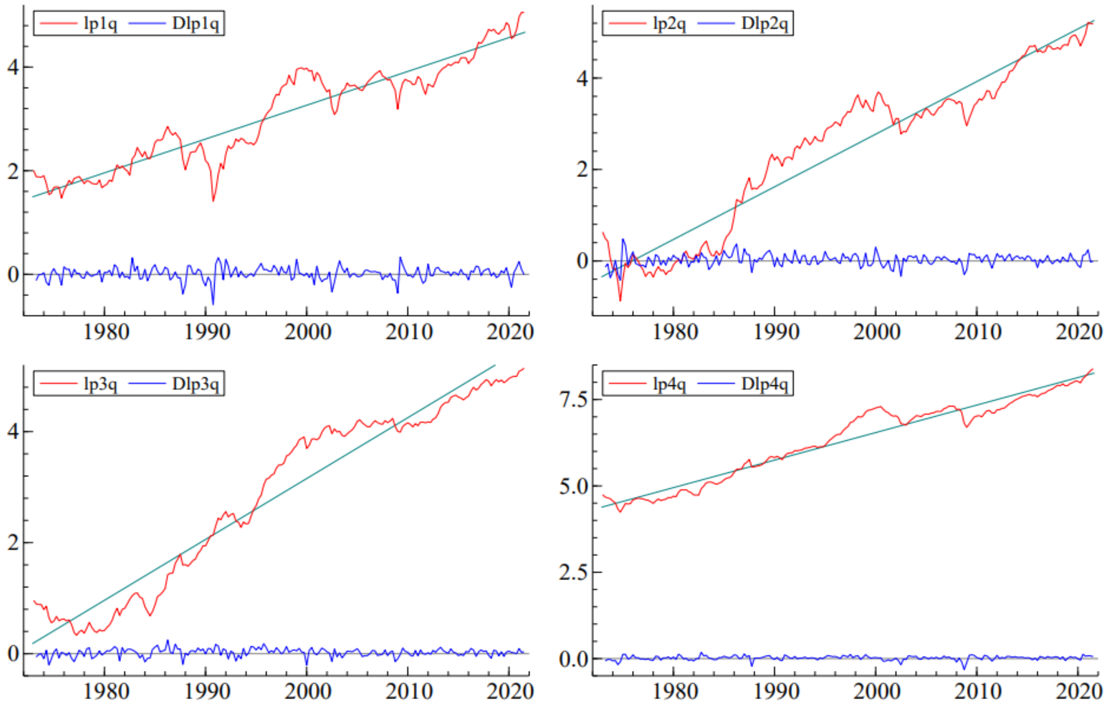
1) Completed in OxMetrics8

2)a.

The figure below depicts graphs for the natural logged time series for each of the four stocks in red, each accompanied by an approximated trend line. In addition, the first difference of each log time series has also been plotted. It can be observed that every time series resembles a stochastic process. Furthermore, the plotted first difference of each time series resembles a stationary one. It should be noted that all 4 time series show a deterministic trend to some extent. However, the properties of a stochastic process will always dominate the properties of a deterministic one. Thus, upon initial inspection lp1q, lp2q, lp3q and lp4q are all difference stationary.



2)b.

Unit root test for lp1q and 4 lags have been included as the data is quarterly.

```
Augmented Dickey-Fuller test for lp1q; regression of Dlp1q on:

               Coefficient    Std.Error      t-value
lp1q_1           -0.096018     0.029794      -3.2227
Constant           0.14095     0.046352       3.0410
Trend            0.0016772   0.00051173       3.2775
Dlp1q_1            0.21748     0.073041       2.9775
Dlp1q_2          -0.073698     0.074457     -0.98981
Dlp1q_3          0.0064857     0.074060     0.087573
Dlp1q_4            0.14822     0.073287       2.0225

sigma = 0.120773  DW = 1.969  DW-lp1q = 0.01699  ADF-lp1q = -3.223
Critical values used in ADF test: 5%=-3.434, 1%=-4.009
RSS = 2.669280949 for 7 variables and 190 observations
```

It can be observed that the t-value for the 4th lag has a t-value greater than 1.96 which is the 5% confidence interval for a standard t-test. Thus, the null hypothesis must be rejected, and it can be concluded that the 4th lag on lp1q is significant. It can also be observed that the trend coefficient for the deterministic process has a t-value greater than 1.96. Thus, the null hypothesis must be rejected, and it can be concluded that the deterministic trend coefficient is significant. This does not contradict the time series lp1q being difference stationary. If there exists both traits of a stochastic process and a deterministic process in a time series, the time series will be classified as a stochastic process. The coefficient of lp1q θ=-0.096018 and its t-value (t-ADF)=-3.2227. The critical values of the ADF distribution are 5%=-3.434; 1%=-4.009. Since the calculated t-value is larger than both 5% and 1% ADF distribution critical values, the null hypothesis, $H0$: θ=0 cannot be rejected at the 1% confidence level, and it can be concluded that lp1q is non-stationary. Finally, to deduce the order of integration of lp1q and verify if it is an I(1) process, a unit root test on dlp1q must be conducted to determine if the first difference of lp1q is I(0).

Unit root test for dLp1q, 4 lags have been retained and the trend has been omitted as this is the first difference

```
Augmented Dickey-Fuller test for Dlp1q; regression of DDlp1q on:

                 Coefficient    Std.Error      t-value
Dlp1q_1            -0.99171      0.15358      -6.4573
Constant           0.017117    0.0092396       1.8526
DDlp1q_1            0.17678      0.13977       1.2648
DDlp1q_2           0.044436      0.11944      0.37203
DDlp1q_3         -0.0019068     0.096056    -0.019851
DDlp1q_4            0.11503     0.073649       1.5619

sigma = 0.122905  DW = 2.029  DW-Dlp1q = 1.702  ADF-Dlp1q = -6.457**
Critical values used in ADF test: 5%=-2.877, 1%=-3.466
RSS = 2.764339271 for 6 variables and 189 observations

Unit-root tests
The dataset is: C:\Users\adcr352\OneDrive - City, University of London'
The sample is: 1973(3) - 2021(3) (194 observations and 1 variables)

Augmented Dickey-Fuller test for Dlp1q; regression of DDlp1q on:

                 Coefficient    Std.Error      t-value
Dlp1q_1            -0.84894     0.071309      -11.905
Constant           0.014017    0.0089726       1.5622

sigma = 0.123663  DW = 1.957  DW-Dlp1q = 1.698  ADF-Dlp1q = -11.91**
Critical values used in ADF test: 5%=-2.877, 1%=-3.465
RSS = 2.920879793 for 2 variables and 193 observations
```

The results show that all lags on dlp1q are not significant. Therefore, the ADF regression is re-iterated without these variables. The coefficient of dlp1q θ=-0.84894 and its t-value (t-ADF)=-11.905 These are the critical values of the ADF distribution, are 5%=-2.877; 1%=-3.465. Since the calculated t-value is smaller than the 1% critical value, the null hypothesis $H0$: θ =0 is rejected at the 1% confidence level, and it can be concluded that dlp1q is stationary of order I(0) and that lp1q is of order (1).

Unit root test for lp2q.

```
Augmented Dickey-Fuller test for lp2q; regression of Dlp2q on:

                 Coefficient    Std.Error      t-value
lp2q_1            -0.040828     0.018759      -2.1764
Constant          0.0010687     0.019838     0.053870
Trend             0.0012165   0.00056711       2.1451
Dlp2q_1             0.27603     0.069813       3.9538
Dlp2q_2            -0.25138     0.070290      -3.5764
Dlp2q_3             0.19131     0.070097       2.7292

sigma = 0.118725  DW = 2.071  DW-lp2q = 0.00577  ADF-lp2q = -2.176
Critical values used in ADF test: 5%=-3.434, 1%=-4.009
RSS = 2.607707405 for 6 variables and 191 observations
```

Unit root test for dlp2q

```
Augmented Dickey-Fuller test for Dlp2q; regression of DDlp2q on:

                 Coefficient    Std.Error      t-value
Dlp2q_1            -0.83068      0.11030      -7.5309
Constant           0.022931    0.0090513       2.5334
DDlp2q_1           0.091489     0.086685       1.0554
DDlp2q_2           -0.17715     0.070177      -2.5243

sigma = 0.119603  DW = 2.068  DW-Dlp2q = 1.666  ADF-Dlp2q = -7.531**
Critical values used in ADF test: 5%=-2.877, 1%=-3.466
RSS = 2.674998526 for 4 variables and 191 observations
```

Unit root test for Lp3q:

```
Augmented Dickey-Fuller test for lp3q; regression of Dlp3q or

                 Coefficient    Std.Error      t-value
lp3q_1            -0.026635     0.013550      -1.9656
Constant           0.017106     0.010501       1.6289
Trend            0.00077389   0.00038467       2.0119
Dlp3q_1             0.19546     0.070608       2.7683

sigma = 0.0703792  DW = 2.025  DW-lp3q = 0.002239  ADF-lp3q =
Critical values used in ADF test: 5%=-3.434, 1%=-4.008
RSS = 0.9361605875 for 4 variables and 193 observations
```

Unit root test for DLp3q:

```
Augmented Dickey-Fuller test for Dlp3q; regression of DDlp3q on:

                 Coefficient    Std.Error      t-value
Dlp3q_1            -0.81036     0.070806      -11.445
Constant           0.017914    0.0053161       3.3698

sigma = 0.0707558  DW = 2.023  DW-Dlp3q = 1.623  ADF-Dlp3q = -11.44**
Critical values used in ADF test: 5%=-2.877, 1%=-3.465
RSS = 0.9562195235 for 2 variables and 193 observations
```

Unit root test for Lp4q:

```
Augmented Dickey-Fuller test for lp4q; regression of Dlp4q on:

                 Coefficient    Std.Error      t-value
lp4q_1            -0.039235     0.016310      -2.4055
Constant            0.17937     0.071318       2.5150
Trend            0.00082404   0.00033377       2.4689
Dlp4q_1             0.34090     0.067858       5.0237

sigma = 0.0584399  DW = 1.977  DW-lp4q = 0.003229  ADF-lp4q = -2.406
Critical values used in ADF test: 5%=-3.434, 1%=-4.008
RSS = 0.6454775008 for 4 variables and 193 observations
```

Unit root test for DLp4q

```
Augmented Dickey-Fuller test for Dlp4q; regression of DDlp4q on:

                 Coefficient    Std.Error      t-value
Dlp4q_1            -0.67323     0.068078      -9.8891
Constant           0.013181    0.0044364       2.9710

sigma = 0.0590632  DW = 1.966  DW-Dlp4q = 1.347  ADF-Dlp4q = -9.889**
Critical values used in ADF test: 5%=-2.877, 1%=-3.465
RSS = 0.6662953433 for 2 variables and 193 observations
```

To summarize the tables above, for all stocks, the deterministic trend coefficient is significant. After performing a unit root test on the log time series and dropping all insignificant variables, it was found that all stocks did not reject the null hypothesis $H0$: θ =0. This was done by comparing the coefficient of the stock (θ) to the critical values of the ADF distribution, which deduced that the log time series was non-stationary. The relevant values can be found in the tables for lp2q, lp3q and lp4q. However, to deduce the order of integration of the log time series and verify if it is an I(1) process, a unit root test must be conducted to determine if the first difference log time series of is I(0). After comparing the coefficient of the delta of the stock (θ) and the critical values of the ADF distribution, it was determined that the null hypothesis $H0$: θ =0 was to be accepted and hence for all stocks the log time series is of order I(1) since the delta log time series was verified to be of order I(0). In conclusion, lp2q, lp3q and lp4q are non-stationary and I(1) because dlp2q, dlp3q and dlp4q are stationary and I(0).

The basis of Holden and Perman (1994) is that different data sets are transformed before they are able to be observed and tested which brings up the question what is the correct transformation to properly interpret the data, one method mentioned is differencing and this could be when the time series resembles a stochastic process hence it must be differenced as there is no trend directing future values but only past values, hence after discounting these lags it becomes clear to see the magnitude of each movement in the time period. Another form of non-stationary process is one that is deterministic which depends on a trend. And as such in order to correctly interpret said process one must detrend so that is it's possible to see the real shifts in time as otherwise they may be skewed by bias.

3)a.

Dynamic ADL model, ADL(1,1) for lp1q=f(lp4q): $lp1qt = \alpha0 + \alpha1\ lp1qt{-}1 + \beta0 lp4qt + \beta1 lp4qt{-}1 + \mu t$

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
lp1q_1	0.929802	0.02616	35.5	0.0000	0.8692
Constant	-0.161885	0.06589	-2.46	0.0149	0.0308
lp4q	1.27418	0.1092	11.7	0.0000	0.4174
lp4q_1	-1.21567	0.1120	-10.9	0.0000	0.3827

sigma	0.0947504	RSS	1.70575113
R^2	0.990705	F(3,190) =	6751 [0.000]**
Adj.R^2	0.990559	log-likelihood	183.91
no. of observations	194	no. of parameters	4
mean(lp1q)	3.08969	se(lp1q)	0.975136

```
AR 1-5 test:      F(5,185)  =   1.8134 [0.1122]
ARCH 1-4 test:    F(4,186)  =   1.1947 [0.3146]
Normality test:   Chi^2(2)  =   76.645 [0.0000]**
Hetero test:      F(6,187)  =   5.0928 [0.0001]**
Hetero-X test:    F(9,184)  =   10.279 [0.0000]**
RESET23 test:     F(2,188)  =   1.5469 [0.2156]
```

In this ADL(1,1) model, there are some discrepancies with the Normality test and with the Hetero tests. This could be because some variables have been omitted, but if included would have led to large residuals (outliers). The model will be unaltered so that the model is as parsimonious as possible (brief testing revealed more than 4 lags would be required to correctly specify the model). Estimated autoregressive coefficient=0.929802. The estimated Impact propensity of lp4q on lp1q is: =1.27418 (immediate change in lp1q due to change in lp4q). The estimated long-run propensity is=0.83350 (4 s.f) (long-run change in lp1q due to permanent change in lp4q).

Nested Models on ADL(1,1):

1. **Static Model:**

In this exclusion restriction test, it's tested whether lp1q(t-1) and lp4q(t-1) have no effect on the dependent variable (lp1q) and hence should be excluded from the model. Test $\boldsymbol{H0}$:$\boldsymbol{\alpha1}$ = $\boldsymbol{\beta1}$ = $\mathbf{0}$ (ADL model doesn't rely on past values)

```
Test for excluding:
lp1q_1
lp4q_1
Subset F(2,190)  =   637.82 [0.0000]**
```

Reject the null hypothesis $\boldsymbol{H0}$:$\boldsymbol{\alpha1}$ = $\boldsymbol{\beta1}$ = $\mathbf{0}$, thus ADL(1,1) model cannot be reduced to a static one.

2. **Autoregressive model:**

In this exclusion restriction test, it's tested whether the ADL model does not rely on lp4q(t) and lp4q(t-1). Test $\boldsymbol{H0}$: $\boldsymbol{\beta0}$ = $\boldsymbol{\beta1}$=$\mathbf{0}$ (i.e. the ADL model does not rely on Lp4q and its lag)

```
Test for excluding:
lp4q
lp4q_1
Subset F(2,190)  =   72.512 [0.0000]**
```

Reject $\boldsymbol{H0}$: $\boldsymbol{\beta0}$ = $\boldsymbol{\beta1}$=$\mathbf{0}$, thus ADL model cannot be reduced to an autoregressive one

3. **Leading indicator model:**

In this exclusion restriction test, it's tested whether the ADL model does not rely on lp1q(t-1) and lp4q(t) where lp4q(t-1) leads to lp1q(t) , AKA: contemporaneity) $\boldsymbol{H0}$: $\boldsymbol{\alpha1}$ = $\boldsymbol{\beta0}$ =$\mathbf{0}$

```
Test for excluding:
lp1q_1
lp4q
Subset F(2,190)  =   692.13 [0.0000]**
```

Reject $H0$: $\alpha 1$ = $\beta 0$ =0, thus this ADL model cannot be reduced to a leading indicator mode

4. **Differenced data model:**

In this is a general restriction test, its tested if the ADL model can transform into a first difference model. Δlp1q(t)= $\alpha 1$ + βΔlp4q(t)+u(t). $H0$:$\alpha 1$ =1 , $\beta 0$ = -$\beta 1$

```
Test for general restrictions:
&0-1=0;&2+&3=0;
GenRes Chi^2(2)  =   7.2615 [0.0265]*
```

reject $H0$:$\alpha 1$ =1 , $\beta 0$ = -$\beta 1$ at the 5% significance level. This ADL model cannot be transformed into a differenced data model

5. **Distributed lag model:**

In this exclusion restriction test, it's tested whether the variable lp1q(t-1) has no effect on the dependent variable (lp1q) and thus reduce the ADL to a distributed lag model. $H0$:$\alpha 1$=0

```
Test for excluding: lp1q_1
Subset F(1,190)  =   1263.1 [0.0000]**
```

Reject $H0$:$\alpha 1$=0, therefore the ADL model cannot be reduced to a distributed lag one.

6. **Partial adjustment model:**

In this exclusion restriction test, it's tested whether the variable lp4q(t-1) has no effect on the dependent variable (lp1q) and thus reduce the ADL to a partial adjustment model. $H0$:$\beta 1$=0

```
Test for excluding: lp4q_1
Subset F(1,190)  =   117.77 [0.0000]**
```

reject $H0$:$\beta 1$=0, therefore the ADL model cannot be reduced to a partial adjustment model

7. **Static model with AR(1) errors:**

In this is a general restriction test, it's tested if the ADL model can transform into a static model. $H0$:$\alpha 1$ = -$\beta 1$ /$\beta 0$ or $\alpha 1 \beta 0$ + $\beta 1$ =0

```
Test for general restrictions:
&0*&2+&3=0;
GenRes Chi^2(1)  =   3.9859 [0.0459]*
```

Reject $H0$: $\alpha 1$ = -$\beta 1$ /$\beta 0$, therefore the ADL model cannot be transformed into a static model with autoregressive errors.

8. **Homogenous equilibrium correction model AKA Unrestricted Error Correction Model**

In this is a general restriction test, it's tested if the ADL model can transform into a Homogenous equilibrium correction model. $H0$: **[β0+β1]/[1-α1]=1** or $\alpha 1$ + $\beta 0$ + β = 1 (long-run proportionality equal to 1)

```
Test for general restrictions:
&0+&2+&3-1=0;
GenRes Chi^2(1)  =   2.2976 [0.1296]
```

Do not reject $H0$:$\alpha 1$ + $\beta 0$ + β = 1, sufficient evidence to suggest that the ADL model can be transformed into a homogenous equilibrium correction model

9. **Dead-Start Model:**

In this exclusion restriction test, it's tested whether the variable lp4q(t) has no effect on the dependent variable (lp1q) and thus reduce the ADL to a Dead-Start Model. $H0$:β0=0

```
Test for excluding: lp4q
Subset F(1,190)  =   136.14 [0.0000]**
```

Reject $H0$:β0=0, therefore the ADL model cannot be reduced to a dead-start model.

3)b

We choose between the ADL(1,1) and the Unrestricted error Correction Model as the best model for the data. Because these are the only models for which we do not reject the validity of the restriction. Hence, choose the Unrestricted error Correction Model since it's more parsimonious

4)a

```
                    Coefficient  Std.Error  t-value  t-prob Part.R^2
Constant               -5.77329    0.09669    -59.7  0.0000   0.9486
lp4q                    1.36400    0.01504     90.7  0.0000   0.9771

sigma                  0.241839  RSS              11.2877777
R^2                    0.977066  F(1,193) =        8223 [0.000]**
Adj.R^2                0.976947  log-likelihood       1.11169
no. of observations         195  no. of parameters          2
mean(lp3q)              2.85293  se(lp3q)             1.59281

AR 1-5 test:      F(5,188)  =   338.18 [0.0000]**
ARCH 1-4 test:    F(4,187)  =   135.35 [0.0000]**
Normality test:   Chi^2(2)  =   4.8240 [0.0896]
Hetero test:      F(2,192)  =  0.96171 [0.3841]
Hetero-X test:    F(2,192)  =  0.96171 [0.3841]
RESET23 test:     F(2,191)  =   74.216 [0.0000]**

Augmented Dickey-Fuller test for residuals; regression of Dresiduals on:

              Coefficient    Std.Error       t-value
residuals_1     -0.067421     0.023145       -2.9129
Dresiduals_1      0.32280     0.069182        4.6659

sigma = 0.075125  DW = 2.015  DW-residuals = 0.11  ADF-residuals = -2.913**
Critical values used in ADF test: 5%=-1.941, 1%=-2.576
RSS = 1.07795821 for 2 variables and 193 observations
```

In order to test for cointegration, both variables must be integrated of the same order. In this case, lp3q and lp4q are both I(1). If the linear combination of these two variables are of order I(0) then the variables are cointegrated and in a regression model, the linear combination is the residuals. Hence a unit root test on the residuals of lp3q and lp4q has been conducted to the left. The test was conducted with four lags, three of which were insignificant and were dropped. Since the t-value is smaller than the ADF critical values it can be deduced that the residuals are of order I(0) hence, lp3q cointegrates with lp4q.

4)b

Econometrics deploys the empirical analysis and application of statistics and mathematics to forecast the future of specified variables. This application is made under the assumption that data in the past have significant weight on the movement of data today and in the future. It is important to remember the hindrance that spurious regression can cause when forecasting models. Spurious regression alludes to the concept that two variables may exhibit similar trends but are fundamentally independent of one another.

Another relationship that can occur between variables is known as spurious regression and in the paper, spurious regression is viewed as sub-optimal and as previously mentioned a hindrance for forecasting data. This is because the biased generated from the random aspect of spurious regression can cause the interpretation of the model to become skewed. The report mentions ways to combat spurious regressions, A very lucrative method of combating spurious regressing or lessening its effects was said to be Campbell's Stochastic Detrending, Which entails discounting the lagged variable y its own past values and accumulating a moving average which is then used to regress the data, all of this combined allows for the data to become detrended and thus lessening the effects of spurious regression via low autocorrelation and safeguarding information about persistent returns.

This has been explored in the previous questions and in this context the theory is from Hendry, but for cointegration to take place, both variables must possess the same order of integration. Then if the linear combination of these two variables are integrated of order I(0) then the variables are said to be cointegrated and in a regression model, the linear combination is the residuals. Hence a unit root test on the residuals of x and y would be in order to ascertain whether there is significant evidence of co-integration.

4)c

When investigating co-integration, the unrestricted error correction model is a more optimal method as it accounts for long-run joint activity as opposed to the 2-step Engel granger model which only investigates the medium run trend. Methods that could be used for the purposes of inducing stationarity could be differencing and detrending. However, differencing could lead to large changes in the data and de-trending could cause the data to become skewed. As a result, Hendry proposes methods such as 'Big Ratios' which involve transforming the data using natural logarithms and smoothing out the volatility associated with sharp movements which made differencing and detrending difficult to do.

5)a

By creating a dynamic model using the independent and dependent variables (with 4 lags) it is possible to check for Granger causality by using F tests. The results are reported below

lp1q and lp4q:

```
Test for excluding:
[0] = Dlp4q_1
[1] = Dlp4q_2
[2] = Dlp4q_3
[3] = Dlp4q_4
Subset F(4,181)  =   5.0488 [0.0007]**
```

Lp2q and lp4q:

```
Test for excluding:
[0] = Dlp4q_1
[1] = Dlp4q_2
[2] = Dlp4q_3
[3] = Dlp4q_4
Subset F(4,181)  =   3.3071 [0.0121]*
```

Lp3q and lp4q:

```
Test for excluding:
[0] = Dlp4q_1
[1] = Dlp4q_2
[2] = Dlp4q_3
[3] = Dlp4q_4
Subset F(4,181)  =   1.2266 [0.3011]
```

lp1q and lp4q: It can be observed that the p-value is not significant hence the null hypothesis H0: "lp4q does not Granger cause lp1q" is rejected. It can be concluded that lp4q is significant in lp1q therefore **lp4q granger causes lp1q**.

lp2q and lp4q: It can be observed that the p-value is not significant hence the null hypothesis H0: "lp4q does not Granger cause lp2q" is rejected. It can be concluded that lp4q is significant in lp2q therefore **lp4q granger causes lp2q**.

lp3q and lp4q: It can be observed that the p-value is significant hence the null hypothesis H0: "lp4q does not Granger cause lp3q" cannot be rejected. It can be concluded that lp4q is not significant in lp3q therefore **lp4q does not granger cause lp3q**.

5)b

In ThurmanFisher, the notion of Granger is defined as the use of lagged values of the independent variable for the purposes of predicting the current values of the dependent variable. This is achieved using the lagged values of both variables and if this holds, the independent (x) is said to Granger cause the dependent (y). The nature of causality is very specific since causality is said to be unidirectional. Causality in one does not necessarily in the other as a result one must reject the non-causality of one to the other but at the same time fail to reject the non-causality of the latter to the former. This notion could be likened to a one-way street. In Hendry, the basis of the concept stems from "joint distribution of a subset of the observable variables is altered by eliminating the history of other variables, then that second group causes the first'. Which in layman's terms would mean that if the existence of a variable caused the importance of the other set of variables to become insignificant then it would imply the former granger causes the other as it shows that a pure auto-regressive relationship does not exist.

This report utilises the theory of Granger causality and applies it to a dataset. This process for which is to set up a regression involving your variables (with the necessary lags) and compute a dynamic equation model using them. For the independent variable which is the variable that granger causes movements in the dependent, the lags are removed, and an F test is conducted to investigate the significance of said lags if the P-value is statistically different from 0, the null hypothesis is rejected, and it can be concluded that the independent variable does indeed Granger cause movements in the dependent.

ThurmanFisher provides an empirical application for the concept of Granger causality, as mentioned previously, lagged values were recorded and then regressed on one another to ascertain the significance of the regression coefficients in order to dispute the null hypothesis: that Granger causality wasn't present. After implementing the F-test on the lagged variables it was possible to reach an outcome regarding the null hypothesis and so it was concluded that eggs came first or rather eggs granger caused chickens.

6)a

```
Series #1/1: DLP1
---------

Normality Test

                    Statistic       t-Test      P-Value
Skewness            -0.097856       4.5047   6.6453e-06
Excess Kurtosis        15.779       363.23      0.00000
Jarque-Bera        1.3190e+05         .NaN      0.00000
---------------
ARCH 1-2 test:    F(2,12707)=   570.08 [0.0000]**
ARCH 1-5 test:    F(5,12701)=   319.27 [0.0000]**
ARCH 1-10 test:   F(10,12691)=   183.42 [0.0000]**
---------------
Box-Pierce Q-Statistics on Raw data
  Q(  5) =  22.7934    [0.0003697]**
  Q( 10) =  29.8353    [0.0009114]**
  Q( 20) =  50.8803    [0.0001655]**
  Q( 50) =  139.227    [0.0000000]**
H0 : No serial correlation ==> Accept H0 when prob. is
```

```
Series #1/1: DLP2
---------

Normality Test

                    Statistic       t-Test      P-Value
Skewness             -0.58233       26.807  2.6621e-158
Excess Kurtosis        15.766       362.91      0.00000
Jarque-Bera        1.3237e+05         .NaN      0.00000
---------------
ARCH 1-2 test:    F(2,12707)=   288.66 [0.0000]**
ARCH 1-5 test:    F(5,12701)=   150.06 [0.0000]**
ARCH 1-10 test:   F(10,12691)=   82.483 [0.0000]**
---------------
Box-Pierce Q-Statistics on Raw data
  Q(  5) =  21.0697    [0.0007859]**
  Q( 10) =  28.2599    [0.0016401]**
  Q( 20) =  42.6825    [0.0022512]**
  Q( 50) =  68.3861    [0.0430083]*
H0 : No serial correlation ==> Accept H0 when prob. is
```

```
Series #1/1: DLP3
---------

Normality Test

                    Statistic       t-Test      P-Value
Skewness             -0.32044       14.751   3.0228e-49
Excess Kurtosis        9.0424       208.15      0.00000
Jarque-Bera            43525.         .NaN      0.00000
---------------
ARCH 1-2 test:    F(2,12707)=   382.01 [0.0000]**
ARCH 1-5 test:    F(5,12701)=   199.49 [0.0000]**
ARCH 1-10 test:   F(10,12691)=   112.84 [0.0000]**
---------------
Box-Pierce Q-Statistics on Raw data
  Q(  5) =  64.8427    [0.0000000]**
  Q( 10) =  77.1674    [0.0000000]**
  Q( 20) =  96.8942    [0.0000000]**
  Q( 50) =  179.775    [0.0000000]**
H0 : No serial correlation ==> Accept H0 when prob. is
```

```
Series #1/1: DLP4
---------

Normality Test

                    Statistic       t-Test      P-Value
Skewness              -1.0560       48.611      0.00000
Excess Kurtosis        25.702       591.64      0.00000
Jarque-Bera        3.5226e+05         .NaN      0.00000
---------------
ARCH 1-2 test:    F(2,12707)=   588.87 [0.0000]**
ARCH 1-5 test:    F(5,12701)=   316.15 [0.0000]**
ARCH 1-10 test:   F(10,12691)=   171.08 [0.0000]**
---------------
Box-Pierce Q-Statistics on Raw data
  Q(  5) =  20.8860    [0.0008512]**
  Q( 10) =  36.9267    [0.0000583]**
  Q( 20) =  62.9716    [0.0000024]**
  Q( 50) =  128.189    [0.0000000]**
H0 : No serial correlation ==> Accept H0 when prob. is
```

We perform Engle's LM ARCH test which evaluates the ARCH effect on dlp1, dlp2 dlp3, dlp4 as these time series are all stationary. The null hypothesis is H0: the ARCH effect is not significantly different from 0. Upon conducting Engle's LM ARCH test, it can be observed that that the F statistic is greater than the p-value. Hence, the null hypothesis can be rejected, and it can be concluded that the ARCH effect is significantly different from 0, up to the ARCH 1-10 level (for dlp1, dlp2 dlp3, dlp4). We also perform the Box-Pierce test to evaluate serial correlation. The null hypothesis is H0: No serial correlation and we can observe that the Q statistic is larger than the p-value meaning we can reject the null of no serial correlation or white noise (for dlp1, dlp2 dlp3, dlp4).

6)b

In order to evaluate the best univariate GARCH representation, a table has been generated below. This table shows the effects of changing parameters on the Schwartz information criteria, which is to be minimized. All non-converging representations have been omitted specifically GED, EGARCH and APARCH were all omitted entirely. The best model for lp1 is **[ARMA(0,1) Skewed student, GJR(1,1)]** since it has the smallest Schwartz information criteria tested. Furthermore, since it uses skewed student distribution and evidence of skewness was tested and was found to be significant as the Test Statistic >p-value (1.934>0.0532) which makes the skewed student a suitable distribution to accompany an asymmetric model such as GJR.

DLp1 (Done in full to showcase the process)

ARMA	Drops	Distribution	Convergence	G@RCH	Miss Res	Miss Res^2	BIC
0,0	N/A	Gauss	Strong	GARCH	2,2,1,0	1,0,0,2	-5.264054
2,2	-	Gauss	Strong	GARCH	0,0,0,0	1,0,0,2	-5.262637

3,3	(3,3)	Gauss	Weak	GARCH	0,0,0	1,0,0,2	-5.261987
1,1	N/A	Student	Weak	GARCH	2,2,1,0	1,0,0,2	-5.347382
1,1	-	Student	Strong	GARCH	2,1,0,0	1,0,0,2	-5.346255
2,2	-	Student	Strong	GARCH	2,2,1,0	1,0,0,2	-5.345120
3,3	-	Student	Weak	GARCH	2,2,1	1,0,0,2	-5.344552
1,1	-	Skewed	Weak	GARCH	2,1,0,0	1,0,0,2	-5.345888
3,3	-	Student	Weak	GJR	1,0,0	1,1,0,2	-5.349343
*0,1	-	Skewed	Strong	GJR	0,0,0,0	1,1,0,2	-5.352001
1,1	-	Skewed	Weak	GJR	1,1,0,0	1,1,0,2	-5.351486
2,2	-	Skewed	Strong	GJR	2,2,1,0	1,1,0,2	-5.350292
1,1	-	Student	Weak	RiskMetrics	2,1,1,0	2,1,0,2	-5.340267
2,2	-	Student	Strong	RiskMetrics	2,2,2,0	2,1,0,2	-5.339157
3,3	-	Student	Weak	RiskMetrics	2,2,1	2,1,0,2	-5.337583
1,1	-	Skewed	Strong	RiskMetrics	2,1,1,0	2,1,0,2	-5.339763
2,2	-	Skewed	Weak	RiskMetrics	2,2,2,0	2,1,0,2	-5.338611
3,3	-	Skewed	Weak	RiskMetrics	2,1,0	2,1,0,2	-5.337151

The best representation for lp2 is **[ARMA(1,0) Skewed student, APARCH(1,1)]** as it possesses the lowest SBIC and is well specified. Furthermore, since it uses skewed student distribution evidence of skewness was tested and was found to be significant as the Test Statistic >p-value (2.639>0.0083) which makes the skewed student a suitable distribution to accompany an asymmetric model such as APARCH. The best representation for lp3 is **[ARMA(1,2) Student, APARCH(1,1)]** as it possesses the lowest SBIC and is very well specified for the squared residuals only misspecified at a 5% confidence level on some values in the residuals. The best representation for lp4 is **[ARMA(3,2) Skewed Student, APARCH(1,1)]** as it possesses the lowest SBIC and is very well specified.

```
TESTS :
---------
Information Criteria (to be minimized)
Akaike         -5.356689  Shibata        -5.356690
Schwarz         -5.352001  Hannan-Quinn    -5.355121
---------------

Q-Statistics on Standardized Residuals
  --> P-values adjusted by 1 degree(s) of freedom
  Q(  5) =  9.08541   [0.0589999]
  Q( 10) =  16.8420   [0.0512491]
  Q( 20) =  25.9398   [0.1318755]
  Q( 50) =  48.5191   [0.4925295]
H0 : No serial correlation ==> Accept H0 when prob. i
```

```
TESTS :
---------
Information Criteria (to be minimized)
Akaike         -6.006230  Shibata        -6.006231
Schwarz         -6.000369  Hannan-Quinn    -6.004270
---------------

Q-Statistics on Standardized Residuals
  --> P-values adjusted by 3 degree(s) of freedom
  Q(  5) =  6.41346   [0.0404889]*
  Q( 10) =  8.91289   [0.2589708]
  Q( 20) =  19.6286   [0.2936634]
  Q( 50) =  68.3892   [0.0224345]*
H0 : No serial correlation ==> Accept H0 when prob. i
```

```
TESTS :
---------
Information Criteria (to be minimized)
Akaike         -5.415486  Shibata        -5.415487
Schwarz         -5.410211  Hannan-Quinn    -5.413721
---------------

Q-Statistics on Standardized Residuals
  --> P-values adjusted by 1 degree(s) of freedom
  Q(  5) =  8.58795   [0.0722658]
  Q( 10) =  14.6099   [0.1022246]
  Q( 20) =  20.2030   [0.3824545]
  Q( 50) =  35.5403   [0.9250393]
H0 : No serial correlation ==> Accept H0 when prob. is
```

```
TESTS :
---------
Information Criteria (to be minimized)
Akaike         -6.685284  Shibata        -6.685286
Schwarz         -6.677665  Hannan-Quinn    -6.682736
---------------

Q-Statistics on Standardized Residuals
  --> P-values adjusted by 5 degree(s) of freedom
  Q( 10) =  10.9138   [0.0531171]
  Q( 20) =  20.0159   [0.1713236]
  Q( 50) =  48.6140   [0.3295732]
H0 : No serial correlation ==> Accept H0 when prob. i:
---------------
```