Instructions

The exam consists of Question 1 and Question 2, each one presenting a number of subquestions. On page 11 and page 13 you will find the Stata commands (do-file) and output (log-file) relative to Question 1. On page 22 and page 24 you will find the Stata commands (do-file) and output (log-file) relative to Question 2. Read carefully the text. Answer all questions. Good luck!

Question 1 (45 points)

This question uses material from Clarke and Batina (2019). "A Replication of 'Is Public Expenditure Productive?' (Journal of Monetary Economics, 1989)." Public Finance Review 47.3, 623-629.

Clarke and Batina (2019) replicate the analysis in Aschauer (1989). The objective of Aschauer (1989) was to empirically investigate the effects of government spending on private investment, answering the question: does higher public capital accumulation 'crowd out' private investment in plant and equipment? "On neoclassical grounds, the answer to this question is seen to depend upon two fundamental, opposing forces. On the one hand, higher public investment raises the national rate of capital accumulation above the level chosen (in a presumed rational fashion) by private sector agents; thus, public capital spending may crowd out private expenditures on capital goods on an ex ante basis as individuals seek to reestablish an optimal intertemporal allocation of resources. On the other hand, public capital - particularly infrastructure capital such as highways, water systems, sewers, and airports - is likely to bear a complementary relationship with private capital in the private production technology. Thus, higher public investment may raise the marginal productivity of private capital and, thereby, 'crowd in' private investment. " (Aschauer, 1989. "Is public expenditure productive?." Journal of Monetary Economics 23.2, p. 177).

Aschauer (1989) formulates an aggregate Cobb-Douglas production function:

$$Y_t = A_t N_i^{e_N} K_i^{e_K} G_i^{e_G} exp(\epsilon_t) \tag{1}$$

where Y_t is private output, $A_t = exp(a_0 + a_1 t)$ is a Hicks-neutral measure of productivity, N_t is aggregate labor, K_t is aggregate private capital, G_t is public capital, ϵ_t is an error term and $(a_1, a_2, e_N, e_K, e_G)$ are the parameters to be estimated ("e" because they are elasticities). Aschauer estimates the following two equations:

$$y_t - k_t = a_0 + a_1 t + a_2(n_t - k_t) + a_3(g_t - k_t) + a_4 cu_t + \epsilon_t, \tag{2}$$

where lower case variables are in logs. The variables are:

y_t: real aggregate output (in logs)

t: a time trend

k_t: aggregate stock of capital (in logs)

t: time trend

n_t: aggregate employment (in logs)

g_t: public capital stock, e.g. stock of nonmilitary public structures and equipment (in logs)

cu_t: capacity utilization (in logs), a metric which is used to compute the rate at which probable output levels are being met or used. This variable aims to control for the influence of the business cycle.

ϵ_t: white noise disturbances, with mean zero and variance σ^2.

The critical parameter in these equations is $a_3(= e_G$ in equation 1), which capture the productivity of public capital.

Note that the context for this question is the same as the second in-class test. Students should therefore be familiar at least with the "story" behind the question (data were provided as well, and the suggested solutions for the test hinted to the importance of cointegration in that context although did not go into it). In addition, part (a), (b), (c), (e) are standard questions asked in class and in past exams (DF test, Johansen, trace, LM-test). Part (e) and (f) require reading of the results – but results do not present major challenges.

(a) Explain (once) the test performed on lines 32-54 of the do-file, and provide its conclusion for all the variables (note that the critical values are reported in the do-file).

Solution. This is a basic Dickey-Fuller test. The student should report the null/alternative hypothesis, test-statistic and discuss the fact that it has a non-standard distribution. At 5% significance level, we fail to reject H_0 and therefore cannot exclude the presence of a unit root for all variables except cu_t. This excludes a cointegrating relationship between this variable and any of the others.

(b) Define the Johansen methodology and list its purpose and advantages in the context of this application over the simple OLS estimation of line 22 of the do-file.

Solution. Students should define $\boldsymbol{x}_t$ as the vector including the key variables, i.e. $y_t - k_t$, $(n_t - k_t)$, $g_t - k_t$, cu_t. Students could first define how a model such as $\boldsymbol{x}_t = A_0 + A_1\boldsymbol{x}_{t-1} + \boldsymbol{u}_t$ is agnostic on all cross-equation dependencies. It therefore does not exclude, as the OLS does, reverse causality and rather allows all variables to enter in all equations, as in all VARs. In addition, it allows to directly study the long-term behavior of the system by checking the existence of any cointegrating relationship between variables. Johansen's method pins down to studying the system: $\boldsymbol{\Delta x_t} = \boldsymbol{\pi x_t} + \boldsymbol{u}_t$, and the properties of $\boldsymbol{\pi}$. See lecture 20, slides 6 onward. A good answer should include details on why the rank of this matrix is informative on cointegration. The perfect answer should at this point or in the next one discuss the fact that we can already expect the n. of cointegrating vectors to be less than 4 as one of the variables is stationary – as seen in part (a).

(c) Define the trace test and comment on the results reported in the log-file (line 41).

Solution. Slide 8, lecture 20. There is one cointegrating vector.

(d) Focus only on the key variable $(y_t - k_t)$. Interpret the results relative to this variable from the cointegration analysis reported on line 43 of the log-file.

Solution. The answer has two parts. Students should discuss both the cointegrating vector and the speed of adjustment parameters. The cointegrating relationship is:

$$(\widehat{y_t - k_t}) = -0.12(n_t - k_t) + 0.19(g_t - k_t) + 0.46cu_t + 2.14$$

Other things being equal, this relationship suggests that in equilibrium output per unit of capital (e.g. private capital productivity) is expected to decrease by 0.12% for each 1% increase in the private labor to capital ratio and increase by 0.19% for each 1% increase in the public capital to private capital ratio. This suggests that in equilibrium there is a crowding-in effect taking place. Any shock that will result in disequilibrium will cause an adjustment in the private capital productivity. This is seen in the coefficient -0.36. A 1% increase private capital productivity above its long-term value will result in a 0.36% decrease next period. The other coefficients can be interpreted as you would in a standard log-log model. It is interesting to note that public capital productivity in the short run also seem positively related to private capital productivity (0.60) – but this number is not statistically zero.

(e) Although we have not discussed it in a VAR setting, the command `veclmar` checks for ARCH effects, as we learned in class in the context of univariate models. Referring to a univariate model, explain what we mean with ARCH effects and present a test that can be performed to detect them.

Solution. Students should define an ARCH model and the LM-test (a Q-test would do as well, but the LM-test is a more direct test introduced in class to discuss ARCH effects). Both tests are standard and have been asked many times, see book and notes.

(f) Abdih and Joutz (2008) find that the residuals of a VECM have better properties when they include a dummy variable representing recessions that are usually related to energy shocks. Intuitively explain an additional, even more important reason, as to why a "recession dummy" might be important to be included in an analysis like the one presented.

Solution. We have seen in class how structural breaks can affect the results of the DF test. This is discussed on p. 227 onward of the textbook and can be seen in the test provided in the do-file: although results on the stationarity of the labor to capital ratio are not changed, the statistic is affected even just by the inclusion of a simple recession dummy. Concerns of structural breaks cause caution then in the interpretation of the results above.

(g) Provide a critical summary of the conclusions from this analysis: is public expenditure productive?

Solution. VECM is preferred to OLS, nonetheless all models suggests a posiive relationship between private and public capital. This can be seen from the OLS results (elasticity of 0.37) as well as the cointegration results (elasticity of 0.19). Nonetheless, the last point also raises concerns about possible breaks affecting the analysis. Finally, the analysis performed has not paid attention to specification issues: how were lag-length selected? All in all, results seem robust but the analysis presents room for improvement.

Question 2 (55 points)

This question is partly based on Benton, A., and A. Philips. "Does the @realDonaldTrump really matter to financial markets?", forthcoming American Journal of Political Science (2019).

Anecdotal evidence suggests that economic policy statements made by US President Donald J. Trump via the microblogging website Twitter have the power to rattle financial market. The academic literature however suggests that hist tweets should not matter to investors. Financial economists argue that financial markets are efficient, with asset prices reflecting all publicly available information (Fama 1970, 1991). Political economists build on this to suggest that only new and unanticipated information about the future political and economic policy direction of government should affect investors' views about the future value of their assets. By this logic, Trump's economic policy tweets should have only mattered to financial markets while his policy agenda was unknown; once the direction of his economic policy views were clear, his tweets would not have provided any new information to investors, leaving financial markets untouched.

This paper examines the impact of Trump's Mexico-related policy tweets on the US dollar-Mexican peso (USD/MXN) exchange rate. This data is ideal for three reasons. First, Trump was a newcomer to national US politics, raising chances that his economic policy statements contained new information about his economic policy views. Second, during the period under examination (January 2015 to February 2018), Trump restated what are clearly negative views on the US-Mexico relationship. Third, Trump frequently expressed his Mexico-related policy views via Twitter. [...] If investors only respond to news about the likely future economic policy direction of government, then Trump's Mexico-related policy tweets should have affected the USD/MXN exchange rate early in his campaign, before his agenda became clear. If on the contrary investors respond both to news about future economic policy directions and about the future policy resolve of government, then Trump's tweets should have affected the exchange rate both before and after his Mexico-related policy views were known.

The main dependent variable is the percentage change in the daily USD/MXN from 1 January 2015 to 2 February 2018. Unit root tests indicate that the dependent variable is stationary.

Figure 1 plots both the raw dollar-peso exchange rate (e.g. 1$ bought 14.75 pesos on Jan 1, 2015) and the % change in the dollar-peso exchange rate. The exchange rate faced periods of substantial volatility, with the most notable spike just after the 2016 US presidential election. The main explanatory variable is the daily presence of a Mexico-related policy tweet. The authors use information from the Trump Twitter Archive, which archives all tweets sent by @realDonaldTrump on GitHub. Trump sent over 14,500 tweets between 1 January 2015 and 2 February 2018.

The authors use generalized autoregressive conditional heteroskedasticity (GARCH) models for their analysis.

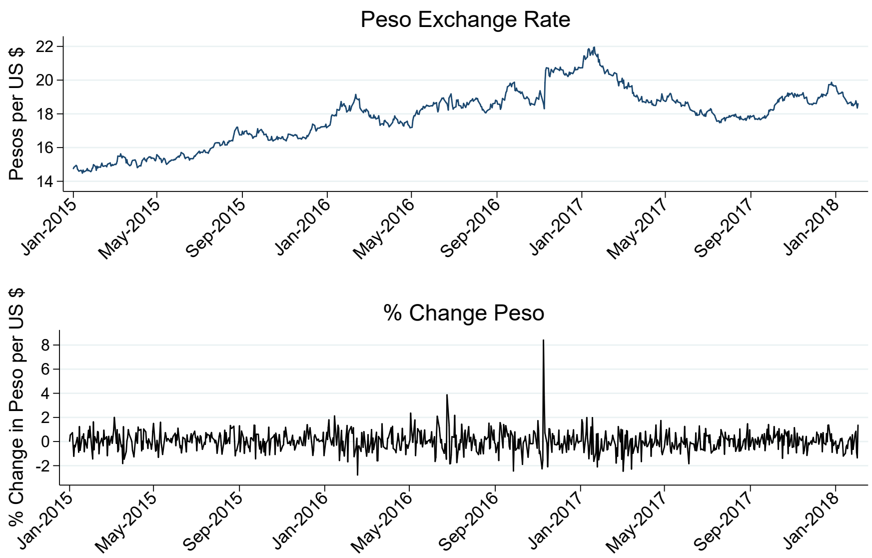


Figure 1: Peso-Dollar exchange rate

In the analysis, the variables are defined as:

`pctchange_peso`: daily % change in the nominal dollar-peso exchange rate

`tweetdum`: indicator variable taking value of 1 if Trump sent a Mexico-related tweet that day, zero otherwise

`pctchangesp500`: percentage change in the US S&P 500 stock market index, capturing shifts in expectations about US economic performance which affect views about the Mexican economy and the exchange rate

`bondspread10yr_pc`: percentage change in the 10 year Mexico-US bond spread

`lnusdstock`: is the change in the log of the Mexican central bank's reported weekly US dollar reserves.

`MexUS_targetratediff`: difference between the Mexican central bank's overnight interest rate and the US federal funds rate.

`BdM_any`: a dummy variable equal to one if Mexico's central bank (at the behest of the foreign exchange commission) offered US dollar auctions or dollar futures contracts that day, zero otherwise.

`USpres2016`: a dummy variable equal to one on 9 November 2016, the day after the 8 November 2016 US presidential election, zero otherwise

`NAFTA_roundsandother`: dichotomous variable equal to one if a NAFTA-related event was being held on that day, zero otherwise.

The authors argue that the Mexican economy is vulnerable to US political events, hence the inclusion of the variables `USpres2016` and `NAFTA_roundsandother`. Similarly, since the Mexican peso is susceptible to US and Mexican macroeconomic performance and policy shocks, the authors include a number of other macro/financial controls (e.g. `pctchangesp500`, `bondspread10yr_pc`...)

This question is an investigation of GARCH models. The story should make sense and be pretty interesting. Part (a), (b), (d) are standard (ACF/PACF and info criteria, GARCH definition and Q-test on residuals). The rest requires a more careful understanding of these models and pushes students' ability to critically evaluate the results.

(a) Figure 2 reports the ACF and PACF of the dependent variable and line 29-32 of the do-file report relevant information criteria. Motivating your choice, discuss whether you agree or disagree with the author's choice to model $\texttt{pctchange\_peso}_t$ as an AR(1) process.

Solutions. The choice of an AR(1) model for $\texttt{pctchange\_peso}_t$ is not fully justified by the AC/PACF or information criteria. Students are expected to show that an AR(1) should have a smooth ACF and a PACF with a spike at lag 1 and this is clearly not present in the shown figures. In addition, students should discuss the AIC/BIC tests (using ln(SSR)) and conclude that they also suggest that an AR(1) does not seem appropriate.

(b) "GARCH models allow us to model both the conditional mean and the conditional error variance as a function of lagged variance, lagged stochastic shocks and exogenous covariates." Define the GARCH(1,1) process estimated by the authors on line 41 of the do-file. In doing so, make sure you explain any assumption needed in the estimation of this model.

Solution. Let $\boldsymbol{x_t}$ be a vector of the covariates excluding the Tweet dummy above. The model estimated is

$$\texttt{pctchange\_peso}_t = a_0 + a_1\texttt{pctchange\_peso}_{t-1} + \delta\texttt{tweetdum}_t + \boldsymbol{x'\gamma} + \epsilon_t \tag{3}$$

$$\epsilon_t = v_t\sqrt{h_t} \tag{4}$$

$$h_t = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{5}$$

We need $\alpha_0 > 0$ and$\alpha_1 + \beta_1 < 1$.

(c) Consider now the GARCH model estimated on line 53 of the do-file, where the tweet dummy has been included not only in the mean equation for the exchange rate but also in the variance equation. Compare the unconditional and conditional mean and variance for `pctchange_peso` and ϵ_t under the two different modeling strategies. In other words, what is the role that the additional control variables play in the determination of the statistical properties of the process?

Solution. Note that the text of the question indicates the type of model estimated (even if students do not know the command `het()`). It tells that the tweet dummy is inserted in the mean AND in the conditional variance equation. This is enough to write down the correct model and the difference in the two models is given exactly by the presence of the tweet dummy in the conditional variance equation. The mean equation for $\texttt{pctchange\_peso}_t$ will therefore be the same. This means estimating:

$$\texttt{pctchange\_peso}_t = a_0 + a_1 \texttt{pctchange\_peso}_{t-1} + \delta \texttt{tweetdum}_t + \boldsymbol{x}'\boldsymbol{\gamma} + \epsilon_t \tag{6}$$

$$\epsilon_t = v_t \sqrt{h_t} \tag{7}$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \pi \texttt{tweetdum}_t \tag{8}$$

Students should calculate the conditional and unconditional first two moments of ϵ_t, i.e.:

$$E(\epsilon_t|\epsilon_{t-1}) = E(v_t \sqrt{\alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta D_t}|\epsilon_{t-1}) = E(v_t)E(\ldots) = 0$$

$$E(\epsilon_t) = E(E(\epsilon_t|\epsilon_{t-1})) = E(0) = 0$$

$$E(\epsilon_t^2|\epsilon_{t-1}) = E_{t-1}(v_t^2(\alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta D_t)) = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta D_t$$

$$E(\epsilon_t^2) = E\Big(E_{t-1}(\epsilon_t^2)\Big) = E(\alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta D_t) = (\alpha_0 + \delta D_t) + \alpha_1 E(\epsilon_{t-1}^2) + \beta_1 E(h_{t-1})$$

Even without full derivation (which we have not produced in class although it is available in the textbook and has been asked in the exam V17, which students had for practice), one can see that the conditional and unconditional variance is affected by the introduction of the dummy just looking at the formulas above. For derivation see the textbook p. 147. Finally, note that an example similar to this is discussed also on p. 155 of the textbook.

(d) Explain the rationale behind the diagnostics checks on lines 43-49 of the do-file.

Solution. The authors are reporting here standardized errors. From (7) once h_t is estimated correctly we should have that the residuals are white noise as $v_t = \epsilon_t / \sqrt(h_t)$. This is a diagnostic performed using a Q-statistic, at different lags (1, 2, 3). The Q-statistic should be defined (see also exam from H18) and results suggest that the residuals are white noise.

(e) On line 52 of the do-file I have estimated a model not present in the original file and received an error message, reported on line 40 p. 21 of the log file. Explain: 1) what would be the rationale of including all variables in the variance-equation and 2) which derivatives does Stata refer to.

Solution. A good number of our time series models have been estimated using maximum likelihood. This happens for GARCH models as well. Hence Stata is forming a likelihood function (perfect answers could include its form, see also p. 152) and numerically taking its derivative to find the estimates for the coefficients in the model that maximize this function. We wrote one in Lecture 5, slide 16. Consider the density for y_t:

$$f(y_t) = \sqrt{\frac{1}{2\pi\sigma^2}} \exp\Big\{ -\frac{1}{2\sigma^2}(y_t - \mu)^2 \Big\}$$

The likelihood function is the joint density of $(y_1, y_2, \ldots, y_T)$, which, by independence, is the product of the individual density. Stata then maximizes this function, by taking derivatives of it. In a GARCH the variance in this model is not a constant and rather has parameters that needs to be estimated.

The error suggests that it is not possible to find such derivatives. Nonetheless, it would make sense to include all variables as it is not clear a-priori which one should be excluded. In other words, there is no theoretical reason (as far as I know) where we should not expect macro variables to affect not only the average ex rate but also their volatility.

While a perfect answers would include a discussion of the form of the likelihood function as above, a good answer could simply give the intuition as to what Stata is doing.

(f) Consider the model estimated on line 53 of the do-file (line 41 of the log-file). Did Trumps' tweet affect the volatility of the exchange rate?

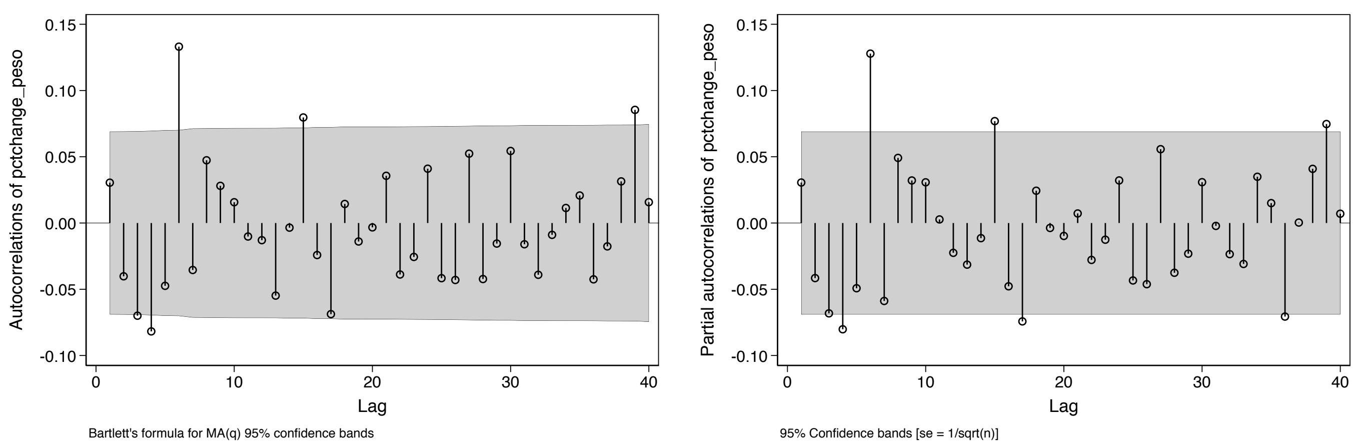
Solution. As shown in equation (8) of these solutions, understanding whether Trump's tweet affect volatility requires interpreting the estimates for the parameter π in equation (8). In the conditional variance equation, the tweet dummy is significant at 10% but negative (-1.114756). One could add (unrequested) that in the mean equation the dummy is an economic and statistical zero (0.022). When it comes to the question, at 10% we find an effect, but a negative one!

(g) Compare and contrast the two models estimated on lines 63-66 of the do-file. Which model would you choose?

Solution. The two models are a GARCH(1,1) and a TGARCH(1,1). The AIC would suggest picking the TGARCH (BIC extremely close), but the negativity constraints are not satisfied in the TGARCH as $\alpha_1 < 0$. It is also a concern in both models that $\alpha_0 < 0$. Overall, if one had to pick, the TGARCH should be disregarded, an EGARCH could be checked but either way these models are not good.

(h) The authors conclude in their paper that social media usage by the government affect financial markets. Discuss whether the models presented in this question are able to answer this question.

Solution. The model estimated simply includes a dummy for whether something was tweeted, and we find marginal significance of the results – of the sign going in the opposite direction than what expected (reduced volatility). However, here the issue is that some of the results above are deeply worrying (non convergence in the maximum likelihood estimation, issues with signs explained above). Hence, care should be exercised in trusting these conclusions.



(a) ACF of `pctchange_peso` (b) PACF of `pctchange_peso`

Figure 2: ACF and PACF of `pctchange_peso`

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** This do file performs the analysis discussed
** for QUESTION 1 - Fall 2019. This is based on:
** Aschauer, David Alan. "Is public expenditure productive?."
** Journal of monetary economics 23.2 (1989): 177-200.

*********************************************

clear all

log using "logfile_q1h19.txt", text replace

use "exam_q1_h19.dta", clear

tsset year

*********************************************
** Basic Estimation in Aschauer (1989)
*********************************************

regress yt_kt t nt_kt gt_kt cu
regress p t gt_it cu

************************************************
** Pre-Testing
** DF critical values:
** 1%  = -3.675
** 5%  = -2.969
** 10% = -2.617
*********************************************
//yt
reg D.yt_kt L.yt_kt
reg D.D.yt_kt D.L.yt_kt

//nt_kt
reg D.nt_kt L.nt_kt
reg D.D.nt_kt D.L.nt_kt

//gt_kt
reg D.gt_kt L.gt_kt
reg D.D.gt_kt D.L.gt_kt

//cu
reg D.cu L.cu
reg D.D.cu D.L.cu

//p
```

```
reg D.p L.p
reg D.D.p D.L.p

//gt_it
reg D.gt_it L.gt_it
reg D.D.gt_it D.L.gt_it


************************************************
** VECM
*********************************************

vecrank yt_kt nt_kt gt_kt cu

vec yt_kt nt_kt gt_kt cu, rank(1)

veclmar


************************************************
** Recession
*********************************************
gen recession=(year == 1974 | year == 1980 | year == 1982 | year ==
 1991)

reg D.nt_kt L.nt_kt recession


log close

```

```
-------------------------------------------------------------------------------------------
      name:  <unnamed>
       log:  /Users/co/Documents/Teaching/Courses Taught/Applied Time Series/Exam/logfi
> q1h19.txt
  log type:  text
 opened on:  18 Nov 2019, 17:37:26

 1 .
 2 . use "exam_q1_h19.dta", clear

 3 .
 4 . tsset year
        time variable:  year, 1949 to 1985
                delta:  1 unit

 5 .
 6 . ********************************************
 7 . ** Basic Estimation in Aschauer (1989)
 8 . ********************************************
 9 .
10 . regress yt_kt t nt_kt gt_kt cu

      Source |       SS           df       MS      Number of obs   =        37
-------------+----------------------------------   F(4, 32)        =    323.33
       Model |  .093182042         4  .02329551   Prob > F        =    0.0000
    Residual |  .002305538        32  .000072048   R-squared       =    0.9759
-------------+----------------------------------   Adj R-squared   =    0.9728
       Total |  .095487579        36  .002652433   Root MSE        =    .00849

------------------------------------------------------------------------------
       yt_kt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           t |   .0103704   .0018073     5.74   0.000     .0066891    .0140518
       nt_kt |   .4401808   .0737391     5.97   0.000     .2899791    .5903824
       gt_kt |   .3787095   .0262646    14.42   0.000     .3252104    .4322087
          cu |   .4114845   .0365627    11.25   0.000     .3370088    .4859602
       _cons |  -1.292136    .381811    -3.38   0.002    -2.06986   -.5144127
------------------------------------------------------------------------------

11 . regress p t gt_it cu

      Source |       SS           df       MS      Number of obs   =        37
-------------+----------------------------------   F(3, 33)        =   4358.14
       Model |  .917211129         3  .305737043   Prob > F        =    0.0000
    Residual |  .002315051        33  .000070153   R-squared       =    0.9975
-------------+----------------------------------   Adj R-squared   =    0.9973
       Total |  .919526179        36  .025542394   Root MSE        =    .00838

------------------------------------------------------------------------------
```

```
             p |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
             t |   .0095906   .0002839    33.78   0.000      .009013    .0101682
         gt_it |   .3634799   .0161002    22.58   0.000     .3307238    .3962359
            cu |   .4236126   .0248119    17.07   0.000     .3731323    .4740929
         _cons |    .774165   .1123446     6.89   0.000     .5455981    1.002732
------------------------------------------------------------------------------

12 .
13 . ************************************************
14 . ** Pre-Testing
15 . ** DF critical values:
16 . ** 1%  = -3.675
17 . ** 5%  = -2.969
18 . ** 10% = -2.617
19 . *********************************************
20 . //yt
21 . reg D.yt_kt L.yt_kt

      Source |       SS           df       MS      Number of obs   =        36
-------------+----------------------------------   F(1, 34)        =      3.73
       Model |  .004044115         1  .004044115   Prob > F        =    0.0619
    Residual |  .036884214        34   .00108483   R-squared       =    0.0988
-------------+----------------------------------   Adj R-squared   =    0.0723
       Total |  .040928329        35  .001169381   Root MSE        =    .03294

------------------------------------------------------------------------------
     D.yt_kt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       yt_kt |
         L1. |  -.2120504   .1098268    -1.93   0.062    -.4352453    .0111444
             |
       _cons |   .9731052    .504339     1.93   0.062     -.051835    1.998045
------------------------------------------------------------------------------

22 . reg D.D.yt_kt D.L.yt_kt

      Source |       SS           df       MS      Number of obs   =        35
-------------+----------------------------------   F(1, 33)        =     30.48
       Model |  .034839741         1  .034839741   Prob > F        =    0.0000
    Residual |  .037722758        33  .001143114   R-squared       =    0.4801
-------------+----------------------------------   Adj R-squared   =    0.4644
       Total |  .072562499        34  .002134191   Root MSE        =    .03381

------------------------------------------------------------------------------
    D2.yt_kt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       yt_kt |
         LD. |  -.9236056   .1672992    -5.52   0.000    -1.263978   -.5832328
```

```
             |
       _cons |  -.0021094   .0057152    -0.37   0.714    -.0137371    .0095183
------------------------------------------------------------------------------

23 .
24 . //nt_kt
25 . reg D.nt_kt L.nt_kt

      Source |       SS           df       MS      Number of obs   =        36
-------------+----------------------------------   F(1, 34)        =      1.04
       Model |  .000679914         1  .000679914   Prob > F        =    0.3150
    Residual |  .022227144        34   .00065374   R-squared       =    0.0297
-------------+----------------------------------   Adj R-squared   =    0.0011
       Total |  .022907058        35  .000654487   Root MSE        =    .02557

------------------------------------------------------------------------------
     D.nt_kt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       nt_kt |
         L1. |  -.0166279   .0163047    -1.02   0.315     -.049763    .0165072
             |
       _cons |    .056913   .0794048     0.72   0.478    -.1044569    .2182829
------------------------------------------------------------------------------

26 . reg D.D.nt_kt D.L.nt_kt

      Source |       SS           df       MS      Number of obs   =        35
-------------+----------------------------------   F(1, 33)        =     30.21
       Model |  .020925774         1  .020925774   Prob > F        =    0.0000
    Residual |  .022855282        33  .000692584   R-squared       =    0.4780
-------------+----------------------------------   Adj R-squared   =    0.4621
       Total |  .043781056        34  .001287678   Root MSE        =    .02632

------------------------------------------------------------------------------
    D2.nt_kt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       nt_kt |
         LD. |  -.9562642   .1739696    -5.50   0.000    -1.310208   -.6023203
             |
       _cons |   -.022816   .0061111    -3.73   0.001    -.0352491   -.0103829
------------------------------------------------------------------------------

27 .
28 . //gt_kt
29 . reg D.gt_kt L.gt_kt

      Source |       SS           df       MS      Number of obs   =        36
-------------+----------------------------------   F(1, 34)        =      3.58
       Model |  .000948089         1  .000948089   Prob > F        =    0.0668
```

```
    Residual |  .008992035        34  .000264472   R-squared       =    0.0954
-------------+----------------------------------   Adj R-squared   =    0.0688
       Total |  .009940124        35  .000284004   Root MSE        =    .01626

------------------------------------------------------------------------------
     D.gt_kt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       gt_kt |
         L1. |   .0679054   .0358649     1.89   0.067    -.0049808    .1407916
             |
       _cons |  -.3159881   .1646894    -1.92   0.063    -.6506773     .018701
------------------------------------------------------------------------------

30 . reg D.D.gt_kt D.L.gt_kt

      Source |       SS           df       MS      Number of obs   =        35
-------------+----------------------------------   F(1, 33)        =      0.65
       Model |  .000033271         1  .000033271   Prob > F        =    0.4274
    Residual |  .001699961        33  .000051514   R-squared       =    0.0192
-------------+----------------------------------   Adj R-squared   =   -0.0105
       Total |  .001733231        34  .000050977   Root MSE        =    .00718

------------------------------------------------------------------------------
    D2.gt_kt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       gt_kt |
         LD. |  -.0603501   .0750949    -0.80   0.427    -.2131318    .0924317
             |
       _cons |  -.0006332     .00124    -0.51   0.613    -.0031559    .0018896
------------------------------------------------------------------------------

31 .
32 . //cu
33 . reg D.cu L.cu

      Source |       SS           df       MS      Number of obs   =        36
-------------+----------------------------------   F(1, 34)        =     11.84
       Model |   .03216652         1   .03216652   Prob > F        =    0.0016
    Residual |   .09234439        34  .002716011   R-squared       =    0.2583
-------------+----------------------------------   Adj R-squared   =    0.2365
       Total |  .124510909        35  .003557455   Root MSE        =    .05212

------------------------------------------------------------------------------
        D.cu |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          cu |
         L1. |  -.4865097   .1413693    -3.44   0.002    -.7738068   -.1992126
             |
       _cons |   2.144997   .6229322     3.44   0.002     .8790462    3.410947
```

```
--------------------------------------------------------------------------------

34 . reg D.D.cu D.L.cu

      Source |       SS           df       MS      Number of obs   =        35
-------------+----------------------------------   F(1, 33)        =     43.36
       Model |  .146410597         1  .146410597   Prob > F        =    0.0000
    Residual |  .111419893        33   .00337636   R-squared       =    0.5679
-------------+----------------------------------   Adj R-squared   =    0.5548
       Total |   .25783049        34   .00758325   Root MSE        =    .05811

------------------------------------------------------------------------------
       D2.cu |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          cu |
         LD. |  -1.085636   .1648626    -6.59   0.000    -1.421051     -.75022
             |
       _cons |  -.0015039   .0098269    -0.15   0.879    -.0214968     .018489
------------------------------------------------------------------------------

35 .
36 .
37 . ************************************************
38 . ** VECM
39 . *********************************************
40 .
41 . vecrank yt_kt nt_kt gt_kt cu

                       Johansen tests for cointegration
Trend: constant                                         Number of obs =      35
Sample:  1951 - 1985                                             Lags =       2
-------------------------------------------------------------------------------
                                                         5%
maximum                                      trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0      20      437.86922          .      48.3912    47.21
    1      27      448.10486     0.44283     27.9200*   29.68
    2      32      457.23315     0.40644      9.6634    15.41
    3      35      462.00536     0.23868      0.1189     3.76
    4      36      462.06484     0.00339
-------------------------------------------------------------------------------

42 .
43 . vec yt_kt nt_kt gt_kt cu, rank(1)

Vector error-correction model

Sample:  1951 - 1985                               Number of obs     =        35
                                                   AIC               =  -24.06313
```

Log likelihood = 448.1049 HQIC = -23.64895
Det(Sigma_ml) = 8.90e-17 SBIC = -22.86329

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_yt_kt	6	.023793	0.5693	38.33906	0.0000
D_nt_kt	6	.017071	0.8027	117.998	0.0000
D_gt_kt	6	.005167	0.9247	356.1751	0.0000
D_cu	6	.041453	0.5568	36.42666	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_yt_kt						
_ce1						
L1.	-.3673863	.1596879	-2.30	0.021	-.6803688	-.0544039
yt_kt						
LD.	1.745721	.3793249	4.60	0.000	1.002258	2.489184
nt_kt						
LD.	-1.013841	.3752999	-2.70	0.007	-1.749416	-.2782668
gt_kt						
LD.	.6003356	.4018903	1.49	0.135	-.1873549	1.388026
cu						
LD.	-.5754542	.2292081	-2.51	0.012	-1.024694	-.1262145
_cons	.009935	.0147692	0.67	0.501	-.0190122	.0388822
D_nt_kt						
_ce1						
L1.	-.2945054	.1145764	-2.57	0.010	-.5190711	-.0699397
yt_kt						
LD.	1.697925	.2721666	6.24	0.000	1.164489	2.231362
nt_kt						
LD.	-.4428407	.2692787	-1.64	0.100	-.9706172	.0849358
gt_kt						
LD.	.0195429	.2883573	0.07	0.946	-.545627	.5847129
cu						
LD.	-.691322	.1644574	-4.20	0.000	-1.013653	-.3689914
_cons	-.0063188	.010597	-0.60	0.551	-.0270884	.0144509

```
-------------+----------------------------------------------------------------
D_gt_kt      |
         _ce1 |
          L1. |   .0615324   .0346761     1.77   0.076    -.0064315    .1294963
              |
        yt_kt |
          LD. |  -.1852085   .0823701    -2.25   0.025     -.346651   -.0237661
              |
        nt_kt |
          LD. |  -.1484826   .0814961    -1.82   0.068     -.308212    .0112468
              |
        gt_kt |
          LD. |   .9045266   .0872702    10.36   0.000     .7334802    1.075573
              |
           cu |
          LD. |   .0899933   .0497724     1.81   0.071    -.0075587    .1875454
              |
        _cons |   -.010049   .0032071    -3.13   0.002    -.0163349   -.0037632
-------------+----------------------------------------------------------------
D_cu         |
         _ce1 |
          L1. |  -.3156232   .2782182    -1.13   0.257    -.8609208    .2296744
              |
        yt_kt |
          LD. |   3.681814   .6608835     5.57   0.000     2.386506    4.977122
              |
        nt_kt |
          LD. |  -1.537604   .6538711    -2.35   0.019    -2.819168   -.2560403
              |
        gt_kt |
          LD. |   -.288923   .7001984    -0.41   0.680    -1.661287    1.083441
              |
           cu |
          LD. |  -1.399028   .3993408    -3.50   0.000    -2.181721   -.6163342
              |
        _cons |  -.0076275   .0257319    -0.30   0.767    -.0580611    .0428061
------------------------------------------------------------------------------

Cointegrating equations

Equation           Parms    chi2     P>chi2
-------------------------------------------
_ce1                   3   40.58489   0.0000
-------------------------------------------

Identification:  beta is exactly identified

                 Johansen normalization restriction imposed
------------------------------------------------------------------------------
```

```
        beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
_ce1         |
       yt_kt |          1          .        .       .            .           .
       nt_kt |   .1200393   .0529118     2.27   0.023     .0163341    .2237445
       gt_kt |  -.1955167   .1204948    -1.62   0.105    -.4316822    .0406488
          cu |  -.4634506   .1764092    -2.63   0.009    -.8092062   -.1176951
       _cons |  -2.145227          .        .       .            .           .
------------------------------------------------------------------------------

44 .
45 . veclmar

   Lagrange-multiplier test
  +--------------------------------------+
  | lag  |      chi2    df   Prob > chi2 |
  |------+-------------------------------|
  |   1  |   25.6604    16     0.05900   |
  |   2  |   17.3955    16     0.36046   |
  +--------------------------------------+
   H0: no autocorrelation at lag order

46 .
47 .
48 . ************************************************
49 . ** Recession
50 . *********************************************
51 . gen recession=(year == 1974 | year == 1980 | year == 1982 | year == 1991)

52 .
53 . reg D.nt_kt L.nt_kt recession

      Source |       SS           df       MS      Number of obs   =        36
-------------+----------------------------------   F(2, 33)        =      3.95
       Model |  .004428295         2  .002214148   Prob > F        =    0.0289
    Residual |  .018478762        33  .000559962   R-squared       =    0.1933
-------------+----------------------------------   Adj R-squared   =    0.1444
       Total |  .022907058        35  .000654487   Root MSE        =    .02366

------------------------------------------------------------------------------
     D.nt_kt |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       nt_kt |
         L1. |   -.028748   .0158004    -1.82   0.078    -.0608942    .0033982
             |
   recession |  -.0386576   .0149414    -2.59   0.014    -.0690561    -.008259
       _cons |   .1190749    .077317     1.54   0.133    -.0382277    .2763775
------------------------------------------------------------------------------
```

```
54 .
55 .
56 . log close
      name:  <unnamed>
       log:  /Users/co/Documents/Teaching/Courses Taught/Applied Time Series/Exam/logfi
> q1h19.txt
  log type:  text
 closed on:  18 Nov 2019, 17:37:29
-----------------------------------------------------------------------------------------
```

```
************************************************

** This do file performs the analysis discussed
** for QUESTION 2 - Fall 2019. This is based on:
** Benton, A., and A. Philips. "Does the@ realDonaldTrump really matter to financial markets.",
** forthcoming American Journal of Political Science (2019).

*********************************************

clear all

log using "logfile_q2h19.txt", text replace

global controls "tweetdum l.pctchangesp500 l.bondspread10yr_pc d.lnusdstock d.MexUS_targetratediff BdM_any USpres2016 l.USpres2016 NAFTA_roundsandother"

use "exam_q2_h19.dta", clear



*********************************************

** Figure 2 and Identification mean process

*********************************************

ac pctchange_peso
pac pctchange_peso

qui: reg pctchange_peso l.pctchange_peso $controls
estat ic
qui: reg pctchange_peso $controls
estat ic



*********************************************

** GARCH effects

*********************************************
arch pctchange_peso l.pctchange_peso $controls, arch(1) garch(1) nolog

predict resids, resid
qui predict cond_var, variance
```

```
qui gen std_resid = resids/sqrt(cond_var)
qui gen std_resid_sq = std_resid^2
wntestq std_resid, lags(1)
wntestq std_resid, lags(2)
wntestq std_resid, lags(3)


arch pctchange_peso l.pctchange_peso $controls, arch(1) garch(1) het($controls) nolog
arch pctchange_peso l.pctchange_peso $controls, arch(1) garch(1) het(tweetdum) nolog



*********************************************

** Model comparison

*********************************************

arch pctchange_peso l.pctchange_peso $controls, arch(1) garch(1) het(tweetdum) nolog
estat ic
arch pctchange_peso l.pctchange_peso $controls, arch(1) garch(1) het(tweetdum) nolog tarch(1)
estat ic

log close
```

```
-------------------------------------------------------------------------------------------
      name:  <unnamed>
       log:  /Users/co/Documents/Teaching/Courses Taught/Applied Time Series/Exam/logfi
> q2h19.txt
  log type:  text
 opened on:  18 Nov 2019, 11:46:00

 1 .
 2 . global controls "tweetdum l.pctchangesp500 l.bondspread10yr_pc d.lnusdstock d.MexUS_t
> etratediff BdM_any USpres2016 l.USpres2016 NAFTA_roundsandother"

 3 .
 4 . use "exam_q2_h19.dta", clear

 5 .
 6 .
 7 .
 8 . ********************************************
 9 .
10 . ** Figure 2 and Identification mean process
11 .
12 . ********************************************
13 .
14 . ac pctchange_peso

15 . pac pctchange_peso

16 .
17 . qui: reg pctchange_peso l.pctchange_peso $controls

18 . estat ic

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
           . |        804 -1006.415  -942.7401      11     1907.48   1959.066
-----------------------------------------------------------------------------
               Note: N=Obs used in calculating BIC; see [R] BIC note.

19 . qui: reg pctchange_peso $controls

20 . estat ic

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
```

```
-------------+---------------------------------------------------------------
           . |        804 -1006.415  -943.4223      10    1906.845   1953.741
-----------------------------------------------------------------------------
               Note: N=Obs used in calculating BIC; see [R] BIC note.

. 
. 
. 
. ********************************************
. 
. ** GARCH effects
. 
. ********************************************
. arch pctchange_peso l.pctchange_peso $controls, arch(1) garch(1) nolog

ARCH family regression

Sample: 3 - 806                                 Number of obs     =        804
Distribution: Gaussian                          Wald chi2(10)     =      15.56
Log likelihood =  -929.726                      Prob > chi2       =     0.1130

--------------------------------------------------------------------------------------
                     |                 OPG
      pctchange_peso |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+----------------------------------------------------------------
pctchange_peso       |
      pctchange_peso |
                 L1. |    .024351   .0340445     0.72   0.474     -.042375     .091077
                     |
            tweetdum |   .0132815   .0580325     0.23   0.819      -.10046    .1270231
                     |
       pctchangesp500 |
                 L1. |   .0559377   .0395168     1.42   0.157    -.0215138    .1333893
                     |
   bondspread10yr_pc |
                 L1. |   .0350685   .0248522     1.41   0.158    -.0136409    .0837778
                     |
          lnusdstock |
                 D1. |   10.61515   16.10443     0.66   0.510    -20.94894    42.17924
                     |
MexUS_targetratediff |
                 D1. |  -1.272865    .520536    -2.45   0.014    -2.293097   -.2526332
                     |
             BdM_any |   .1193477   .0598129     2.00   0.046     .0021166    .2365788
                     |
          USpres2016 |
                 --. |  -1.512456   84818.18    -0.00   1.000    -166242.1    166239.1
                 L1. |    8.52483   7816.193     0.00   0.999    -15310.93    15327.98
                     |
```

```
   NAFTA_roundsandother |   .0932701   .1397222     0.67   0.504    -.1805804    .3671206
                  _cons |  -.0186346   .0358608    -0.52   0.603    -.0889205    .0516513
---------------------+----------------------------------------------------------------
ARCH                 |
                arch |
                 L1. |   .0769638   .0270614     2.84   0.004     .0239245    .1300031
                     |
               garch |
                 L1. |   .8450199   .0656279    12.88   0.000     .7163916    .9736482
                     |
               _cons |   .0484788   .0290683     1.67   0.095     -.008494    .1054516
--------------------------------------------------------------------------------------

30 .
31 . predict resids, resid
   (2 missing values generated)

32 . qui predict cond_var, variance

33 . qui gen std_resid = resids/sqrt(cond_var)

34 . qui gen std_resid_sq = std_resid^2

35 . wntestq std_resid, lags(1)

   Portmanteau test for white noise
   ---------------------------------------
    Portmanteau (Q) statistic =     0.4525
    Prob > chi2(1)            =     0.5012

36 . wntestq std_resid, lags(2)

   Portmanteau test for white noise
   ---------------------------------------
    Portmanteau (Q) statistic =     0.4544
    Prob > chi2(2)            =     0.7968

37 . wntestq std_resid, lags(3)

   Portmanteau test for white noise
   ---------------------------------------
    Portmanteau (Q) statistic =     1.7508
    Prob > chi2(3)            =     0.6257

38 .
39 .
40 . arch pctchange_peso l.pctchange_peso $controls, arch(1) garch(1) het($controls) nolog
   numerical derivatives are approximate
   flat or discontinuous region encountered
```

```
41 . arch pctchange_peso l.pctchange_peso $controls, arch(1) garch(1) het(tweetdum) nolog

   ARCH family regression -- multiplicative heteroskedasticity

   Sample: 3 - 806                                      Number of obs   =        804
   Distribution: Gaussian                               Wald chi2(10)   =      14.36
   Log likelihood = -928.0875                           Prob > chi2     =     0.1573

   ------------------------------------------------------------------------------------
                        |                 OPG
         pctchange_peso |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
   ---------------------+--------------------------------------------------------------
   pctchange_peso       |
         pctchange_peso |
                    L1. |   .0229936   .0331503     0.69   0.488    -.0419799    .0879671
                        |
               tweetdum |   .0224462   .0565912     0.40   0.692    -.0884704    .1333628
                        |
         pctchangesp500 |
                    L1. |   .0572399   .0394856     1.45   0.147    -.0201504    .1346302
                        |
      bondspread10yr_pc |
                    L1. |   .0367846   .0246838     1.49   0.136    -.0115949     .085164
                        |
             lnusdstock |
                    D1. |   10.01577   16.26289     0.62   0.538    -21.85891    41.89045
                        |
   MexUS_targetratediff |
                    D1. |  -1.247495   .5378157    -2.32   0.020    -2.301594   -.1933957
                        |
                BdM_any |   .1141022   .0595931     1.91   0.056    -.0026982    .2309026
                        |
             USpres2016 |
                    --. |  -1.513976   2604.896    -0.00   1.000    -5107.016    5103.988
                    L1. |   8.527756   1134.162     0.01   0.994     -2214.39    2231.445
                        |
   NAFTA_roundsandother |   .0798833     .13139     0.61   0.543    -.1776363     .337403
                  _cons |  -.0196001   .0373185    -0.53   0.599     -.092743    .0535428
   ---------------------+--------------------------------------------------------------
   HET                  |
               tweetdum |  -1.114756   .6579774    -1.69   0.090    -2.404368    .1748556
                  _cons |  -2.814345   .4990637    -5.64   0.000    -3.792492   -1.836198
   ---------------------+--------------------------------------------------------------
   ARCH                 |
                   arch |
                    L1. |   .0688467   .0244841     2.81   0.005     .0208587    .1168346
                        |
                  garch |
```

```
                 L1. |   .8544119   .0550155    15.53   0.000     .7465835    .9622404
------------------------------------------------------------------------------------

. 
. 
. 
. ********************************************
. 
. ** Model comparison
. 
. ********************************************
. 
. arch pctchange_peso l.pctchange_peso $controls, arch(1) garch(1) het(tweetdum) nolog

ARCH family regression -- multiplicative heteroskedasticity

Sample: 3 - 806                                  Number of obs   =        804
Distribution: Gaussian                           Wald chi2(10)   =      14.36
Log likelihood = -928.0875                       Prob > chi2     =     0.1573

------------------------------------------------------------------------------------
                     |                 OPG
      pctchange_peso |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------------+--------------------------------------------------------------
pctchange_peso       |
      pctchange_peso |
                 L1. |   .0229936   .0331503     0.69   0.488    -.0419799    .0879671
                     |
            tweetdum |   .0224462   .0565912     0.40   0.692    -.0884704    .1333628
                     |
      pctchangesp500 |
                 L1. |   .0572399   .0394856     1.45   0.147    -.0201504    .1346302
                     |
   bondspread10yr_pc |
                 L1. |   .0367846   .0246838     1.49   0.136    -.0115949     .085164
                     |
         lnusdstock |
                 D1. |   10.01577   16.26289     0.62   0.538    -21.85891    41.89045
                     |
MexUS_targetratediff |
                 D1. |  -1.247495   .5378157    -2.32   0.020    -2.301594   -.1933957
                     |
             BdM_any |   .1141022   .0595931     1.91   0.056    -.0026982    .2309026
                     |
          USpres2016 |
                 --. |  -1.513976   2604.896    -0.00   1.000    -5107.016    5103.988
                 L1. |   8.527756   1134.162     0.01   0.994     -2214.39    2231.445
                     |
NAFTA_roundsandother |   .0798833     .13139     0.61   0.543    -.1776363     .337403
```

```
                _cons |  -.0196001   .0373185    -0.53   0.599     -.092743    .0535428
---------------------+----------------------------------------------------------------
HET                  |
             tweetdum |  -1.114756   .6579774    -1.69   0.090    -2.404368    .1748556
                _cons |  -2.814345   .4990637    -5.64   0.000    -3.792492   -1.836198
---------------------+----------------------------------------------------------------
ARCH                 |
                 arch |
                  L1. |   .0688467   .0244841     2.81   0.005     .0208587    .1168346
                      |
                garch |
                  L1. |   .8544119   .0550155    15.53   0.000     .7465835    .9622404
--------------------------------------------------------------------------------------

52 . estat ic

   Akaike's information criterion and Bayesian information criterion

   -----------------------------------------------------------------------------
          Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
   -------------+---------------------------------------------------------------
              . |        804         .  -928.0875      15    1886.175   1956.519
   -----------------------------------------------------------------------------
                  Note: N=Obs used in calculating BIC; see [R] BIC note.

53 . arch pctchange_peso l.pctchange_peso $controls, arch(1) garch(1) het(tweetdum) nolog
   > ch(1)

   ARCH family regression -- multiplicative heteroskedasticity

   Sample: 3 - 806                                 Number of obs     =        804
   Distribution: Gaussian                          Wald chi2(10)     =      21.80
   Log likelihood = -924.8017                      Prob > chi2       =     0.0162

   --------------------------------------------------------------------------------------
                        |                 OPG
         pctchange_peso |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
   ---------------------+----------------------------------------------------------------
   pctchange_peso       |
         pctchange_peso |
                    L1. |   .0343943   .0317941     1.08   0.279     -.027921    .0967096
                        |
               tweetdum |   -.006067   .0599344    -0.10   0.919    -.1235363    .1114023
                        |
         pctchangesp500 |
                    L1. |   .0681428   .0358083     1.90   0.057    -.0020403    .1383259
                        |
      bondspread10yr_pc |
                    L1. |   .0276071    .025643     1.08   0.282    -.0226523    .0778665
```

```
                      |
          lnusdstock  |
                 D1.  |   10.34933   15.58921     0.66   0.507    -20.20495    40.90361
                      |
MexUS_targetratediff  |
                 D1.  |  -1.214277   .5098728    -2.38   0.017    -2.213609   -.2149443
                      |
             BdM_any  |   .1366726   .0515383     2.65   0.008     .0356593    .2376858
                      |
          USpres2016  |
                 --.  |  -1.535542   1434.567    -0.00   0.999    -2813.236    2810.165
                 L1.  |   8.516001   740.3987     0.01   0.991    -1442.639    1459.671
                      |
NAFTA_roundsandother  |   .2529498   .1322614     1.91   0.056    -.0062778    .5121774
               _cons  |  -.0169625   .0392824    -0.43   0.666    -.0939545    .0600295
----------------------+----------------------------------------------------------------
HET                   |
            tweetdum  |  -1.557858   3.984024    -0.39   0.696    -9.366401    6.250686
               _cons  |   -5.00012   .6372736    -7.85   0.000    -6.249153   -3.751087
----------------------+----------------------------------------------------------------
ARCH                  |
                arch  |
                 L1.  |  -.0259172   .0093108    -2.78   0.005    -.0441662   -.0076683
                      |
               tarch  |
                 L1.  |     .05606   .0108793     5.15   0.000     .0347369     .077383
                      |
               garch  |
                 L1.  |   .9889193   .0081029   122.05   0.000     .9730379    1.004801
---------------------------------------------------------------------------------------

54 . estat ic

Akaike's information criterion and Bayesian information criterion

-----------------------------------------------------------------------------
       Model |        Obs  ll(null)  ll(model)      df         AIC        BIC
-------------+---------------------------------------------------------------
           . |        804         .  -924.8017      16    1881.603   1956.637
-----------------------------------------------------------------------------
               Note: N=Obs used in calculating BIC; see [R] BIC note.

55 .
56 . log close
      name:  <unnamed>
       log:  /Users/co/Documents/Teaching/Courses Taught/Applied Time Series/Exam/logfi
> q2h19.txt
  log type:  text
 closed on:  18 Nov 2019, 11:48:01
```