ECON 1123 Section 11

Slides at github.com/cjleggett/1123-section

Outline

- Name Circle
- Final Exam
- Lecture Recap + Exercises

Name Circle

Name Circle

- Name
- Favorite Cambridge Restaurant

Final Exam

Logistics

- 9am on Tuesday, May 9
  - Please come a few minutes early!
- Will be in several rooms, so stay tuned for your assignment
- Bring:
  - A pen (not a pencil)
  - A simple calculator
  - 2 double-sided sheets of notes

Exam Format

- Two packets just like the midterm: one with info/tables, another with questions
- 4 sections (compared to two for the midterm)
- Similar types of questions as the midterm, but with Instrumental Variables and Time-Series questions as well.

My Advice for Studying

- Make cheat sheet, then look at practice exams, then solutions, then update
- Look at problem set suggested solutions
- After the above 2, go to office hours or **post on Slack!**
- Learn how to use tables
- Go to review session (if held)
- Come to my exam walkthrough (midterm or final?)
- Review section notes
- Review lecture notes

My Advice for Taking the Exam

- Read from Packet 1 carefully
- Be careful about which table you're looking at!
- Unless otherwise specified, use bullet points!
- Practice Exam Solutions are much more detailed than necessary! Just write what you need to answer the question.
- Show work for partial credit!

Lecture Recap

Newey-West

One Step Ahead Forecasting

- If we choose lags using BIC, then we don’t normally need our standard errors to account for serial correlation. Why?
- When do we need HAC standard errors?
  - Multi-step ahead forecasting models
  - Distributed Lag Models (no lags of Y)

One Step Ahead Forecasting

- Using past data to predict next data point
- If we choose lags using BIC, then we don't normally need our standard errors to account for serial correlation. Why?
- When do we need HAC standard errors?
    - Multi-step ahead forecasting models
    - Distributed Lag Models (no lags of Y)

Multi-step ahead forecasting

- Using past data to predict several data points ahead
- Eg: Predict inflation at this point next year
- In this case, errors will be serially correlated
- Intuitively, if we make a mistake in predicting the next month because of a large event, we will also make a mistake in predicting the next month
- We account for this using Newey-West Standard Errors

Newey-West Standard Errors

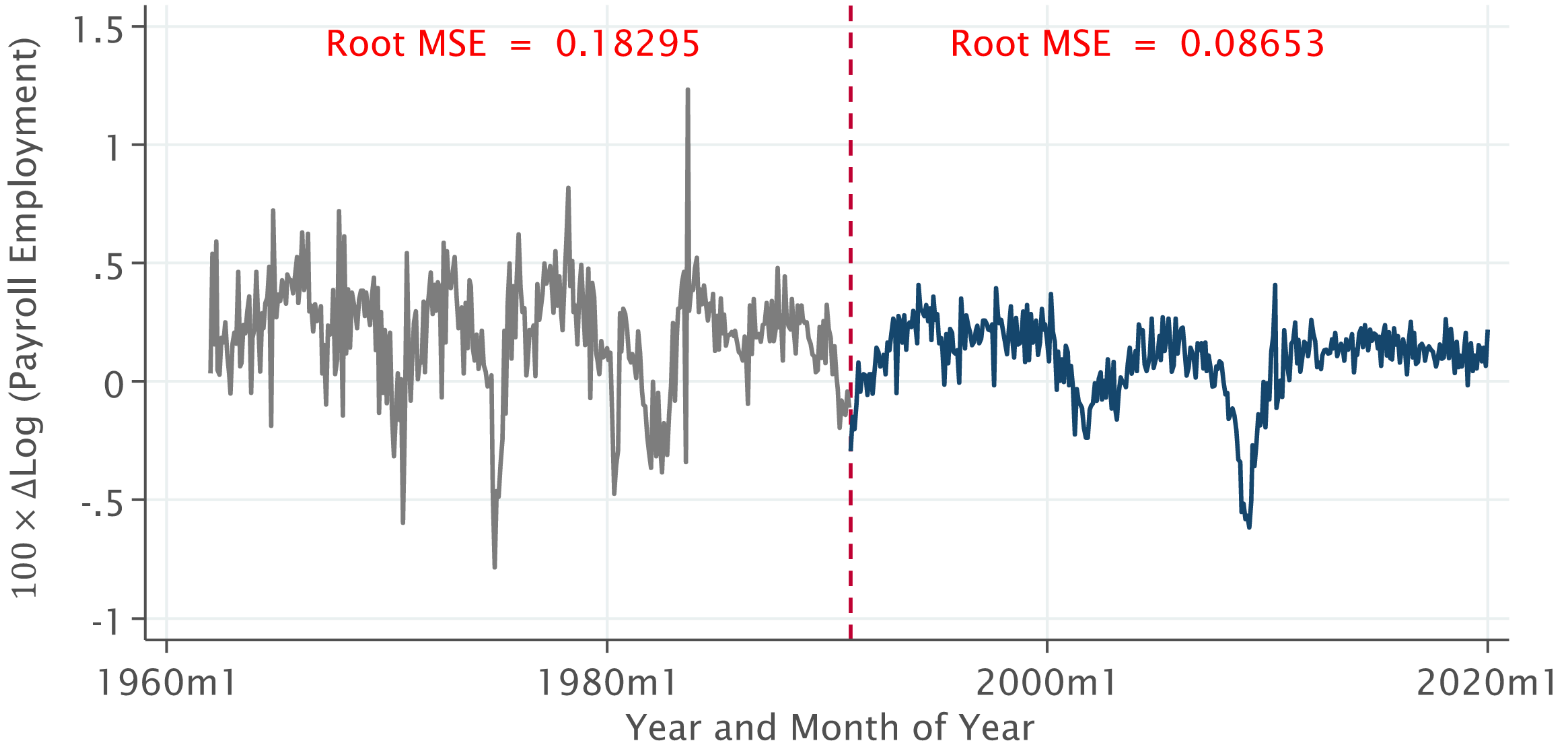
- Works by estimating standard errors using just m lags, and weighting using a triangular kernel
- m must be chosen. Too small leads to bias. Too large leads to variance.
- General rule of thumb is to choose $m = 1.3T^{1/2}$

Exercises: 1

Review: Stationarity Breaks

Chow Test (Structural Break)

- Decide on a time you want to test for a break (covid? 2008?)
  - Indicator D_t is 0 if $t < r$, and 1 if $t \geq r$
- Fully interact AR(1) model with indicator for after this time
  - $Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 D_t + \beta_3 D_t \times T_{t-1} + u_t$
- Do normal F test for whether slope/intercept are equal before and after date

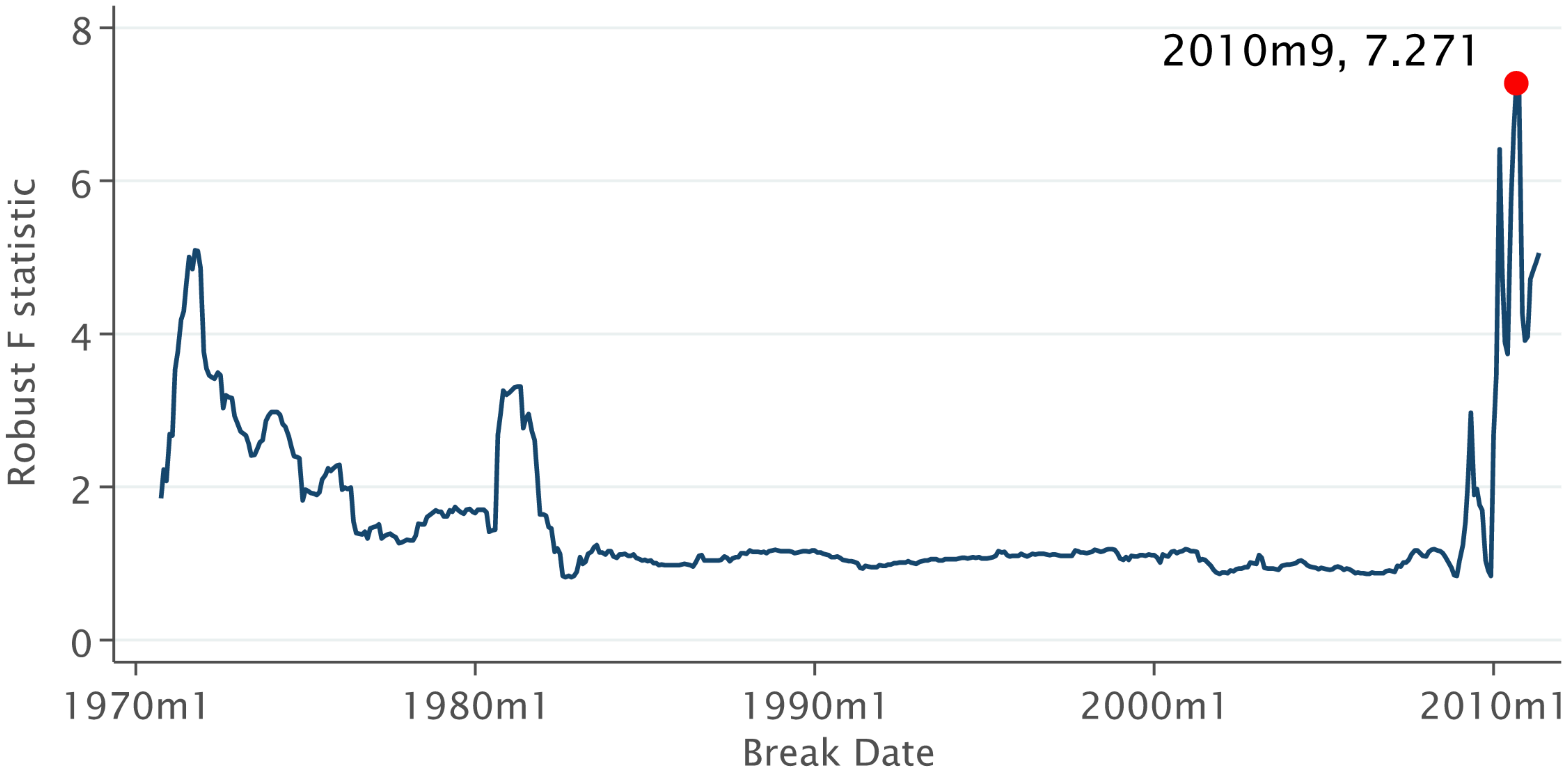

Root MSE = 0.18295
Root MSE = 0.08653
100 × ΔLog (Payroll Employment)
1.5
1
.5
0
-.5
-1
1960m1
1980m1
2000m1
2020m1
Year and Month of Year

QLR Test (Structural Break)

- QLR is maximum Chow F statistic over all possible breaks in middle 70% of time span
- Why restrict this?

QLR Test (Structural Break)

- QLR is maximum Chow F statistic over all possible breaks in middle 70% of time span
- Why restrict this?
  - So we have enough data on either side



2010m9, 7.271
Robust F statistic
0
2
4
6
8
1970m1
1980m1
1990m1
2000m1
2010m1
Break Date

QLR Test Critical Values

- QLR = max(F tests)
- This is a distribution itself!
- Critical values of this are difficult, and were derived semi-recently (1993)
- We calculate this with a computer, but need to know # of restrictions:
    - 1 restriction for dummy variable
    - p restrictions for lags of Y
    - q restrictions for lags of X
    - total of 1 + p + q

What to do when we detect a break?

- Split data at the break
- Use only second-half data

Exercises: 1.1

TABLE 14.6 Critical Values of the QLR Statistic with 15% Trimming

Number of Restrictions (q)	10%	5%	1%
1	7.12	8.68	12.16
2	5.00	5.86	7.78
3	4.09	4.71	6.02
4	3.59	4.09	5.12
5	3.26	3.66	4.53
6	3.02	3.37	4.12
7	2.84	3.15	3.82
8	2.69	2.98	3.57
9	2.58	2.84	3.38
10	2.48	2.71	3.23

Forecast Errors

Forecasting Terminology

- Forecasts are for observations not in our dataset
  - (Like fitted values)
- Forecast errors are the errors on out-of-sample data
  - (Like residuals)

Forecast Interval

- We want to quantify uncertainty around $\hat{Y}_{T+1}$
- We typically want to construct a 68% forecast interval
- To do this we need Root Mean Squared Forecast Error (RMSFE)

$$\hat{Y}_{T+1} \pm RMSFE$$

- How do we find RMSFE?

Method 1: RMSE

1. Square all the residuals of your data
2. Take the mean of the square residuals
3. Multiply by the degrees of freedom ($\frac{T}{T-K}$)
4. Take square root of the above

Method 1: RMSE

- Disadvantage: Assumes errors are constant throughout the distribution

Method 2: POOS RMSFE

1. Choose a point at which to split your data
2. Train a model using just the first section of data
3. Use that model to make predictions for the second part of the data
4. Take the difference between the predictions and actual values
5. Square these differences and then take the average of them
6. Finally, take the square root of the average

Method 2: POOS RMSFE

- Advantage: predicts errors based on more recent values
- Disadvantages:
  - Still assumes errors are constant within a certain window
  - Still backwards-looking

Method 3: Time-Varying Volatility

- Idea: Use model to predict future errors
- 3 ways to do this:
    - Realized volatility
    - ARCH
    - GARCH

Realized Volatility

- Average of squared errors over last m days
- Uses constant weights on all previous m days

$$\frac{1}{m}\sum_{\tau=t-m+1}^{t}(\hat{u}_\tau)^2$$

ARCH

- AutoRegressive Conditional Heteroskedasticity
- Fit a model where we predict variance at time t based on prior values:

$$\sigma_t^2 = \phi_0 + \phi_1 u_{t-1}^2 + \phi_2 u_{t-2}^2 + \phi_3 u_{t-3}^2$$

GARCH

- Generalized AutoRegressive Conditional Heteroskedasticity
- Fit a model where we predict variance at time t based on prior values **and** prior variances
- Very similar in practice to realized volatility

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \phi_1 u_{t-1}^2$$

Great work this semester!

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