Empirical Macroeconomics

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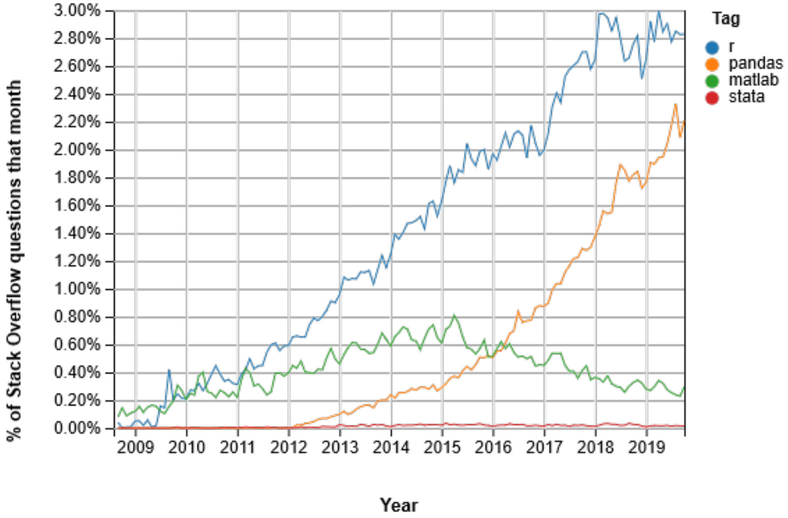
Housekeeping

Classes and Evaluation

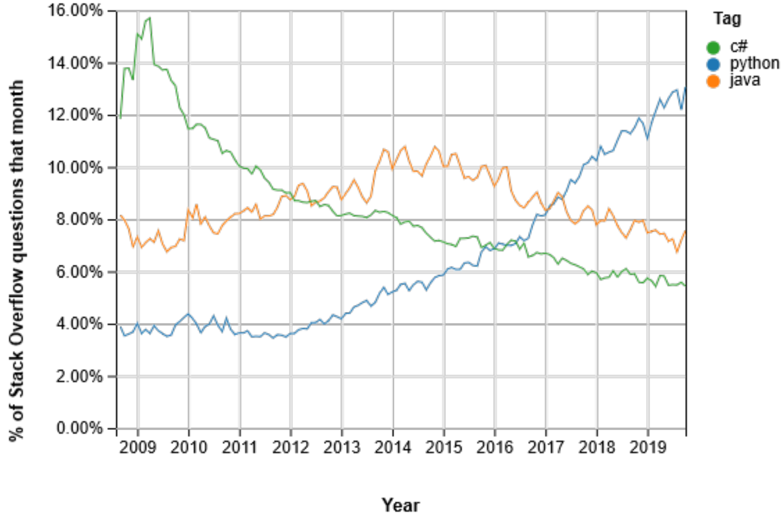
- No textbook but based on papers
- Requires background in Macroeconomics and Econometrics
- We use Python
- Evaluation: 50% home-works, 50% final

Python

Looking forward



(a) Statistical packages



(b) Python ascending

Figure: The Recent evolution of languages

https://www.ft.com/content/4c17d6ce-c8b2-11e8-ba8f-ee390057b8c9

Applied Macroeconomics

Broad methodological tool

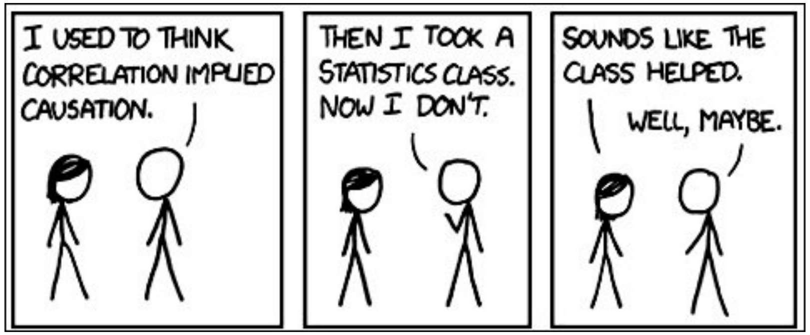


Figure: More to it than this

- Cutting edge time series techniques
- Useful both for finance and macroeconomics
- Forecast will be useful for ML techniques

Empirical Macroeconomics Program

Method: reproduce classic papers

- I cover the paper in class
- Homework: you reproduce and discuss in class
- 3 papers on the identification of shocks

1.SVAR

First paper: Fundamental Shocks

- Blanchard and Quah (1989): The Dynamic Effects of Aggregate Demand and Supply Disturbances
- Classic reference for the identification of structural shocks using Structural Vector Autoregression models
- Agnostic approach: broad identification assumption consistent across many models
- Homework requires you to apply the technique to a different country than the US

2.FAVAR-DFM

Second paper: Non-Fundamental Shocks

- Bernanke, Ben, Jean Boivin, and Piotr Eliasz. 2005 "Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach."
- One of the first paper that applied FAVAR to macro
- Increase the information you can use to identify the shocks, possibly solving non fundamentalness issues maintaining the agnostic approach of SVAR
- Bridge between big data and SVAR
- Homework requires you to extend code to reproduce figures and tables in the paper

3.DSGE

Third paper: Non-Recoverable Shocks

- Blanchard, Olivier J., Jean-Paul L'Huillier and Guido Lorenzoni. 2013. "News, Noise, and Fluctuations: An Empirical Exploration."
- Agnostic approach might not always work: sometimes there is the need for an economic structure
- This is relevant if you are interested in shocks that are not fully observed by the economic agents
- Homework requires you to extend code to reproduce figures and tables in the paper

A brief history

The Probability Approach in Econometrics SIMS Nobel lecture

- The progress in Econometrics since its beginning in the 1930's is full of ups and down and the field itself has different school of thoughts
- In this first replication (warm up for Python) we "reproduce" Chris Sims Nobel Lecture on the historical evolution of Econometrics :
    1. 1930's-1940's : Tinbergen-Haavelmo project
    2. 1950's-1970's: Keynesian large macro-econometric models versus single equations Monetarist model
    3. 1970's-1980's: Rational Expectations
    4. 1980's-2000's: VAR and SVAR
    5. 2000's-today:
        1. Evolution on SVAR
        2. DSGE

A brief history

The Probability Approach in Econometrics

- Tinbergen: multiple equations with error terms, discuss
- Critique by Keynes: model with errors can always fit, discuss
- Haveelmo Haavelmo1943. If errors have probability structure then we estimate parameters building likelihood of the model. Haavelmo set up an example:

$$
\begin{aligned}
C_t &= \beta + \alpha Y_t + \epsilon_t \\
I_t &= \theta \left(C_t - C_{t-1} \right) + \eta_t \\
Y_t &= C_t + I_t
\end{aligned}
$$

A brief history

Haavelmo example

Substitute for Y_t (identity)

$$\begin{aligned} C_t(1-\alpha) - \alpha I_t &= \beta + \epsilon_t \\ -\theta C_t + I_t &= -\theta C_{t-1} + \eta_t \end{aligned}$$

and write it into a system

$$\begin{bmatrix} 1-\alpha & -\alpha \\ -\theta & 1 \end{bmatrix} \begin{bmatrix} C_t \\ I_t \end{bmatrix} = \begin{bmatrix} \beta \\ 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ -\theta & 0 \end{bmatrix} \begin{bmatrix} C_{t-1} \\ I_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ \eta_t \end{bmatrix}$$

$$\Gamma_0 X_t = C + \Gamma_1 X_{t-1} + U_t$$

where $U_t \sim N(0, D)$ and assume further: 1) that U_t is independent of U_τ for $t \neq \tau$ and 2) that U_t is independent of X_τ for all t and τ.

A brief history

The likelihood in a dynamic setting

The starting point is to have the joint probability distribution of $f_{X^T}(X^T;\psi)$ where $X^T = X_T, X_{T-1}, .., X_0$ is the all sample , ψ are the parameters, and treat is as the likelihood to be maximized.
In dynamic settings the marginalization of the joint probability distribution of the data is essential to overcome the time interdependence between the observations.
Start by the distribution of the first observation to be $f_{X_0}(X_0;\psi)$ (in a stationary environment think of the unconditional distribution) then consider writing the joint distribution of the first and second observation as the production of the conditional distribution and the marginal distribution:

$$f_{X_1}(X_1, X_0;\psi) = f_{X_1|X_0}(X_1|X_0;\psi)\, f_{X_0}(X_0;\psi)$$

A brief history

The likelihood in a dynamic setting

from distribution and the marginal distribution:

$$f_{X_1}(X_1, X_0; \psi) = f_{X_1|X_0}(X_1|X_0; \psi)\, f_{X_0}(X_0; \psi)$$

you can do that for the whole sample and get

$$f_{X^T}(X^T; \psi) = f_{X_0}(X_0; \psi) \prod_{t=1}^{T} f_{X_t|X_{t-1}}(X_t|X_{t-1}; \psi)$$

or in logs

$$L(\psi) = log\left(f_{X_0}(X_0; \psi)\right) + \sum_{t=1}^{T} log\left(f_{X_t|X_{t-1}}(X_t|X_{t-1}; \psi)\right)$$

A brief history

Back to Haavelmo

Obtain the reduced form by inverting Γ_0 (must be invertible to go back structure of the model) and obtain the reduced form:

$$X_t = \Gamma_0^{-1} C + \Gamma_0^{-1} \Gamma_1 X_{t-1} + \Gamma_0^{-1} U_t$$

$$X_t = A + BX_{t-1} + V_t$$

where $V_t \sim N(0, \Omega)$, and

$$\begin{aligned} f(X_t | X_{t-1}) &= N(A + BX_{t-1}, \Omega) \\ &= N\left(\Gamma_0^{-1} C + \Gamma_0^{-1} \Gamma_1 X_{t-1}, \Gamma_0^{-1} D \left(\Gamma_0^{-1}\right)'\right) \end{aligned}$$

A brief history

The likelihood in Haavelmo model

The Log-likehood of the reduced form is

$$\mathcal{L}(\psi_r) = -Tn/2 + T/2 log \left|\Omega^{-1}\right| \\ - 0.5 \sum_{t=1}^{T} \left[(X_t - A - BX_{t-1})' \, \Omega^{-1} \, (X_t - A - BX_{t-1}) \right]$$

which you can write in terms of the structural model as

$$\mathcal{L}(\psi) = -(Tn/2) + (T/2) \, log \left|\Gamma_0\right|^2 - (T/2) \, log \left|D\right| \\ - 0.5 \sum_{t=1}^{T} \left[(\Gamma_0 X_t - C - \Gamma_1 X_{t-1})' \, D^{-1} \, (\Gamma_0 X_t - C - \Gamma_1 X_{t-1}) \right]$$

and find the parameters by maximizing it (can use the reduced form if exactly identified, order and rank condition)

A brief history

The Cowles Commission

This approach was extended and developed by the Cowles Commission and resulted into large Macroeconometrics models of hundreds of equations. But there were issues as the size of the models implied hundreds of parameters which forced to impose many restrictions and exclusions (in the Haavelmo example I_{t-1} is excluded together with higher order lags) both on the equations and the covariance matrix:

- starting from a tight structural form and then obtaining the reduce form could result in a bad probability model for the joint distribution of the sample
- variables that only appear on the RHS (call them Z_t) imply that they must be exogenous (again different definitions) to be able to learn the parameters of interests : $f_{X^T}(X^T; \psi)$

A brief history

The Monetarist approach: an example of endogeneity

- Friedman and Meiselman (1963) used single-equation regressions to argue that the relation between money and income was more stable than that between what they called "autonomous expenditure" and income. They thought that money was exogenous.
- Simultaneously other economists were estimating single equations explaining money with income and interest rates. (Sims 1972, Mehra 1978). Someone was wrong, or both?

A brief history

Rational Expectations: cross equation restrictions

- required that models that included explicit expectations of the future in behavioral equations should base those expectations on the full model's own dynamic structure which created a new comprehension of causality (asset prices)
- policy behavior was required to accurately model expectations in the private sector
- Maximum likelihood estimation of complete systems embodying rational expectations at the scale needed for policy modeling was not possible

A brief history

Granger-Causality-Rational Expectations, Money and Income

According to efficient market hypothesis (with constant real interest rate) the price of a stock must respect:

$$(1+r)\,P_t = E_t\left[P_{t+1} + D_{t+1}\right]$$

where D are the dividend. The arbitrage and a boundness condition imply:

$$P_t = \sum_{j=1}^{\infty} E_t \left(\frac{1}{1+r}\right)^j D_{t+j}.$$

Which says that the price incorporates the market's best forecast of the Present Value of dividends.

A brief history

Granger-Causality-Rational Expectations

Suppose

$$D_t = d + u_t + \delta u_{t-1} + v_t$$

and you observe u_t. Then

$$E_t\left[D_{t+j}\right] = \begin{cases} d + \delta u_t & \textit{for } j = 1 \\ d & \textit{for } j = 2, 3... \end{cases}$$

This implies

$$P_t = \frac{d}{r} + \frac{\delta u_t}{1+r}$$

and lagging and rearranging $\delta u_{t-1} = (1+r) P_{t-1} - (1+r) \frac{d}{r}$ which allows to rewrite the dividend

$$D_t = d + u_t - (1+r) P_{t-1} + (1+r) \frac{\delta}{r} + v_t.$$

where Prices Granger Cause dividends.

A brief history

VAR-SVAR: smaller models little restrictions

In 1980 Sims writes "Macroeconomics and Reality" were he estimates a VAR and a SVAR. VAR's are models of the joint behavior of a set of time series with restrictions or prior distributions that, at least initially, are symmetric in the variables. The advantage is that the probability distribution is now well behaved. Once estimated It is possible to introduce theory explicitly, but with restraint, so that VAR's became usable for policy analysis. Blanchard and Watson (1986) and Sims (1986) showed two different approaches to doing this.

A brief history

Today

Since SVAR's limit themselves to isolate for example monetary policy, treating the rest of the economy as a single "black box" system, they can not easily provide conditional forecasts. Low commodity prices due to supply disruptions, high or low productivity growth, decline in the value of the dollar, fiscal policy changes.

- data reduction models nested with SVAR, FAVAR, Global SVAR, DFM
- Back to structural models but with microfoundations : DSGE
- Bayesian methods imported from physics (MCMC) to permit feasible estimates (implications)

Readings

- (*) Sims Cristopher A., "STATISTICAL MODELING OF MONETARY POLICY AND ITS EFFECTS", Nobel Lecture 2011