MA Advanced Macroeconomics:
1. Introduction: Time Series and Macroeconomics

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Spring 2016

What's This Course About?

- You have probably already taken lots of macro: Principles, Intermediate, Advanced, Masters Part 1....
- What's left to learn?
- Well, mostly you've learned small models that teach useful principles. Monetary policy is effective in the short-run but not in the long run; technological progress is the source of long-run growth. That kind of thing.
- These are valuable in helping you understand how the world works but how useful would that be if you had to work for a finance ministry or a central bank?
- Imagine if Janet Yellen or Mario Draghi asked you what would happen if they took action X versus action Y?
- Ideally, they would want to know how consumption, investment, output, and inflation would respond next quarter and the quarter after that, and so on.
- General principles wouldn't help you much.

Macroeconomics as an *Applied* Subject

- Beyond establishing general principles, macroeconomists aim to produce models that are as useful as possible for policy analysis and forecasting.
- The main purpose of this module is to introduce you to the types of models being used in modern applied macro.
- The course will have three parts:

  1. **Time Series as a Framework for Modern Macro**: We will discuss how time series provides a way to think about empirical macro, focusing particularly on Vector Autoregressions which are popular econometric models for forecasting and "what if?" scenario analysis.
  2. **Dynamic Stochastic General Equilibrium (DSGE) Models**: Theoretically-founded models. We will cover the methods used to derive these models and simulate them on a computer. We will start with Real Business Cycle models and then move on to New-Keynesian models.
  3. **Financial Markets, Banking and Systemic Risk**: We will cover risk spreads, credit rationing, financial intermediation, bank runs, banking regulation, systemic risk and bank balance sheet adjustments.

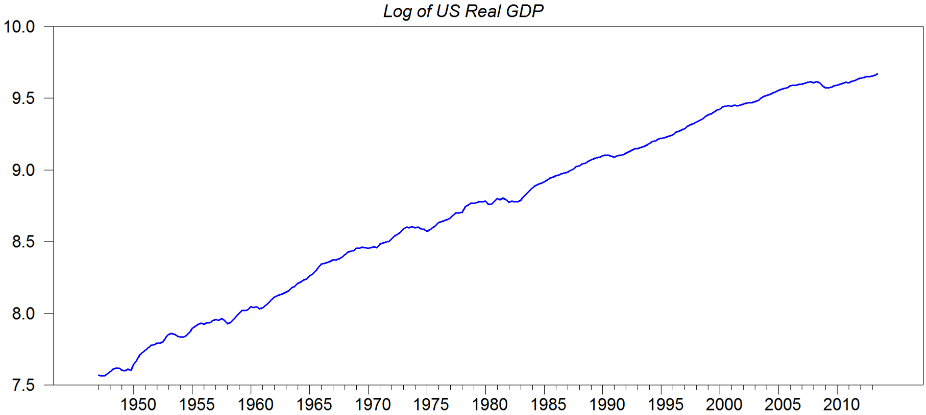
Trends and Cycles

- Macroeconomists tend to break series into a "non-stationary" long-run trend and a "stationary" cyclical component.
- "Business cycle analysis" relates to this modelling and explaining the cyclical components of the major macroeconomic variables.
- Fine in theory, but how is this done in practice?
- Simplest method: Log-linear trend
  - Estimated from regression

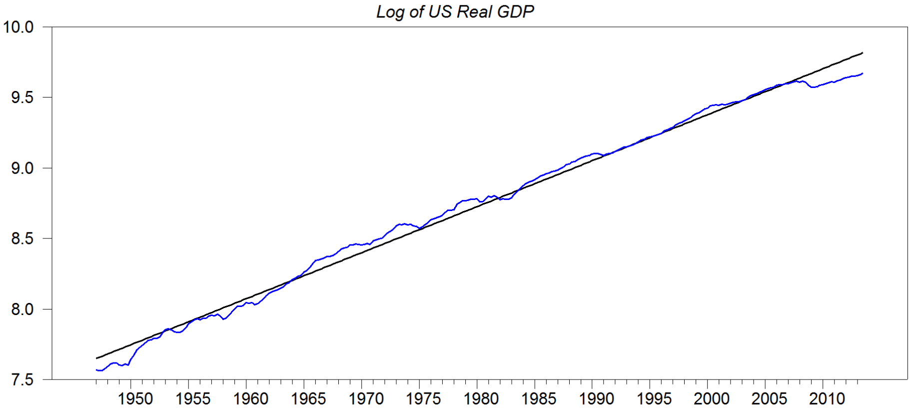
$$\log(Y_t) = y_t = \alpha + gt + \epsilon_t$$

  - Trend component $\alpha + gt$.
  - Zero-mean stationary cyclical component ϵ_t.
  - Log-difference Δy_t (equivalent to growth rate) has two components: Constant trend growth g and the change in cyclical component $\Delta\epsilon_t$.

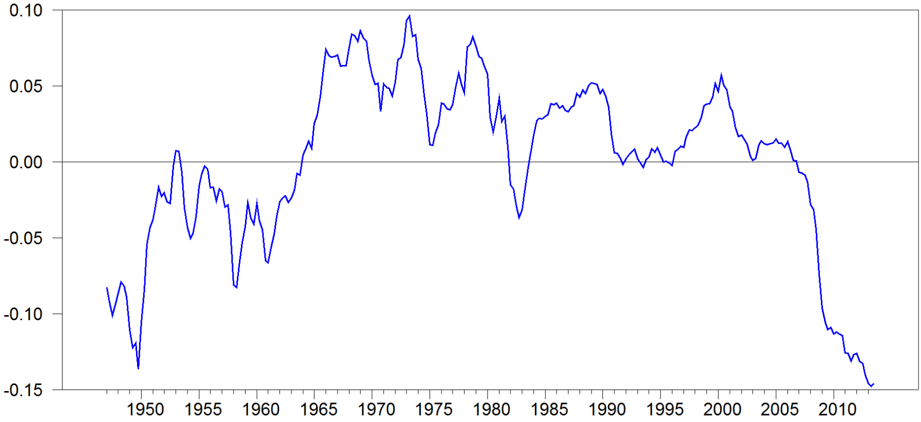
Trends and Cycles in US GDP: Cycles Are Pretty Small



Simplest Example: Log-Linear Trend



Cycles From a Log-Linear Trend Model



Potential Problems: A Stochastic Trend Model

- Drawing straight lines to detrend series can provide misleading results. For example, suppose the correct model is

$$y_t = g + y_{t-1} + \epsilon_t$$

- Growth has a constant component g and a random bit ϵ_t.
- Cycles are just the accumulation of all the random shocks that have affected Δy_t over time.
- There is no tendency to revert to the trend: Expected growth rate is always g no matter what has happened in the past.
- In this case Δy_t is stationary: First-differencing gets rid of the non-stationary stochastic trend component of the series.
- In this example, if we fitted a log-linear trend line through the series, there might appear to be a mean-reverting cyclical component but there is not.
- So detrending times series is not generally as simple as drawing a straight line.

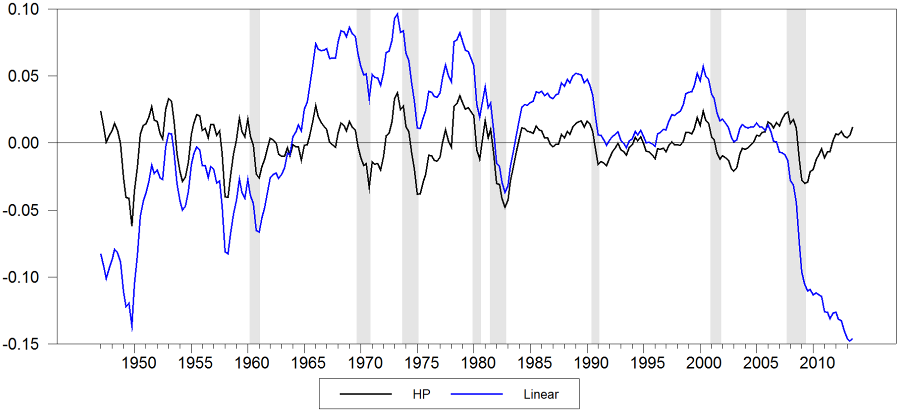
Variations in Trend Growth: The Hodrick-Prescott Filter

- A more realistic model should be one in which we accept that growth rate of the trend probably varies a bit over time leaving a cycle that moves up and down over time.
- Hodrick and Prescott (1981) suggested choosing the time-varying trend Y_t^* so as to minimize

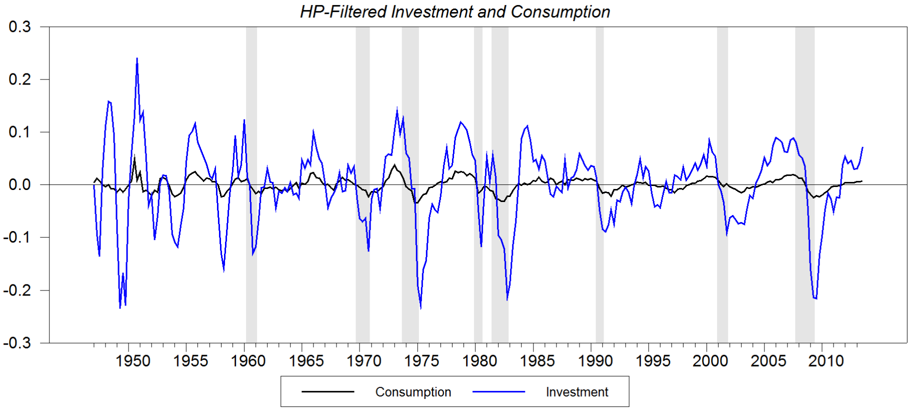
$$\sum_{t=1}^{N}\left[\left(Y_t - Y_t^*\right)^2 + \lambda\left(\Delta Y_t^* - \Delta Y_{t-1}^*\right)\right]$$

- This method tries to minimize the sum of squared deviations between output and its trend $\left(Y_t - Y_t^*\right)^2$ but also contains a term that emphasises minimizing the change in the trend growth rate $\left(\lambda\left(\Delta Y_t^* - \Delta Y_{t-1}^*\right)\right)$.
- How do we choose λ and thus weight the goodness-of-fit of the trend versus smoothness of the trend?
- $\lambda = 1600$ is the standard value used in business cycle detrending. We will discuss this choice in more detail in a few weeks.
- Many DSGE modellers apply a HP filter to their data and then analyse only the cyclical components.

HP-Filtered Cycles Correspond Well to NBER Recessions



Investment Cycles Are Bigger than Consumption Cycles



The AR(1) Model and Impulse Responses

- Cyclical components are positively autocorrelated (i.e. positively correlated with their own lagged values). and also exhibit random-looking fluctuations.
- One simple model that captures these features is the AR(1) model (Auto-Regressive of order 1):

$$y_t = \rho y_{t-1} + \epsilon_t$$

- Suppose an AR(1) series starts out at zero. Then there is a unit shock, $\epsilon_t = 1$ and then all shocks are zero afterwards.
- Period t, we have $y_t = 1$, period $t + 1$, we have $y_{t+1} = \rho$, period $t + n$, we have $y_{t+n} = \rho^n$ and so on.
- The shock fades away gradually. How fast depends on the size of ρ. The time path of y after this hypothetical shock is known as the **Impulse Response Function**.
- Can think of this as the path followed from t onwards when shocks are $(\epsilon_t + 1, \epsilon_{t+1}, \epsilon_{t+2}, ...)$ instead of $(\epsilon_t, \epsilon_{t+1}, \epsilon_{t+2}, ...)$, i.e. the incremental effect in all future periods of a unit shock today.
- IRF graphs are commonly used to illustrate dynamic properties of macro data.

Volatility: Shocks and Propagation Mechanisms

- Consider the AR(1) model

$$y_t = \rho y_{t-1} + \epsilon_t$$

- Suppose the variance of ϵ_t is σ_ϵ^2.
- The long run variance of y_t is the same as the long-run variance of y_{t-1} and (remembering that ϵ_t is independent of y_{t-1}) this is given by

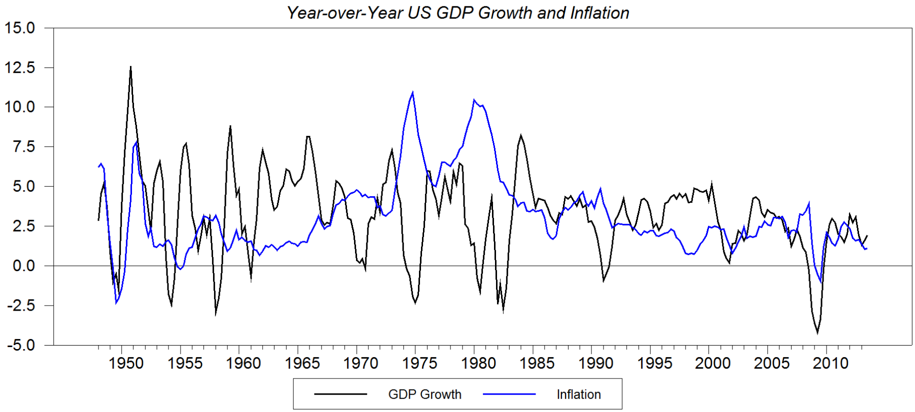
$$\sigma_y^2 = \rho^2 \sigma_y^2 + \sigma_\epsilon^2$$

- Simplifies to $\sigma_y^2 = \frac{\sigma_\epsilon^2}{1-\rho^2}$
- The variance of output depends positively on both shock variance σ_ϵ^2 and also on the persistence parameter ρ.
- So the volatility of the series is partly due to size of shocks but also due to the strength of the **propagation mechanism**.

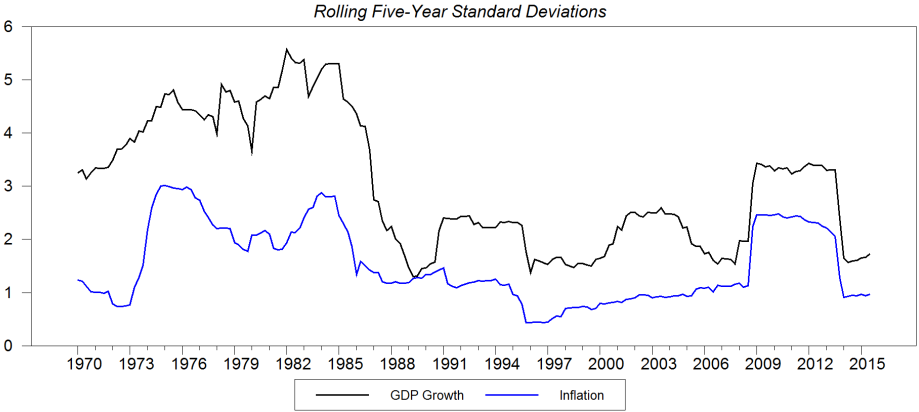
Example: The Great Moderation

- An interesting pattern: Output and inflation became substantially less volatile after the mid-1980s. This was widely dubbed "The Great Moderation"
- This pattern occurred in all the world's major economies.
- What was the explanation?
- Smaller shocks? (Smaller values of ϵ_t)
  1. Less random policy shocks?
  2. Smaller shocks from goods markets or financial markets?
  3. Smaller supply shocks?
- Weaker propagation mechanisms? (Smaller values of ρ)
  1. Did policy become more stabilizing?
  2. Did the economy become more stable, e.g. better inventory management, increased share of services?
  3. Some had thought that financial modernization had stabilized the economy. Less clear now!
- Does the 2008-2009 global recession and subsequent slow recovery spell the end for the Great Moderation?

Less Extreme Movements in Output Growth and Inflation



The Great Moderation: Substantial Reductions in Volatility



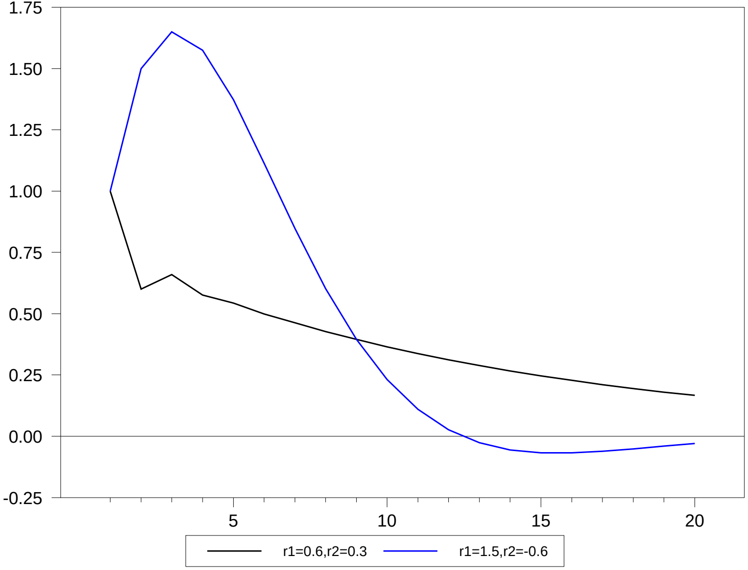
More Complex Dynamics: The AR(2) Model

- Not all impulse response functions just erode gradually of time as in the AR(1) model.
- Macroeconomic dynamics can often be far more complicated.
- Consider the AR(2) model:

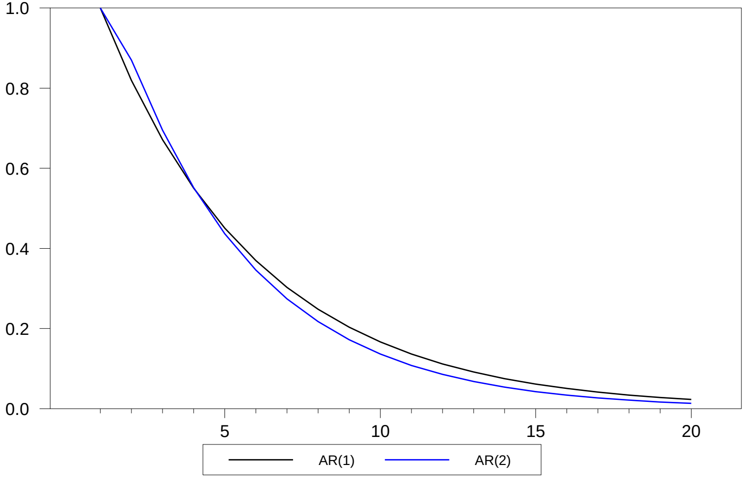
$$y_t = \alpha + \rho_1 y_{t-1} + \rho_2 y_{t-2} + \epsilon_t$$

- This type of model can generate various types of impulse response functions such as oscillating or hump-shaped responses.
- AR(3) and higher models can generate even more complex responses.
- Lesson: The dynamic properties of your model will depend upon how many lags you allow.
- Practitioners constructing empirical models often run battery of lag selection tests to decide upon the appropriate lag length.

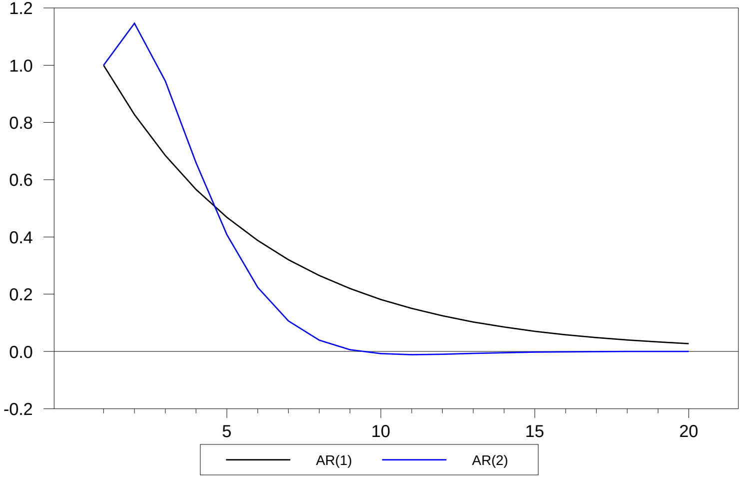
Two Examples of AR(2) Impulse Responses



Consumption Dynamics Seem to be AR(1)



Output AR(2) Model Shows A Small Humped-Shape IRF



Lag Operators and Lag Polynomials

- The lag operator is a useful piece of terminology that is sometimes used in time series modelling. The idea is to use an "operator" to move the series back in time, e.g. $Ly_t = y_{t-1}$ and $L^2 y_t = y_{t-2}$.
- Sometimes economists will specify a model that has a bunch of lags using a polynominal in lag operators e.g. the model

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \epsilon_t$$

can be written as

$$y_t = A(L) y_t + \epsilon_t$$

where

$$A(L) = a_1 L + a_2 L^2$$

- Alternatively, you could write

$$B(L) y_t = \epsilon_t$$

where $B(L) = 1 - a_1 L - a_2 L^2$.

Vector Autoregressions

- AR models are a very useful tool for understanding the dynamics of individual variables.
- But they ignore the *interrelationships* between variables.
- Vector Autoregressions (VARs) model the dynamics of n different variables, allowing each variable to depend on lagged values of all of the variables.
- Can examine impulse responses of all n variables to all n shocks.
- Simplest example is two variables and one lag:

$$
\begin{aligned}
y_{1t} &= a_{11} y_{1,t-1} + a_{12} y_{2,t-1} + e_{1t} \\
y_{2t} &= a_{21} y_{1,t-1} + a_{22} y_{2,t-1} + e_{2t}
\end{aligned}
$$

- Invented by Chris Sims (1980). Now used as a central tool in applied macroeconomics.

What Are These Shocks?

Macroeconomists now spend a lot of time examining the shocks in VAR models and their effects. But what are the shocks? Lots of possibilities:

1. Policy changes not due to the systematic component of policy captured by the VAR equation.
2. Changes in preferences, such as attitudes to consumption versus saving or work versus leisure.
3. Technology shocks: Random increases or decreases in the efficiency with which firms produce goods and services.
4. Shocks to various frictions: Increases or decreases in the efficiency with which various markets operate, such as the labour market, goods markets, or financial markets.

Time Series as a Framework for Empirical Macro

- The time series perspective—cycles being determined by various random shocks which are propagated throughout the economy over time—is central to how modern macroeconomists now view economic fluctuations.
- VARs are a very common framework for modelling macroeconomic dynamics and the effects of shocks.
- But while VARs can describe how things work, they cannot explain *why* things work that way.
- To have real confidence in a description of how the economy works, we ideally want to know how people in the economy behave and why they they behave that way.
- That's where economic theory comes in.
- DSGE models aim to have the dynamic structure of VARs (shocks and propagation mechanisms, IRFs) but are derived from economic theory in which all agents are rational and optimizing.