Lecture 10

Business Cycle Measurement

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Universidad de Costa Rica
EC3201 - Teoría Macroeconómica 2

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Introduction

Introduction

- Before we go on to build models of aggregate economic activity that can explain why business cycles exist and what, if anything, should be done about them, we must understand the key features that we observe in economic data that define a business cycle.
- In this lecture, we examine the regularities in the relationships among aggregate economic variables as they fluctuate over time.

Deviations from trend versus cycles

- Typically, we think of a time series as the sum of four components:

$$\text{series} = \text{trend} + \text{cycle} + \text{seasonal} + \text{irregular}$$

- After removing the trend and the seasonal components, we are left with the business cycle and the irregular component. We refer to this as deviations from trend.
- For simplicity, in this lecture we neglect the irregular component and refer to deviations from trend as "cycles".

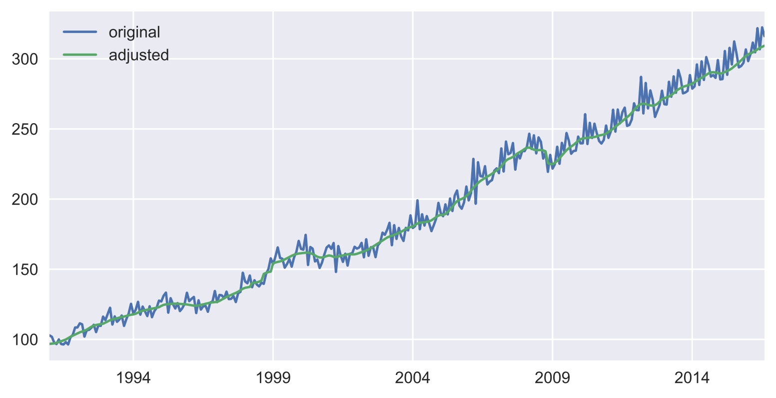
Seasonally adjusted data

- The data we are studying in this lecture, and most data that is used in macro research and in formulating macro policy, is seasonally adjusted.
- That is, in most macro time series, there exists a predictable seasonal component.
- There are various methods for seasonally adjusting data, but the basic idea is to observe historical seasonal patterns and then take out the extra amount that we tend to see on average during a particular season.

Example 1:

Seasonally adjusted IMAE

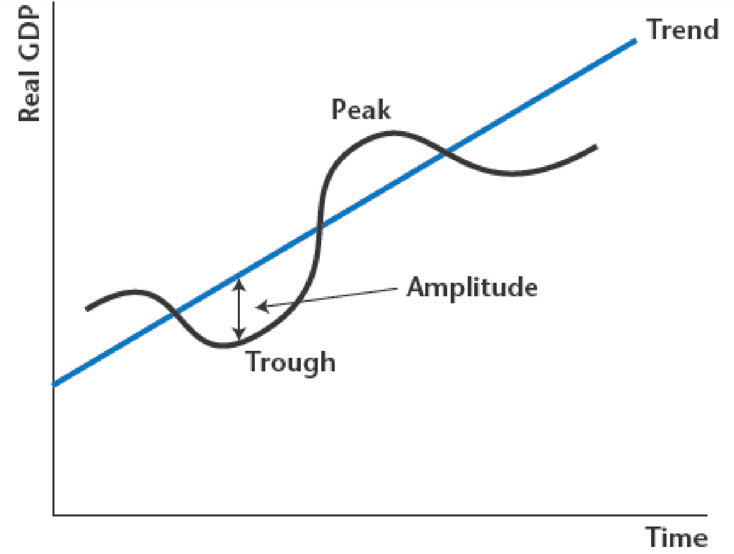
Seasonal adjustment tends to smooth a time series with a seasonal component.



Trend versus cycle

- The primary defining feature of business cycles is that they are fluctuations about trend in real GDP.
- We represent the trend in real GDP with a smooth curve that closely fits actual real GDP, with the trend representing that part of real GDP that can be explained by long-run growth factors.
- What is left over, the deviations from trend, we take to represent business cycle activity.

Idealized business cycle



The need for stationary series

- Many modeling techniques assume that variables are stationary:
    - ARMA
    - DSGE
- To work with non-stationary series, we usually transform (filter) the original data to obtain a stationary series.
- In this lecture, we will analyze the properties of one such transformation: the HP filter.

Separating trend from cycle

- The techniques used to separate trend from cycle are called filters.
- There are plenty of them! For example:

HP	Hodrick-Prescott
FOD	First-Order Differencing
BN	Beveridge-Nelson
UC	Unobservable Components
LT	Linear trend
SEGM	Segmented trend
FREQ	Frequency Domain Masking
MLT	Commong deterministic trend
MINDEX	One-dimensional index
COIN	Cointegration

The Hodrick-Prescott filter

Disaggregation of a time series

- We have a sample of T observations on random variable Y_t:

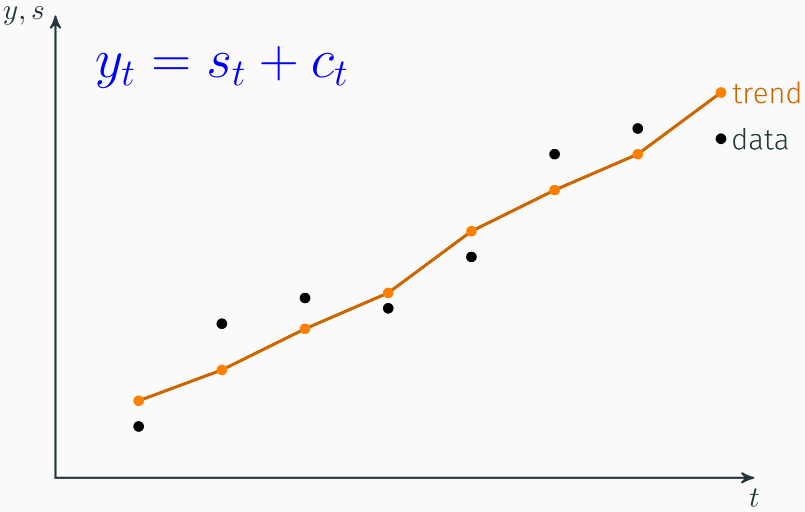
$$\{y_1, y_2, \ldots, y_T\}$$

- Y_t has two components: growth (trend) s_t and cycle c_t.

$$y_t = s_t + c_t$$

- We assume that the trend is a *smooth* curve, although not necessarily a straight line.

Data trend



Conflicting objectives

- To "extract" the trend, we look for a new series

$$\{s_1, s_2, \ldots, s_T\},$$

  balancing two conflicting objectives:
    1. the fit to the original series
    2. the resulting trend must be smooth
- The relative importance of these two factors is weighed with a parameter λ.

Formally, the trend is defined by:

$$s_i^{HP} = \underset{s_1,\dots,s_T}{\operatorname{argmin}} \left\{ \sum_{t=1}^{T} (y_t - s_t)^2 + \lambda \sum_{t=2}^{T-1} \left[(s_{t+1} - s_t) - (s_t - s_{t-1}) \right]^2 \right\}$$

$$= \underset{s_1,\dots,s_T}{\operatorname{argmin}} \left\{ \sum_{t=1}^{T} (y_t - s_t)^2 + \lambda \sum_{t=2}^{T-1} (s_{t+1} - 2s_t + s_{t-1})^2 \right\}$$

A little trick from linear algebra

Let's define these matrices

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_T \end{bmatrix} \qquad S = \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_T \end{bmatrix}$$

$$A_{T-2 \times T} = \begin{bmatrix} 1 & -2 & 1 & 0 & \dots & 0 & 0 & 0 & 0 \\ 0 & 1 & -2 & 1 & \dots & 0 & 0 & 0 & 0 \\ & & & & \ddots & & & & \\ 0 & 0 & 0 & 0 & \dots & 0 & 1 & -2 & 1 \end{bmatrix}$$

Rewriting the optimization problem

$$s_i^{HP} = \underset{s_1,\dots,s_T}{\operatorname{argmin}} \left\{ \sum_{t=1}^{T} (y_t - s_t)^2 + \lambda \sum_{t=2}^{T-1} (s_{t+1} - 2s_t + s_{t-1})^2 \right\}$$

$$= \underset{S}{\operatorname{argmin}} \left\{ (Y - S)'(Y - S) + \lambda (AS)'(AS) \right\}$$

$$= \underset{S}{\operatorname{argmin}} \left\{ Y'Y - 2Y'S + S'(I + \lambda A'A)S \right\}$$

Solving the problem

- Taking the FOC

$$S^{HP} = \underset{S}{\operatorname{argmin}} \left\{ Y'Y - 2Y'S + S'(I + \lambda A'A)S \right\}$$

$$\Rightarrow -2Y + 2\left(I + \lambda A'A\right)S = 0$$

- Then, the HP filter is

$$S^{HP} = \left(I + \lambda A'A\right)^{-1} Y \qquad \text{(trend)}$$

$$C^{HP} \equiv Y - S^{HP} = \left[I - \left(I + \lambda A'A\right)^{-1}\right] Y \qquad \text{(cycle)}$$

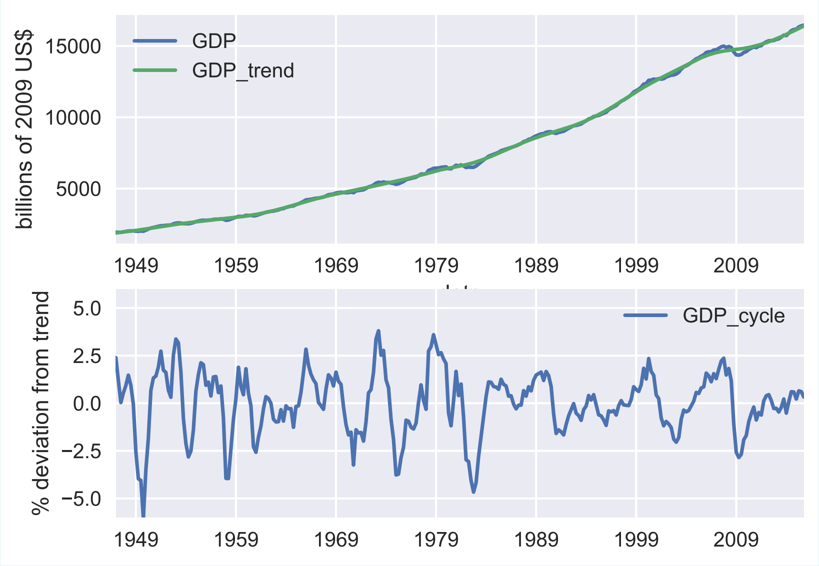
Choosing λ

- The result of filtering is very sensitive to the choice of λ
- As a rule of thumb, λ is chosen depending on frequency of data.
    - Annual $\Rightarrow 100$
    - Quarterly $\Rightarrow 1600$
    - Monthly $\Rightarrow 14400$

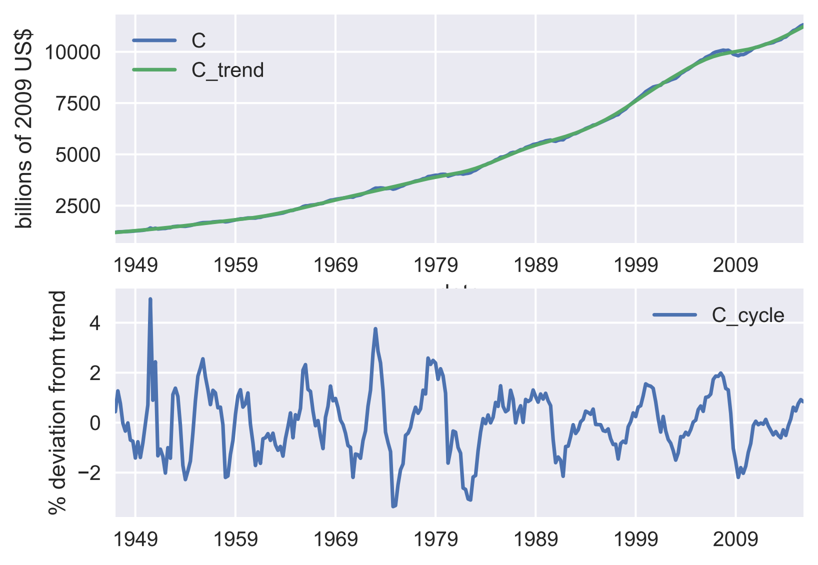
Example 2:

Filtered series when $\lambda = 1600$

USA real GDP, 2009 dollars



USA real consumption, 2009 dollars

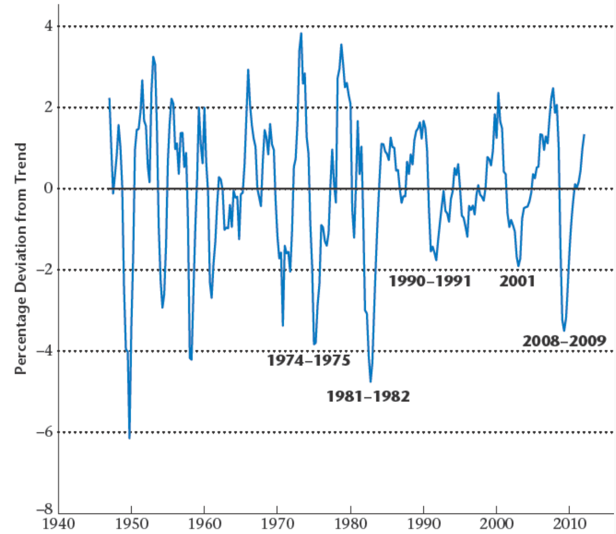


Regularities in GDP fluctuations

Forecasting business cycles

- Business cycles are quite irregular: the changes in real GDP are unpredictable; it's very difficult to predict the timing of a business cycle upturn or downturn.
- Business cycles are quite regular, however, in terms of comovements: macroeconomic variables move together in highly predictable ways.

Real GDP cycles from 1947 to 2012



Persistent but irregular

- Real GDP cycles are persistent:
  - when real GDP is above trend, it tends to stay above trend
  - when it is below trend, it tends to stay below trend.
- Real GDP cycles are quite irregular.
  1. The time series of real GDP cycles is quite choppy.
  2. There is no regularity in the amplitude of fluctuations in real GDP about trend. Some of the peaks and troughs represent large deviations from trend, whereas other peaks and troughs represent small deviations from trend.
  3. There is no regularity in the frequency of fluctuations in real GDP about trend. The length of time between peaks and troughs in real GDP varies considerably.

Forecasting implications

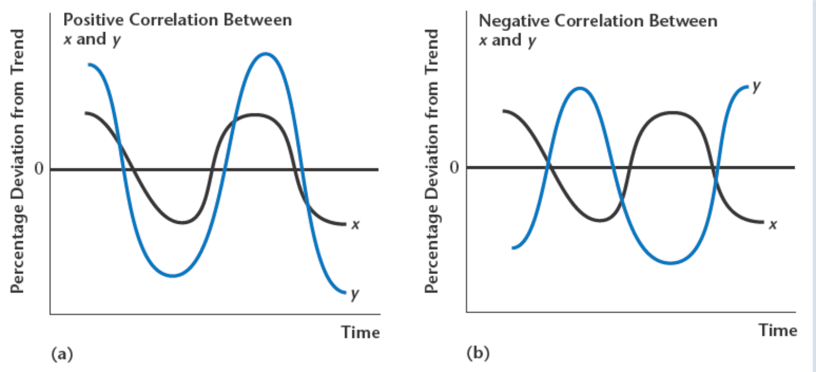
- Because real GDP cycles are persistent, short-term forecasting is relatively easy.
- But because they are irregular longer-term forecasting is difficult:
    - the choppiness of fluctuations in real GDP makes these fluctuations hard to predict
    - the lack of regularity in the amplitude and frequency of fluctuations implies that it is difficult to predict the severity and length of recessions and booms.

Comovement

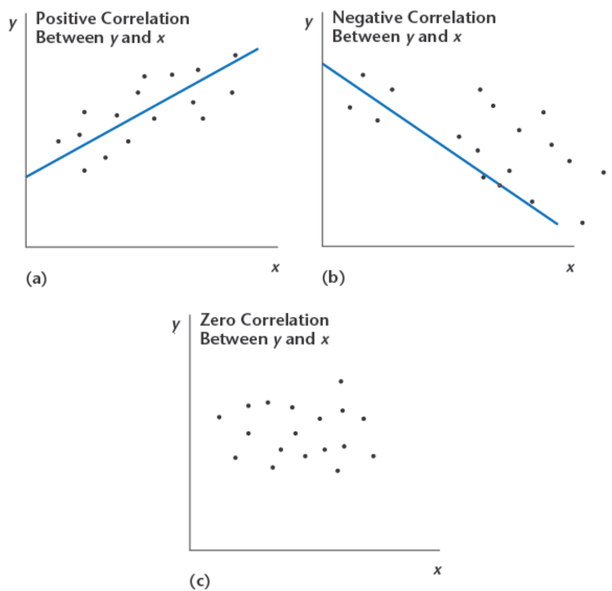
Comovement: looking for (contemporary) correlation

- While real GDP fluctuations are irregular, macro variables fluctuate together in strongly regular patterns.
- We refer to these patterns in fluctuations as comovement.
- Macro variables are measured as time series; for example, real GDP is measured in a series of quarterly observations over time.
- When we examine comovements in macro time series, typically we look at these time series two at a time.
- A good starting point is to plot the data.

Plotting in time domain



Plotting a scatter plot



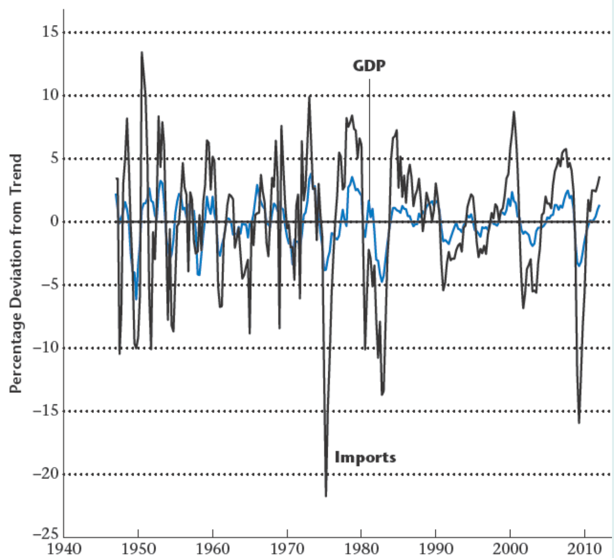
Comovement with real GDP

- Primary interest: how an individual macro variable comoves with real GDP.
- An economic variable is said to be:
    - procyclical if its cycles are positively correlated with the real GDP cycles,
    - countercyclical if its cycles are negatively correlated with the real GDP cycles,
    - acyclical if it is neither procyclical nor countercyclical

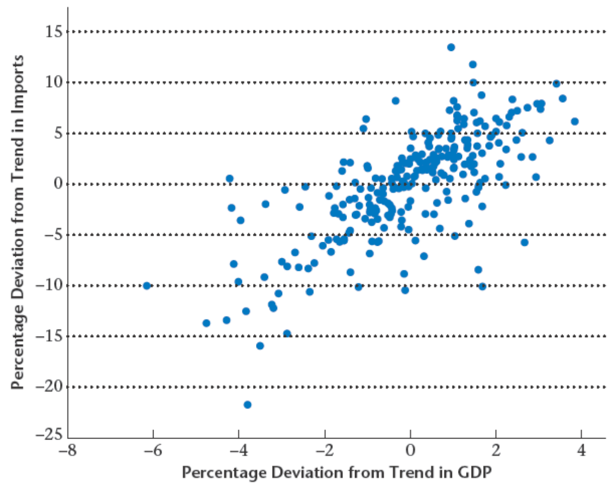
Example 3:

Imports comovement

Imports and GDP are clearly positively correlated, so imports are procyclical.



We again observe the positive correlation between imports and GDP, as a positively sloped straight line would best fit the scatter plot. Again, imports are procyclical.

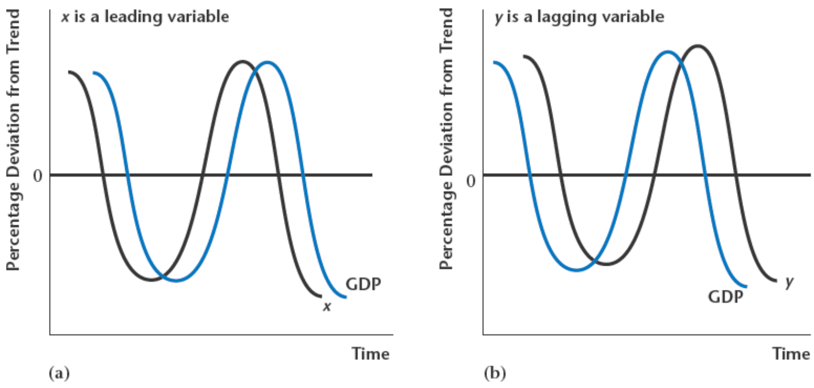


Leading and lagging variables

An important element of comovement is the leading and lagging relationships that exist in macroeconomic data.

- A leading variable is a macro variable that tends to aid in predicting the future path of real GDP
- If real GDP helps to predict the future path of a particular macroeconomic variable, then that variable is said to be a lagging variable.
- A coincident variable is one which neither leads nor lags real GDP.

Idealized cycles in real GDP and two variables



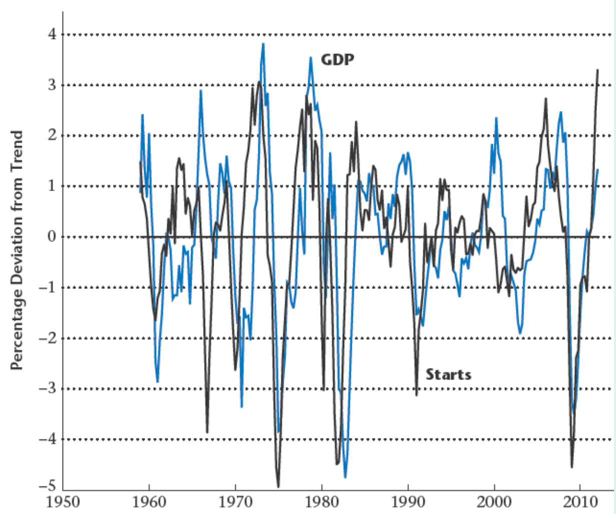
Some leading indicators

- A knowledge of the regularities in leading relationships among economic variables can be very useful in macro forecasting and policymaking.
- Typically, macro variables that efficiently summarize available information about future macro activity are potentially useful in predicting the future path of real GDP.
- For example,
    - the stock market
    - the number of housing starts

Example 4:

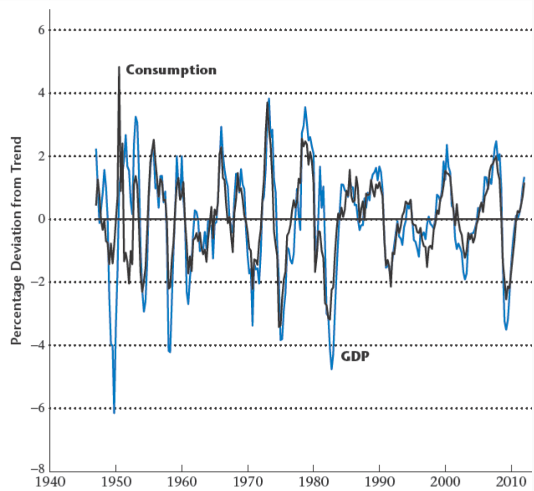
Housing starts as a leading indicator

Percentage deviations in housing starts are divided by 10 so we can see the comovement better. Housing starts clearly lead real GDP (note the timing of turning points in particular).



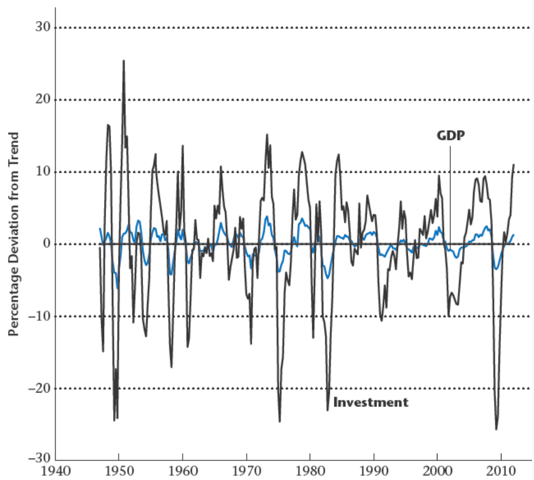
Consumption

It's procyclical, coincident, and less variable than GDP.



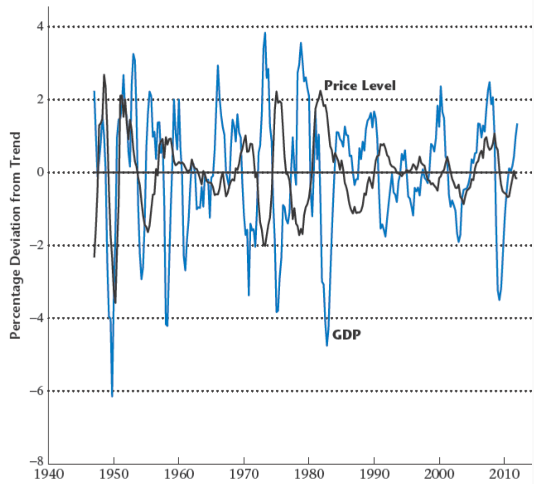
Investment

It’s procyclical, coincident, and more variable than GDP.



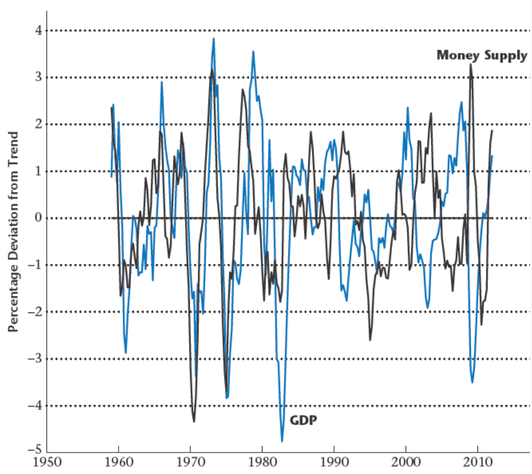
Price level

It's countercyclical, coincident, and less variable than real GDP



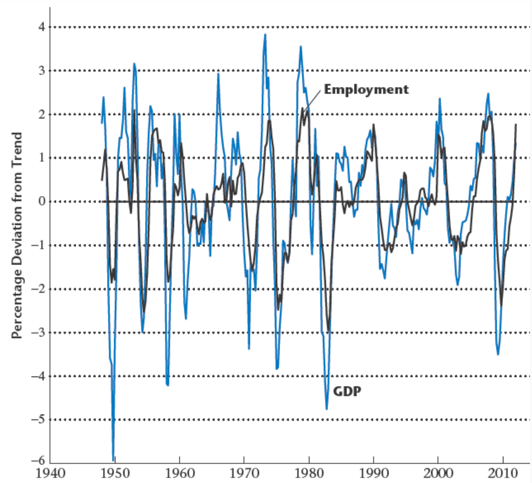
Money supply

It's procyclical and leading variable, and it is less variable than real GDP.



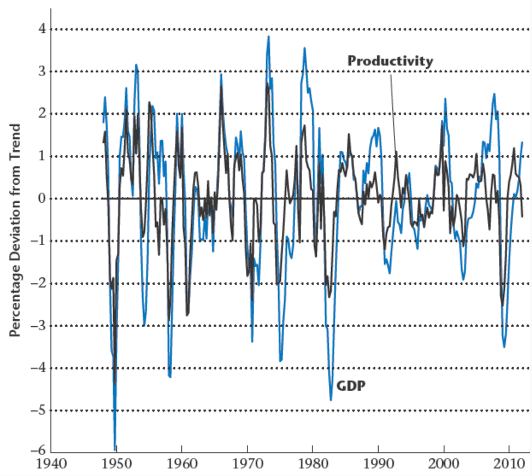
Employment

It's procyclical, it is a lagging variable, and it is less variable than real GDP.



Labor productivity

Average labor productivity is procyclical and coincident, and it is less variable than is real GDP.



Summary of results

Correlation coefficients and variability of cycles

	Correlation Coefficient	Standard Deviation*
Consumption	0.78	76.6
Investment	0.85	489.9
Price Level	-0.19	56.3
Money Supply	0.20	81.0
Employment	0.80	63.0
Avg. Labor Productivity	0.80	62.4

* % of standard deviation of GDP

Summary of business cycle facts

	Cyclicality	Lead/Lag	Variation Relative to GDP
Consumption	Procyclical	Coincident	Smaller
Investment	Procyclical	Coincident	Larger
Price Level	Countercyclical	Coincident	Smaller
Money Supply	Procyclical	Leading	Smaller
Employment	Procyclical	Lagging	Smaller
Real Wage	Procyclical	?	?
Avg. Labor Productivity	Procyclical	Coincident	Smaller

Some warnings

Canova main results

1. The practice of solely employing the HP1600 filter in compiling business cycle statistics is problematic.
2. The idea that there is a single set of facts which is more or less robust to the exact definition of business cycle is misleading.
3. The empirical characterization of the B.C. obtained with multivariate detrending methods is different from the one obtained with univariate procedures.
4. The practice of building theoretical models whose numerical versions quantitatively match one set of regularities obtained with a particular concept of cyclical fluctuation warrants a careful reconsideration.

U.S. Business Cycle: standard deviations

Filter	GNP	Consumption	Investment	Hours	Real wage	Productivity	Capital
HP1600	1.76	0.49	2.82	1.06	0.70	0.49	0.61
HP4	0.55	0.48	2.70	0.89	0.65	0.69	0.14
FOD	1.03	0.51	2.82	0.91	0.98	0.67	0.63
BN	0.43	0.75	3.80	1.64	2.18	1.14	2.64
UC	0.38	0.34	6.72	4.14	2.24	4.09	1.22
LT	4.03	0.69	2.16	0.69	1.71	1.00	1.56
SEGM	2.65	0.52	3.09	1.01	1.10	0.54	0.97
FREQ1	1.78	0.46	3.10	1.20	1.07	0.66	1.41
FREQ2	1.14	0.44	3.00	1.16	1.11	0.69	1.26
MLT	6.01	0.67	2.36	0.46	1.21	1.00	1.05
MINDEX	3.47	0.98	2.65	1.14	1.27	0.72	1.85
COIN	4.15	0.71	3.96	0.75	1.68	1.09	1.30

(absolute for GNP, all others relative to GNP)

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