Time series data and macroeconomics

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Macroeconomics as an applied subject

Beyond establishing general principles, macroeconomists aim to produce models that could be useful. For instance for policy analysis or forecasting. In general empirical macroeconomists do four things:

1. Describe and summarize macroeconomic data (data description)
2. Make macroeconomic forecasts (forecasting)
3. Quantify what we know and don't know about the true structure of the macro economy (structural inference)
4. Advise on macroeconomic policy (policy analysis)

Time series data

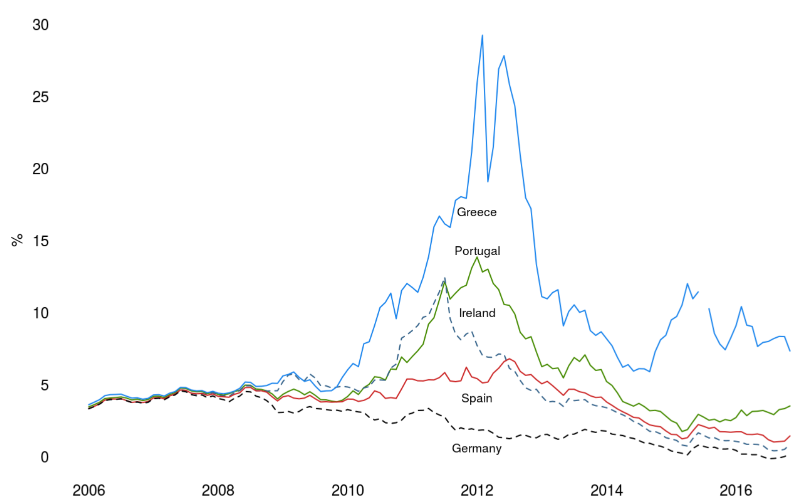

Figure 1: 10-year interest rates on government bonds. Data source: Eurostat

Empirical macroeconomics relies on data. Similar to other scientific disciplines, time series data is often used for analysis. Time-series data can provide insights over trends or developments over time as illustrated in figure 1, illustrating the effect of the sovereign debt crisis in the Eurozone and its effect on, in this case, bond yields. This is a simple descriptive example, often the data is analysed using sophisticated statistical and mathematical models. Time series data are repeated observations over time for a certain indicator, e.g. GDP per capita, inflation, unemployment rate, etc., and can provide interesting information on trends and cycles. In this respect, when analysing time series data it is very important to be aware of the short and long term trends that the data exhibits.

As an example, let's look at some non-economic data that receives a lot of attention: the global average temperature (figure 2). The figure illustrates that the data exhibits both short and long term fluctuations. In this case temperature anomalies are used to capture short term fluctuations from the long term trend. Here we see that from year to year there are swings up and down, but unmistakably there is clear upward trend over time.

An anomaly is often calculated by subtracting the long-term mean and dividing by the standard deviation: $\frac{X_t - \overline{X}}{\sigma_X}$

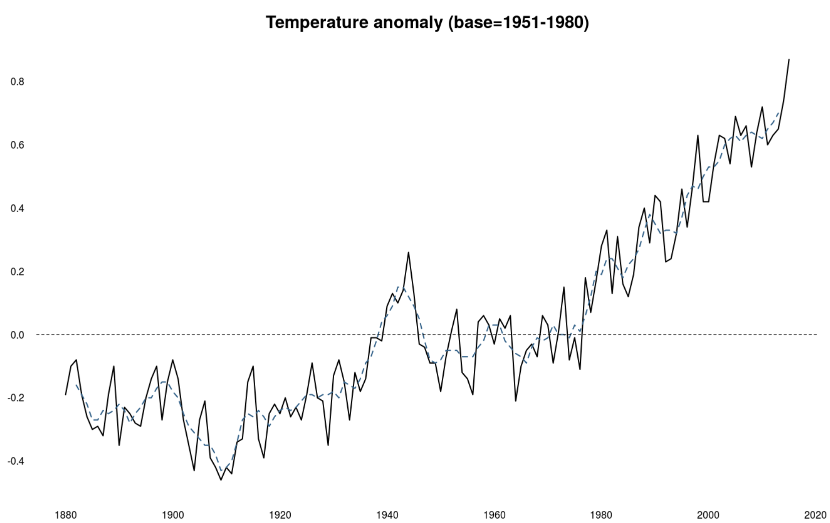

Figure 2: Global average temperature anomaly. Base period is 1951-1989. Data source: NASA.

In economic data series we are also often interested in the short term fluctuations such as business cycles. Therefore to analyse the data it needs to be broken down into:

Short term is relative here. In general the business cycle is the movement around the long term trend.

- A non-stationary long-run trend,
- A stationary cyclical component

Let's continue by examining some economic data: GDP per capita in the U.K. since 1700 as shown in figure 3.

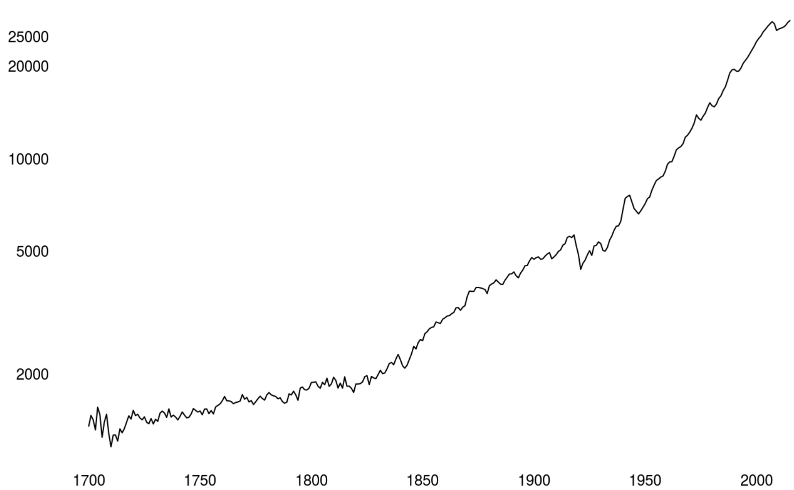

Figure 3: Trends and cycles in U.K. GDP per capita. The data is plotted using a log-scale for the y-axis. This is to account for the scale differences over time. Data source: Bank of England

Detrending data

ONE OF THE SIMPLEST WAY TO DETREND TIME SERIES DATA IS BY USING A LOG-LINEAR TREND MODEL

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

$\alpha + gt$ is the trend component; ϵ is the stationary cyclical component, with zero-mean.

Figure 4 shows the GDP per capita data for the U.K. since 1946, and plotted along the observed data is a line showing the fit of the log-linear model. For this sub-sample of the data, the figure illustrates the same upward trend over time compared to figure 3. The lower panel shows the cycles from the trend, i.e. the observed data subtracted from the trend line. These cycles are equivalent to the growth rate. Noticeable is the strong recession in 2008-2009.

Using the natural log we can first-difference the model to get an equivalent of the growth rate Δy_t which comprises of constant trend growth g and the change in cyclical component $\Delta\epsilon_t$.

Note that $\Delta y_t = \frac{y_t - y_{t-1}}{y_{t-1}}$, taking log is approximately $\Delta y_t = log(y_t) - log(y_{t-1})$.

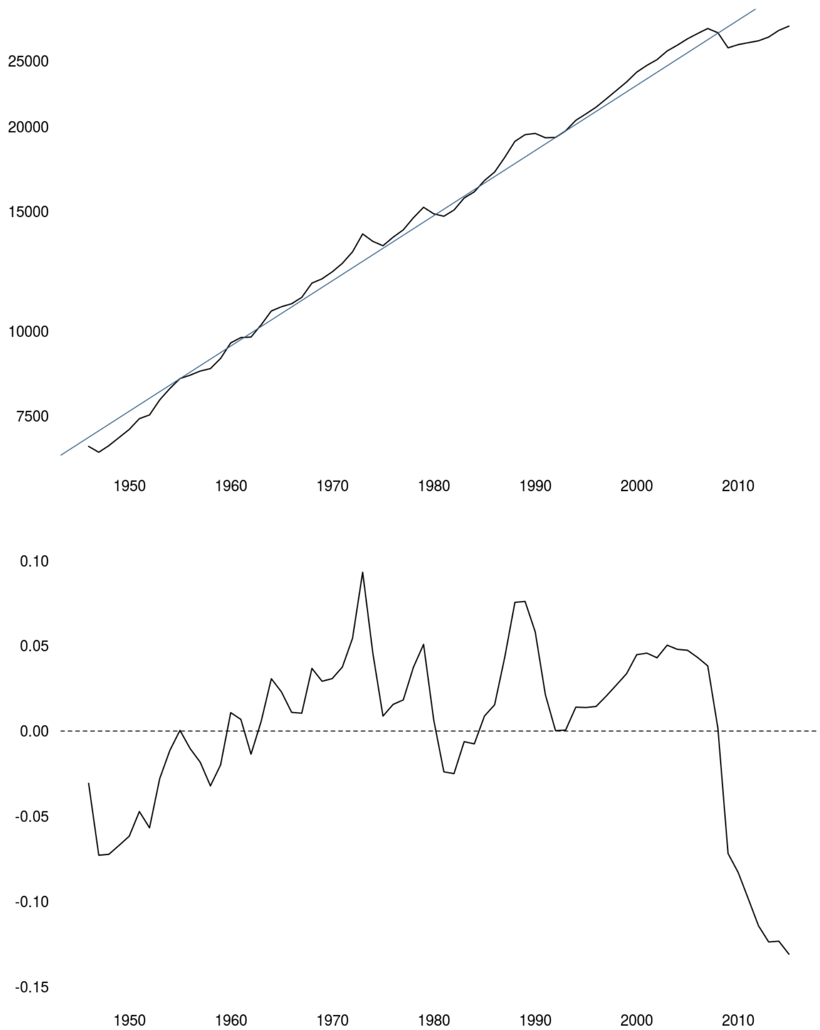

Figure 4: GDP per capita in the U.K. since 1946. Raw data (upper panel) and cycles from the data fitted with a log-linear model (lower panel) Data source: Bank of Engeland

Caveats of using a straight line

RELYING ON A STRAIGHT LINE TO DETREND DATA CAN PROVIDE MISLEADING RESULTS. Suppose that the correct model is

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

Note that cycles are the accumulation of all the random shocks that have affected Δy_t over time. Growth in the data has a constant component g and random component ϵ_t. This is a random walk with drift.

The expected growth rate will be g, irrespective of what happened in the past. In this case Δy_t is stationary; so taking the first-difference will get rid of the non-stationary stochastic trend component (y_{t-1}) in the data. If we fit a log-linear line to the data, there might appear to be a mean-reverting cyclical component, which is not there.

i.e. there is no tendency to revert to the trend.

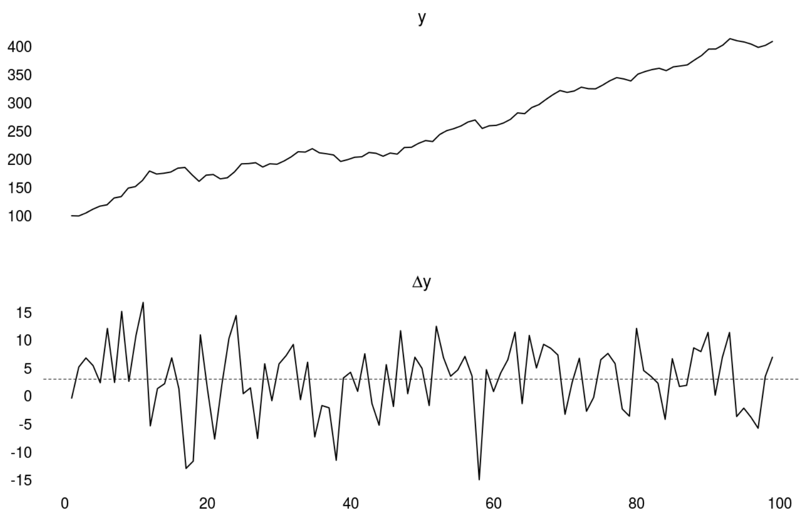

Figure 5: Example of a caveat with regard to linear detrending

Hodrick-Prescott filter

MORE REALISTICALLY WE ACCEPT THAT THE GROWTH RATE VARIES OVER TIME. A popular method for detrending data is the Hodrick-Prescott filter which uses a time-varying trend Y_t^* to minimize

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

This method minimizes the sum of squared deviations between the output and its trend: $(Y_t - Y_t^*)^2$, but also contains a term that emphasizes minimizing the change in the trend growth rate: $\lambda(\Delta Y_t^* - \Delta Y_{t-1}^*)$ Figure 6 shows GDP per capita data for the U.K. using the HP-filter.

$\lambda = 1600$ is the standard value used in business cycle detrending (this based on the Kalman filter). Often the HP filter is used and only the cyclical components are analyzed.

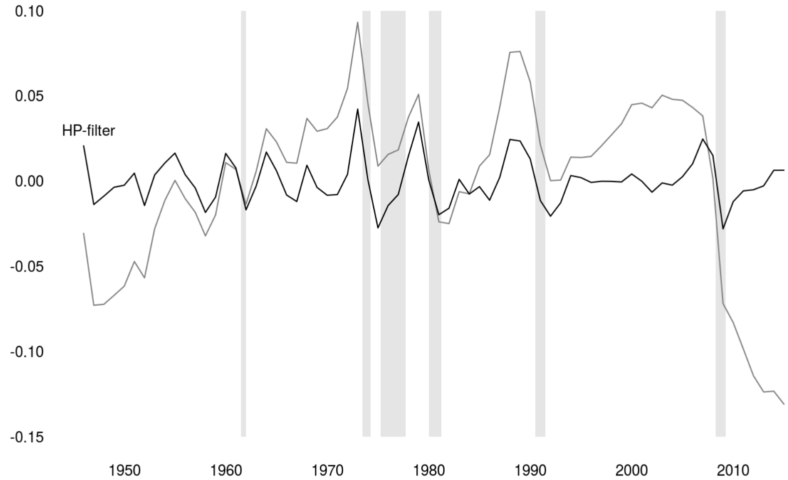

Figure 6: GDP per capita data for the U.K. detrended using a HP-filter. The grey shaded areas indicate the recessions and the light-grey line indicates cycles from the log-linear model. Data source: Bank of England.

Interestingly detrending U.S. GDP per capita data with a HP-filter seems to provide a better fit with recessions as illustrated by the figure 7.

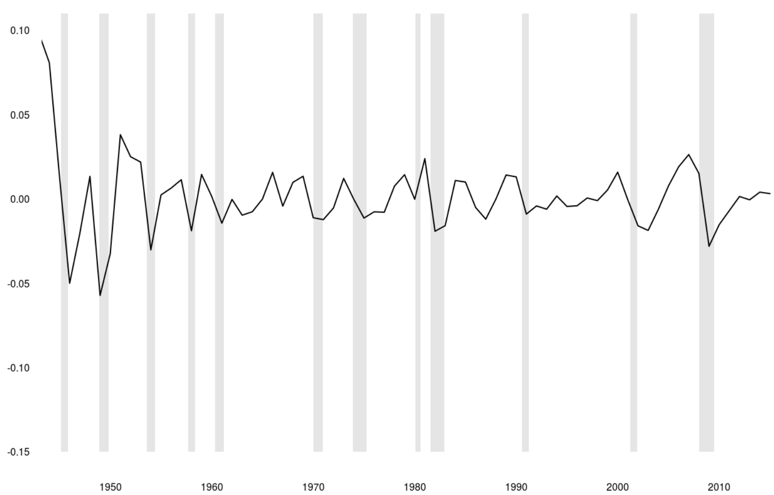

Figure 7: GDP per capita data for the U.S.A. detrended using a HP-filter. The grey shaded areas indicate the recessions. Data source: Federal Reserve

Using the HP-filter we can analyse the difference of different components of GDP such as consumption and investment (figure 8). The figure illustrates that consumption cycles tend to be much smaller than investment cycles.

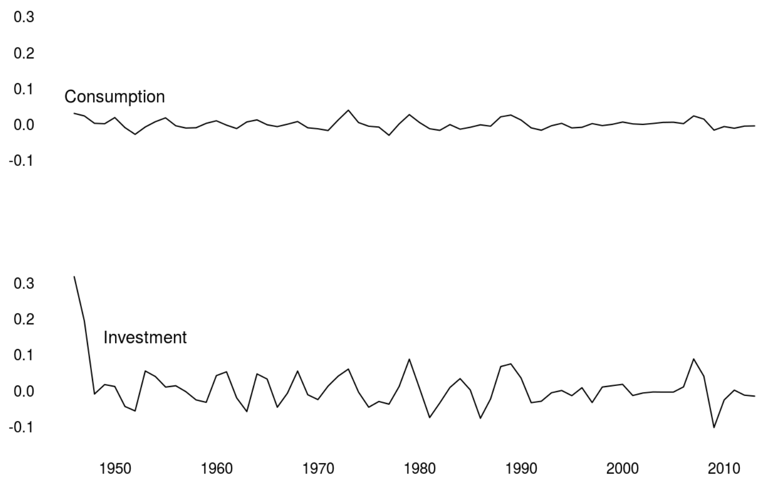

Figure 8: Detrended data for consumption and investment in the U.K. Note the large value in investments in the beginning of the time series in 1946, just after the Second World War. Data source: Bank of England.

AR(1) model

CYCLICAL COMPONENTS ARE POSITIVELY AUTOCORRELATED AND ALSO EXHIBIT RANDOM-LOOKING FLUCTUATIONS. A simple way to capture these features is the $AR(1)$ model or Auto-Regressive model of order 1

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

ρ determines the speed at which a shock in ϵ_t fades away. The time path of y after this shock is the Impulse Response Function (IRF).

Can think of this as the path followed from t onward 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.

Let's consider volatility which will be determined by the size of the shock but also by the strength of the propagation mechanism. ϵ_t has variance σ^2_ϵ. The long-run variance of y_t is the same as the long-run variance of y_{t-1}, which is given by:

$$\sigma^2_y = \rho^2 \sigma^2_y + \sigma^2_\epsilon$$

$$\sigma^2_y = \frac{\sigma^2_\epsilon}{1-\rho^2}$$

The variance of output (y_t) depends positively on both shock variance σ^2_ϵ and the persistence of parameter ρ.

Suppose an AR(1) series starts at 0 and there is a shock $\epsilon_t = 1$ followed by 0 shocks for $t+1$. For period t, $y_t = 1$, period $t+1$, $y_{t+1} = \rho$, period $t+n$, $y_{t+n} = \rho^n$.

Note that ϵ_t is independent of y_{t-1}

Example: The Great Moderation

AN INTERESTING PATTERN THAT EMERGED IN ALL THE WORLD'S MAJOR ECONOMIES SINCE THE MID-1980S WAS THAT OUTPUT

AND INFLATION BECAME SUBSTANTIALLY LESS VOLATILE. This has widely been dubbed as The Great Moderation. Figure 10 shows this pattern for the U.K. where fluctuations in GDP growth and inflation have become less extreme and there have been substantial reductions in volatility.

This effect could be due to

1. Smaller shocks (lower values for ϵ_t)
   - Less random policy shocks
   - Smaller shocks from goods and/or financial markets
   - Smaller supply shocks
2. Weaker propagation mechanisms (lower values for ρ)
   - Policy became more stabilizing
   - More stable economy
   - Stabilisation of economy due to financial modernisation

Although the reasons behind the Great Moderation are still discussed, one thing that is clear is that is is unclear whether it will continue after the 2008-2009 Great Recession.

The effects of the Great Moderation are best illustrated by U.S. data as in figure 9.

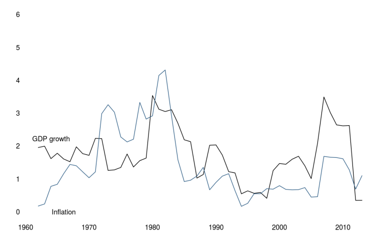

Figure 9: Volatility, measured 5-year moving average standard deviation, in U.S. economic growth and inflation. Data source: U.S. Treasury.

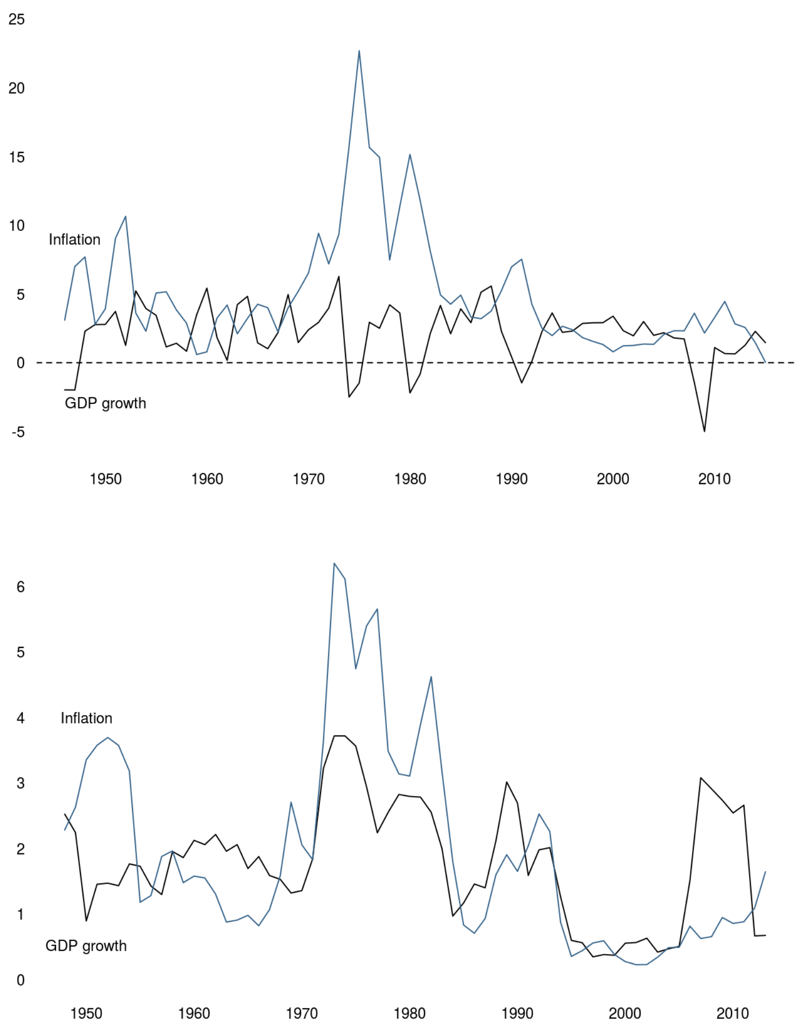

Figure 10: Year-over-year U.K. GDP growth and inflation (upper panel) and volatility, measured 5-year moving average standard deviation, in U.K. economic growth and inflation. Data source: Bank of England

AR(p) model

NOT ALL IRFS ERODE GRADUALLY OF TIME AS IN THE $AR(1)$ MODEL. Macroeconomic dynamics are often more complicated. Consider $AR(2)$ model

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

Based on the values of ρ_1 and ρ_2, the IRF can take on various forms such as oscillating or hump-shaped. More complex responses can be generated by $AR(3)$ models. The dynamic properties of the model will depend on the number of lags that are included. Figure gives the IRFs for two $AR(2)$ models, illustrating the different shapes the function can take.

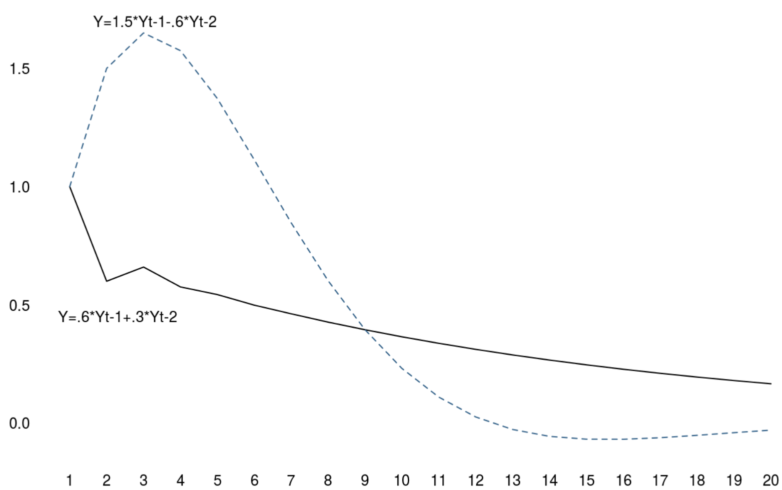

Figure 11: Example of the Impulse Response Function of two different $AR(2)$ models.

Example: Commodity prices

Preceding the 2008-2009 Great Recession was the 2007-2008 food price crisis which saw a large increase in a number of food prices. Let's examine the price dynamics for one crop in particular, rice, which is one of the main staple foods in the world. Figure 12 plots the nominal prices and illustrates that over time there has been increase, with most notable the peak in 2008.

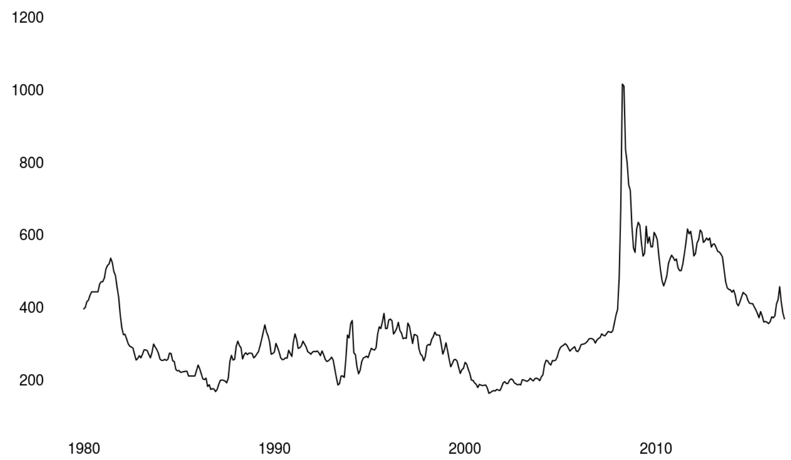

Figure 12: Nominal prices for rice. Data source: IMF

When analysing commodity prices it is important to account for income however, so we deflate the prices using the U.S. Producer Price Index (PPI). The data is deflated setting 2010 as base year (figure 14). Examining the development in real prices the data shows that the sharp increase in 2007-2008, for predominantly the staple foods, was not very remarkable in historic terms, at least for rice.

See lecture slides for decomposition of rice prices.

We proceed by looking at the volatility of the prices. As already

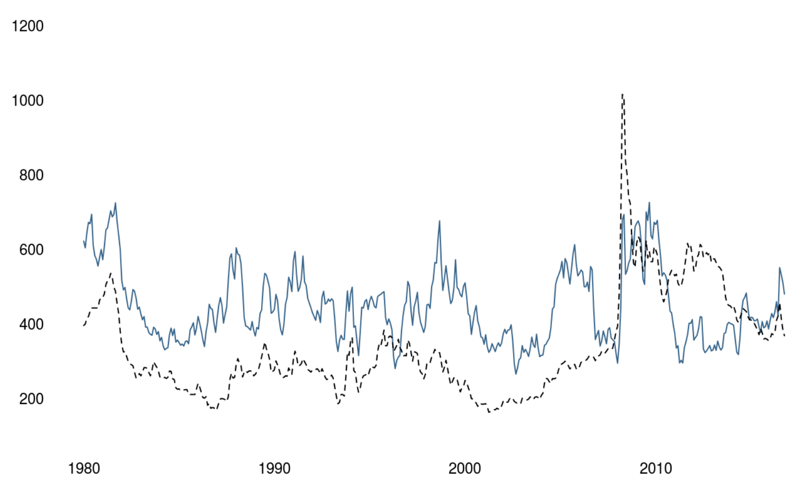

Figure 13: Real (in blue) and nominal prices (dashed, black) for rice. Nominal prices are deflated using the U.S. Producer Price Index for grains. Data source: IMF, U.S. Buro for Labor Statistics.

mentioned, economic time series data often exhibits trends. Following standard practice in the research on commodity prices we will focus on the variance of the change in logarithmic prices to analyse volatility.

I.e. we examine $Price \ \ change = log(Prices_t) - log(Prices_{t-1})$

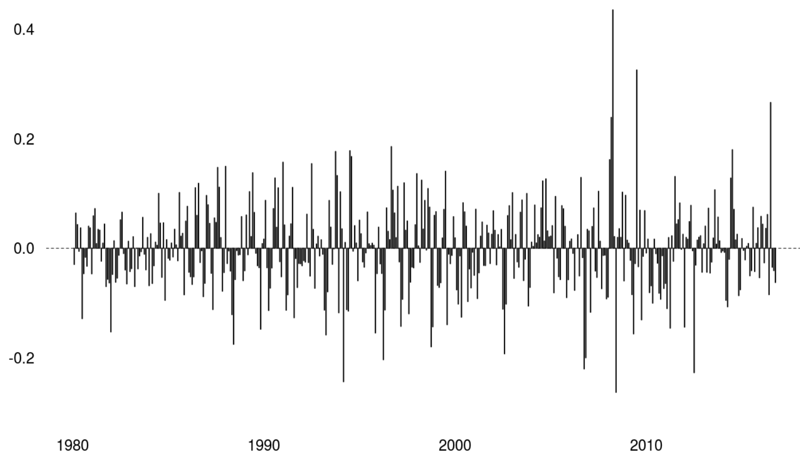

Figure 14: Volatility in international rice prices. Data source: IMF.

Can fit an AR model to the data and simulate the IRF using the estimated coefficients.

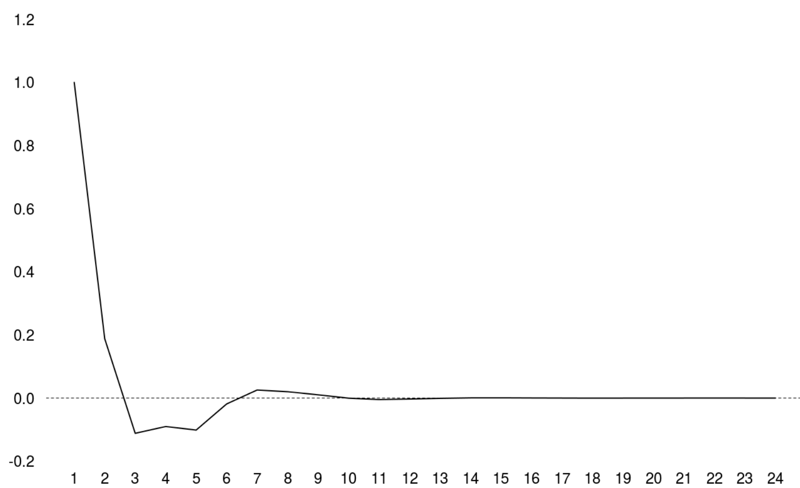

Figure 15: Impulse Response Function based on $AR(4)$ model fitted to the rice prices. Shock is 1 at $Y = 1$. Estimated coefficients are $b1 = 0.19, b2 = -0.15, b3 = -0.04, b4 = -0.09$

Lag operators

THE LAG OPERATOR is a useful piece of terminology that is sometimes used in time series modelling. The idea is that an operator moves the series back in time

$$Ly_t = y_{t-1}$$
$$L^2y_t = y_{t-2}$$

Sometimes the lag operator will be used in the model specification when a model includes a number of lags. For instance the following model,

$$y_t = a_1y_{t-1} + a_2y_{t-2} + \epsilon_t$$

can also be written as

$$y_t = A(L)y_t + \epsilon_t,\ A(L) = a_1L + a_2L^2$$

Alternatively you can also write the model as $B(L)y_t = \epsilon_t$, where $B(L) = 1 - a_1L + a_2L^2$.

VAR

AR models are useful in understanding the dynamics of individual variables, but they ignore the relationships between variables. Vector Autoregressions (*VAR*) model the dynamics between n different variables, allowing each variable to depend on the lagged values of all the variables. Such a model allows to examine the impulse response of all n variables to all n shocks. Simplest variation is a model with two variables and one lag:

$$y_{1t} = a_11y_{1,t-1} + a_12y_{2,t-1} + \epsilon_{1t}$$
$$y_{2t} = a_21y_{1,t-1} + a_22y_{2,t-1} + \epsilon_{2t}$$

What are these shocks we talk about anyway? There are a lot of sources for shocks such as i) policy changes, ii) changes in preferences, iii) technology shocks, and iv) shocks to various frictions like the efficiency with which markets work.