Predicting the real economy wih stock prices

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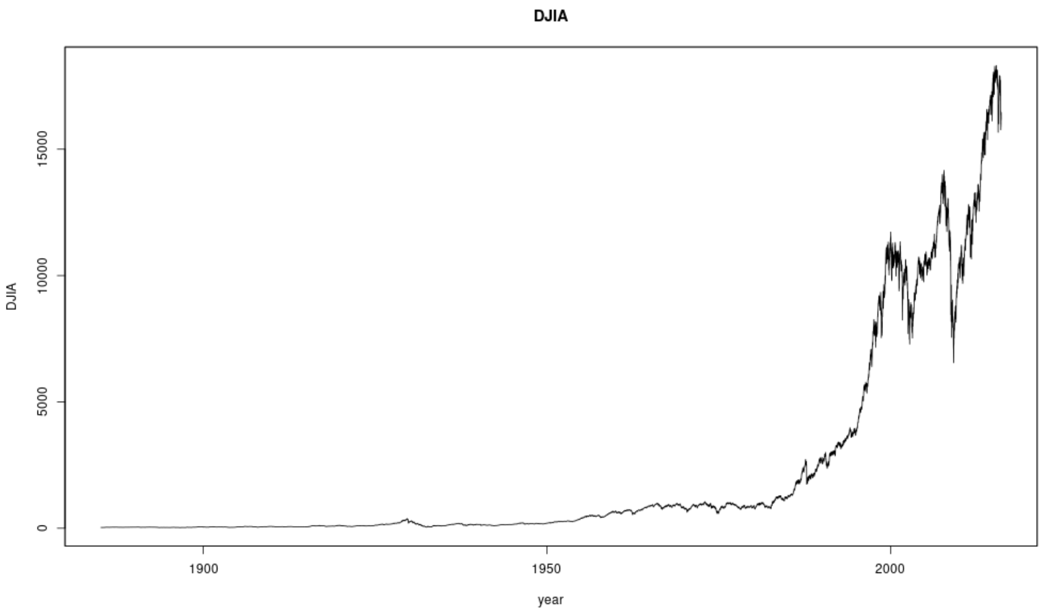
1 Predicting real economy variables with asset prices

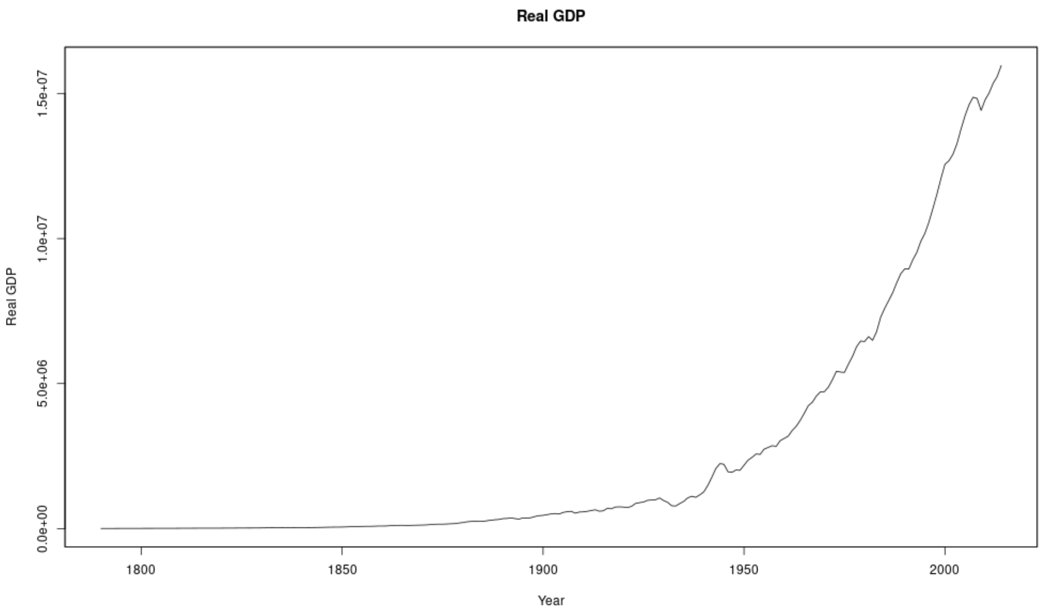
Look at the case of US.

As real variable we use (changes in) GDP. The asset price we consider is the stock market, represented with the DJIA. The use of the DJIA is due to the desire to have as long a time series as possible. At the webpage `https://www.measuringworth.com` you will find daily series of DJIA going back to 1885, as well as annual GDP estimates going back to 1790.

Figure 1 DJIA and Real GDP

DJIA





let $dGDP$ be the (log) change in GDP, and R_m the annual return on the DJIA

We will estimate the relationship

$$dGDP_t = a + b_1 dGDP_{t-1} + b_2 R_{m,t-1} + \varepsilon_t$$

If the change in the stock price predicts the future GDP, the coefficient b_2 will be significant. Let us test this

We do so in a VAR context.

Show some of the `R` commands.

This is the full sequence of commands

```
library(vars)
library(xts)
source ("~/data/2016/measuringworth/read_gdp.R")

dGDP <- diff(log(RealGDP))
names(dGDP) <- "dGDP"

source ("~/data/2016/measuringworth/read_dja.R")
                                        # DJIA is a daily zoo, need to pull end of year
                                        # observations and take returns
DJIA <- as.xts(DJIA)
Rm <- na.omit(annualReturn(DJIA))
Rm <- zooreg(coredata(Rm),frequency=1,start=1885)
names(Rm) <- "Rm"

data <- merge(dGDP,Rm,all=FALSE)
reg <- VAR(data)
summary(reg)
causality(reg,cause="Rm")
reg.irf <- irf(reg,response="dGDP",impulse="Rm")
plot(reg.irf)
```

And here is some of the output

The data

```
> head(data)
            dGDP          Rm
1885 0.003455458  0.27692691
1886 0.078195630  0.04440066
1887 0.070125639 -0.08413860
1888 0.055903941  0.04811580
1889 0.028330104  0.06196036
1890 0.092714255 -0.14147205
```

Running the VAR

```
> reg <- VAR(data)
> summary(reg)

VAR Estimation Results:
```

```
========================
Endogenous variables: dGDP, Rm
Deterministic variables: const
Sample size: 128
Log Likelihood: 244.631
Roots of the characteristic polynomial:
0.1998 0.1998
Call:
VAR(y = data)


Estimation results for equation dGDP:
=====================================
dGDP = dGDP.l1 + Rm.l1 + const

        Estimate Std. Error t value Pr(>|t|)
dGDP.l1 0.184333   0.074256   2.482   0.0144 *
Rm.l1   0.116795   0.017072   6.842 3.11e-10 ***
const   0.022976   0.004344   5.289 5.31e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.0412 on 125 degrees of freedom
Multiple R-Squared: 0.3248,Adjusted R-squared: 0.314
F-statistic: 30.07 on 2 and 125 DF,  p-value: 2.18e-11


Estimation results for equation Rm:
===================================
Rm = dGDP.l1 + Rm.l1 + const

        Estimate Std. Error t value Pr(>|t|)
dGDP.l1 -0.20318    0.39273  -0.517    0.606
Rm.l1    0.08772    0.09029   0.972    0.333
const    0.02990    0.02297   1.301    0.196


Residual standard error: 0.2179 on 125 degrees of freedom
Multiple R-Squared: 0.008534,Adjusted R-squared: -0.00733
F-statistic: 0.5379 on 2 and 125 DF,  p-value: 0.5853

Covariance matrix of residuals:
         dGDP      Rm
dGDP 0.001698 0.00141
Rm   0.001410 0.04749

Correlation matrix of residuals:
       dGDP     Rm
```

```
dGDP 1.0000 0.1571
Rm   0.1571 1.0000
```

The coefficient on R_m is significant, there is evidence that R_m predicts $dGDP$. This can also be checked by a test for Granger causality

```
> causality(reg,cause="Rm")
$Granger

Granger causality H0: Rm do not Granger-cause dGDP

data:  VAR object reg
F-Test = 46.806, df1 = 1, df2 = 250, p-value = 6.001e-11
```

Another way to investigate it is by the impulse-response picture

```
> reg.irf <- irf(reg,response="dGDP",impulse="Rm")
> plot(reg.irf)
```