

# Forecasting the Real Economy with Financial Variables – the case of stock prices

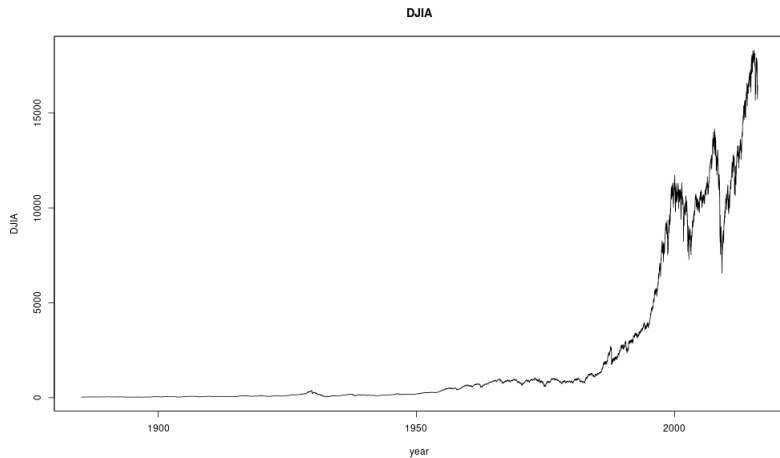
## Predicting real economy variables with asset prices

Look at an US case.

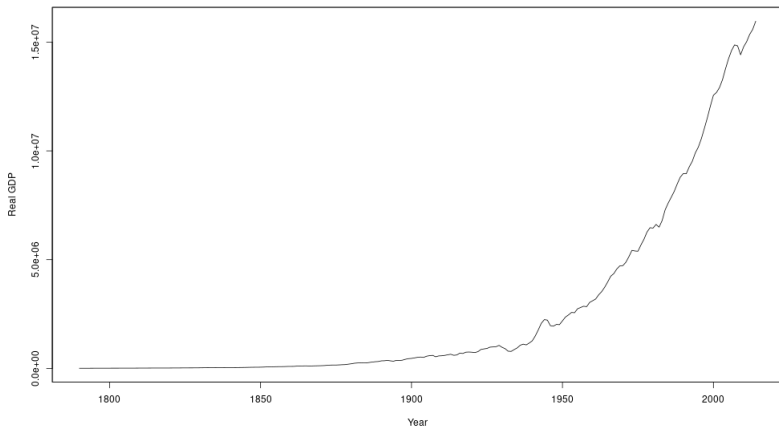
As real variable we use (changes in) GDP. The asset price we consider is the stock market, represented with the DJIA. The use of the DJIA is due to the desire to have as long a time series as possible. At the webpage <https://www.measuringworth.com> you will find daily series of DJIA going back to 1885,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

# Predicting real economy variables with asset prices

DJIA



Real GDP



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.

```
library(quantmod)
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 z
# observations and
```

```
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	***

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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

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)
```

