

Predicting the real economy with financial asset liquidity

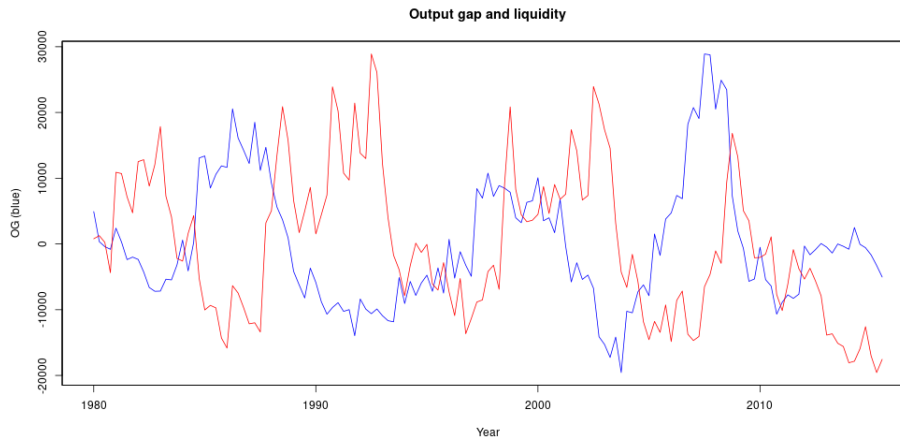
Introduction

We look at using financial asset market liquidity as a predictive variable, predicting macroeconomic aggregates. The paper that originally showed that liquidity is a viable variable for predicting the state of the economy was Næs, Skjeltorp, and Ødegaard (2011). We will show some of this style of analysis. We also show some analysis using data for Norway, which is also discussed in Skjeltorp and Ødegaard (2009).

Descriptives showing that there may be a link between liquidity and the real economy

We use data for Norway, and want to investigate a link between liquidity and real economy, measured by GDP. We will show a plot with liquidity and a measure of the state of the real economy, the output gap, in the same picture. The output gap is a measure of how far the economy is from full production, usually estimated by the difference between the current GDP and a rolling mean. (Technically, this is calculated using what is called a HP filter (Hodrick-Prescott).)

The figure shows how liquidity and the economy seems to be moving in opposite directions.



Output Gap and Liquidity, Norway

Showing how this picture is generated in R
Reading data (to illustrate)

```
library(zoo)
Liq <- read.zoo("../data/liq_measures_ose_quarterly.txt",header=1)
Liq <- as.zooreg(Liq)
RelSpread <- zooreg(as.matrix(Liq$RelSpread),
                    frequency=4,
                    start=c(1980,1))
GDP <- read.table("gdp_mainland_norway.csv",
                 sep=";",skip=5,header=FALSE)
gdp <- zooreg(GDP[,2],frequency=4,
              start=c(1978,1))
names(gdp)[1] <- "GDP"
```

To calculate the output gap, this is done using a HP filter, available in the R library `mFilter`.

```
library(mFilter)
gdp.hp <- hpfilter(gdp,freq=40000)
og <- zooreg(gdp.hp$cycle,frequency=4,start=c(1978,1))
data <- merge(og,RelSpread,all=FALSE)
plot(data$og,main="Output gap and liquidity"
      ,xlab="Year",ylab="OG",col="blue")
par(new=T)
plot(RelSpread,col="red",axes=F,ylab="",xlab="")
axis(4)
mtext(side=4,"Relative Spread")
dev.off()
```

Predicting GDP Norway with spread – VAR analysis

We look at an example from Norway. Predict GDP for mainland Norway, using the relative spread as the explanatory variable. The following shows the R code for running a VAR - Vector Autoregression analysis. This is an in-sample analysis.

Reading in the data. Some details hidden in separate input routines (typical way of doing it, a small file with R code massaging the input into an R object.

```
> library(vars)
> outdir <- "../..//results/2016_02_var_analysis/"
>
> source ("/home/bernt/data/2016/ssb/read_quarterly_gdp.R")
> head(qGDP)
1978(1) 1978(2) 1978(3) 1978(4) 1979(1) 1979(2)
 247094  249853  250733  255300  257066  257132
>
> source("../..//data/read_quarterly_norwegian_liquidity_data.R")
> head(RelSpread)
 1980(1)  1980(2)  1980(3)  1980(4)  1981(1)  1981(2)
0.0391982 0.0396895 0.0386271 0.0338552 0.0496760 0.0494737
>
> dGDP <- diff(log(qGDP))
> names(dGDP) <- "dGDP"
```


The following is the data we work with

```
> data <- merge(dGDP,RelSpread,all=FALSE)
```

```
> head(data)
```

	dGDP	RelSpread
1980(1)	0.013019691	0.0391982
1980(2)	-0.011668339	0.0396895
1980(3)	0.002693454	0.0386271
1980(4)	0.004024743	0.0338552
1981(1)	0.017495227	0.0496760
1981(2)	-0.002339087	0.0494737

Running the VAR is now just

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

VAR Estimation Results:

=====

Endogenous variables: dGDP, RelSpread

Deterministic variables: const

Sample size: 142

Log Likelihood: 975.925

Roots of the characteristic polynomial:

0.8623 0.2435

Call:

VAR(y = data)

Estimation results for equation dGDP:

=====
dGDP = dGDP.l1 + RelSpread.l1 + const

	Estimate	Std. Error	t value	Pr(> t)	
dGDP.l1	-0.224744	0.082735	-2.716	0.00744	**
RelSpread.l1	-0.240555	0.079313	-3.033	0.00289	**
const	0.016686	0.003324	5.019	1.56e-06	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01045 on 139 degrees of freedom

Multiple R-Squared: 0.08967, Adjusted R-squared: 0.07658

F-statistic: 6.846 on 2 and 139 DF, p-value: 0.001459

See here the relevant coefficient, that the coefficient on the relative spread is -0.24 , negative and significant at the 1% level. The remaining output is not relevant for asking the question we want, but note that the real variable does not predict the spread.

Estimation results for equation RelSpread:

=====

RelSpread = dGDP.l1 + RelSpread.l1 + const

	Estimate	Std. Error	t value	Pr(> t)	
dGDP.l1	-0.084815	0.047154	-1.799	0.074239	.
RelSpread.l1	0.843497	0.045204	18.660	< 2e-16	***
const	0.006424	0.001895	3.390	0.000909	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.005958 on 139 degrees of freedom

Multiple R-Squared: 0.7337, Adjusted R-squared: 0.7299

F-statistic: 191.5 on 2 and 139 DF, p-value: < 2.2e-16

Covariance matrix of residuals:

	dGDP	RelSpread
dGDP	1.093e-04	-6.487e-06
RelSpread	-6.487e-06	3.550e-05

Correlation matrix of residuals:

	dGDP	RelSpread
dGDP	1.0000	-0.1041
RelSpread	-0.1041	1.0000

Run the test for causality

```
> causality(reg,cause="RelSpread")
```

```
$Granger
```

Granger causality H0: RelSpread do not Granger-cause dGDP

```
data: VAR object reg
```

```
F-Test = 9.199, df1 = 1, df2 = 278, p-value = 0.00265
```

```
$Instant
```

H0: No instantaneous causality between: RelSpread and dGDP

```
data: VAR object reg
```

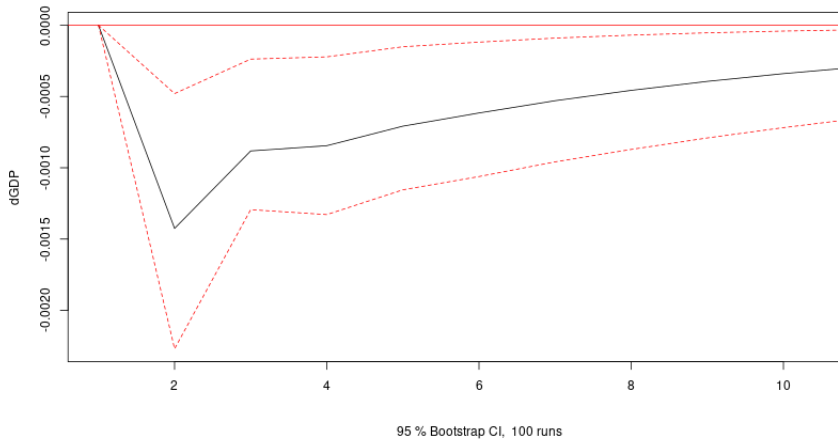
```
Chi-squared = 1.5236, df = 1, p-value = 0.2171
```

which confirms that RelSpread Granger-causes dGDP.

This is also shown in the impulse-response

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

Orthogonal Impulse Response from RelSpread



Predicting GDP Norway with spread – Out of Sample Analysis

We look at an example from Norway. Predict (changes in) GDP for mainland Norway, using the relative spread as the explanatory variable.

To confirm predictive power, one usually need to look into the out-of-sample performance of a given predictive variable to really conclude that the forecasting power is there.

We will therefore do some forecasting exercises.

Let us first show the R code for doing this
The reading of the data is similar to before

```
> library(forecast)
> outdir <- "../..//results/2016_02_out_of_sample_forecasts/"
> source ("/home/bernt/data/2016/ssb/read_quarterly_gdp.R")
> head(qGDP)
1978(1) 1978(2) 1978(3) 1978(4) 1979(1) 1979(2)
 247094  249853  250733  255300  257066  257132
>
> source("../..//data/read_quarterly_norwegian_liquidity_data.R")
> head(RelSpread)
 1980(1)  1980(2)  1980(3)  1980(4)  1981(1)  1981(2)
0.0391982 0.0396895 0.0386271 0.0338552 0.0496760 0.0494737
> names(RelSpread) <- "RelSpread"
>
> dGDP <- diff(log(qGDP))
> names(dGDP) <- "dGDP"
```

```
> # now do out - of
> lRelSpread <- lag(RelSpread,-1)
> names(lRelSpread) <- "lRelSpread"
> # use two lags of
> ldGDP <- lag(dGDP,-2)
> data <- merge(dGDP,ldGDP,RelSpread,lRelSpread,all=FALSE)
```

The above has gotten the data in the right form for analysis. Here I have aligned the predictive lagged variables to match the dependent variables, you may want to check that. Is the current dGDP and Spread aligned with the previous quarter Spread, and two quarters ago dGDP?

```
> head(data)
```

	dGDP	ldGDP	RelSpread	lRelSpread
1980(2)	-0.011668339	0.013237630	0.0396895	0.0391982
1980(3)	0.002693454	0.013019691	0.0386271	0.0396895
1980(4)	0.004024743	-0.011668339	0.0338552	0.0386271
1981(1)	0.017495227	0.002693454	0.0496760	0.0338552
1981(2)	-0.002339087	0.004024743	0.0494737	0.0496760
1981(3)	-0.004511960	0.017495227	0.0458140	0.0494737

```
> dGDP <- data$dGDP
```

```
> ldGDP <- data$ldGDP
```

```
> RelSpread <- data$RelSpread
```

```
> lRelSpread <- data$lRelSpread
```

Now, ready to do the forecasting exercise. Do it by using the first 10 years (40 observations) to start estimation. Then a for loop over the remaining days, each time doing the prediction.

```
> n <- length(dGDP)
[1] 142
> actual <-NULL
> predicted0 <- NULL
> predicted1 <- NULL
>
> START <- 40
>
```

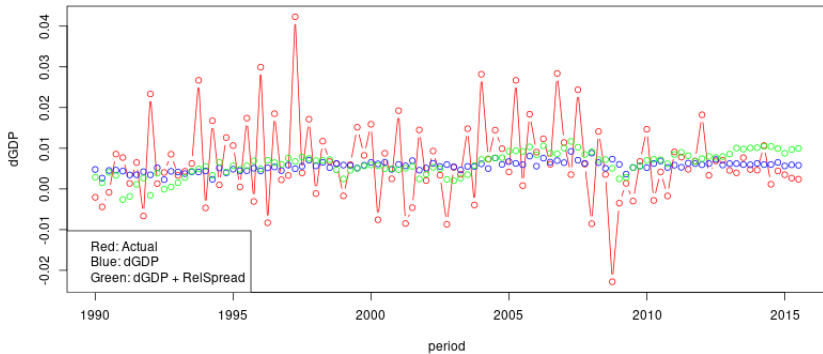
```
> for (t in START:n){
+   g <- dGDP[1:(t-1)]
+   lg <- ldGDP[1:(t-1)]
+   lsp <- lRelSpread[1:(t-1)]
+   pred0 <- lm( g ~ lg )
+   pred1 <- lm( g ~ lg + lsp)
+   nd0 <- data.frame(lg <- ldGDP[t])
+   fc0 <- forecast.lm(pred0, nd0 ,h=1)
+   predicted0 <- c(predicted0, fc0$mean)
+   nd1 <- data.frame(lsp <-lRelSpread[t], lg <- ldGDP[t])
+   fc1 <- forecast.lm(pred1, nd1, h=1)
+   predicted1 <- c(predicted1, fc1$mean)
+   actual <- c(actual,dGDP[t])
+ }
```

Now, let us compare the forecasts

The following is the R code for creating this picture.

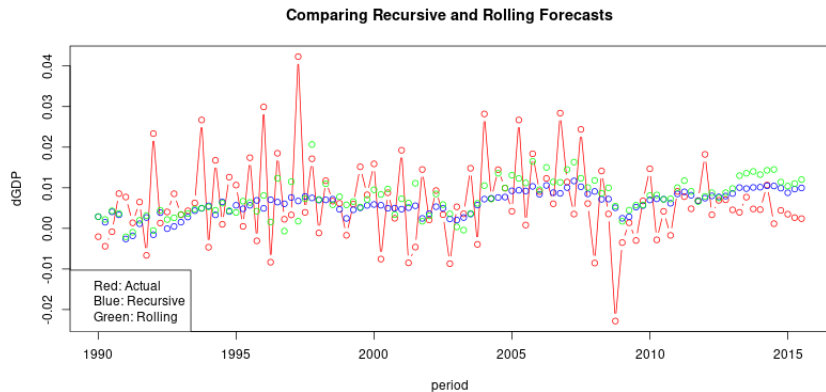
```
> x <- index(dGDP)[START:n]
>
> filename <- paste0(outdir, "comparing_forecasts_with_with")
> postscript(filename,height=5,width=10,horizontal=FALSE)
> plot(c(predicted0,predicted1,actual)~c(x,x,x),
+       type="n",xlab="period",ylab="dGDP",
+       main="Comparing Forecasts with / without Spread")
> lines(actual~x,type='b',col="red")
> points(predicted0~x,,col="blue")
> points(predicted1~x,,col="green")
>
> text(1995,-0.013,"Red: Actual")
> text(1995,-0.016,"Blue: 1dGDP")
> text(1995,-0.019,"Green: 1dGDP + 1Spread")
> dev.off()
```

Comparing Forecasts without and with spread




```
> predicted2 <- NULL
>
> # now doing forecast
> for (t in START:n){
+   g <- dGDP[(t-START+1):(t-1)]
+   lg <- ldGDP[(t-START+1):(t-1)]
+   lsp <- lRelSpread[(t-START+1):(t-1)]
+   pred2 <- lm( g ~ lg + lsp)
+   nd2 <- data.frame(lsp <-lRelSpread[t], lg <- ldGDP[t])
+   fc2 <- forecast.lm(pred2, nd2 ,h=1)
+   prediction <- fc2$mean
+   predicted2 <- c(predicted2, prediction)
+ }
>
```

Compare the two methods graphically



Again, R code that produced this graph

```
> filename <- paste0(outdir, "comparing_forecasts_recursive")
> postscript(filename,height=5,width=10,horizontal=FALSE)
> plot(c(predicted1,predicted2,actual)~c(x,x,x),
+      type="n",xlab="period",ylab="dGDP",
+      main="Comparing Recursive and Rolling Forecasts")
> lines(actual~x,type='b',col="red")
> points(predicted1~x,,col="blue")
> points(predicted2~x,,col="green")
>
> text(1995,-0.013,"Red: Actual")
> text(1995,-0.016,"Blue: Recursive")
> text(1995,-0.019,"Green: Rolling")
```

Now, finally, some numbers for doing the comparison of forecasting performance.

First, just the first few actual numbers (which is after year 10).

```
> head(cbind(actual,predicted0,predicted1,predicted2))
      actual predicted0 predicted1 predicted2
[1,] -0.0020493868 0.004777306 0.002887876 0.0028878764
[2,] -0.0044126042 0.002648651 0.001499642 0.0021917203
[3,] -0.0008367517 0.004537217 0.004064054 0.0043157129
[4,] 0.0085492579 0.004616494 0.003324567 0.0036604472
[5,] 0.0077134356 0.004370217 -0.002618097 -0.0020811801
[6,] 0.0013654204 0.003442451 -0.001833177 -0.0009533538
```

The various summary stats.

```
> p <- length(actual)
> res0 <- actual-predicted0
> mse0 <- sum(res0^2)/p
> mse0
[1] 9.560838e-05
> mae0 <- sum(abs(res0))/p
> mae0
[1] 0.006948177
>
> res1 <- actual-predicted1
> mse1 <- sum(res1^2)/p
> mse1
[1] 9.499064e-05
> mae1 <- sum(abs(res1))/p
> mae1
[1] 0.007300568
>
```

```
> res2 <- actual-predicted2
> mse2 <- sum(res2^2)/p
> mse2
[1] 9.768683e-05
> mae2 <- sum(abs(res2))/p
> mae2
[1] 0.007389973
>
> resR <- actual-predicted0
> resU <- actual-predicted1
> p=length(resR)
> h=1
> MSEr <- sum(resR^2)/p
> MSEr
[1] 9.560838e-05
> MSEu <- sum(resU^2)/p
> MSEu
[1] 9.499064e-05
```

```
> ENCNEW <- (p-h+1)* (sum(resR^2-resU*resR)/p)/MSEu
> ENCNEW
[1] 3.319659
> MSEF <- (p-h+1)*(MSEr-MSEu)/MSEu
> MSEF
[1] 0.6698309
> MSEu/MSEr
[1] 0.9935388
```

```
> # doing same comp
> resU <- actual-predicted2
> p=length(resR)
> h=1
> MSEr <- sum(resR^2)/p
> MSEr
[1] 9.560838e-05
> MSEu <- sum(resU^2)/p
> MSEu
[1] 9.768683e-05
```



```
> ENCNEW <- (p-h+1)* (sum(resR^2-resU*resR)/p)/MSEu
> ENCNEW
[1] 7.887039
> MSEF <- (p-h+1)*(MSEr-MSEu)/MSEu
> MSEF
[1] -2.191495
> MSEu/MSEr
[1] 1.021739
```

Randi Næs, Johannes A Skjeltop, and Bernt Arne Ødegaard. Stock market liquidity and the Business Cycle. *Journal of Finance*, LXVI:139–176, February 2011.

Johannes Skjeltop and Bernt Arne Ødegaard. The information content of market liquidity: An empirical analysis of liquidity at the Oslo Stock Exchange. Working Paper, Norges Bank (Central Bank of Norway), November 2009.