



## Econometrics 2, Class 1

Problem Set #14  
December 19, 2005



## #14.1 Interpretation of IV and GMM estimations

We will go through this on the blackboard.



## #14.2 Monetary policy rules for the US

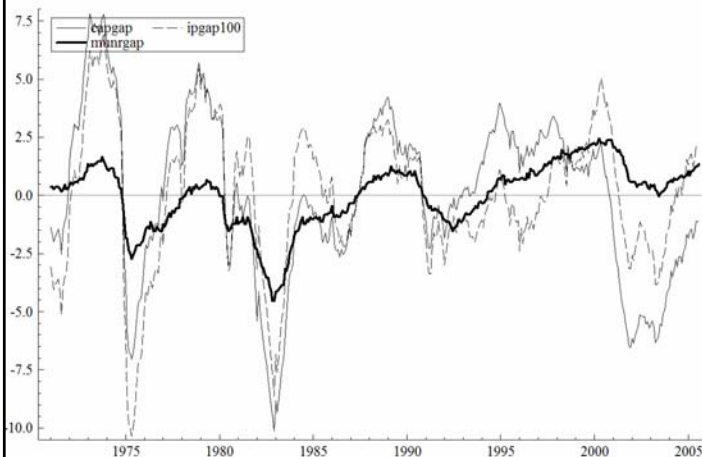
Now consider a particular data set for the estimation of monetary policy rules for the US, 1971 : 1 – 2005 : 8. The data file MonetaryPolicy.xls contains the following 11 variables:

ff	Average effective Federal funds rate.
fftarget	Target for the Federal funds rate.
bond	Average 10 years bond yield.
inf	Inflation from year to year.
infexcl	Inflation from year to year excluding food and energy.
caputil	Capacity utilization.
capgap	Measure of output gap: deviation of caputil from mean.
ip	Industrial production.
ipgap	Measure of output gap: deviation of ip from a smooth HP trend.
unr	Unemployment rate.
unrgap	Measure of output gap: deviation of unr from mean.

We want to estimate a monetary policy rule of the form (14.1) and we focus on the period with Greenspan as a chairman for the Federal Reserve Board: 1987 : 1 – 2005 : 8.



## (1a) Graph of three measures of output gap



They generally follow each other.

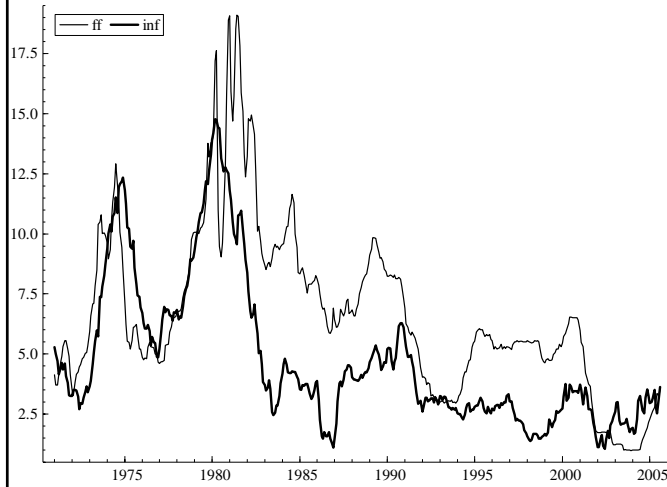
N.B. I have transformed ipgap and unrgap to aid comparison with capgap.

$\text{munrgap} = -\text{unrgap}$

$\text{ipgap100} = \text{ipgap} * 100$



### (b) Inflation and policy instrument

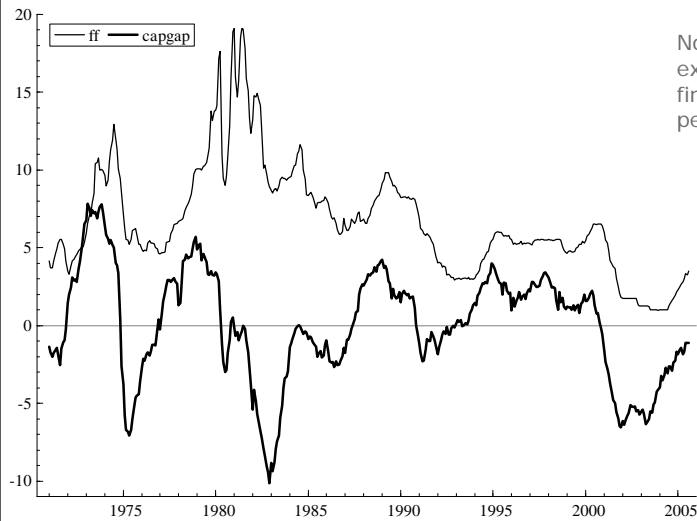


Generally seem to be low federal fund rates when inflation is low.

Not so obvious in the later period.



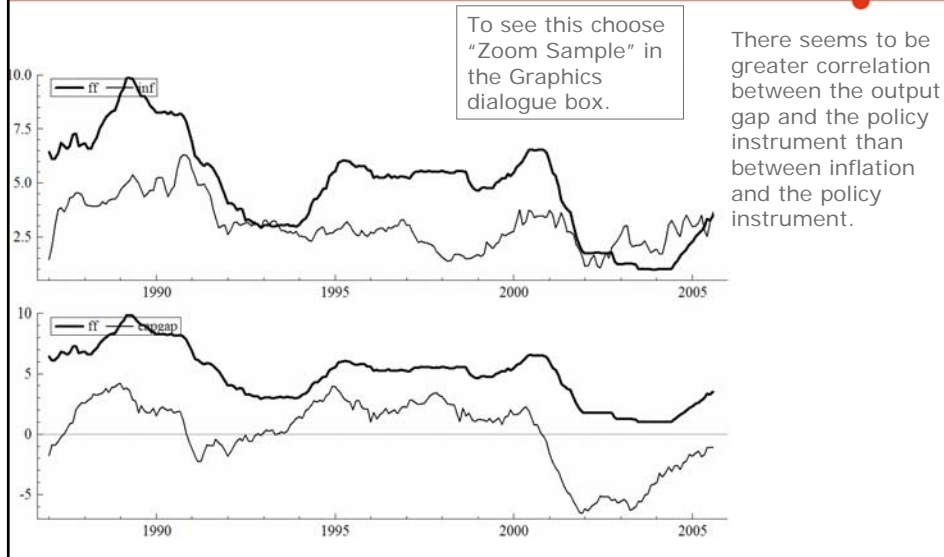
### (c) Relation between output gap and policy instrument



No clear relationship, except perhaps in the final years of the period.



## The Greenspan years 1987:1-2005:8



## (2) The instruments

First, we measure inflation by the variable  $inf$  and the output gap by the variable  $capgap$ . As instruments we take lag one and two of all variables, i.e.

$$z_t = (1, ff_{t-1}, ff_{t-2}, bond_{t-1}, bond_{t-2}, inf_{t-1}, inf_{t-2}, infexcl_{t-1}, infexcl_{t-2}, capgap_{t-1}, capgap_{t-2}, ipgap_{t-1}, ipgap_{t-2}, unrgap_{t-1}, unrgap_{t-2})'$$

The Ox program `MonetaryPolicy.ox` estimates the model by GMM, where the weights matrix is based on a heteroskedasticity and autocorrelation consistent (HAC) estimator.

For this exercise you need to use OxEdit...



## The code

```
//load the procedures for GMM estimation
#include <oxstd.h>
#include <Z:\Econometrics 2\PS14\gmm.ox>

//*****
// Specify moment conditions
// theta[0][],theta[1][],...,theta[k-1][] denote the k parameters
// y[][0],y[][1],...,y[][p] denote the p model variables
// z denote the k instruments
mom(const theta)
{
  //simple taylor rule (no smoothing)
  ufunc = y[][0]-theta[0][]-theta[1][]*y[][1]-theta[2][]*y[][2];

  //interest rate smoothing
  //ufunc = y[][0] - theta[0][]*(1-theta[3][])
  //           - theta[1][]*(1-theta[3][]) *y[][1]
  //           - theta[2][]*(1-theta[3][]) *y[][2]
  //           - theta[3][] *y[][3];
  return ufunc.*z;
}
//*****
```

These files include the procedures needed for GMM estimation.

// signifies a comment

\* signifies that the two vectors are multiplied together row by row. These are the moment conditions:  $E[u_t z_t] = 0$ .

Here we have defined the residuals from the simple Taylor rule:

$$r_t = \alpha_0 + \alpha_1 \cdot E[\pi_{t+12} - \pi^* | \mathcal{I}_t] + \alpha_2 \cdot E[y_t | \mathcal{I}_t] + \epsilon_t,$$



## The code (cont.)

```
//this is the main program block
main()
{
  decl t1,t2;
  t1=timer();

  //import data
  decl data = loadmat("MonetaryPolicyData.xls");

  //extract the 8 data series
  decl ff = data[][ 0]; // Federal funds rate (effective)
  decl fftarget = data[][ 1]; // Federal funds rate (target)
  decl bond = data[][ 2]; // bond rate (10Y constant maturity)
  decl inf = data[][ 3]; // inflation CPI
  decl infexcl = data[][ 4]; // inflation CPI excluding food and energy
  decl caputil = data[][ 5]; // capacity utilization
  decl capgap = data[][ 6]; // Output gap based on caputil
  decl ip = data[][ 7]; // Industrial production
  decl ipgap = data[][ 8]; // Output gap based on ip
  decl unr = data[][ 9]; // unemployment rate
  decl unrgap = data[][10]; // Output gap based on unr
}
```

This code just reads the data into the specified arrays.



## The code (cont.)

```
//Exercise set, simple taylor rule, lags: 1-2
y = (ff~lags(inf,-12))~capgap [192:rows(ff)-1-12][]; //start: 12=1972:1, 192=1987:1
z = (ones(rows(ff),1)~
    lags(ff      ,(1,2))~
    lags(bond    ,(1,2))~
    lags(inf     ,(1,2))~
    lags(infexcl ,(1,2))~
    lags(capgap  ,(1,2))~
    lags(ipgap   ,(1,2))~
    lags(unrgap  ,(1,2)) ) [192:rows(ff)-1-12][];
gmm("hac",1,13,0,0);
//gmm("hc",1,0,0,0);
//gmm("iid",0,0,0,0);
```

Here we define  $y$  (model variables) and  $z$  (instruments). Use *capgap* to get the same results as me.

You need to use these when answering question (4).



## The code (cont.)

```
//Model (M1)-(M3) simple taylor rule lags: 1-6,9,12
//y = (ff~lags(inf,-12))~capgap [192:rows(ff)-1-12][]; //start: 12=1972:1, 192=1987:1
//z = (ones(rows(ff),1)~
//    lags(ff      ,(1,2,3,4,5,6,9,12))~
//    lags(inf     ,(1,2,3,4,5,6,9,12))~
//    lags(capgap  ,(1,2,3,4,5,6,9,12)) ) [192:rows(ff)-1-12][];
//gmm("iid",0,0,0,0);
//gmm("hc",1,0,0,0);
//gmm("hac",1,13,0,0);

//Model (M4)-(M6) Interest rate smoothing
//y = (ff~lags(inf,-12))~capgap~lags(ff,{1}) [192:rows(ff)-1-12][];
//z = (ones(rows(ff),1)~
//    lags(ff      ,(1,2,3,4,5,6,9,12))~
//    lags(inf     ,(1,2,3,4,5,6,9,12))~
//    lags(capgap  ,(1,2,3,4,5,6,9,12)) ) [192:rows(ff)-1-12][];
//gmm("iid",1,0,0,0);
//gmm("hc",1,0,0,0);
//gmm("hac",1,13,0,0);
```

We will use this code later for questions (7) onwards.



## The code (cont.)

```
//graph
SetDrawWindow("Data and estimated policy rule");
DrawTMatrix(0,(y[][0]      )',{"Actual"}      , 1988,1, 12, 0,2);
DrawTMatrix(0,(y[][0]-ufunc)',{"Predicted"}   , 1988,1, 12, 0,3);
ShowDrawWindow();

t2=timer();
print("\nElapsed time: ",timespan(t1,t2),"\n");
}
```

Finally, the program draws a graph of the actual and predicted values of the federal funds rate and displays how much time it has used reaching these results!



## OxEdit

```
OxEdit - [MonetaryPolicy.ox]
File Edit Search View Modules Window Help
//load the procedures for GMM estimation
#include <oxstd.h>
#include <Z:\Econometrics 2\PS14\gmm.ox>

//*****
// Specify moment conditions
// theta[0][],theta[1][],...,theta[k-1][] denote the k parameters
// y[][0],y[][1],...,y[][p] denote the p model variables
// z denote the k instruments
mom(const theta)
{
//simple taylor rule (no smoothing)
ufunc = y[][0]-theta[0][]-theta[1][]*y[][1]-theta[2][]*y[][2];

//interest rate smoothing
//ufunc = y[][0] - theta[0][]*(1-theta[3][])
//          - theta[1][]*(1-theta[3][])*y[][1]
//          - theta[2][]*(1-theta[3][])*y[][2]
//          + theta[3][]*ufunc;
}
```

Here you can open, save etc.

Use this to run the program.

The first thing you need to do is to change this to the directory where you have placed your files!



### (3) The results

```

*****
* One-step GMM *
*****
      Estimate   Std.error   t-ratio
Theta 1      -0.13447      2.1382   -0.062889
Theta 2       1.6833     0.67117    2.5079
Theta 3       0.41710     0.11821    3.5285

Observations      212
Criteria func.    1.877631

*****
* Two-step efficient GMM *
*****
      Estimate   Std.error   t-ratio
Theta 1       1.1378     0.90572    1.2563
Theta 2       1.3147     0.27053    4.8599
Theta 3       0.44276    0.071385   6.2024

Observations      212
Criteria func.    0.047440
J-statistic      10.057252  [0.610938] in a Chi2(12)
    
```

We get the results of one-step, two-step and iterated GMM (next slide). One-step GMM uses the identity matrix as the weight. Two-step GMM uses two iterations, where the second is based on the estimates from the first. (See p. 13 in the GMM note.)

We concentrate on the results from "iterated GMM" for the remainder of this exercise. This means that the iteration process continues until the estimates stabilize.



### The results (cont.)

```

*****
* Iterated GMM, 22 iterations *
*****
      Estimate   Std.error   t-ratio
Theta 1       1.8595     0.50198    3.7044
Theta 2       1.1090     0.15559    7.1276
Theta 3       0.47347     0.040123   11.800

Observations      212
Criteria func.    0.044132
J-statistic      9.355903  [0.672268] in a Chi2(12)

*****
Details:
Based on HAC estimator (Bartlett kernel [bandwidth=13]) of the optimal weight.
Kernel weights:
1.000 0.923 0.846 0.769 0.692 0.615 0.538 0.462 0.385 0.308 0.231
0.154 0.077 0.000 0.000 0.000 0.000

Elapsed time: 2.54
    
```

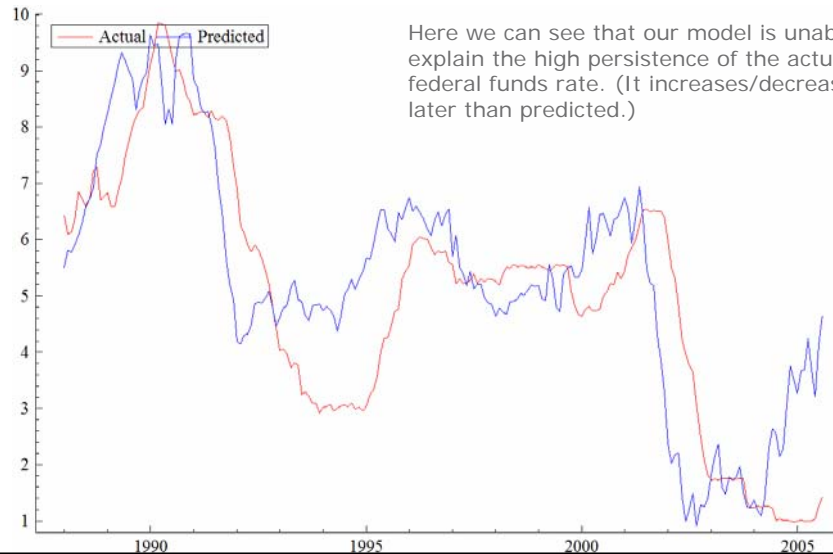
We allow for autocorrelation up to lag 12, because  $u$  includes a 12-month forecast and will thus automatically be autocorrelated. This is done using a HAC estimator of the weight matrix.

The Hansen test for no overidentification (accepted). We have 12 overidentifying moment conditions.

The coefficients have the expected signs and magnitudes and are significant.



### Actual vs. predicted federal funds rate



Here we can see that our model is unable to explain the high persistence of the actual federal funds rate. (It increases/decreases later than predicted.)



### (4) Estimation under assumption of IID errors, and with an HC estimator

```

*****
* Iterated GMM, 4 iterations *
*****

      Estimate   Std.error   t-ratio
Theta 1         0.67075     0.43358     1.5470
Theta 2         1.4017      0.13940    10.055
Theta 3          0.40025     0.039373   10.166

Observations           212
Criteria func.         0.518215
J-statistic           109.861526  [6.37357e-018] in a Chi2(12)

*****
Details:
Based on IID estimator of the optimal weight.
Elapsed time: 1.22
    
```

The assumption of IID errors changes the magnitude of the estimates, and we now find that the model is overidentified.



## Allowing for heteroskedasticity but no autocorrelation

```
*****
* Iterated GMM, 28 iterations *
*****

      Estimate   Std.error   t-ratio
Theta 1         1.3429     0.29565    4.5423
Theta 2         1.1797     0.094742   12.451
Theta 3         0.49412    0.025624   19.284

Observations           212
Criteria func.         0.356254
J-statistic           75.525894 [2.92214e-011] in a Chi2(12)

*****
Details:
Based on HC estimator of the optimal weights.

Elapsed time: 1.63
```

Again, the magnitude of the estimates is affected, and the model is overidentified.

We ought, of course, to take account of autocorrelation!



## (5) Using a measure of inflation excluding food and energy prices, *infexcl*

```
*****
* Iterated GMM, 26 iterations *
*****

      Estimate   Std.error   t-ratio
Theta 1         1.7941     0.23740    7.5571
Theta 2         1.2194     0.072030   16.929
Theta 3         0.35142    0.022323   15.743

Observations           212
Criteria func.         0.044112
J-statistic           9.351769 [0.672627] in a Chi2(12)

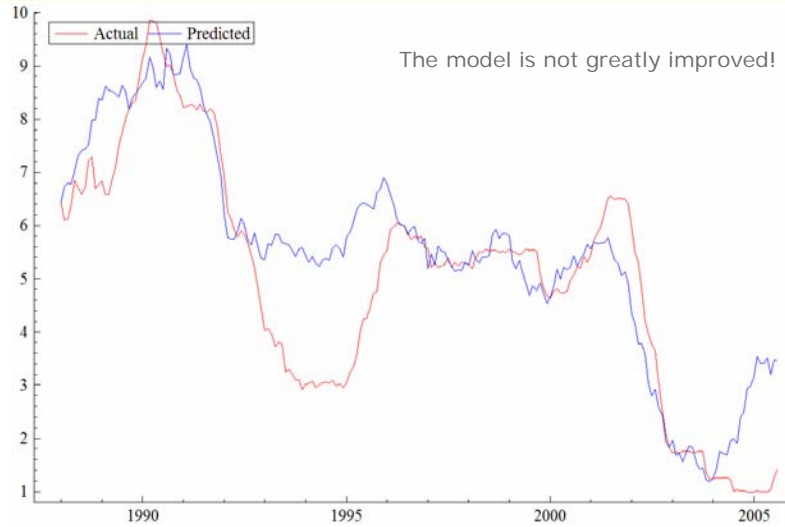
*****
Details:
Based on HAC estimator (Bartlett kernel [bandwidth=13]) of the optimal weight.
Kernel weights:
  1.000  0.923  0.846  0.769  0.692  0.615  0.538  0.462  0.385  0.308  0.231
  0.154  0.077  0.000  0.000  0.000  0.000

Elapsed time: 2.81
```

This is a robustness test. *infexcl* might be the relevant inflation target, since food and energy price changes are often temporary and volatile.



Using *infxcl* (cont.)



(6) Using a different measure of the output gap, *unrgap*

```
*****
* Iterated GMM, 58 iterations *
*****

      Estimate   Std.error   t-ratio
Theta 1         1.4572     0.37317    3.9049
Theta 2         1.2140     0.12192    9.9568
Theta 3        -1.2030     0.13114   -9.1738

Observations           212
Criteria func.         0.049606
J-statistic           10.516430  [0.57075] in a Chi2(12)

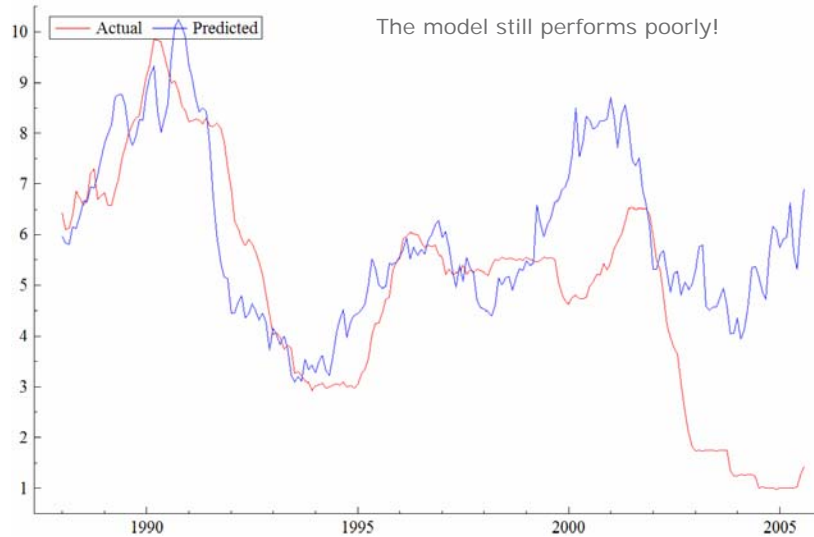
*****
Details:
Based on HAC estimator (Bartlett kernel [bandwidth=13]) of the optimal weight.
Kernel weights:
  1.000  0.923  0.846  0.769  0.692  0.615  0.538  0.462  0.385  0.308  0.231
  0.154  0.077  0.000  0.000  0.000  0.000

Elapsed time: 3.83

Another robustness check. Note the negative coefficient for the output gap. This
is because low unemployment means that there is a positive gap.
```



Using *unrgap* (cont.)



(7) Adding lags

```

*****
* Iterated GMM, 41 iterations *
*****
              Estimate   Std.error   t-ratio
Theta 1          1.1959    0.75062    1.5932
Theta 2          1.3333    0.21426    6.2231
Theta 3          0.35512   0.062007   5.7272

Observations                212
Criteria func.             0.046618
J-statistic                 9.883077   [0.987334] in a Chi2(22)

*****
Details:
Based on HAC estimator (Bartlett kernel [bandwidth=13]) of the optimal weight.
Kernel weights:
  1.000  0.923  0.846  0.769  0.692  0.615  0.538  0.462  0.385  0.308  0.231
  0.154  0.077  0.000  0.000  0.000  0.000
Elapsed time: 5.73
    
```

These are the results presented on p. 21 of the GMM note, which can be obtained using the example given in *MonetaryPolicy.ox*.



### More lags (cont.)



### (8) Allowing for interest rate smoothing

Now we extend the model to allow for interest rate smoothing. In particular we consider a model of the form

$$r_t = (1 - \rho) \cdot \{\alpha_0 + \alpha_1 \cdot E[\pi_{t+12} - \pi^* | \mathcal{I}_t] + \alpha_2 \cdot E[y_t | \mathcal{I}_t]\} + \rho \cdot r_{t-1} + \epsilon_t, \quad (14.2)$$

where the actual interest rate depends on the lagged dependent variable.

We noted previously that the federal funds rate was more highly persistent than our model could explain. It is thus natural to add a lag of the dependent variable.

The moment conditions are the same, i.e.  $E[u_t z_t] = 0$ , with the residuals appropriately redefined.



### (9) Estimation of the new model

```
*****
* Iterated GMM, 110 iterations *
*****
      Estimate   Std.error   t-ratio
Theta 1      -0.83545     0.73142    -1.1422
Theta 2       1.7385     0.24586     7.0710
Theta 3       1.0714     0.15584     6.8750
Theta 4       0.92838    0.010849    85.575

Observations      212
Criteria func.    0.048828
J-statistic      10.351625  [0.973976] in a Chi2(21)
```

Note that the coefficient to the lagged interest rate is close to one, and that the coefficient to the new information is below 1/10!

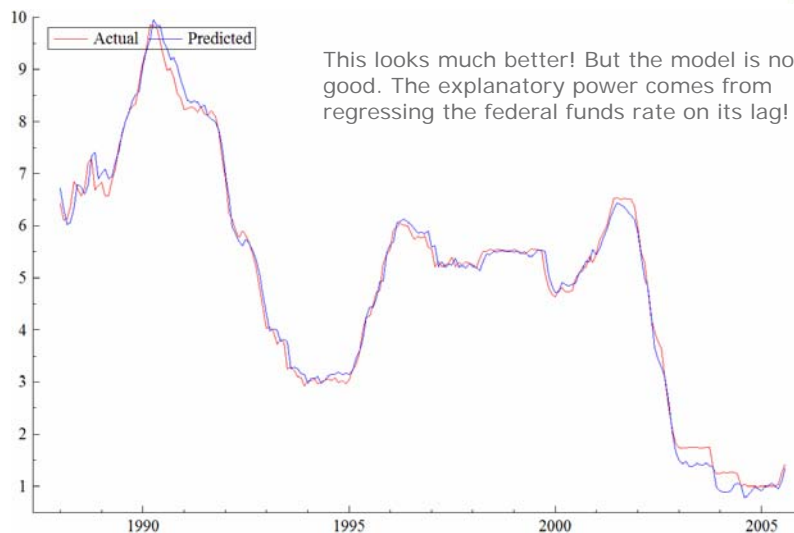
```
*****
Details:
Based on HAC estimator (Bartlett kernel [bandwidth=13]) of the optimal weight.
Kernel weights:
  1.000  0.923  0.846  0.769  0.692  0.615  0.538  0.462  0.385  0.308  0.231
  0.154  0.077  0.000  0.000  0.000  0.000

Elapsed time: 14.44
```

If you want to replicate these results yourself, note that you need to change the code in two places!



### Interest rate smoothing (cont.)



This looks much better! But the model is not good. The explanatory power comes from regressing the federal funds rate on its lag!



### (10) Why is the lagged dependent variable so important?

- The coefficient to the lagged interest rate is close to unity.
- This could reflect that the time series for the interest rate is close to behaving as a unit root process.
- Assumptions 1 and 2 in the GMM note (LLN and CLT) are thus violated.
- This means that the tools used here are not valid!
- The literature has focussed on the "success" of the Taylor-rule empirically (since the coefficients support the theory), but the tools used to demonstrate this are invalid given the data. 😊



### (11) Are the results still sensitive to the chosen specification?

See the results presented in the GMM note. What doesn't change is the importance of the lagged federal funds rate.

(12) Repeat the exercise for 1971:1 to  
1987:12



I will let you try this yourselves!

Finally...



- Thank you for this semester!
- As ever, you are always welcome to send an e-mail if you have any questions.
- GOOD LUCK WITH THE EXAM!