Econometrics with EViews :

Analysis of whether the recent increase in US Savings Rate since 2008 is Structural or Transitory

Is the US Savings rate increase (post crisis) structural or transitory?

So, now that we are out of the financial crisis, the Fed are '*normalising*' rates and everyone is happy and swimming in disposable income (right?), lets begin the post mortem and investigate one of the major economic shifts post crisis – *The significant increase in the US Savings rate from 2008 onwards.*

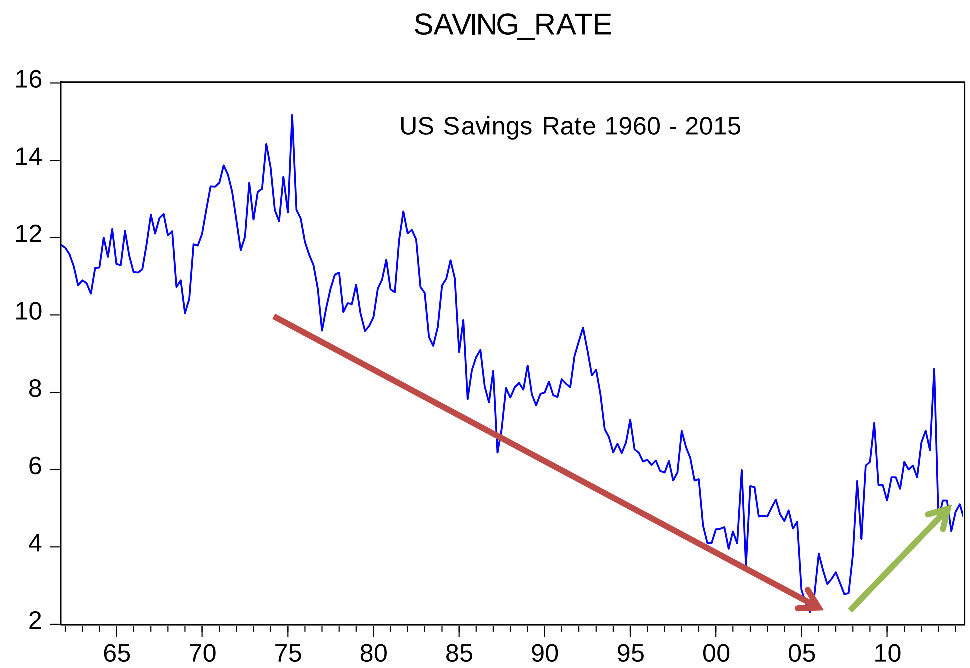
The Problem

From around 1975 up until the start of the financial crisis in 2008, there was a steady decline in the US Saving Rate (personal saving as % of disposable income) from around 12% to below 4%, heading into Lehman.

When the crisis struck, the Saving Rate began to increase, up to a peak of around 8%.

What we would like to investigate, is whether this represents a Structural change or a Transitory / Temporary change in the Saving Rate.

To do this we will use some of the tools in the Econometricians tool kit and make use of the software EViews, to investigate this hypothesis.



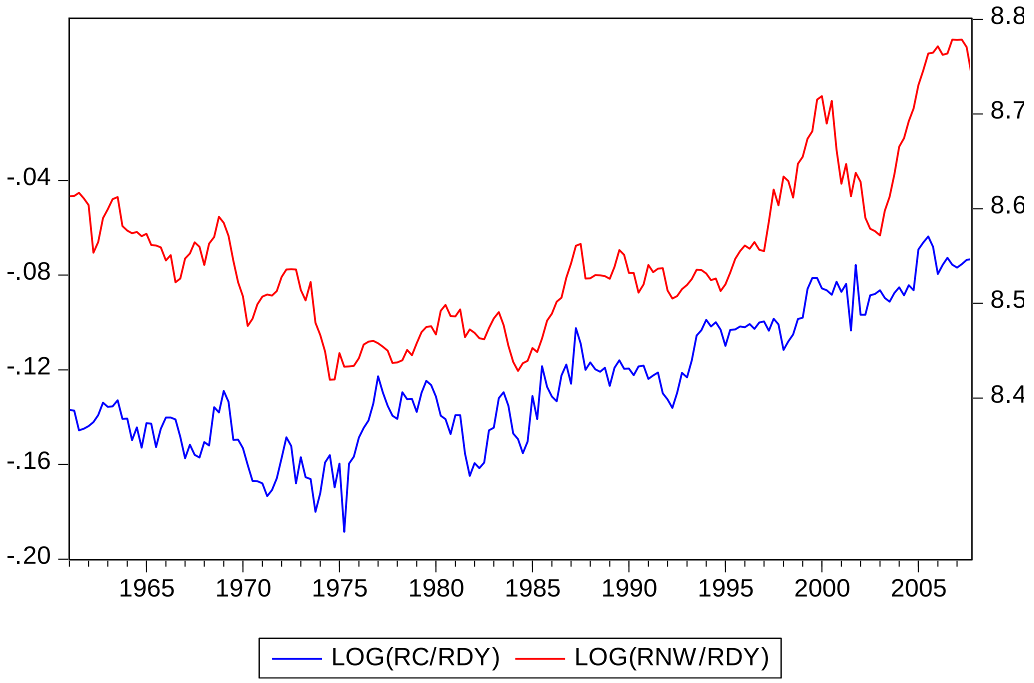
Method

To solve this problem we will estimate and evaluate a model of private consumption and use this model to assess whether the significant increase in the household saving ratio soon after the onset of the 2008 financial crisis can be considered permanent (hence constituting a structural break in the U.S. consumption function) or a transitory development.

Using various US data from before during and after the 2008 financial crisis.

1. First to get a visual on our data we will plot the logs of Real Consumption (RC) vs Real Disposable Income (RDY) and Real Net Worth (RNW) vs RDY.

EViews command: “plot log(rc/rdy) log(rnw/rdy)”



So we are comparing the ratio of consumption to disposable income in real terms to the ratio of net worth to disposable income in real terms.

We can see the gap narrowed from the mid 1970’s onwards.

Interestingly from about 2002 up until the financial crisis (where this chart stops) the major spike in Real Net Worth is largely due to the increase in US Housing prices, a precursor to the Housing Crash of 2008.

2. Regressing log (rc/rdy) on log (rnw/rdy) we can see the Durbin Watson stat is very low, suggesting positive autocorrelation in the residuals.

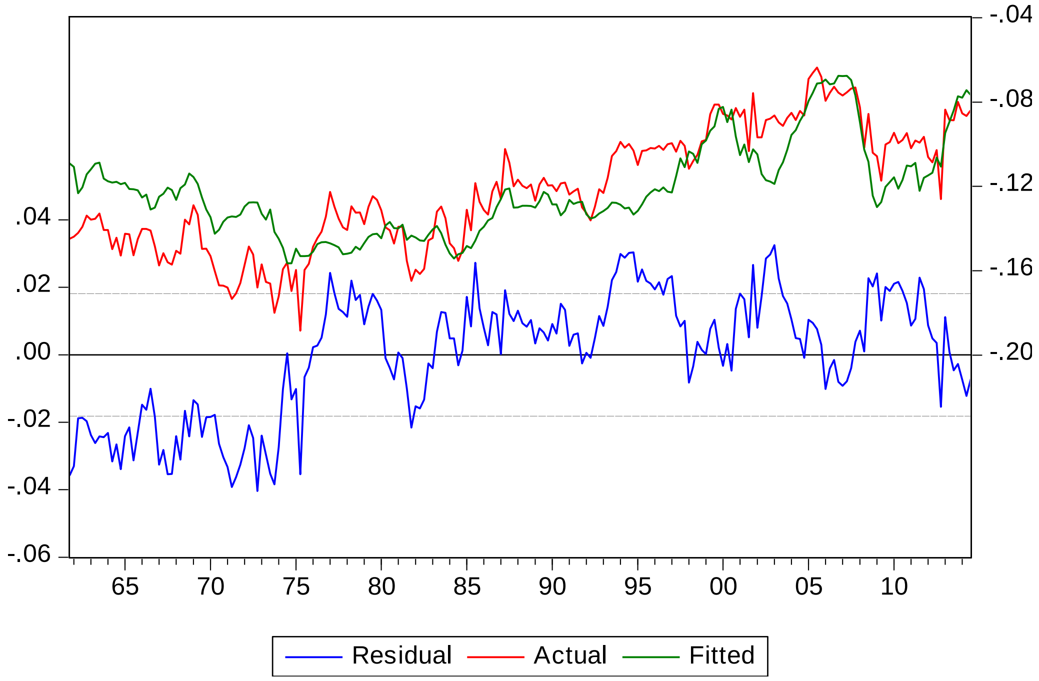
EViews - [Equation: UNTITLED Workfile: M1_DATA::usa_cy\]
File Edit Object View Proc Quick Options Add-ins Window Help
View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: LOG(RC/RDY)
Method: Least Squares
Date: 12/23/15 Time: 22:08
Sample: 1961Q4 2014Q3
Included observations: 212

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.239552	0.122164	-18.33229	0.0000
LOG(RNW/RDY)	0.247416	0.014271	17.33733	0.0000

R-squared	0.588705	Mean dependent var	-0.121659
Adjusted R-squared	0.586747	S.D. dependent var	0.028245
S.E. of regression	0.018157	Akaike info criterion	-5.170095
Sum squared resid	0.069235	Schwarz criterion	-5.138429
Log likelihood	550.0301	Hannan-Quinn criter.	-5.157297
F-statistic	300.5830	Durbin-Watson stat	0.206103
Prob(F-statistic)	0.000000		

Viewing the residuals we can see that they were negative up until 1975, when they levelled out (albeit oscilating wither side of the flat line).



This suggests there may be a structural break at this point.

Indeed, if we include a dummy variable at the suspected breakpoint (sb_1974_4) we see the regression results improve substantially:

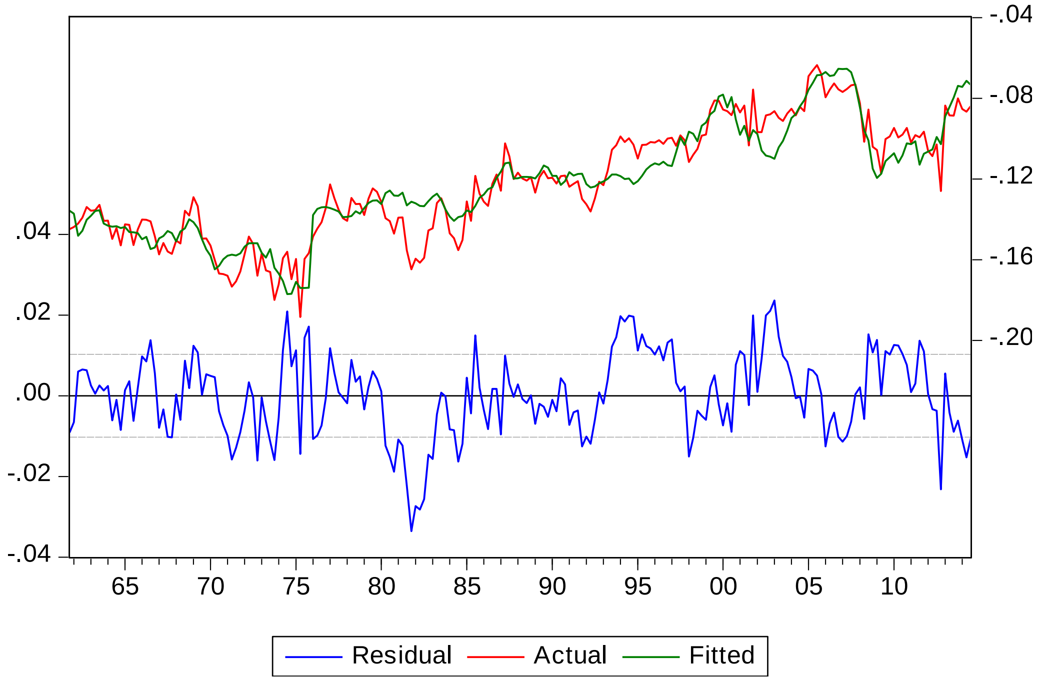
Dependent Variable: LOG(RC/RDY)
Method: Least Squares

Sample: 1961Q4 2014Q3
Included observations: 212

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.954763	0.070392	-27.76980	0.0000
LOG(RNW/RDY)	0.215222	0.008213	26.20410	0.0000
SB_1975_4	-0.034245	0.001619	-21.15466	0.0000

R-squared	0.869066	Mean dependent var	-0.121659
Adjusted R-squared	0.867813	S.D. dependent var	0.028245
S.E. of regression	0.010269	Akaike info criterion	-6.305279
Sum squared resid	0.022041	Schwarz criterion	-6.257780
Log likelihood	671.3596	Hannan-Quinn criter.	-6.286081
F-statistic	693.6135	Durbin-Watson stat	0.668712
Prob(F-statistic)	0.000000		

And the residuals look a lot more consistent with the dummy variable included, although there are still significant periods of positive autocorrelation post structural break, which will require further modifications to the model specification.



We will now specify our long-run predictive equation for real consumption in the US.

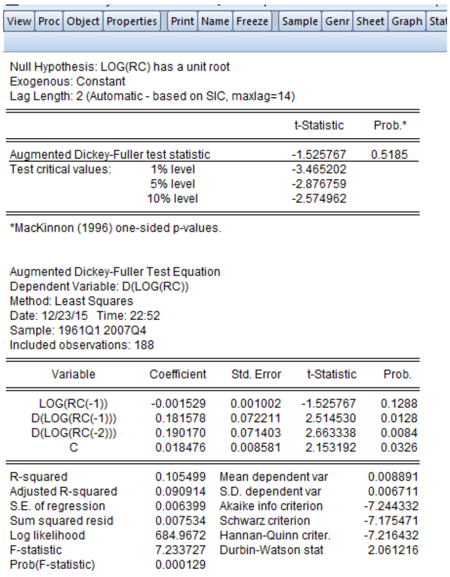
$$\ln rc_t = \beta_0 + \beta_1 \ln rdy_t + \beta_2 \ln rnw_t + \epsilon_t$$

where **rc** is real consumption, **rdy** is real disposable income, and **rnw** is real net worth.

Our sample period is 1961:1 to 2007:4

EViews command: “Smpl 1961:1 2007:4”

To determine the statistical properties of our model we will test for Unit Root in each of our variables prior to the financial crisis in 2008.



Null Hypothesis: LOG(RC) has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.525767	0.5185
Test critical values:	1% level	-3.465202	
	5% level	-2.876759	
	10% level	-2.574962	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LOG(RC))
Method: Least Squares
Date: 12/23/15 Time: 22:52
Sample: 1961Q1 2007Q4
Included observations: 188

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(RC(-1))	-0.001529	0.001002	-1.525767	0.1288
D(LOG(RC(-1)))	0.181578	0.072211	2.514530	0.0128
D(LOG(RC(-2)))	0.190170	0.071403	2.663338	0.0084
C	0.018476	0.008581	2.153192	0.0326

R-squared	0.105499	Mean dependent var	0.008891
Adjusted R-squared	0.090914	S.D. dependent var	0.006711
S.E. of regression	0.006399	Akaike info criterion	-7.244332
Sum squared resid	0.007534	Schwarz criterion	-7.175471
Log likelihood	684.9672	Hannan-Quinn criter.	-7.216432
F-statistic	7.233727	Durbin-Watson stat	2.061216
Prob(F-statistic)	0.000129		

We can see that log (RC) has a p-value of 0.51 (so we cannot reject the null that Real Consumption has a unit root) the coefficient on the log (RC) also supports this.

(Also, if we were to take 1st differences we would see the data becomes stationary.)

This variable is therefore non stationary (along with our other variables) meaning we can investigate for Cointegration.

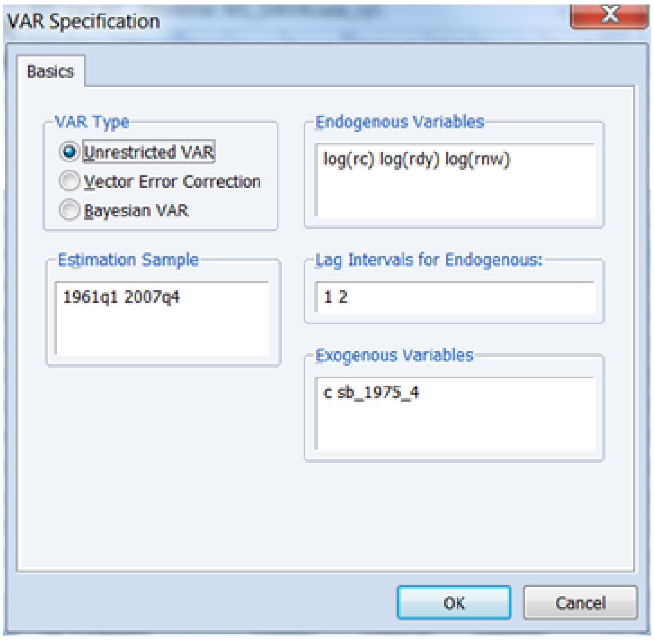
<u>Cointegration</u>

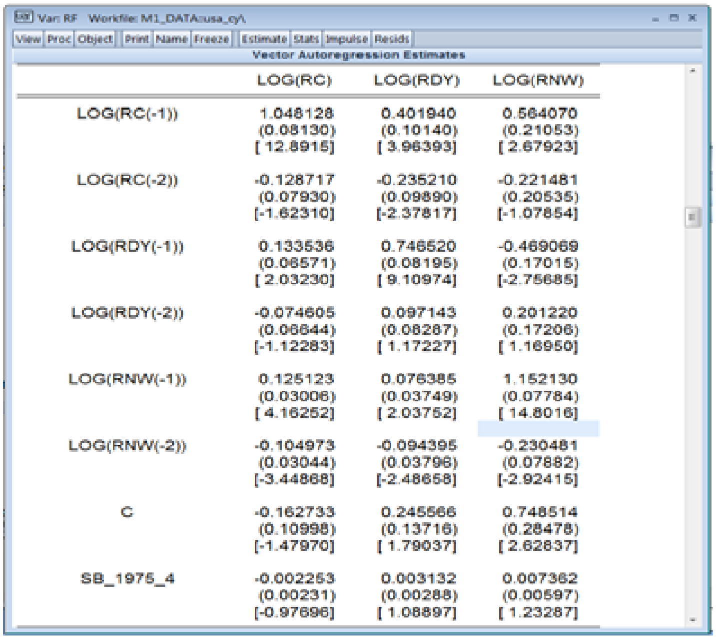
As all of our variables are I(1) and possibly cointegrated we will use Johansens max eigenvalue statistic to try and identify a trend / long-run relationship.

Before we decide how to proceed with our VAR, we will check for cointegration. If we don't see any cointegration then we will run our VAR in 1st differences. If we do have cointegration among the variables, then we will run a VECM model.

In the first instance we will run a simple VAR in levels, (rather than 1st differences) with 2 lags and not concern ourselves with whether or not the variables log(RC) log(RDY) log(RNW) are cointegrated yet, to get a feel for the data.

First we will estimate a Vector Auto Regression model (VAR) including a dummy variable to allow for the hypothesised structural break in 1975 (sb_1975_4). Note the dummy variable as an Exogenous Variable.




Vector Autoregression Estimates

	LOG(RC)	LOG(RDY)	LOG(RNW)
LOG(RC(-1))	1.048128	0.401940	0.564070
	(0.08130)	(0.10140)	(0.21053)
	[12.8915]	[3.96393]	[2.67923]
LOG(RC(-2))	-0.128717	-0.235210	-0.221481
	(0.07930)	(0.09890)	(0.20535)
	[-1.62310]	[-2.37817]	[-1.07854]
LOG(RDY(-1))	0.133536	0.746520	-0.469069
	(0.06571)	(0.08195)	(0.17015)
	[2.03230]	[9.10974]	[-2.75685]
LOG(RDY(-2))	-0.074605	0.097143	0.201220
	(0.06644)	(0.08287)	(0.17206)
	[-1.12283]	[1.17227]	[1.16950]
LOG(RNW(-1))	0.125123	0.076385	1.152130
	(0.03006)	(0.03749)	(0.07784)
	[4.16252]	[2.03752]	[14.8016]
LOG(RNW(-2))	-0.104973	-0.094395	-0.230481
	(0.03044)	(0.03796)	(0.07882)
	[-3.44868]	[-2.48658]	[-2.92415]
C	-0.162733	0.245566	0.748514
	(0.10998)	(0.13716)	(0.28478)
	[-1.47970]	[1.79037]	[2.62837]
SB_1975_4	-0.002253	0.003132	0.007362
	(0.00231)	(0.00288)	(0.00597)
	[-0.97696]	[1.08897]	[1.23287]

We then run a lag selection (using lag length criteria in EViews) which suggests an optimal lag length of 2.

VAR Lag Order Selection Criteria
Endogenous variables: LOG(RC) LOG(RDY)

LOG(RNW)
Exogenous variables: SB_1975_4
Date: 12/23/15   Time: 23:04
Sample: 1961Q1 2007Q4
Included observations: 188

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-144.3095	NA	0.000962	1.567123	1.618768	1.588048
1	1858.354	3920.106	5.92e-13	-19.64206	-19.43548*	-19.55836
2	1881.214	44.01784	5.11e-13	-19.78951	-19.42799	-19.64303*
3	1888.470	13.74153	5.20e-13	-19.77096	-19.25451	-19.56171
4	1893.605	9.558736	5.42e-13	-19.72984	-19.05845	-19.45782
5	1909.986	29.97403*	5.02e-13*	-19.80836*	-18.98204	-19.47356
6	1917.486	13.48474	5.10e-13	-19.79241	-18.81115	-19.39484
7	1921.254	6.653068	5.40e-13	-19.73674	-18.60054	-19.27640
8	1926.338	8.816529	5.64e-13	-19.69509	-18.40395	-19.17197

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

We will now test for autocorrelation using our two lags.

Var: RF   Workfile: M1_DATA::usa_cy\
View | Proc | Object | Print | Name | Freeze | Estimate | Stats | Impul

VAR Residual Serial Correlation LM T...
Null Hypothesis: no serial correlation at ...
Date: 04/29/15   Time: 08:46
Sample: 1961Q1 2007Q4
Included observations: 188

Lags	LM-Stat	Prob
1	13.60887	0.1369
2	8.080797	0.5260
3	21.40155	0.0110
4	24.25051	0.0039
5	10.65281	0.3003
6	6.404718	0.6988
7	6.217350	0.7180
8	14.69451	0.0997
9	3.494151	0.9415
10	8.069861	0.5271
11	11.93950	0.2167
12	7.993124	0.5348

Probs from chi-square with 9 df.

The LM test suggests we can't reject the null hypothesis (of no autocorrelation) up to two lags, but we can reject at three and four. We will continue with the model as it stands.

We will now test for heteroscedasticity. Both the White tests suggest no homoscedasticity at a 5% confidence level.

Var: RF Workfile: M1_DATA::usa_cy\

View | Proc | Object | Print | Name | Freeze | Estimate | Stats | Impulse | Resids

VAR Residual Heteroskedasticity Tests: No Cross Terms (only levels and squares)
Date: 04/29/15 Time: 08:51
Sample: 1961Q1 2007Q4
Included observations: 188

Joint test:

Chi-sq	df	Prob.
101.0340	78	0.0409

Individual components:

Dependent	R-squared	F(13,174)	Prob.	Chi-sq(13)	Prob.
res1*res1	0.116413	1.763434	0.0523	21.88569	0.0572
res2*res2	0.121184	1.845667	0.0396	22.78260	0.0444
res3*res3	0.143907	2.249920	0.0094	27.05452	0.0122
res2*res1	0.075922	1.099678	0.3622	14.27336	0.3549
res3*res1	0.093777	1.385048	0.1706	17.63000	0.1721
res3*res2	0.086720	1.270927	0.2346	16.30334	0.2331

Var: RF Workfile: M1_DATA::usa_cy\

View | Proc | Object | Print | Name | Freeze | Estimate | Stats | Impulse | Resids

VAR Residual Heteroskedasticity Tests: Includes Cross Terms
Date: 04/29/15 Time: 08:53
Sample: 1961Q1 2007Q4
Included observations: 188

Joint test:

Chi-sq	df	Prob.
174.3249	138	0.0198

Individual components:

Dependent	R-squared	F(23,164)	Prob.	Chi-sq(23)	Prob.
res1*res1	0.189984	1.672400	0.0349	35.71704	0.0441
res2*res2	0.258297	2.483157	0.0005	48.55974	0.0014
res3*res3	0.184410	1.612237	0.0463	34.66910	0.0561
res2*res1	0.131433	1.078993	0.3737	24.70949	0.3654
res3*res1	0.140953	1.169968	0.2791	26.49919	0.2779
res3*res2	0.126293	1.030691	0.4304	23.74303	0.4182

And finally the jarque-bera model for normality suggests we can reject the joint normal distribution of errors. This non-normality may be related to heteroscedasticity which would explain the excess kurtosis.

Command | Capture

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Impulse | Resids | Zoom

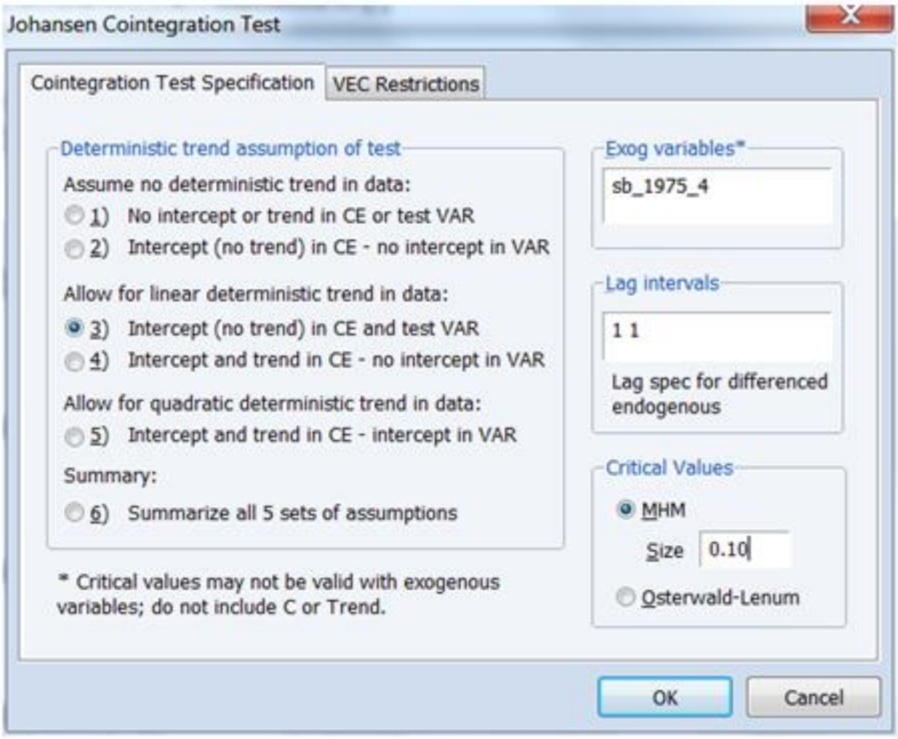
VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Date: 12/09/15 Time: 17:55
Sample: 1961Q1 2007Q4
Included observations: 188

Component	Skewness	Chi-sq	df	Prob.
1	0.063186	0.125097	1	0.7236
2	0.593770	11.04695	1	0.0009
3	-0.730546	16.72250	1	0.0000
Joint		27.89456	3	0.0000

Component	Kurtosis	Chi-sq	df	Prob.
1	3.416643	1.359799	1	0.2436
2	7.168479	136.1137	1	0.0000
3	4.207812	11.42735	1	0.0007
Joint		148.9009	3	0.0000

Component	Jarque-Bera	df	Prob.
1	1.484896	2	0.4759
2	147.1607	2	0.0000
3	28.14986	2	0.0000

Now we can use the Johansens test with just one lag (one less than the VAR model) as we will run the model in 1st differences rather than levels.



The results suggest that we can reject the null hypothesis of no cointegration (or zero cointegrating vectors) using a 6 percent significance level. Furthermore, we cannot reject the null hypotheses of at most 1 cointegrating vectors versus the alternative of 2. Therefore, we assume that there exists one (and only one) cointegrating vector.

Date: 12/23/15 Time: 23:17
Sample: 1961Q1 2007Q4
Included observations: 188
Trend assumption: Linear deterministic trend
Series: LOG(RC) LOG(RDY) LOG(RNW)
Exogenous series: SB_1975_4
Warning: Critical values assume no exogenous series
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.121551	29.37115	29.79707	0.0559
At most 1	0.023458	5.006875	15.49471	0.8081
At most 2	0.002890	0.544155	3.841466	0.4607

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized		Max-Eigen	0.05	

No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.121551	24.36428	21.13162	0.0169
At most 1	0.023458	4.462720	14.26460	0.8076
At most 2	0.002890	0.544155	3.841466	0.4607

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

LOG(RC)	LOG(RDY)	LOG(RNW)
-109.1283	91.50951	19.65479
18.30836	3.704395	-17.49804
2.695061	4.237255	-8.575024

Unrestricted Adjustment Coefficients (alpha):

D(LOG(RC))	0.000654	-0.000538	0.000249
D(LOG(RDY))	-0.001676	-0.000898	9.11E-05
D(LOG(RNW))	-0.002990	0.000792	0.000668

1 Cointegrating Equation(s): Log likelihood 1887.402

Normalized cointegrating coefficients (standard error in parentheses)

LOG(RC)	LOG(RDY)	LOG(RNW)
1.000000	-0.838550	-0.180107
	(0.03626)	(0.02948)

Adjustment coefficients (standard error in parentheses)

D(LOG(RC))	-0.071400
	(0.04910)
D(LOG(RDY))	0.182930
	(0.06138)
D(LOG(RNW))	0.326294
	(0.12681)

2 Cointegrating Equation(s): Log likelihood 1889.634

Normalized cointegrating coefficients (standard error in parentheses)

LOG(RC)	LOG(RDY)	LOG(RNW)
1.000000	0.000000	-0.804968
		(0.06468)
0.000000	1.000000	-0.745168
		(0.07731)

Adjustment coefficients (standard error in parentheses)

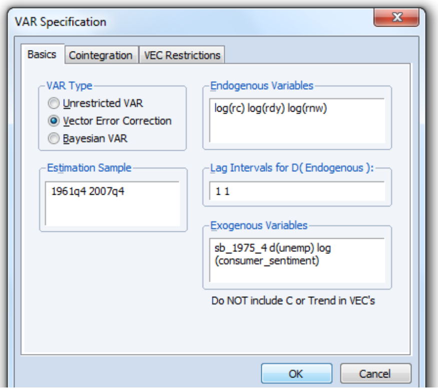
D(LOG(RC))	-0.081259	0.057877
	(0.04959)	(0.04104)
D(LOG(RDY))	0.166484	-0.156723
	(0.06180)	(0.05115)
D(LOG(RNW))	0.340789	-0.270681
	(0.12842)	(0.10629)

So we now have strong evidence that there exists one long run relationship in our model.

<u>VECM</u>

We now construct an Error Correction Model (ECM) that can explain the actual behaviour of consumption during the sample period.

Note how we use the unemployment rate D(UNEMP) and the consumer confidence index Log(CONSUMER_SENTIMENT) as exogenous variables. These variables are proxies for changes in the level of income uncertainty facing the household sector.



Effectively, we are allowing for the fact that these two variable can influence the Short Run dynamic behaviour of Consumption.

Here is the top half of the output from this model. It shows the Long Run part of our model and effectively our long run model is: log(RC) = -1.47 + 0.88 log(RDY) + 0.13 log(RNW)

Notice the positive rather than negative coefficients, this is because EViews normalises the results with all the variables on the LHS and the equation set equal to Zero.

Vector Error Correction Estimates
Date: 01/06/16 Time: 17:43
Sample: 1961Q4 2007Q4
Included observations: 185
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
LOG(RC(-1))	1.000000
LOG(RDY(-1))	-0.880073 (0.03558) [-24.7351]
LOG(RNW(-1))	-0.138658 (0.02921) [-4.74684]
C	1.471620

The lower part of the output shows the Error Correction term for the (lagged) residuals from our Log Run equation described above :

Error Correction:	D(LOG(RC))	D(LOG(RDY))	D(LOG(RNW))
CointEq1	-0.172499 (0.04089) [-4.21814]	0.102577 (0.06175) [1.66114]	0.084605 (0.13010) [0.65030]

Notice how the coefficient on the Consumption (log(RC)) variable [-4.21] is negative and significant and the coefficient of RDY [1.66] is positive. This makes sense as any correction from a state of disequilibrium would be expected to show that and increase in Consumption would lead to an increase in Disposable Income. The coefficient on Real Net Worth RNY, is less significant [0.65], this makes sense as the stock of Net Worth will have a much longer lag time from any increase in disposable income (eg: a long lag before it shows up in house price appreciation). This further confirms our hypothesis that we have cointegration.

Also looking at the two variables we added: Unemployment [-5.66] and Sentiment [5.48], the do indeed have the respective coefficients we would expect.

D(UNEMP)	-0.007664 (0.00135) [-5.66283]	-0.004488 (0.00204) [-2.19595]	0.001524 (0.00431) [0.35395]
LOG(CONSUMER_SEN TIMENT)	0.019015 (0.00347) [5.48058]	0.010113 (0.00524) [1.93037]	0.029187 (0.01104) [2.64415]

We now run a unit root test for the (log) level of consumer sentiment and the change in the unemployment rate and to verify they are separately consistent with our stationarity assumption. We can see both are stationary

Series: LOG(CONSUMER_SENTIMENT) Workfile: M1_DATAcusa_cy\

Augmented Dickey-Fuller Unit Root Test on LOG(CONSUMER_SENTIMENT)

Null Hypothesis: LOG(CONSUMER_SENTIMENT) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.862839	0.0517
Test critical values:	1% level	-3.465202	
	5% level	-2.876759	
	10% level	-2.574962	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LOG(CONSUMER_SENTIMENT))
Method: Least Squares
Date: 02/22/15 Time: 19:48
Sample: 1961Q1 2007Q4
Included observations: 188

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(CONSUMER_SENTIMENT(-1))	-0.107859	0.037676	-2.862839	0.0047
D(LOG(CONSUMER_SENTIMENT(-1)))	-0.192067	0.072339	-2.655097	0.0086
C	0.480680	0.168380	2.854727	0.0048

Series: D(UNEMP) Workfile: M1_DATAcusa_cy\

Augmented Dickey-Fuller Unit Root Test on D(UNEMP)

Null Hypothesis: D(UNEMP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.572965	0.0000
Test critical values:	1% level	-3.465202	
	5% level	-2.876759	
	10% level	-2.574962	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(UNEMP,2)
Method: Least Squares
Date: 02/22/15 Time: 19:45
Sample: 1961Q1 2007Q4
Included observations: 188

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(UNEMP(-1))	-0.539604	0.062942	-8.572965	0.0000
C	-0.006552	0.021580	-0.303585	0.7618

<u>Restricted VECM</u>

We will now create our ECM model with the restriction placed on RNY.

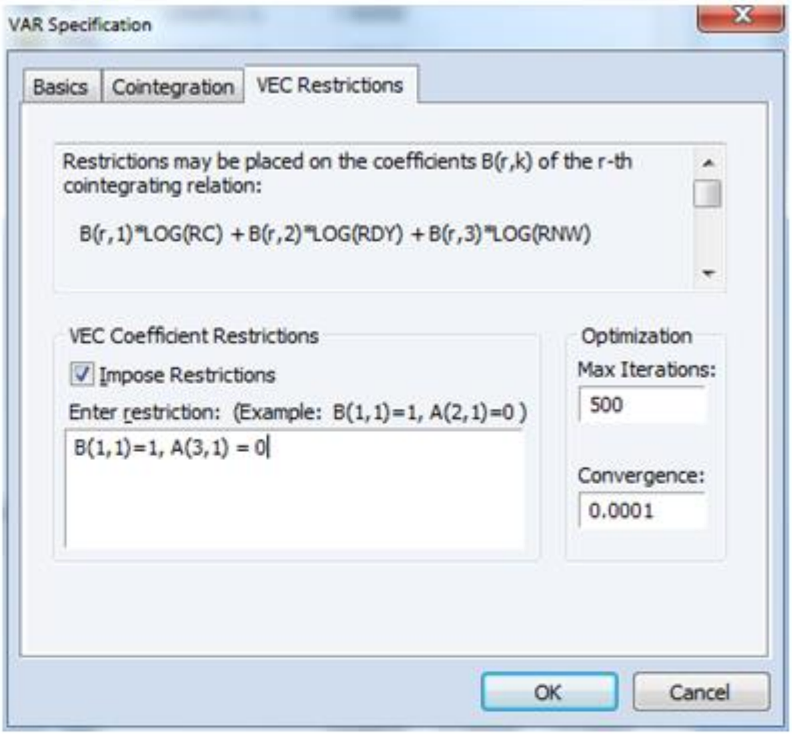
Here is part of the output from our VECM model. We can see the restriction placed on Real Net Wealth. We have imposed weak exogenity on Real Net Worth.

Error Correction:	D(LOG(RC))	D(LOG(RDY))	D(LOG(RNW))
CointEq1	-0.176020	0.090362	0.000000
	(0.03898)	(0.05918)	(0.00000)
	[-4.51615]	[1.52685]	[NA]

The results of the estimation suggest that in the long run, Income and Wealth have a positive and significant effect on Consumption, with Real Wealth being Weakly Exogenous at the 5% confidence level, since both consumption and income are endogenous (flow) variables and dependent on each other, while Real Wealth (a stock) takes time to react to disequilibria in consumption relative to its long-run path.

We account for the weak exogeneity of log(RNW) by imposing “A(3,1) = 0" on the fitted model.

This will be the final model from which we will run forecasting.



The results of this suggest we can accept the null hypothesis at 5% that log(RNW) can be treated as weakly exogenous.

Forecasting

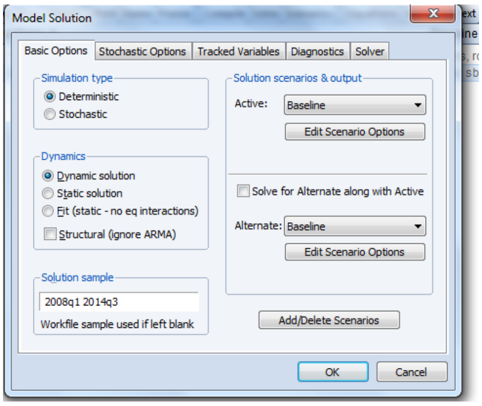
We will now forecast the US savings rate for the crisis and post crisis period 2008:1 - 2014:3. As we are forecasting the Savings Rate, we need to add the following accounting identity:

Our equation is adapted from the U.S. National Income and Product Accounts (NIPA) -

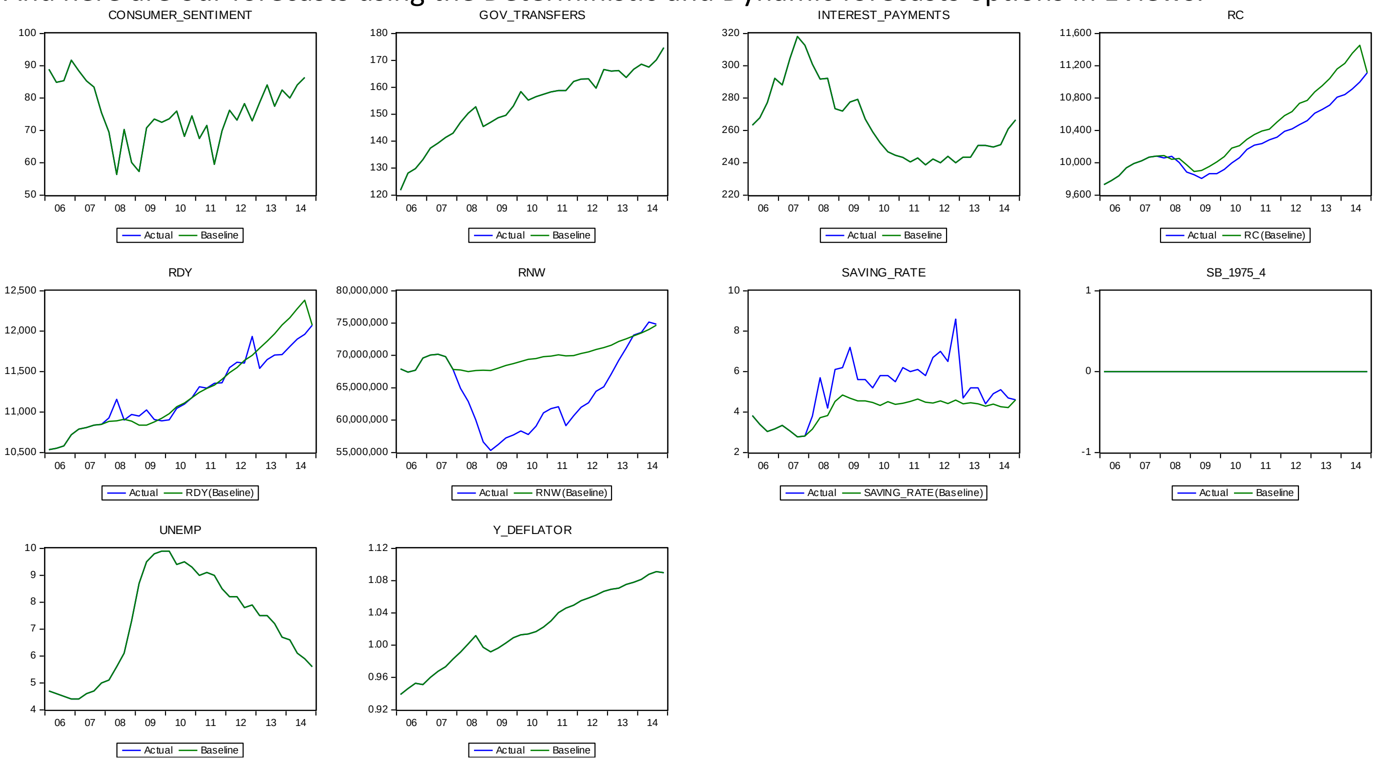
saving_rate=100*(rdy - (rc + ((gov_transfers + interest_payments/y_deflator))))/rdy

We do this because we are predicting real values not nominal values and so need to add the deflator element to account for this.

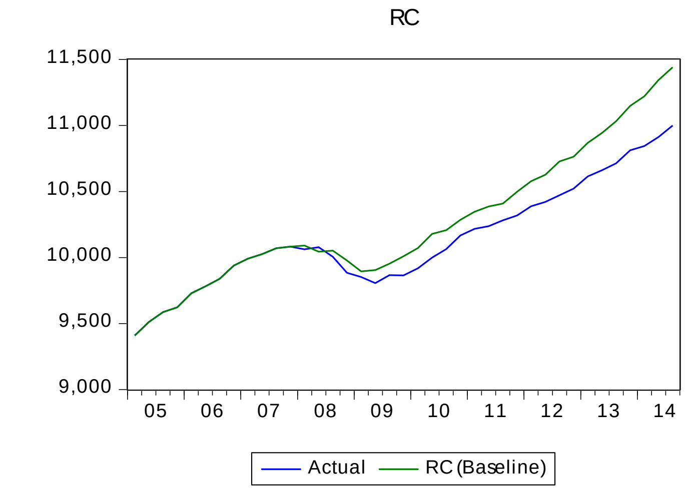
We calculate the deterministic (or point) baseline forecast series for 2008:1 – 2014:3 using “solve” command:

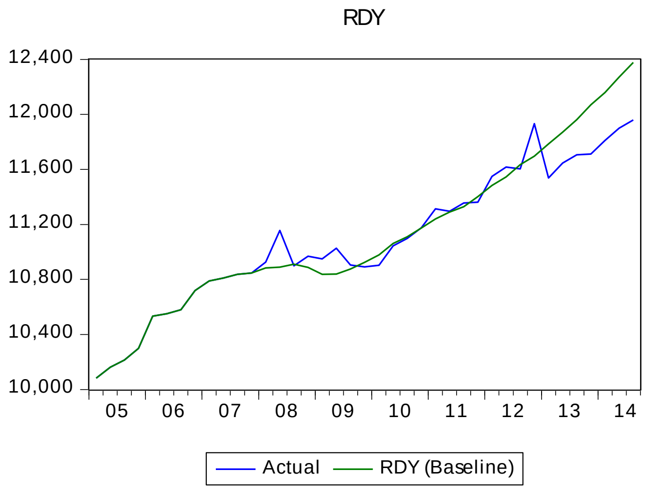


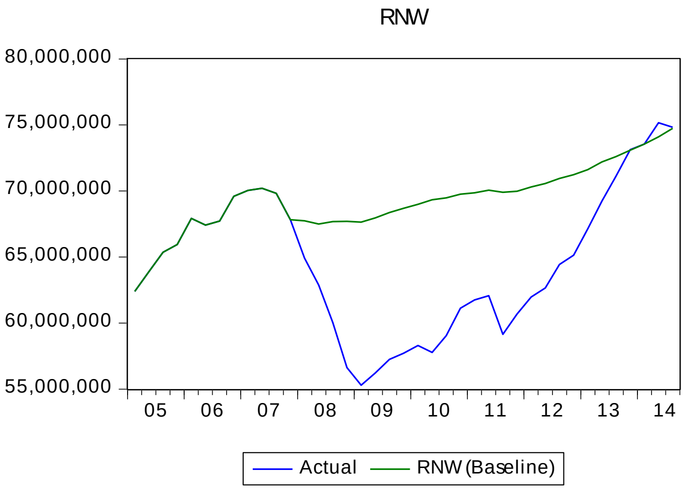
And here are our forecasts using the Deterministic and Dynamic forecasts options in EViews.

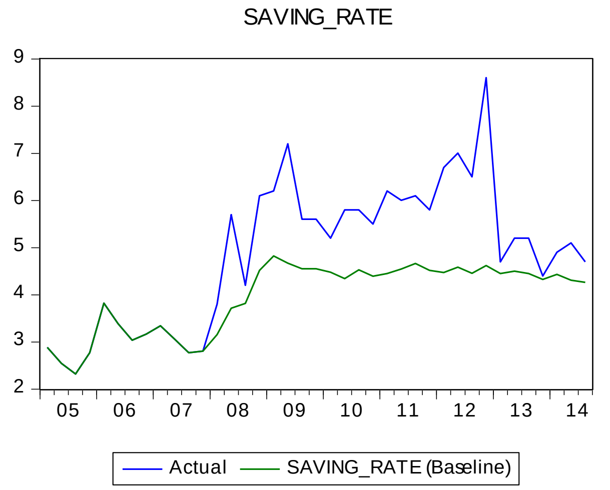


Taking a closer look at the variables we care about:









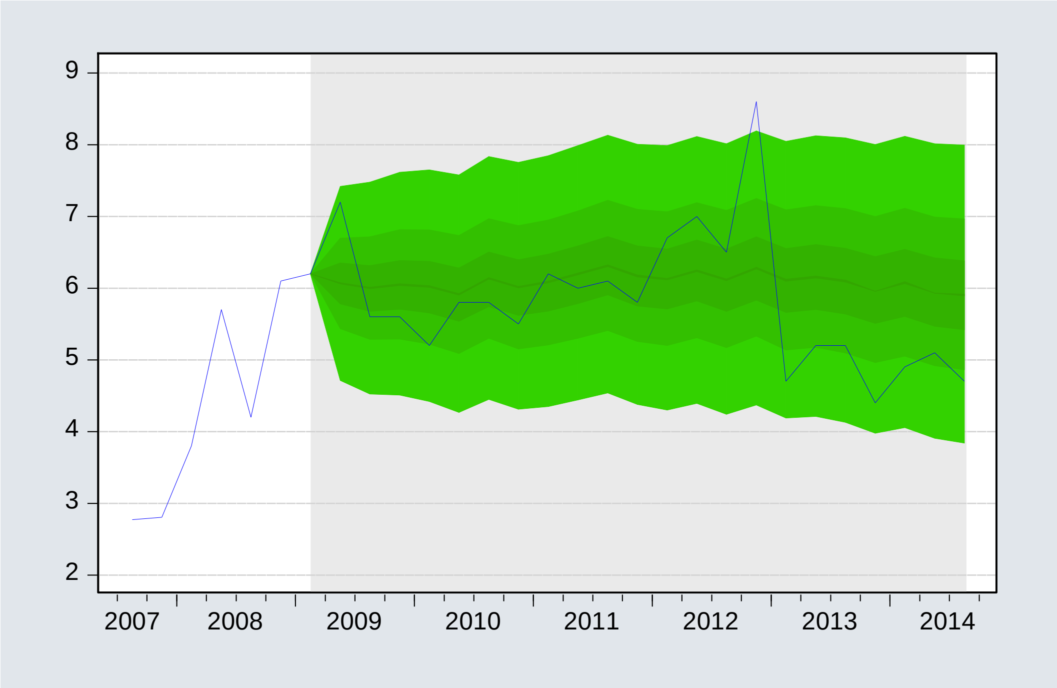
Looking closer at the forecast for RC, we can see we are consistently over predicting, now where could this be coming from? Well, note our RDY forecast does a pretty good job, but our model is Over predicting RNW and therefore Over predicting RC. As a corollary we are seeing an Under prediction for the Saving Rate, which logically follows.

So we can say that the Dynamic simulation (using EViews) tends to under predict the Saving Rate, but that our model is Specified correctly, it just does a weaker job of estimating the RNW variable.

This reflects the I(1) nature of the variables involved, the limited serial correlation in their innovation sequences, and the fact that prior to 2008 both variables were trending upwards.

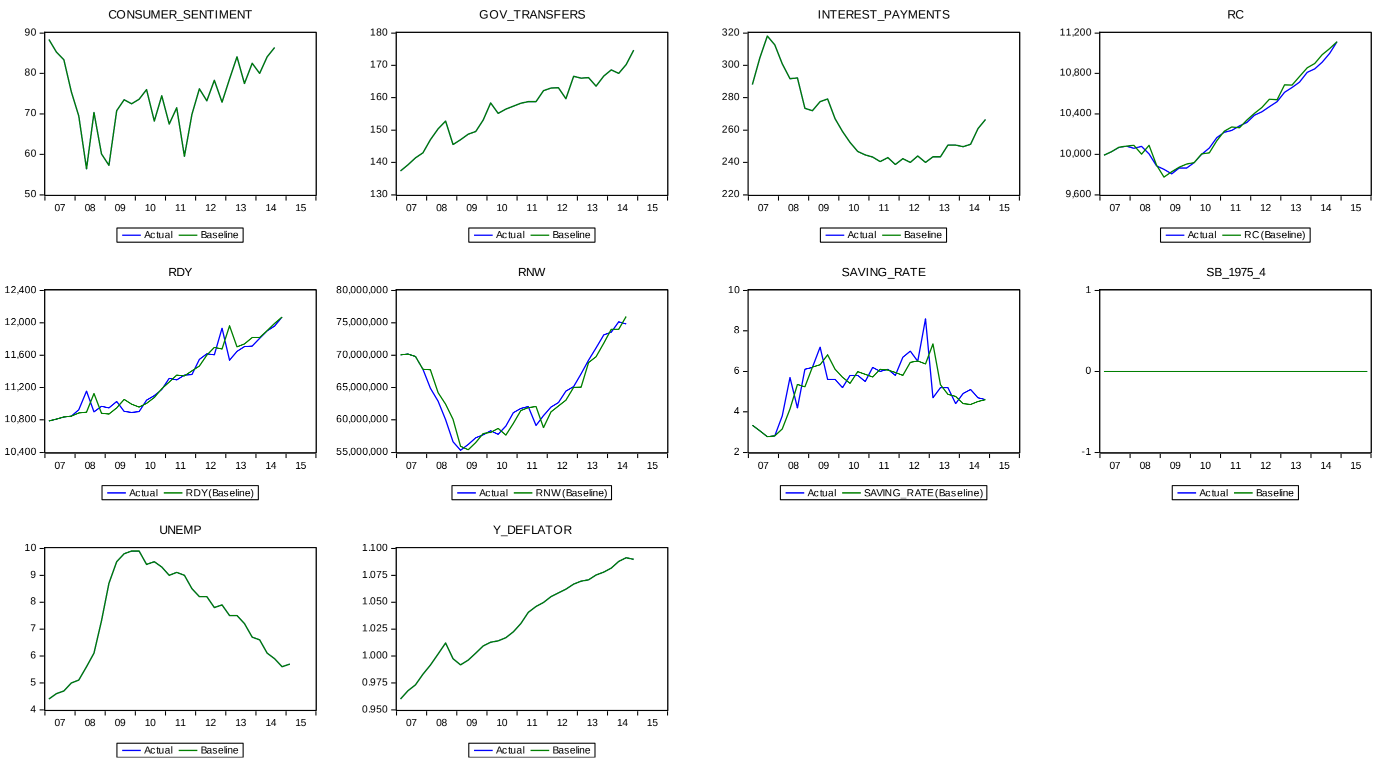
Because of their I(1) nature, a dynamic forecast will effectively use the last known value of these variables to generate out-of-sample forecasts. Consequently, the forecasting model does not do good job of predicting the impact of the global financial crisis on real consumption, and its predictions for the saving ratio appear to be systematically below the actual saving outcome.

As the previous analysis considers only a single, dynamic simulation using the baseline model. A better assessment of the model can be made using the stochastic simulator to produce a fan chart.



The fan chart shows that the model is useful in predicting the Saving Rate, as the fan chart mostly encompasses the actual Saving Rate. Note the slight downward bias in the forecast is due to the starting data (if we moved the start date forward a few quarters the trend would be closer to the flat line).

Now we will use a “Static” forecast which should be more accurate as the forecast errors do not build up as in the previous dynamic forecast:



We can see the forecast in this case is much closer to the actual data. Given that we are conducting an out-of-sample forecast, the superior forecast of the static solution implies that the forecasting error in the consumption equation is largely from the errors in forecasting RDY and RNW, not from changes in the estimated parameters.

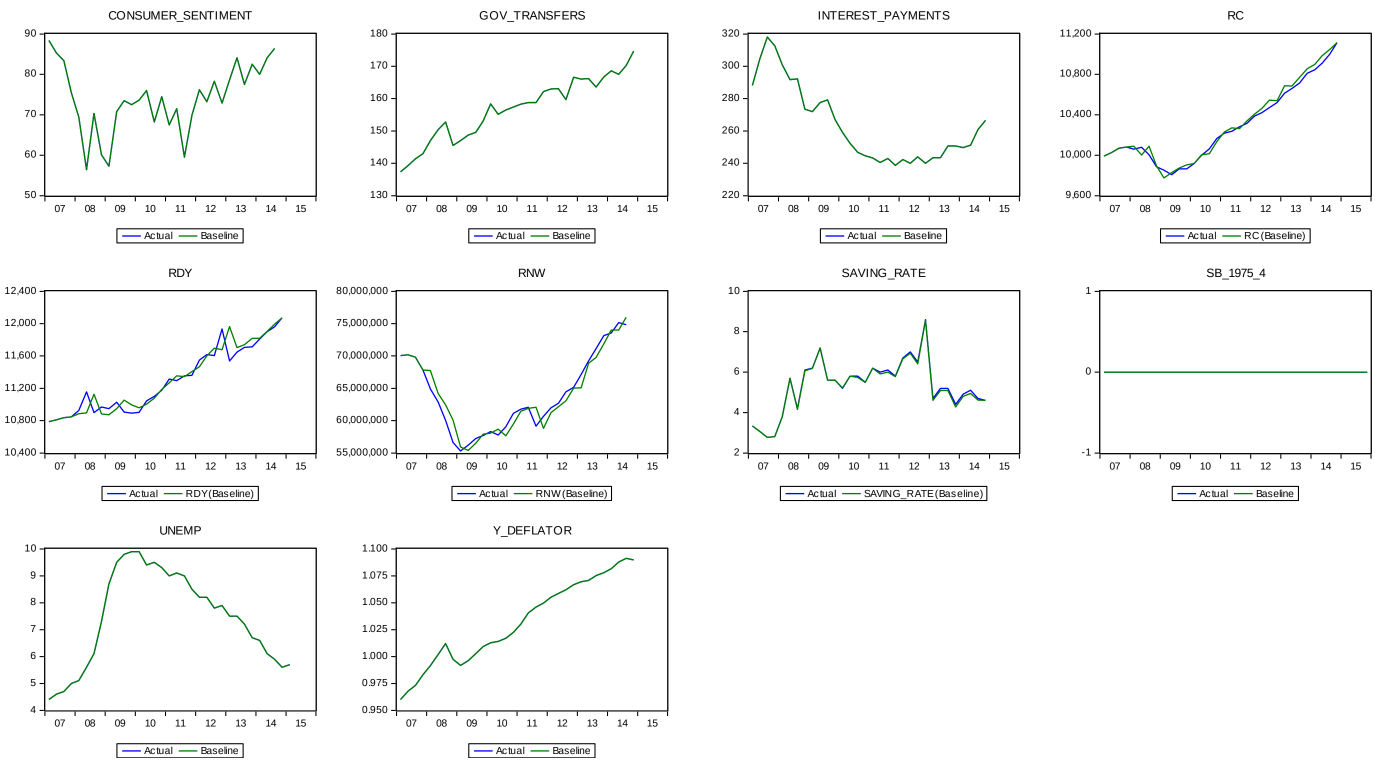
This experiment provides suggestive evidence that there is no structural change in the consumption function/saving behaviour. The increase in the saving ratio can be predicted rather well using the (lagged, actual) values of real income and real net worth.

This improved performance implies the forecasting error in the consumption equation may stem largely from the errors in forecasting disposable income and net worth.

We can go even further and use a “single equation forecast” This is the forecast that ignores all the interactions between the endogenous variables in the model. In this mode, the simulator is in effect using the actual values of income and net worth to produce the forecast of consumption, and hence, the saving ratio. Moreover, the dynamic interdependencies in the system are “turned-off” so that there are no equation interactions between periods.

A comparison of the “fit” forecast against the actual outcome of the saving ratio will reveal whether the model – with parameter estimates derived using data prior to the crisis – can forecast the out-of-sample saving ratio. It is essentially the Chow Forecast Test for structural stability, using parameter estimates derived from a system estimator (i.e., VECM).

The results here are even more impressive:



This result provides further evidence that the major driving forces behind the increase in the saving ratio during the great recession were the negative shocks to income and net worth, not a change in the underlying saving behaviour (specifically, the response of real consumption to income and net worth) of the American household.

We therefore conclude that one should expect the saving ratio in the post-crisis period to revert to its norm (i.e., lower) level once real income (and wealth) levels recover to pre-crisis levels.

Lastly, let's use the basic long-run equation involving log(rc), log(rdy) and log(rnw) to perform a simple out-of-sample forecasting experiment. Using ordinary least squares, run a regression of log(rc) on log(rdy), log(rnw), the structural break dummy (i.e., sb_1975_4) and a constant over the period 1961Q1 to 2014Q3.

Estimates shown here:

Equation: LR_MODEL Workfile: M1_DATA::usa_cy\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: LOG(RC)
Method: Least Squares
Date: 03/02/15 Time: 17:26
Sample (adjusted): 1961Q1 2014Q3
Included observations: 215 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.817128	0.073472	-24.73215	0.0000
LOG(RDY)	0.826511	0.012270	67.36177	0.0000
LOG(RNW)	0.186085	0.010196	18.25032	0.0000
SB_1975_4	-0.024609	0.002743	-8.970575	0.0000

R-squared	0.999640	Mean dependent var	8.535303
Adjusted R-squared	0.999635	S.D. dependent var	0.513828
S.E. of regression	0.009822	Akaike info criterion	-6.389916
Sum squared resid	0.020356	Schwarz criterion	-6.327207
Log likelihood	690.9160	Hannan-Quinn criter.	-6.364579
F-statistic	195143.6	Durbin-Watson stat	0.713000
Prob(F-statistic)	0.000000		

We now conduct a "Chow Forecast Test", which calculates an F-statistic that assesses whether the forecasts from the within sample regression (above) can predict out-of-sample results (in this case, real consumption for 2008Q1 – 2014Q3)

The small value of the F-statistic suggests that there is no structural break in the long-run relationship.

Equation: FINAL_REGRESSION Workfile: M1_DATA::usa_cy\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Chow Forecast Test
Equation: FINAL_REGRESSION
Specification: LOG(RC) C LOG(RDY) LOG(RNW) SB_1975_4
Test predictions for observations from 2008Q1 to 2014Q3

	Value	df	Probability
F-statistic	0.957963	(27, 181)	0.5294
Likelihood ratio	28.31671	27	0.3948

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.002536	27	9.39E-05
Restricted SSR	0.020286	208	9.75E-05
Unrestricted SSR	0.017749	181	9.81E-05
Unrestricted SSR	0.017749	181	9.81E-05

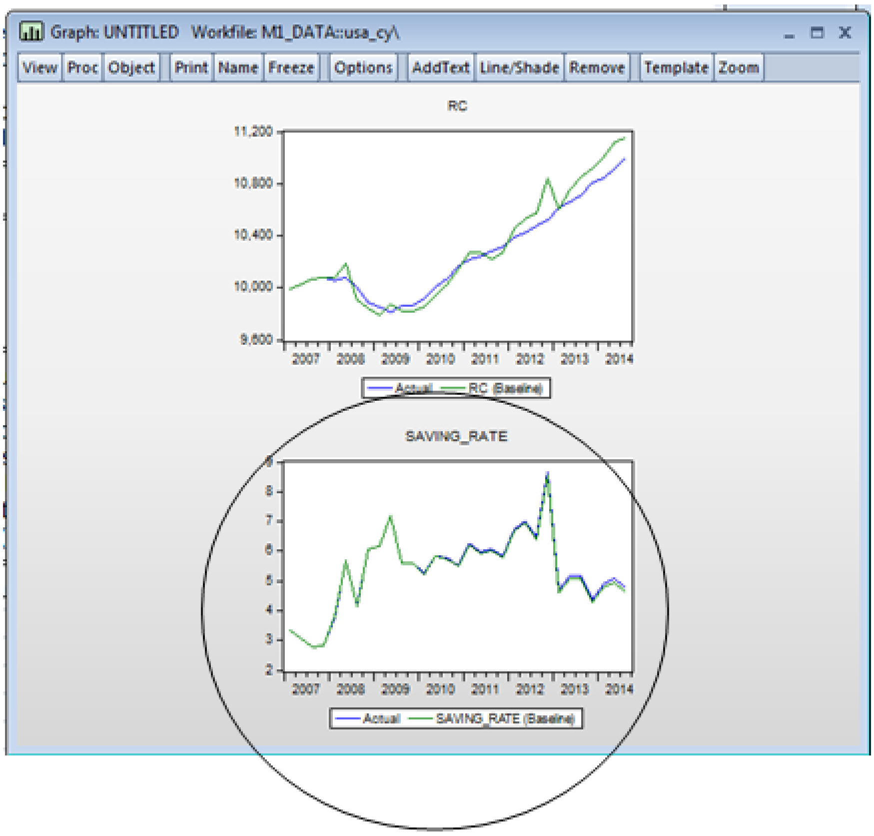
LR test summary:

	Value	df
Restricted LogL	680.1534	208
Unrestricted LogL	694.3118	181

Unrestricted log likelihood adjusts test equation results to account for observations in forecast sample

Unrestricted Test Equation:
Dependent Variable: LOG(RC)
Method: Least Squares
Date: 12/24/15 Time: 00:42
Sample: 1961Q4 2007Q4
Included observations: 185

We use the regression above to predict the out-of-sample saving ratio over the 2008Q1 – 2014Q3 horizon



The result implies : The long-run model without any short-run dynamics is able to produce acceptable out-of-sample forecasts of real consumption and the household saving ratio. Yet further evidence there has not been a structural change in U.S. household consumption habits because of the global financial crisis.

<u>Conclusions</u>

The underlying relationship between real consumption, real disposable income and real net worth did not change because of the onset of the financial crisis

The observed movements in the saving rate after 2008:1 appear to be the result of changes in disposable income and real net worth, the latter in particular being adversely affected by the financial crisis.

Given that the coefficient estimates have not changed significantly, one can expect the saving rate: to return to its pre-2008 level once the lingering effects of the financial crisis abate (that is, if real income and real net worth return to their 2007 levels respectively). And: to remain persistently higher that its pre-2008 level if the effects of the financial crisis persisted (that is, real income and real net worth did not return to their 2007 levels respectively).