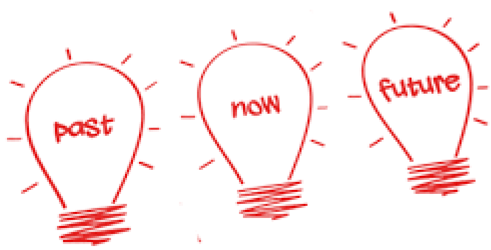

TIME SERIES FORECASTING

ABSTRACT

An analysis on US savings rate data to identify the adequate time series model, estimate the parameters, and forecast two years into the future.
Tool used: SAS

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Executive Summary

Saving rate is defined as personal saving as a percentage of total disposable personal income. Economists believe that shifts in this rate contribute to business fluctuations. When people save more of their income they spend less for goods and services which could reduce gross and net national product.

In this case study we analyze 100 quarterly observations of the U.S. saving rate for the years 1955~1979. The data has been seasonally adjusted prior to publication by the U.S. Department of Commerce, which means we do not need to separately identify any non-stationary property in the time series. The tool used is SAS.

In the sections below which are named – model identification, estimation, and forecasting – we go

- Identify the right model (AR / MA / ARMA) based on correlations from the data,
- Estimate the parameters (p, q) so that we have the right residual diagnostics and the simplest possible model, and
- Forecast the savings rate for the next two years, conditional on the past observed data.

Model Identification and Estimation

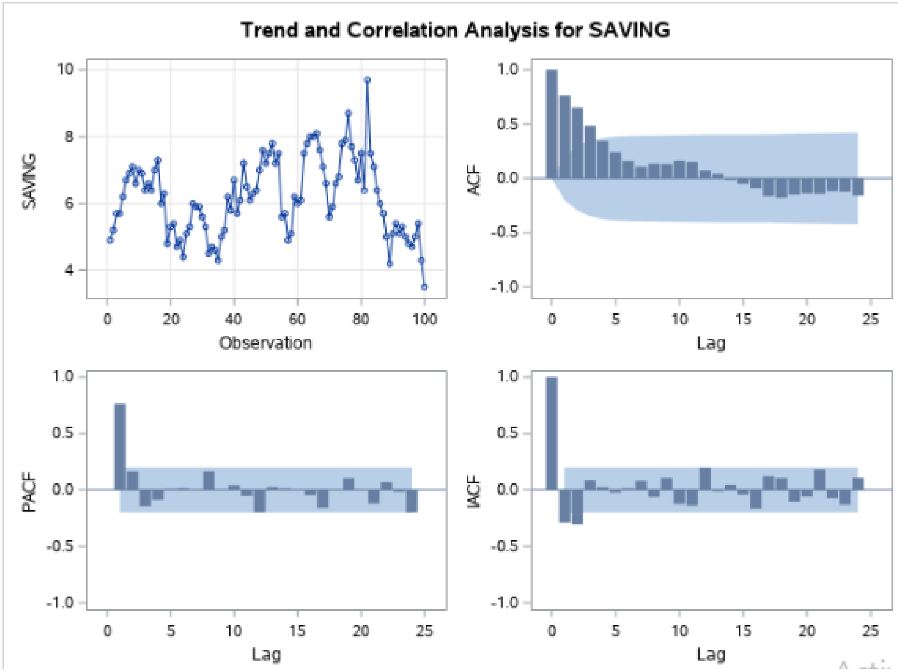
We read the data into SAS. Let us a have a look at the data, at least the first few observations.

Obs	DATE	SAVING	ONE
1	55Q1	4.9	1
2	55Q2	5.2	1
3	55Q3	5.7	1
4	55Q4	5.7	1
5	56Q1	6.2	1
6	56Q2	6.7	1
7	56Q3	6.9	1
8	56Q4	7.1	1
9	57Q1	6.6	1
10	57Q2	7.0	1

We use 'PROC ARIMA IDENTIFY' to inspect the ACF and PACF of the time series data.

```
/*Identifying model*/
proc arima data = CASE;
identify var = SAVING;
run;
/*From the plot...PACF cuts off at 1 and ACF exponentially declines...we will try fitting AR(1)*/

/*Fit AR(1)*/
proc arima data = CASE;
identify var = SAVING;
estimate p = 1 plot;
run;
```

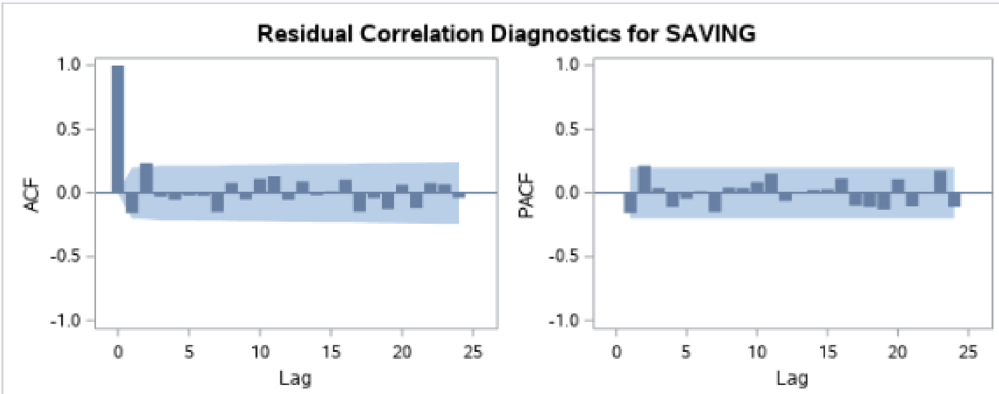


Observations:

- The ACF looks to decrease exponentially.
- The PACF appears to be cutting off at a lag of 1.
- These symptoms are those of an AR(1) model. So we tried to fit an AR(1) – output below

Conditional Least Squares Estimation					
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	5.81151	0.36834	15.78	<.0001	0
AR1,1	0.82620	0.06286	13.14	<.0001	1

Autocorrelation Check of Residuals									
To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	8.61	5	0.1255	-0.151	0.239	-0.022	-0.047	-0.013	-0.015
12	15.69	11	0.1530	-0.143	0.083	-0.044	0.115	0.135	-0.046
18	20.75	17	0.2376	0.095	-0.009	0.017	0.110	-0.139	-0.031
24	26.56	23	0.2753	-0.119	0.071	-0.112	0.084	0.074	-0.029



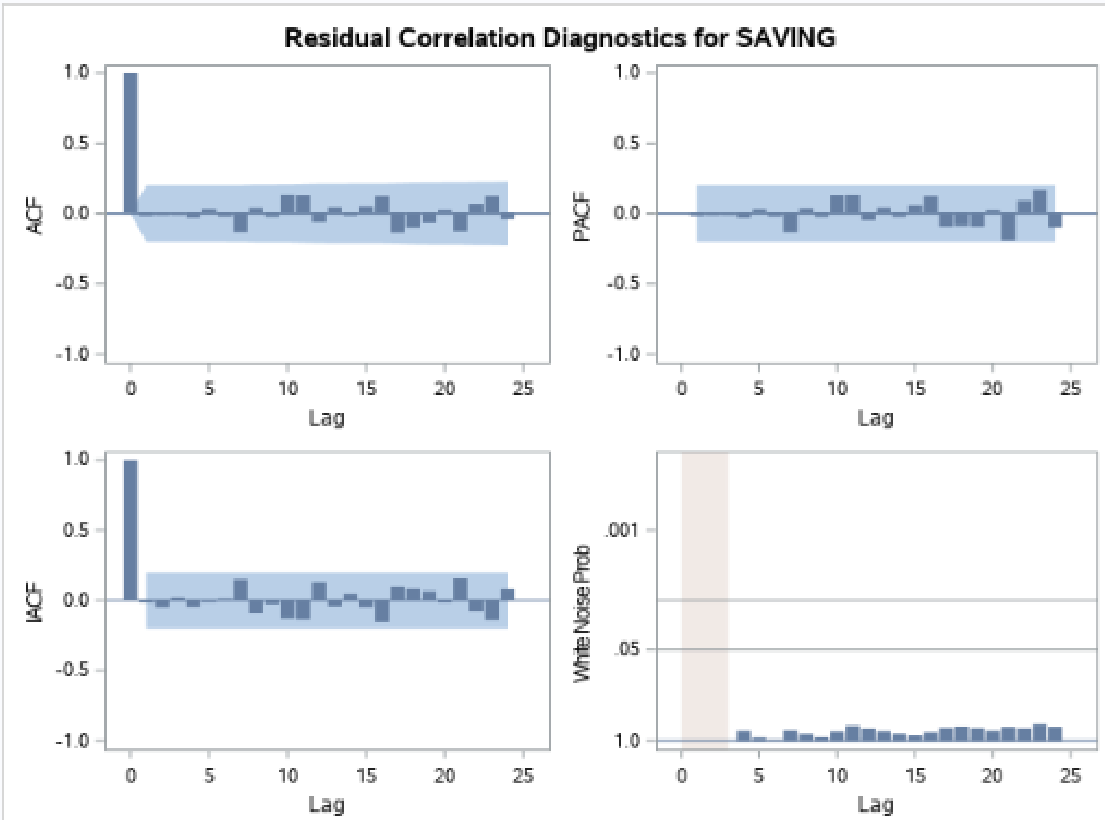
Observations:

- The parameter AR1, 1 comes out to be statistically significant which is a good sign for us.
- However, the ACF of residuals still doesn't match the properties of a white noise yet. Since it cuts-off at 2, we feel we need to add an MA(2) component. This is also validated from the residual autocorrelation table.
- So we fit an additional MA(2) component and continue to diagnose.

```
/*Fit ARMA(1,2)*/
proc arima data = CASE;
identify var = SAVING;
estimate p = 1 q = 2 plot;
run;
```

Conditional Least Squares Estimation					
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	5.73975	0.37535	15.29	<.0001	0
MA1,1	0.08073	0.12028	0.67	0.5037	1
MA1,2	-0.30654	0.11214	-2.73	0.0075	2
AR1,1	0.79878	0.08897	8.98	<.0001	1

Autocorrelation Check of Residuals									
To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	0.21	3	0.9761	-0.007	-0.001	-0.001	-0.020	0.037	-0.011
12	6.80	9	0.6584	-0.123	0.046	-0.014	0.140	0.136	-0.052
18	12.51	15	0.6404	0.052	-0.005	0.058	0.132	-0.124	-0.088
24	18.11	21	0.6421	-0.056	0.032	-0.117	0.077	0.135	-0.028

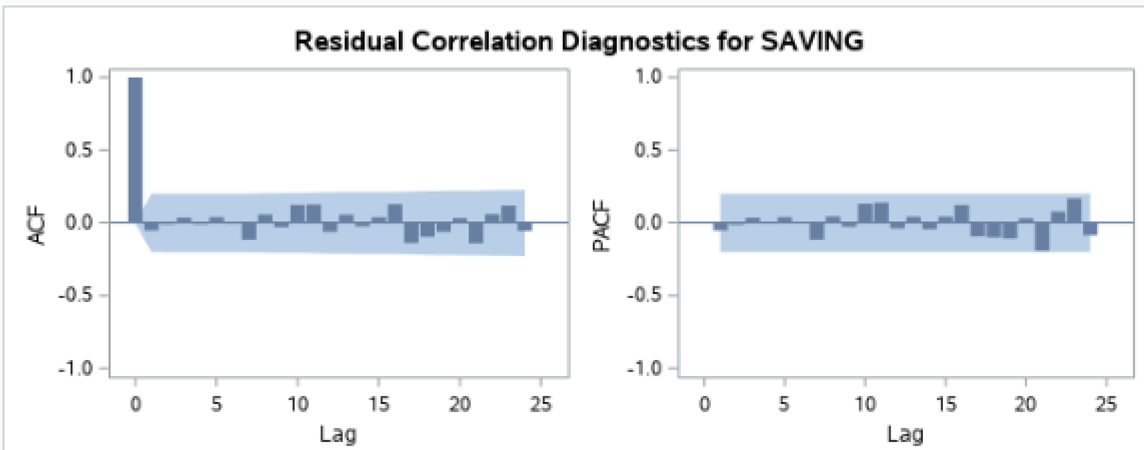


Observations:

- From the output we see that all parameters except MA1,1 are significant. We should bring in some remedy for this.
- Also, ACF and PACF of residuals behave almost like those of white noise.
- However, we should simplify the model here since MA1, 1 is not significant.
- We try to shrink the MA1,1 parameter in the ARMA(1, 2) model.

```
/*Fit ARMA(1,2) suppressing MA1,1*/
proc arima data = CASE;
identify var = SAVING;
estimate p = 1 q = (2) plot;
run;
```

Conditional Least Squares Estimation					
Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MU	5.79867	0.33940	17.08	<.0001	0
MA1,1	-0.33434	0.10617	-3.15	0.0022	2
AR1,1	0.75532	0.07765	9.73	<.0001	1



Model for variable SAVING	
Estimated Mean	5.798668

Autoregressive Factors	
Factor 1:	1 - 0.75532 B**(1)

Moving Average Factors	
Factor 1:	1 + 0.33434 B**(2)

Observations:

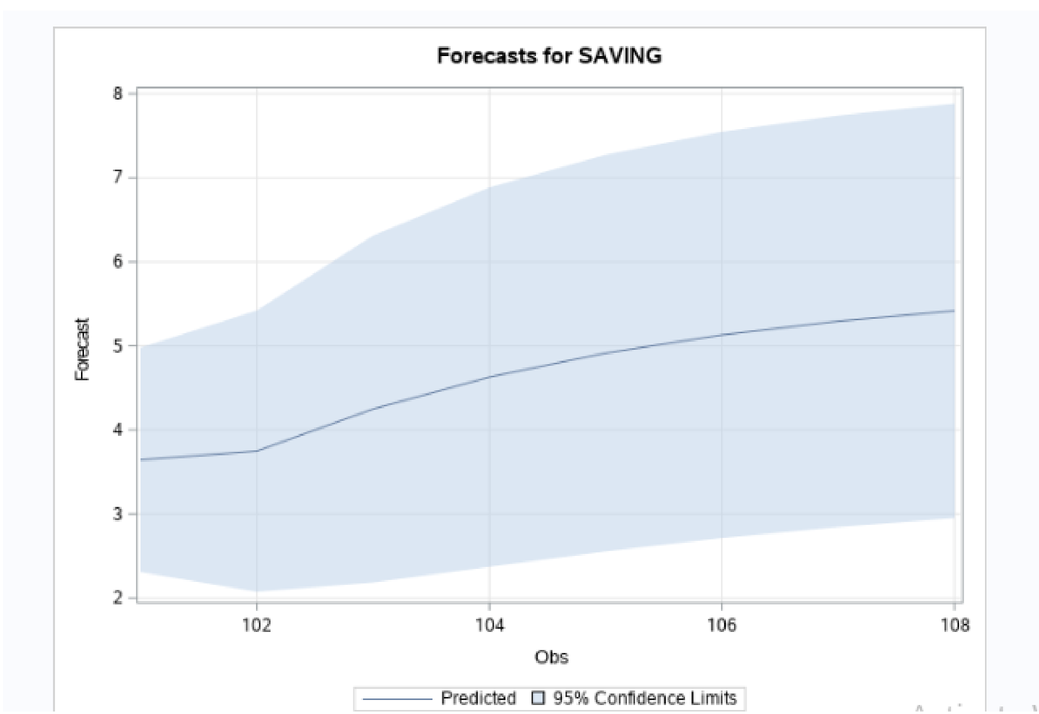
- Now, the residuals ACF and PACF have stabilized better towards those of white noise.
- So our final ARMA (1, 2) model parameters (mu, phi_1, and theta_2) are as shown above.
- So we now move to forecasting.

Forecasting

We forecast savings rate for the next 8 quarters (2 years) using PROC ARIMA FORECAST in SAS.

```
/*Forecast for next two years*/
proc arima data = CASE;
identify var = SAVING;
estimate p = 1 q = (2) plot;
forecast lead = 8;
run;
```

Forecasts for variable SAVING				
Obs	Forecast	Std Error	95% Confidence Limits	
101	3.6452	0.6815	2.3095	4.9810
102	3.7489	0.8541	2.0749	5.4229
103	4.2504	1.0534	2.1857	6.3151
104	4.6292	1.1518	2.3717	6.8868
105	4.9154	1.2044	2.5549	7.2759
106	5.1315	1.2333	2.7142	7.5488
107	5.2947	1.2496	2.8457	7.7438
108	5.4180	1.2587	2.9510	7.8851



Above are the predictions for 2 years, along with the 95% confidence intervals for each of the predictions.