Analysis of Consumer Credit Time Series

January 1993 through December 2002

Submitted to

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Submitted by

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Abstract

This paper studies different univariate forecasting models for consumer credit. The time series in the study is composed of consumer credit from January 1993 through December 2002. The last eighteen observations of the series are withheld in each model in order to compare the fitted versus forecasted values. The study results show that the decomposition model outperformed all other competing models in forecasting. The resulting forecasting equation is:

$$\hat{Y}_t = (862337.6 + 7991.38t)\, S_t$$

where t is the time period and S_t is the seasonal index for that time period

The decomposition model, however, was not the best model in fitting the series. Conversely, the best model in fitting the data (Winters) was not very useful in forecasting the series.

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I. Introduction

There is agreement in the economic literature that institutional factors such as financial innovations in the consumer credit industry contributed to the trend of exponential growth in consumer credit. However, some economists tend to argue that in addition to financial innovations, consumer credit growth may be due also to macroeconomic bias in recent years for balanced budget or even surpluses. These analysts argue that in a situation of austere budget stance, in order to achieve a modest rates of economic growth, consumers had to borrow on increasing scale (*most recently, see:* Wray, 2003 and Wray and Papadimitriou, 2003). Given the structural fiscal stance as well as the structural external negative balance, "moderate growth requires that the private sector run deficits" (Godley 1999; Godley and Izurieta, 2001; Papadimitriou et al, 2002). According to analyses published by The Levy Economics Institute (Godley 1999, 2003; Godley and Izurieta 2001; Godley and Wray 1999; Papadimitriou and Wray, 2001) the expansion was highly "unsustainable and faced an almost inevitable crash". According to these analysts the end of the consumer led growth had to come when households and firms tried to bring their spending back into line with their incomes. This would imply that in such a situation, there will be a slump in consumer credit too.[1]

Can we use the historical data of the past years to accurately forecast future growth in consumer credit, or do we need to relate the consumer credit series to multiple independent variables? To answer this question we assume that growth of financial innovation is a continuous trend and thus we assert that it can be treated as an exogenous factor. Therefore, if it is the case that financial innovation are responsible for growth in consumer credit, the series can be accurately forecasted using univariate model. On the other hand, if univariate models are not promising, it can be asserted that, as suggested by the analysts above, there are grounds for exploring the impact of structural macroeconomic conditions for the level of consumer credit.

This paper studies different univariate forecasting models for consumer credit. The time series in the study is composed of consumer credit from January 1993 through December 2002[2]. The data is seasonal (there are greater levels in consumer borrowing during Christmas holidays) and

[1] At this time, household debt may be still at high level, since consumers will be responsible for principal and interest payments for borrowing in the previous periods.

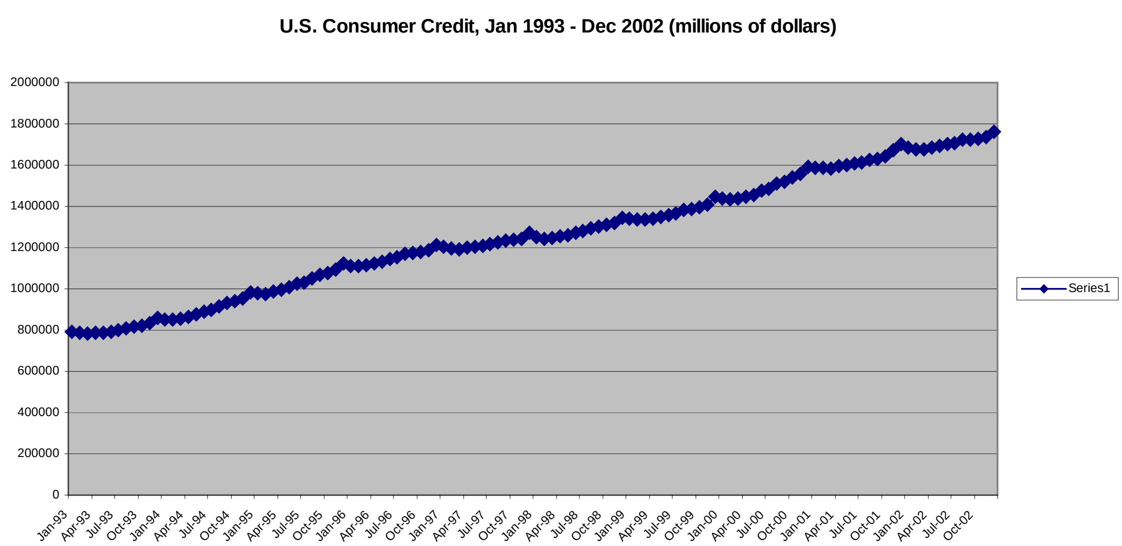
[2] Beginning with the October, 2003 release (of August data), the monthly G.19 consumer credit statistics incorporate student loans extended by the federal government and by SLM Holding Corporation (SLM)—the parent company of Sallie Mae. With this addition, the historical data on consumer credit has been revised back to 1977, which shifts the level of consumer credit about 3 percent on average between 1977:Q1 and 2003:Q2.

exhibits an exponential trend. The last 18 observations of the series are withheld in each model in order to compare the fitted versus forecasted values.

II. Data Description

The time series in the study is composed of consumer credit from January 1993 through December 2002. For this study we will look at seven different forecasting models, each presented as minicases 2 through 8. The model types included are naïve, simple seasonal, seasonal decomposition, Winter's, two variations of first differences, and finally ARIMA. For each minicase we will discuss the approach taken as well as the summary statistics for both the fit and the forecast. We will then review the forecasting performance of all models, look at their practical significance and finally draw a conclusion. Appendix A lists the raw data which is in the form of year, month, and consumer credit in millions of dollars. Figure I-A shows the plot of the raw consumer credit data, expressed in millions of dollars.

Figure I-A



As expected, the data is seasonal (there are greater levels in consumer borrowing during Christmas holidays) and exhibits an exponential trend. A review of the raw data revealed no obvious outliers.

III. Minicase 2

In this minicase two models are utilized, a naïve model and a seasonal naïve model. Data from July 1993 through June 2001 is used to fit the models, and the forecast is compared against July 2001 to December 2002 data.

The naïve model states that this month's consumer credit will be equal to last month.

$Y_t = Y_{t-1} + e1_t$

The graph in Figure II-A shows how the fitted model mirrors the actual data, lagging one month behind. The last 12 months of the graph represent the forecast, which is assumes that the value of the last period will repeat in the future.

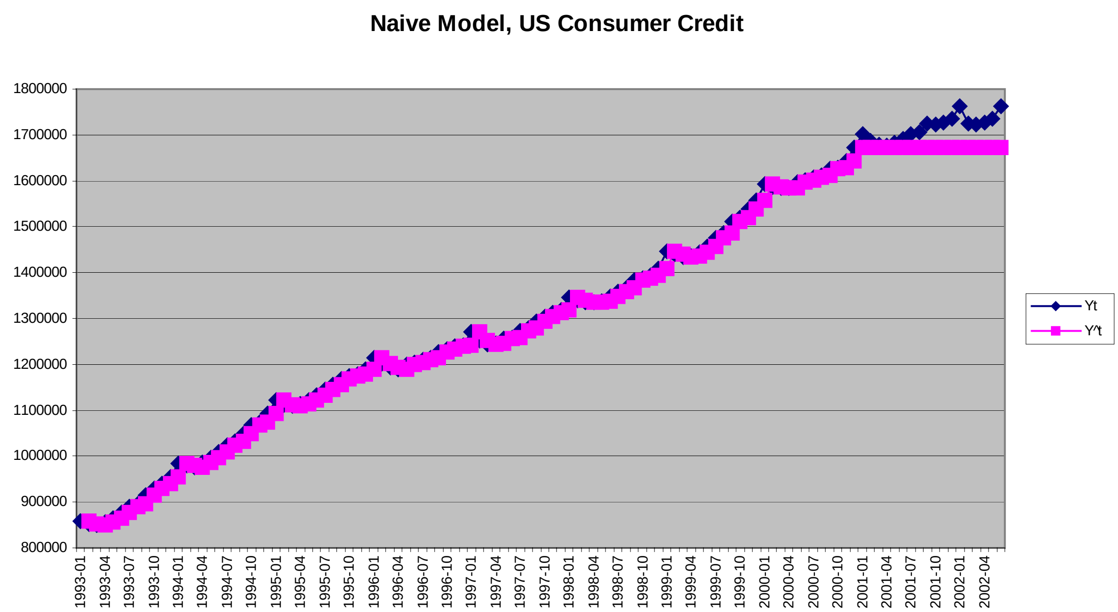


Figure II-A

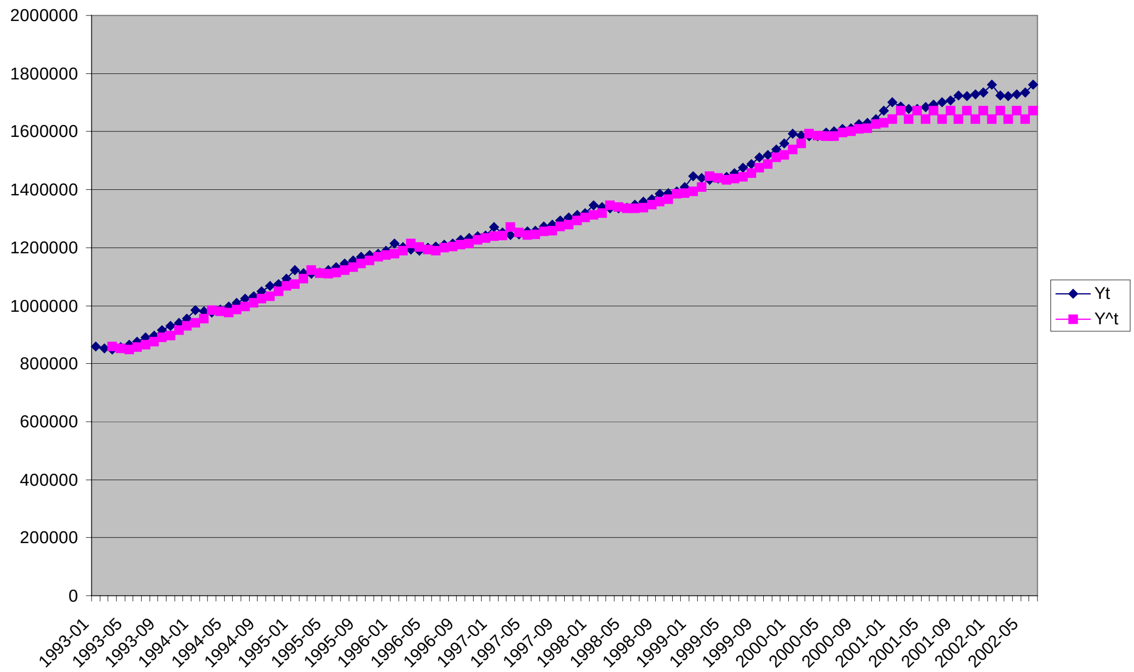
The seasonal naïve model states that this month's consumer credit will be equal to the consumer credit of one year ago.

$Y_t = Y_{t-12} + e2_t$

The seasonal naive fit and forecast of the last withheld 18 months are shown in Figure II-B below. The fit reflects the small seasonal peaks, but due to the upward trend, the fitted value is consistently underestimated. The forecasted values are also under estimated, since the model assumes a seasonality that is within the range of the values of the previous 18 periods, while the actual values continue their growing trend.

Figure II-B

Seasonal Naive, Fit and Forecast of last 12 months



<u>Analysis - Fit</u>

The mean error of the fitted naïve model is 8553.66. We would want this number to be as close to zero as possible. The mean error of the seasonal model is higher, 103027.27. As we have seen from the graphs, the seasonal model consistently underestimates due to the substantial upward trend in the series. Therefore the mean of this model does not benefit from the averaging of negative and positive errors, as does the naïve model.

The RSE for the naïve model is 13520 and 107968 for the seasonal. The standard deviation has increased and the confidence intervals have broadened by using the seasonal model. This suggests that selecting an appropriate lag period is less important than accounting for the upward trend.

The MPE for the naïve model is 0.006% and 0.080% for seasonal. It should be noticed that this statistic benefits from the naïve model's mix of positive and negative errors as opposed to the seasonal model's errors, which are all positive. The MAPE is 0.009% and 0.080%, very close for both models.

Since we are aware of the intrinsic benefit the naïve model has in terms of mean error and mean percentage error, we will look primarily at RSE and MAPE to determine the best model fit. Based on these two statistics, the naive model is the preferred fit.

Analysis - Forecast

The forecasted mean errors of the models are 43364 and 110176. Although the naïve model has only one known number to forecast off of – the next to last month of consumer credit, that model performs better on this statistic. The seasonal model does not result in a better projection.

The RSE for the forecasted naïve model is 64120 and 145619 for the seasonal. As with the fitted models, using the seasonal model has broadened the prediction interval. Again, the seasonal model is at a disadvantage when forecasting, so its forecasted RSE rose proportionally higher than the naive when compared against the fitted values.

The forecasted MPE for the naïve model is 0.025% and 0.064% for the seasonal. This figure is not much higher than fitted for the naïve. However, the seasonal model decreased from the fitted MPE. Finally, MAPE for the forecasts were the same as the MPE for each model. Neither model was able to fully accommodate the upward trend of the series, although the naive model showed better statistics.

Implications

Both models are not satisfactory. Employing the seasonal naive model shows that selecting an appropriate lag period is less important than accounting for the upward trend. Over the range of a single year, the seasonal model gives a bigger prediction interval. The seasonal model fared better in the conversion from fitted to forecasting. That model could be vastly improved if a good estimate of the trend is found.

IV. Minicase 5

In this minicase a model is developed using the time series decomposition method. This model breaks the data down into three components: trend, cycle, seasonal, and error.

The graph of actual values as shown in Figure I-A demonstrates a definitely upward trend and seasonality, with no apparent troughs and peaks. Therefore these series can be modeled with the equation:

Y_t = TSe

Where T = trend, S = seasonal influences, and e = error.

The first step in decomposition is to identify the seasonal component by calculating the seasonal moving averages. The unadjusted and final seasons indices derived are listed in Table III-A below.

The final seasonal indices are the monthly indices. Using them we calculate the deseasonalized values by dividing the actual consumer credit by the index. Excel’s regression tool is then used to fit a line to the deseasonalized values to determine the trend line.

Table III-A
Unadjusted and Final Seasonal Indices

Month	Average	Final Seasonal Index
1	1.022484	**1.02224219**
2	1.007871	**1.00763245**
3	0.996598	**0.99636145**
4	0.991963	**0.99172786**
5	0.992772	**0.99253703**
6	0.992381	**0.99214583**
7	0.994896	**0.99466033**
8	0.994053	**0.99381744**
9	1.000785	**1.0005474**
10	1.002121	**1.00188366**
11	1.001855	**1.00161782**
12	1.005065	**1.00482653**
Total:	12.00284	12

Figure III-A shows the actual and deseasonalized values along with the trend line.

The resulting equation is: Trend = 862,337.6 + 7,991.38t, where t = time period. Both the intercept and the coefficient are statistically significant.

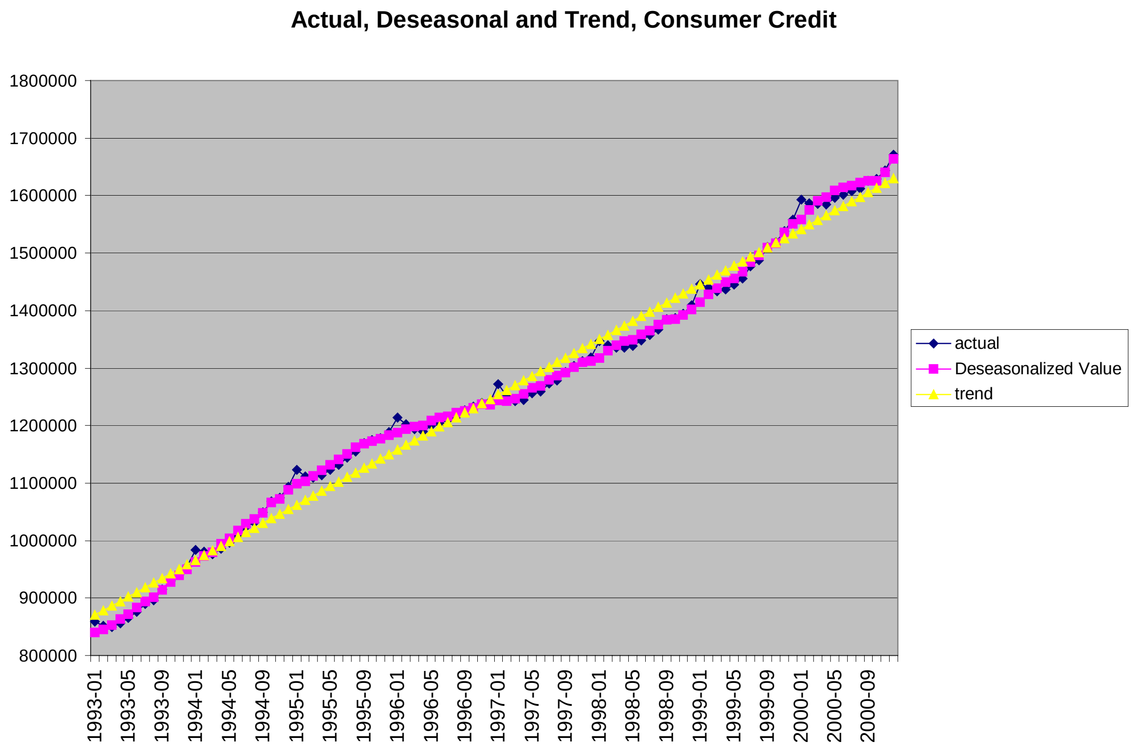


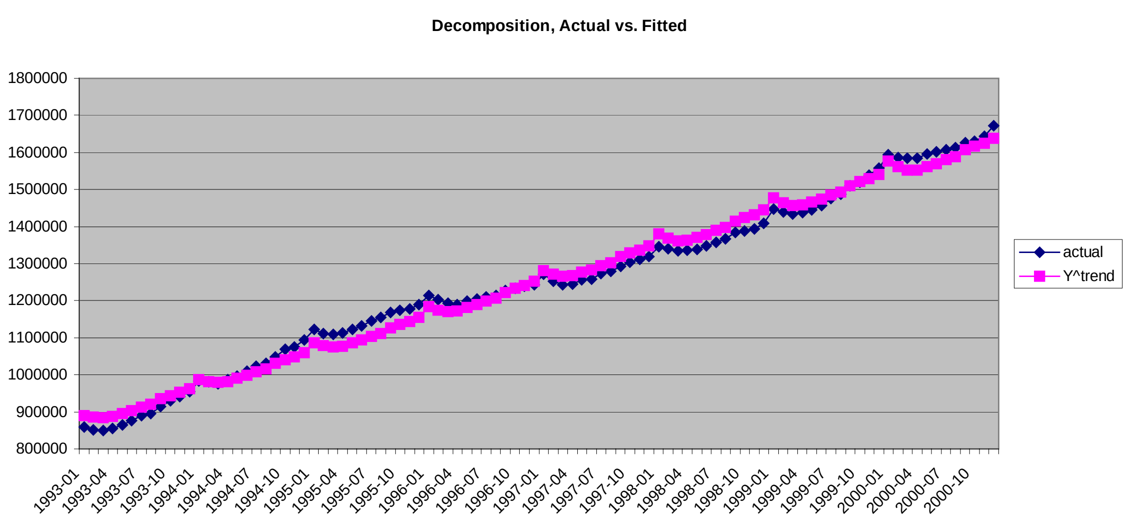
Figure III-A

Analysis-Fit

The series have now been decomposed into seasonal and trend components and we can fit data from 1993 to 2002 into the model.

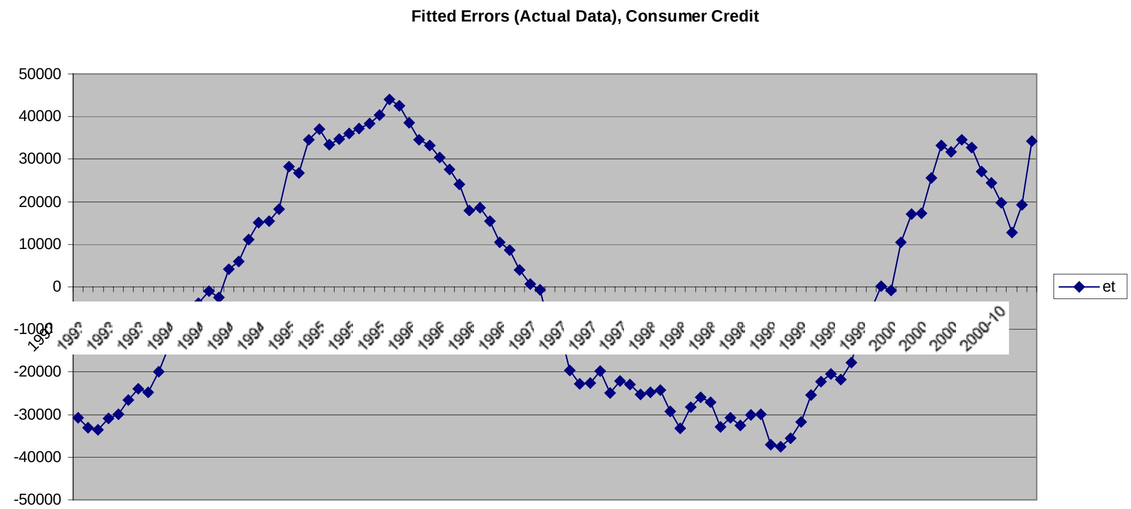
Figure III-B shows the fitted versus actual data. The model captures the trend and seasonality in fitting. However, the fitted values tend periodically to be bellow or above the actuals.

Figure III-B



This can be observed also by plotting the errors. Figure III-C, illustrates the variation of the fitted errors about zero, which show that the actual values are consistently under or above the fitted values of this model, as some of the errors are bellow and some above zero.

Figure III-C



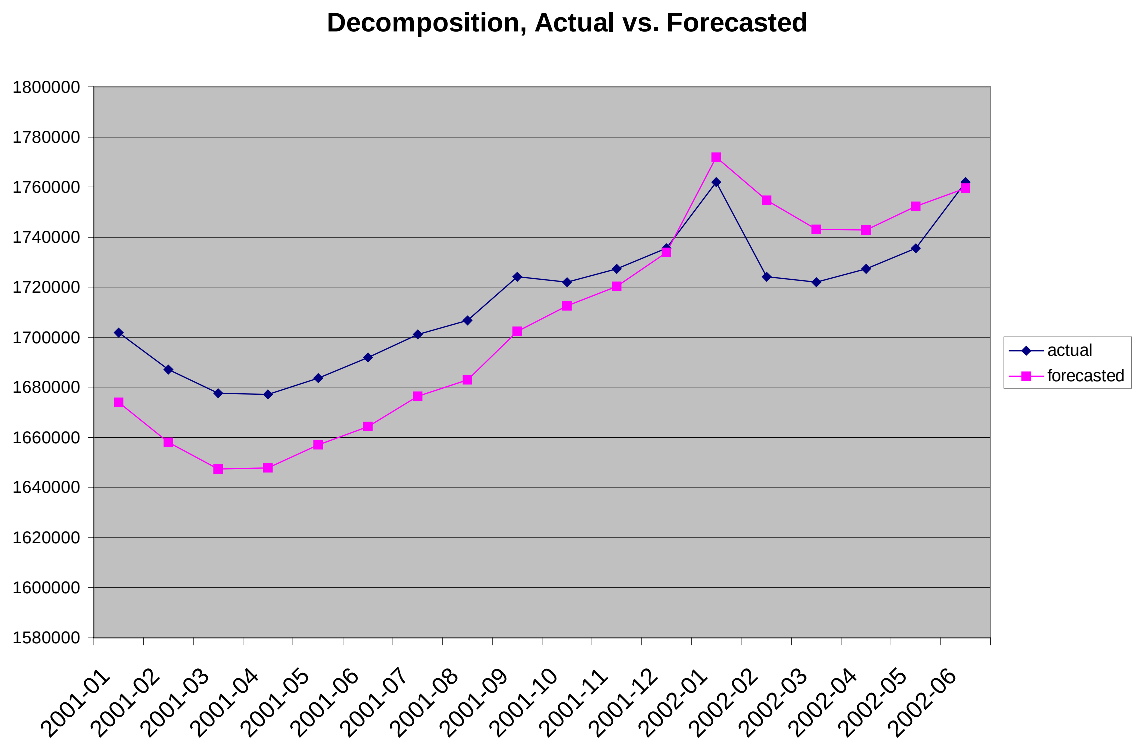
Analysis – Forecast

After fitting, the next step is to analyze forecasting using that model. The months of July 1993 through December 2002 are forecasted and compared against actuals. Table III-A lists the actual, forecast and forecast error values for the last 18 observations of the series.

Table III-A: Seasonal Decomposition Forecasts and Errors			
Obs#	Actuals	Forecast	Errors
98	1701855.59	1673923.71	27931.88
99	1687002.91	1658052.609	28950.3
100	1677718.42	1647468.574	30249.85
101	1677195.83	1647732.27	29463.56
102	1683644.44	1657008.439	26636
103	1691993.07	1664283.965	27709.11
104	1701250.5	1676450.646	24799.85
105	1706654.59	1682971.987	23682.6
106	1724225.03	1702364.535	21860.49
107	1721954.5	1712644.539	9309.96
108	1727410.97	1720194.424	7216.55
109	1735540.27	1733735.07	1805.2
110	1761967.92	1771953.301	-9985.38
111	1724225.03	1754681.174	-30456.14
112	1721954.5	1743016.289	-21061.79
113	1727410.97	1742835.639	-15424.67
114	1735540.27	1752189.405	-16649.13

Figure III-D charts the forecasted values for the last 18 months and actual for the decomposition model and Figure III-E illustrates the scatter of forecast errors about the mean of zero. The model tends to either under or overforecast.

Figure 3D



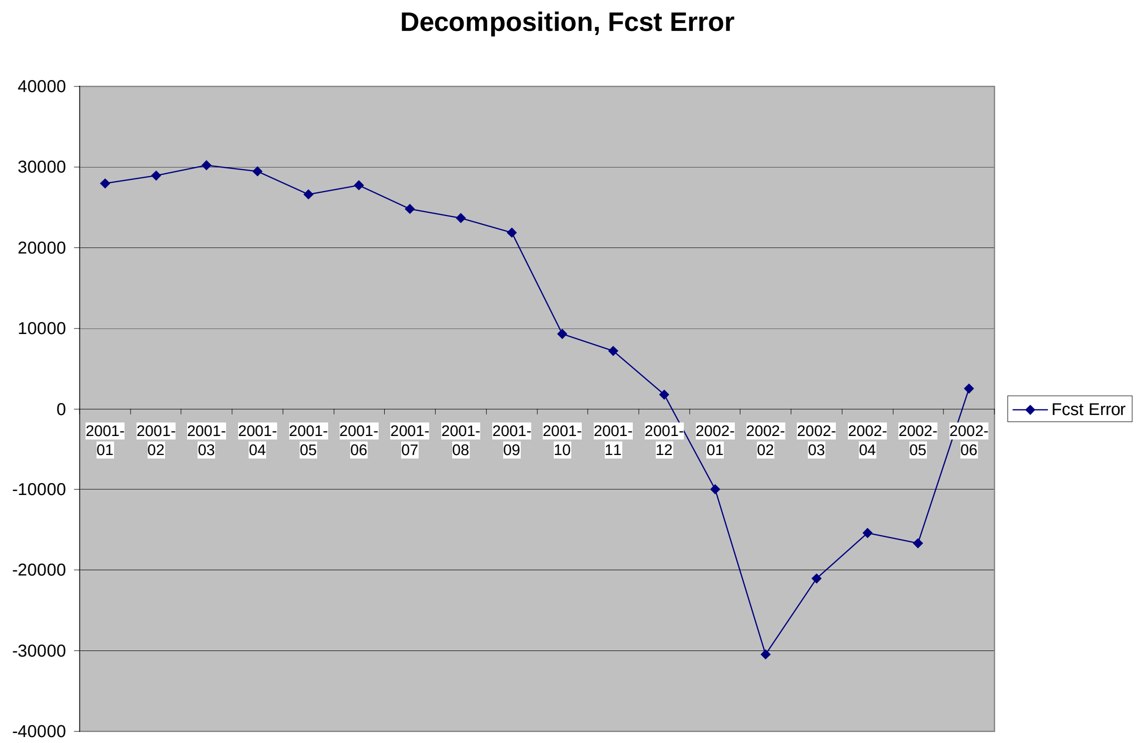


Figure Figure III-E

Overall, the forecast looks fairly good, however most of the forecasts before December 2001 are lower than the actual and after that forecasts are higher. Although the model picked the seasonal increase in consumer credit in December 2001, it failed to account for the smaller trend increase after January 2002. this is due to the inability of this model to account for cyclical factors, which were present during this period. The model assumed that the trend if increase will continue at the same rate, while there was a slump in consumer credit during this recessionary period, which was also marked with increased uncertainty. This indicates that the model does not pick up cyclical influences that most likely contributed to the slower growth of consumer credit during the recession.

The summary statistics for the fit and forecast are listed in Table III-B. The MPE, as well as the MAPE statistics are very close for fitted (0.019) and for forecast (0.011), as well to zero, which is encouraging. The RSE for the forecasted has decreased from 25745.99 to 22579.24 indicating that the scatter of actual value about the forecasted values has decreased.

Table III-B : Decomposition Model

Fitted	
n	96
ME	-3.63048628
SSE	62971355480
RSE	25745.99723
MAD	23083.9407
MPE	-0.00052896
MAPE	0.019031512

Forecasted	
n	18
ME	9365.49
SSE	8666979451
RSE	22579.24535
MAD	19762.94288
MPE	0.005582341
MAPE	0.011591739

Implications

Our goal was to have a good estimate of the trend. We observed that there are not apparent peaks and troughs and thus did not expect that seasonality would be of much importance, however this model confirmed that even if we find a good account of the trend, there is need for incorporating cyclical elements in our forecast of consumer credit.

This decomposition model is an improvement over the models used in minicase 2, with regards to all the forecasting statistics. With regards to fitting, the naive model scores better than decomposition in RSE and MAPE. The RSE in decomposition decreases from fit to forecast, as a contrast in the naive and seasonal naive models, where RSE increase from fit to forecast. In decomposition, RSE statistics has the lowest value in comparison to the models from minicase 2.

Decomposition is better in forecasting consumer credit than naive and seasonal naive models, because there are clearly identified both trend and seasonality which characterize the series. Forecasts over longer horizons could deteriorate, due to business cycle impact on consumer credit, that is not picked up by the model.

V. Minicase 6

Another model that adjusts for seasonality and trend is Winters' Three-Parameter Exponential Smoothing. Winters' differs from the simple decomposition we performed earlier in that it uses an exponentially weighted moving average to estimate the three factors representing the constant, the trend (slope) and the seasonality.

The equation for the Winters' model is:

$Y_{t+1} = (S_t + b_t) I_{t-L+1} + e_{t+1}$

Where S_t is the smoothed non-seasonal level of the series at the end of period t

b_t is the smoothed trend in period t

I_{t-L+1} is the smoothed seasonal index for period t + 1 and L is the length

Of the seasonal cycle

e_{t+1} is the error in period t + 1

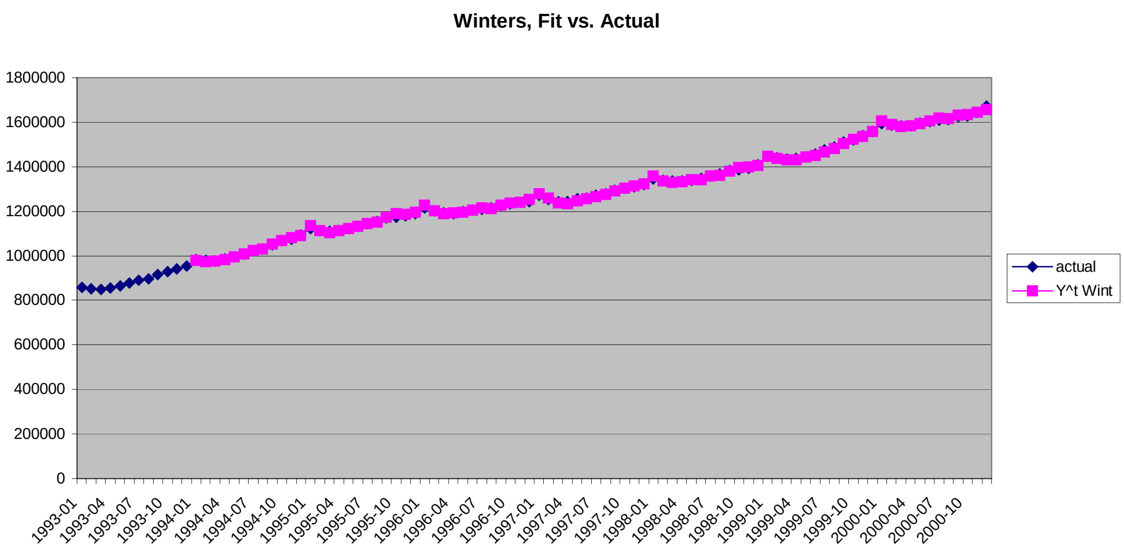
A critical step in using the Winters' model is the initialization of the parameters S_t, b_t and I_t. These parameters can be estimated using simple decomposition, using the seasonal indices and trend line of the moving average.

Two other estimating alternatives are the regression decomposition method and backforecasting. Backforecasting entails reversing the order of the data, with the most recent actuals being first and fitting a model to these observations. This model backforecasts Y_0 and Y_{-1}, which can be used as starting values of the original series. To obtain the starting values for the consumer credit model we take the mean of the first 12 observations, which is 890352.3, and is centered on month 6.5. The trend is estimated by taking the differences between the first five months of year 1 and year 2 and dividing by the total observations in that period. The seasonal index I_{t-L+1} is calculated by $Y_t/(S_t+b_t)$and is adjusted with each observation. The Excel feature 'solver' was used to optimize the values of the three smoothing parameters.

Analysis – Fit

The graph in Figure IV-A shows actuals versus fit, which looks very good. The mean error is good at –83.58. MAPE is excellent at 0.003%. Fig IV-A shows that the fitted values are reflecting both the trend and the seasonality of the actual. The Winters model is the best model so far in fitting (RSE = 5547).

Fig IV-A



<u>Analysis – Forecast</u>

Using this model the next eighteen months are forecasted (July 2001 through December 2002) and compared against actuals. The actual and forecasting results are listed in Table IV-A.

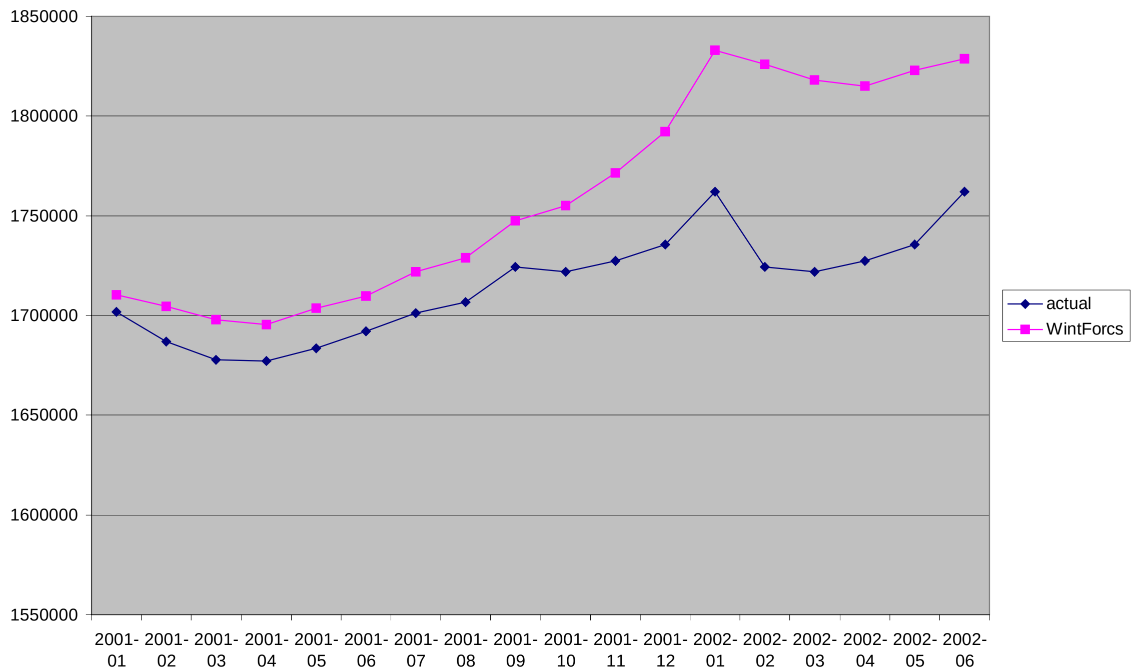
Table IV-A: Winters' Forecast Value and Errors

year	actual	Winters Forecasts	errors
2001-07	1701856	1710290	-8434.74
2001-08	1687003	1704480	-17477.2
2001-09	1677718	1697787	-20068.6
2001-10	1677196	1695475	-18279.3
2001-11	1683644	1703601	-19956.5
2001-12	1691993	1709679	-17685.6
2002-01	1701251	1721892	-20641.1
2002-02	1706655	1729009	-22354.6
2002-03	1724225	1747522	-23296.8
2002-04	1721955	1755050	-33095.7
2002-05	1727411	1771405	-43994.5
2002-06	1735540	1792243	-56702.6
2002-07	1761968	1832978	-71010.1
2002-08	1724225	1826024	-101799
2002-09	1721955	1818139	-96184.3
2002-10	1727411	1814957	-87546.2
2002-11	1735540	1822955	-87414.6
2002-12	1761968	1828763	-66795.2

The graph in Figure IV-B shows the last 18 months of the graph being the forecast versus actual values. Winters tends to overforecast the actual values, but overall catches the trend and seasonality. The distance between actual and forecasted increases with time. Even though Winters does better in fitting so far, it still remains inferior to the decomposition model in forecasting.

Figure IV-B

Winters, Actual vs. Forecast



The statistics of the fit and forecast are listed in Table IV-B. The mean error of the forecast has worsened compared to the fit. The RSE for the forecast jumped up. MPE of the forecast improved over fitted to an excellent, close to zero MAPE of the forecast is still close to zero although a bit higher.

Table IV-B : Winters Summary Statistics

Fitted	
n	84
ME	-83.58
SSE	2554273414
RSE	5547.465952
MAD	4349.732781
MPE	-8.523E-05
MAPE	0.003339005

Forecasted	
n	12
ME	-45152.06
SSE	53963288940
RSE	70041.08466
MAD	45152.05716
MPE	-0.026152346
MAPE	0.026152346

Implications

The statistics for Winters did not improve from decomposition for forecasting. For fitting, Winters's MAPE is the best in comparison to all previous models. Thus Winters' model is the best fitting model up to this point, but at a similar level with decomposition with respect to forecasting. Where the decomposition model tended to either underforecast or overforecast, the Winters model tends to overforecast, which one can assert, makes it more reliable. Therefore, it is expected that the analyst will find that this model will yield a better forecast for each month, after accounting for its tendency to overforecast. It could be useful to see if this overforecasting is valid also for previous periods, or is amplified by recessionary periods.

VI. Minicase 7

Minicase 7 uses an Excel spreadsheet to compare 18 different models. These models use a combination of first differences and exponentially weighted averages. Each model is a variation on the main model :

$\hat{Y}_t = Y_{t-1} + e_t$ (where $\hat{Y}_t$ is either the forecasted or the fitted value)

Models 2 through 4 are exponentially weighted moving averages, with the smoothing constant set at .10, .40 and .80 respectively. These formulas model no trend and no seasonality.

Models 5 through 8 model no trend but seasonality. Model 5 is the same as model 1 except it is seasonal. Models 6 through 8 modify model 5 to be an exponentially weighted moving average, as we did in models 2 through 4.

Models 9 through 12 are designed to model trend but no seasonality. They are the same as models 1 through 4 but with a variable added to account for trend – E_t , which equals the mean error found in models 1 through 4 respectively.

Models 13 through 16 make similar modifications to models 5 through 8, the variable E_t is added to account for trend.

Finally, models 17 and 18 include both first and seasonal differencing. Their formulas are:

$$Y_t = Y_{t-12} + (Y_{t-1} - Y_{t-13}) + e_t$$

The first term in the equation accounts for seasonality. The terms in parentheses are an estimate of the trend.

Model 18 takes model 17 and adds in the mean differences found in that model in order to calculate second differences.

Analysis – Fit

For this study we will look at three statistics: Sum of Standard Errors (SSE), Mean Standard Error (MSE) and Bayesian Information Criterion (BIC). BIC is a statistic that weighs the residual standard error and model complexity. The BIC statistic is often used by forecasters to help them choose among models where there is no other basis for selection. Based on the principle of parsimony, a low BIC value indicates that the model is simple yet effective.

In our spreadsheet we will be looking for the two models with the lowest BIC value. Models 9 and 12 have shown the best results of the 18 models. Model 9 has a BIC of 1935.541 while model 12 has a BIC of 1940.179.

Models 9 to 12 are Models 1 to 4 where mean errors have been added to the previous fitted values. When the mean errors are zero then the forecasts of models 1 to 4 will be identical to the forecasts of models 9 to 12.

$$Y9\hat{}_t = Y1\hat{}_t + E(e1_t) \quad (9)$$

$$e9_t = Y9_t - Y9\hat{}_t$$

$$Y12\hat{}_t = Y3\hat{}_t + E(e4_t) \quad (12)$$

$$e12_t = Y12_t - Y12\hat{}_t$$

Table V-A shows the fit statistics of Model 9, which looks to be the best model according to the value of BIC.

Table V-A: Statistics for Best Model 9 (Fitting)

SSE	9642158745
MSE	114787604.1
BIC	1935.541
MIN/RSE	-2.635
MAX/RSE	2.663
MSE/MIN(MSE)	1

Figure V-A shows the actual data, the fit and the forecast values of the last 18 months that have been withheld, as a result of applying model 9.

Figure V-A

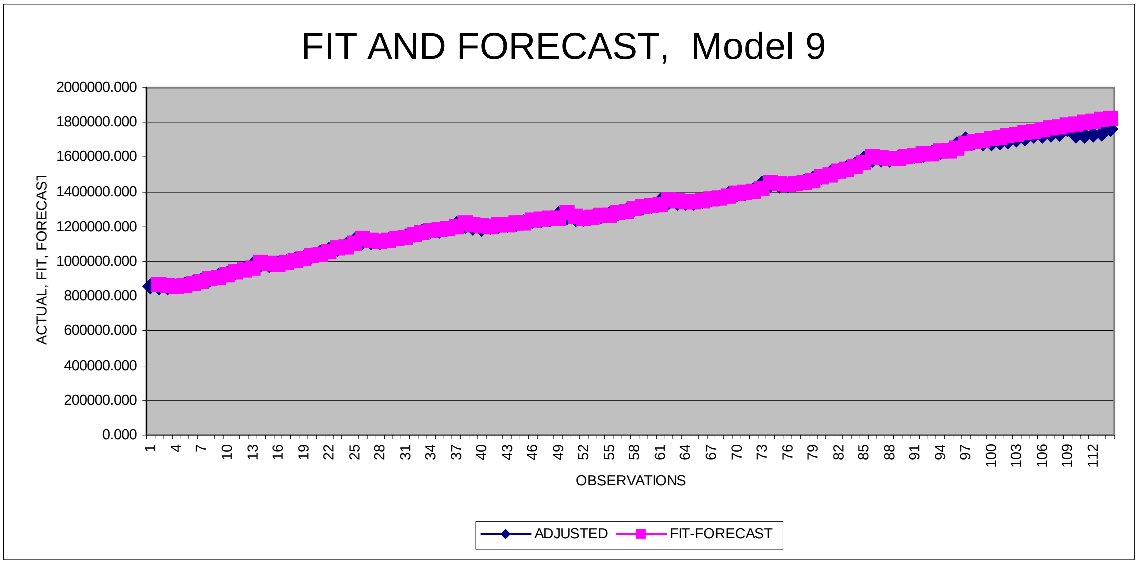


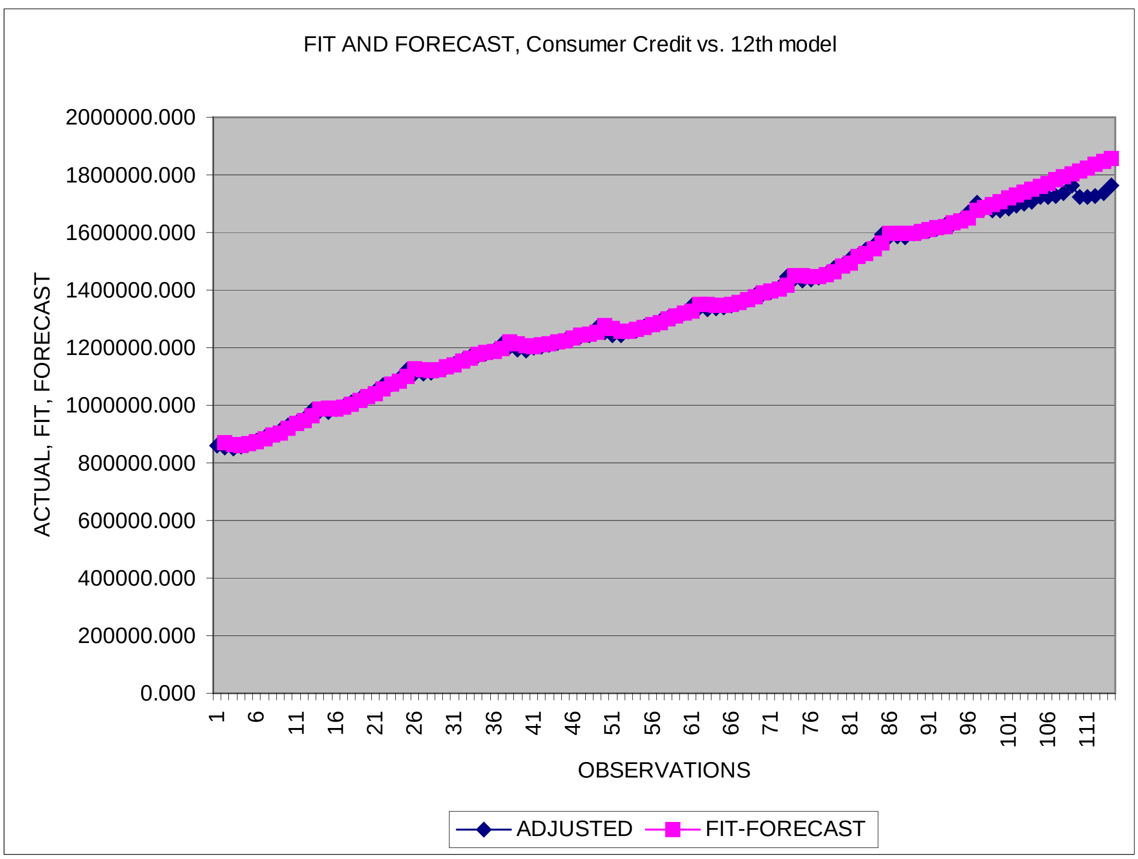
Table V-B shows the fit statistics of Model 12, which appears to be the second best model according to the value of BIC. Also, the SSE is much higher for model 12 in comparison to model 9.

Table V-B: Statistics for Second Best Model 12 (Fitting)

SSE	10189507327.644
MSE	121303658.662
BIC	1940.179
MIN/RSE	-2.202
MAX/RSE	2.70
MSE/MIN(MSE)	1.06

Figure V-B shows the fit and forecast of model 12 and the actual data.

Figure V-B



Analysis – Forecast

Table V-C shows comparison between the forecast statistics of the best Model 9 and the second best Model 12.

Table V-C

Forecast	**Model 9**	**Model 12**
SUM ERR	-678597.8082	-2377582
MEAN	-37699.87823	-132087.9
STDDEV	27373.43613	92093.69
MIN ERROR	-81130.38321	-270210.5
MAX ERROR	21713.67393	34643.42
TREND t-VALU	-5.843147952	-6.085123

Graphic comparison between the forecasts of the last 12 months of Models 9 and 12 are shown in together in Figure V-C, and demonstrate that these models do not pick up seasonality and cycle and are pretty off with regard to trend.

Figure V-C

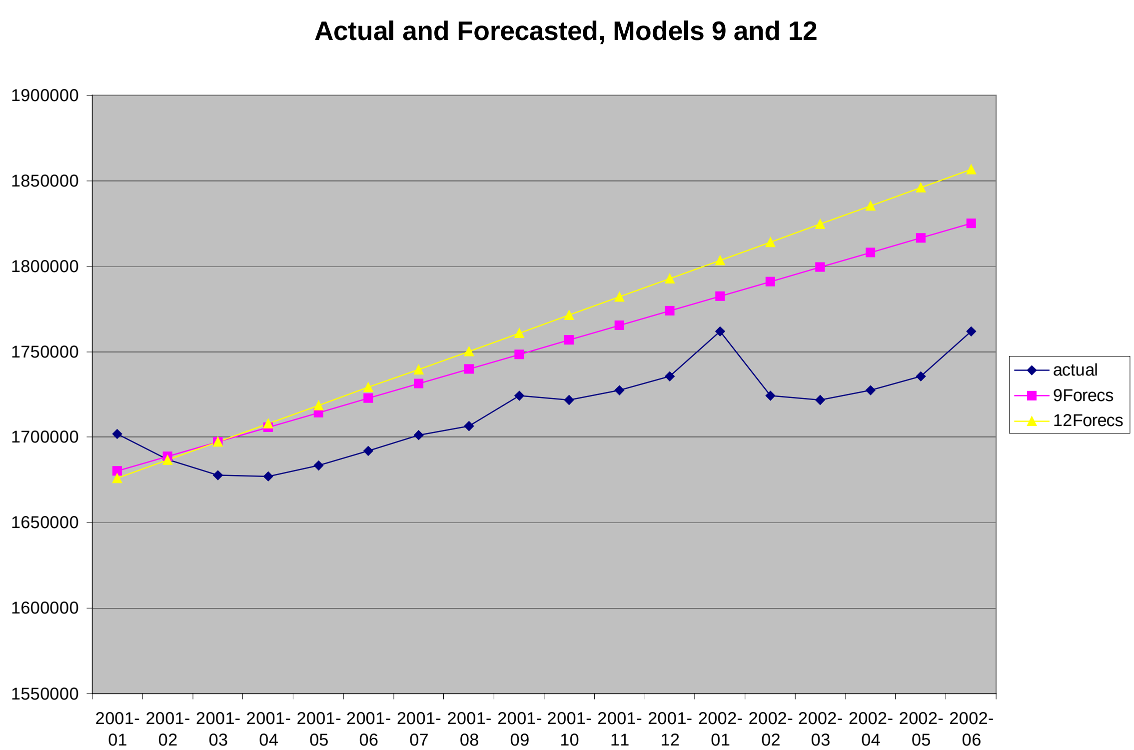
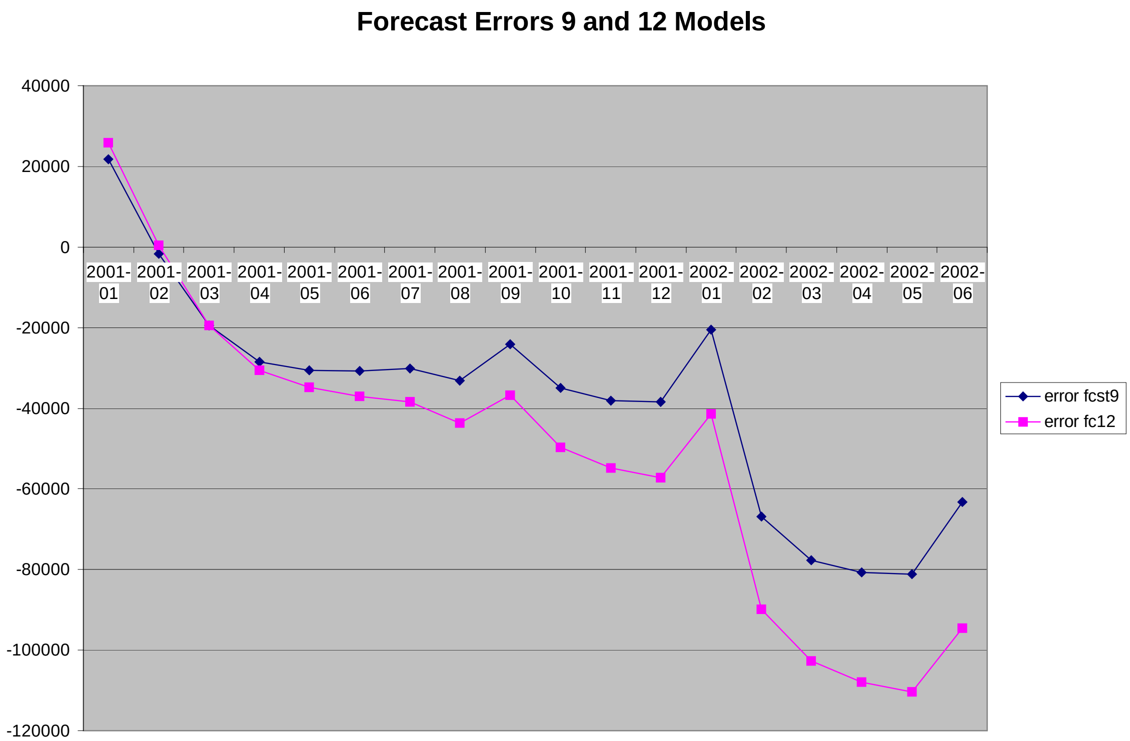


Figure V-D shows the forecast errors of each model. The errors move together, which means that both models are quite similar in their forecasting. However, Model 9 has errors closer to zero in comparison to the forecast errors of model 12.

Figure V-D



Implications

Although Model 9 and 12 rate the best with respect to BIC in fitting, they score poor in forecasting, due to the fact that they do not model trend and seasonality, as well as do not pick up cyclical changes. Hense these models should not be relied upon forecasting consumer credit series. Both models remain inferior to decomposition in forecasting and Winters in fitting.

VII. Minicase 8

Finally, we explore the Autoregressive Integrated Moving Average (ARIMA) models. The ARIMA model-building approach is based on two restrictions : a) the forecasts are linear functions of the sample observations ; and b) the aim is to find models that provide an adequate description of the characteristics of an observed time series with a few parameters as possible. With this last model we will try to extract all possible information from the time series so that there is no pattern left in the residuals. In other words, the errors will be distributed as white noise.

First Model : ARIMA (0,0,0)

First we run model ARIMA (0,0,0). As seen from the statistics in Table VI-A bellow, the Durbin-Watson is not satisfactory, and the BIC is quite high. Both the R squared and the adjusted R squared are dismal. The graph shows that the most likely, the optimistic and pessimistic forecast are quite off. The ACFs in Figure VI-B show a pattern of exponential decline, which suggest that we need to take an AR (1). This also suggests a nonstationary (non-constant) mean. The PACFs in Figure VI-C show a single high peak at lag 1.

Table VI-A: Statistics for ARIMA (0,0,0)

CONST 1249864.0599

Within-Sample Statistics

Sample size 96	Number of parameters 0
Mean 1.25e+006	Standard deviation 2.24e+005
R-square 4.312e-010	Adjusted R-square 0.01042
Durbin-Watson 0.003604	** Ljung-Box(18)=896 P=1
Forecast error 2.229e+005	BIC 2.229e+005
MAPE 0.1543	RMSE 2.229e+005
MAD 1.824e+005	

Figure VI-I: Fit and forecast of ARIMA (0,0,0)

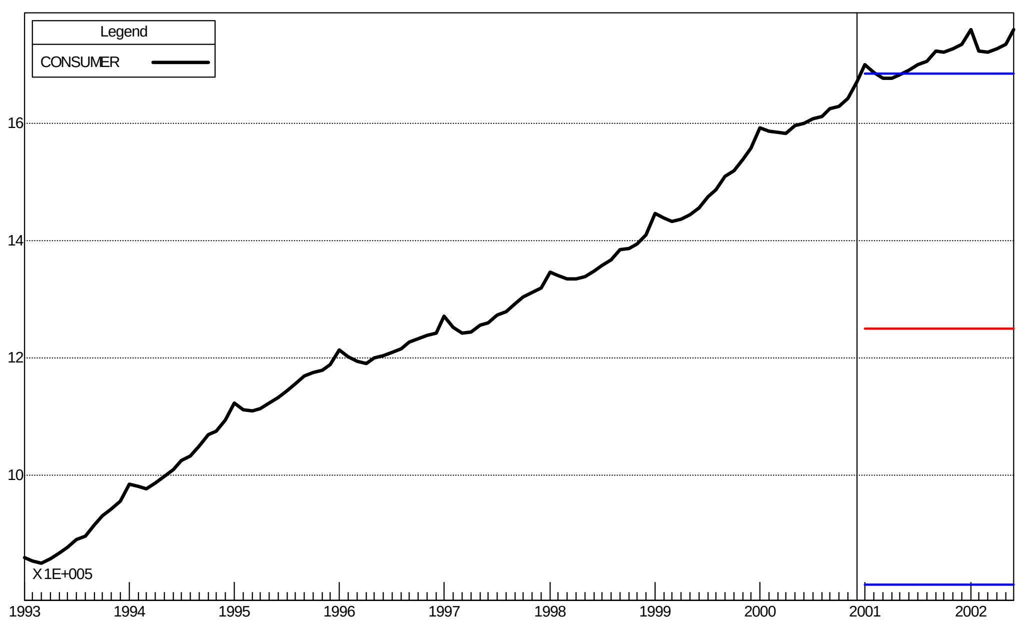


Figure VI-B: ACFs of ARIMA (000)

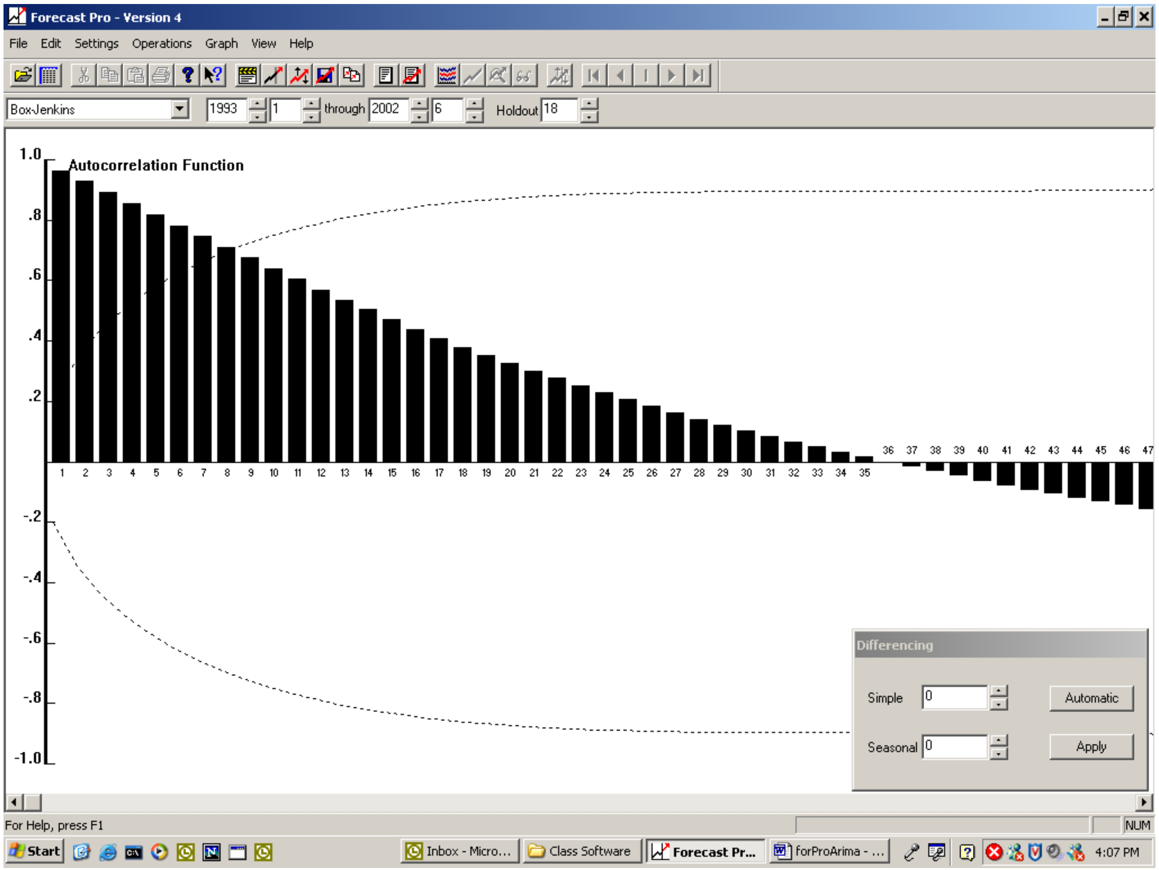
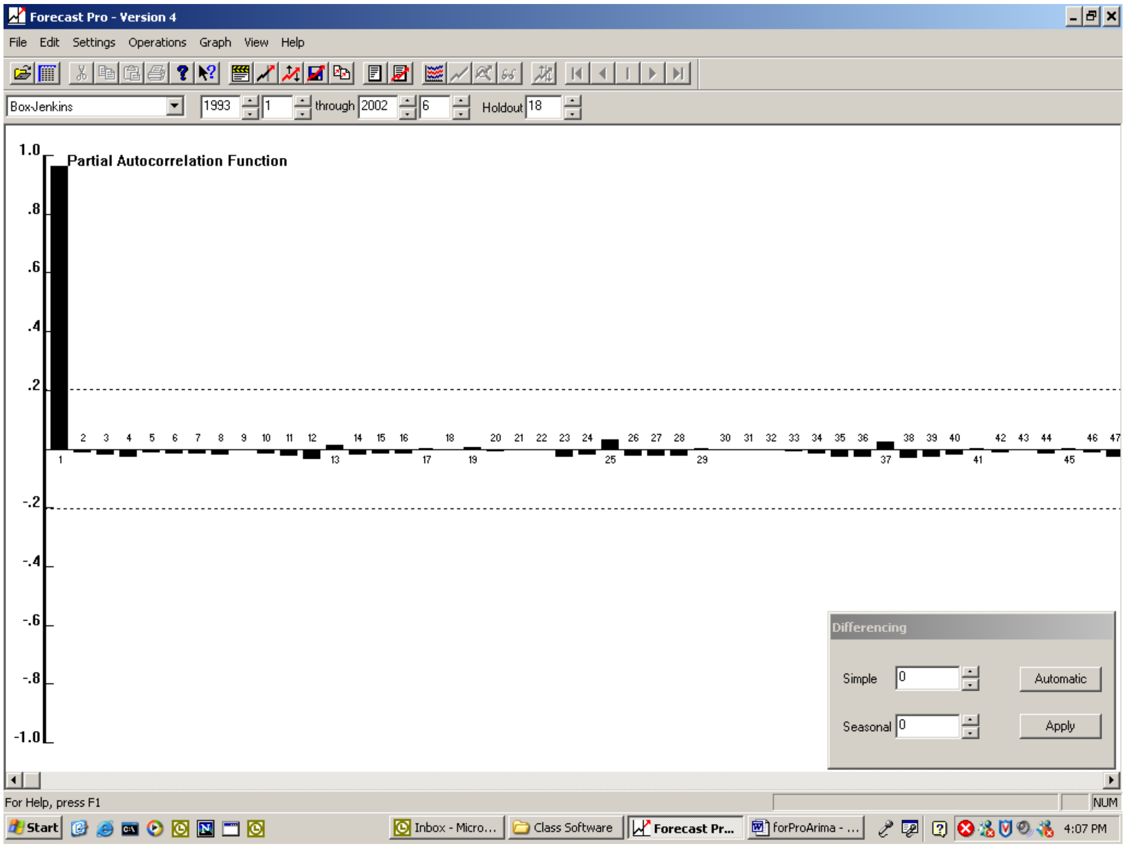


Figure VI-C: PACFs for ARIMA (0,0,0)



Second Model: ARIMA (1,0,0)

Both ACFs and PACFs of the first model suggest an autoregressive model ARIMA (1,0,0). The statistics bellow show that there is great improvement in the Durbin Watson statistics and an improvement in BIC, even though it still remains quite high. Both the R squared and the adjusted R squared have improved dramatically. The coefficient [a1] is statistically significant. The Ljung-Box (18) has decreased dramatically from 896 to 284 with a P value of 1. All these statistics suggest that we are moving in the right direction and that the AR (1) that we used is justified. Now we will try to improve the performance of the model by taking first differences.

Table VI-B: Statistics for ARIMA (1,0,0)

Term Coefficient Std. Error t-Statistic Significance
----

a[1] 0.9999 0.0000 20302.4636 1.0000
_CONST 77.4087

Within-Sample Statistics

Sample size 96 Number of parameters 1
Mean 1.25e+006 Standard deviation 2.24e+005
R-square 0.9964 Adjusted R-square 0.9964
Durbin-Watson 1.054 ** Ljung-Box(18)=284.3 P=1
Forecast error 1.345e+004 BIC 1.37e+004
MAPE 0.008907 RMSE 1.338e+004
MAD 1.09e+004

Figure VI-D: Fit and forecast of ARIMA (1,0,0)

Third Model: ARIMA (1,1,0)

With ARIMA (1,1,0) the BIC improves a little bit, but still remains high. The Durbin-Watson is excellent, which means that we have solved the autocorrelation problem. But as the graph shows forecasting does not improve. The value of the coefficient [a1] went down from 0.99 to 0.4724 but it still remains statistically significant. Both the R squared and the adjusted R squared remained high. All these statistics show that we are moving in the right direction in our search for the best model.

As shown in Figure VI-E, the ACFs show high seasonal peaks at lag 12, 24, and 36. The PACFs as shown in Figure VI-F show a high peak at lag 12. This suggests a need to take seasonal differences.

Table VI-C: Statistics for ARIMA (1,1,0)

Term	Coefficient	Std. Error	t-Statistic	Significance
a[1]	0.4724	0.0930	5.0794	1.0000

Within-Sample Statistics

Sample size 96	Number of parameters 1
Mean 1.25e+006	Standard deviation 2.24e+005
R-square 0.9972	Adjusted R-square 0.9972
Durbin-Watson 2.132	** Ljung-Box(18)=113.9 P=1
Forecast error 1.193e+004	BIC 1.215e+004
MAPE 0.007131	RMSE 1.187e+004
MAD 8815	

Figure VI-E: Forecast of Model ARIMA(1,1,0)

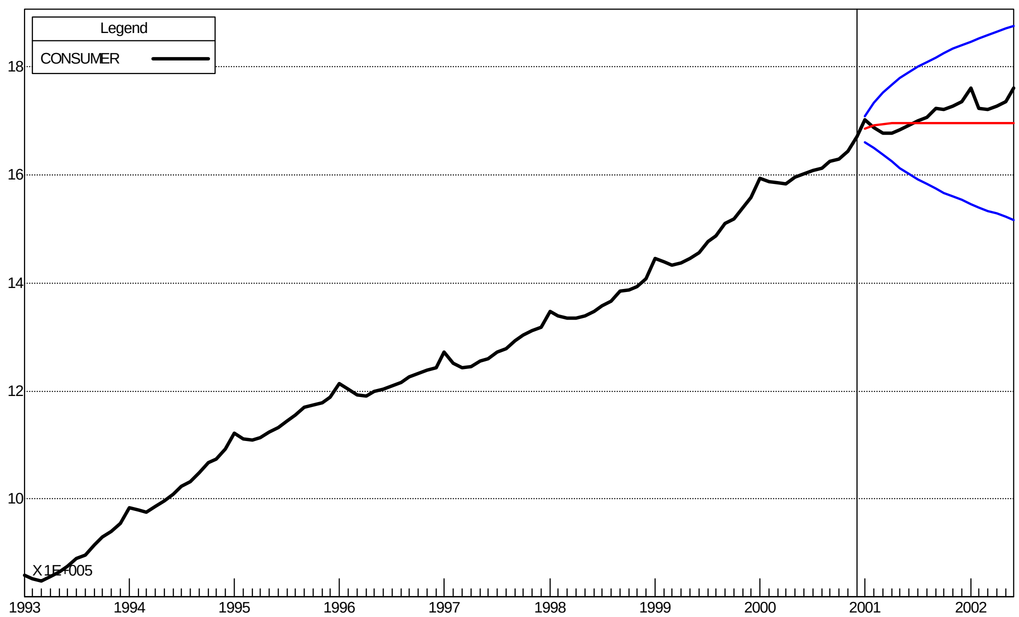


Figure VI-F: ACFs for ARIMA (1,1,0)

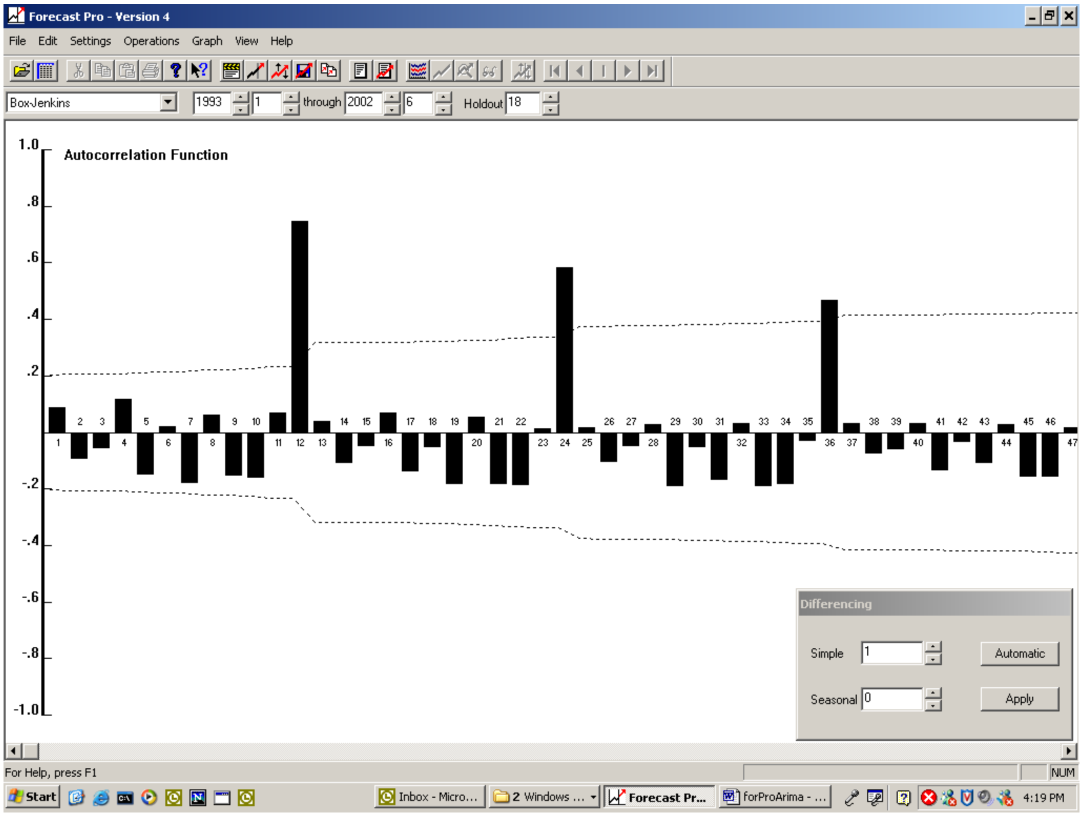
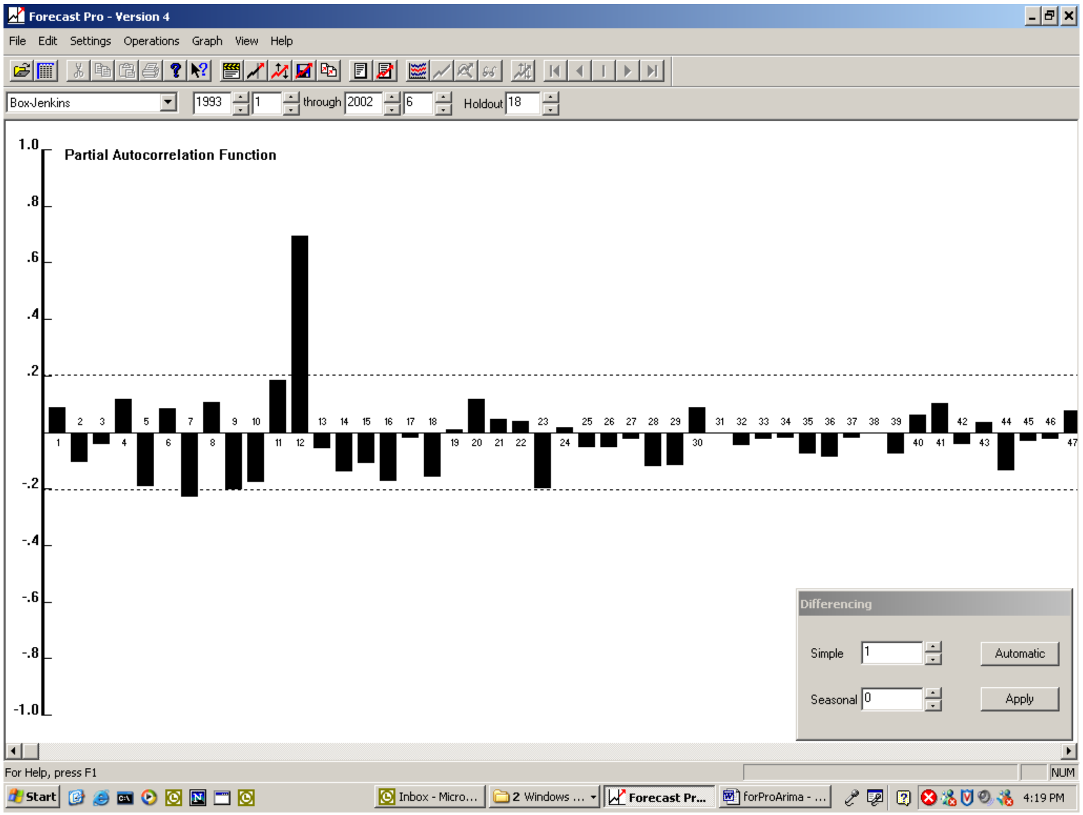


Figure VI-G: PACFs for ARIMA(1,1,0)



Fourth Model: ARIMA (1,1,0)*(0,1,0)

After taking first and seasonal differences, the forecast becomes reasonable as shown on Figure VI-H. Our forecast error (or RSE) has now reached a reasonable level. The BIC value went down significantly, and the Durbin-Watson statistics approached a perfect level of 2.059. Both the R squared and the adjusted R squared remained quite good. The value of the a[1] coefficient went down from 0.4724 to 0.2318 but remained statistically significant nonetheless. The pessimistic forecast of the model is the closest to the actual. The seasonality is captured by the model. The pessimistic results of model tend to over-forecast arguably because of the impact of the recession whish in not captured in the model (the model assumes that the past will repeat itself). According the PACFs error PACFs shown in figure VI-G and VI-H, it appears that we need to take an MA(1).

Table VI-D: Statistics for ARIMA (1,1,0)*(0,1,0)

Term	Coefficient	Std. Error	t-Statistic	Significance
a[1]	0.2318	0.1082	2.1436	0.9650

Within-Sample Statistics

Sample size 96	Number of parameters 1
Mean 1.25e+006	Standard deviation 2.24e+005
R-square 0.9995	Adjusted R-square 0.9995
Durbin-Watson 2.059	** Ljung-Box(18)=43.61 P=0.9993
Forecast error 5025	BIC 5119
MAPE 0.00286	RMSE 4999

Figure VI-H: Fit and forecast of ARIMA (1,1,0)*(0,1,0)

Figure VI-I: ACFs for ARIMA (1,1,0)*(0,1,0)

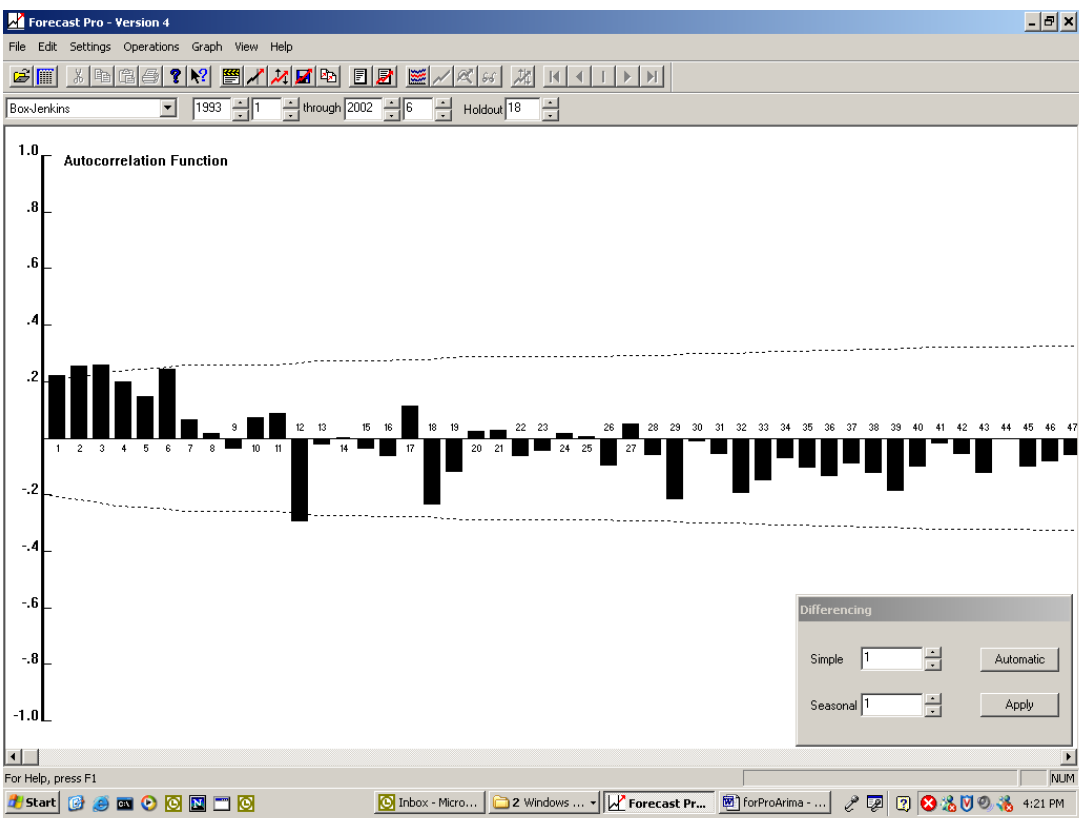


Figure VI-G: PACFs for ARIMA (1,1,0)*(0,1,0)

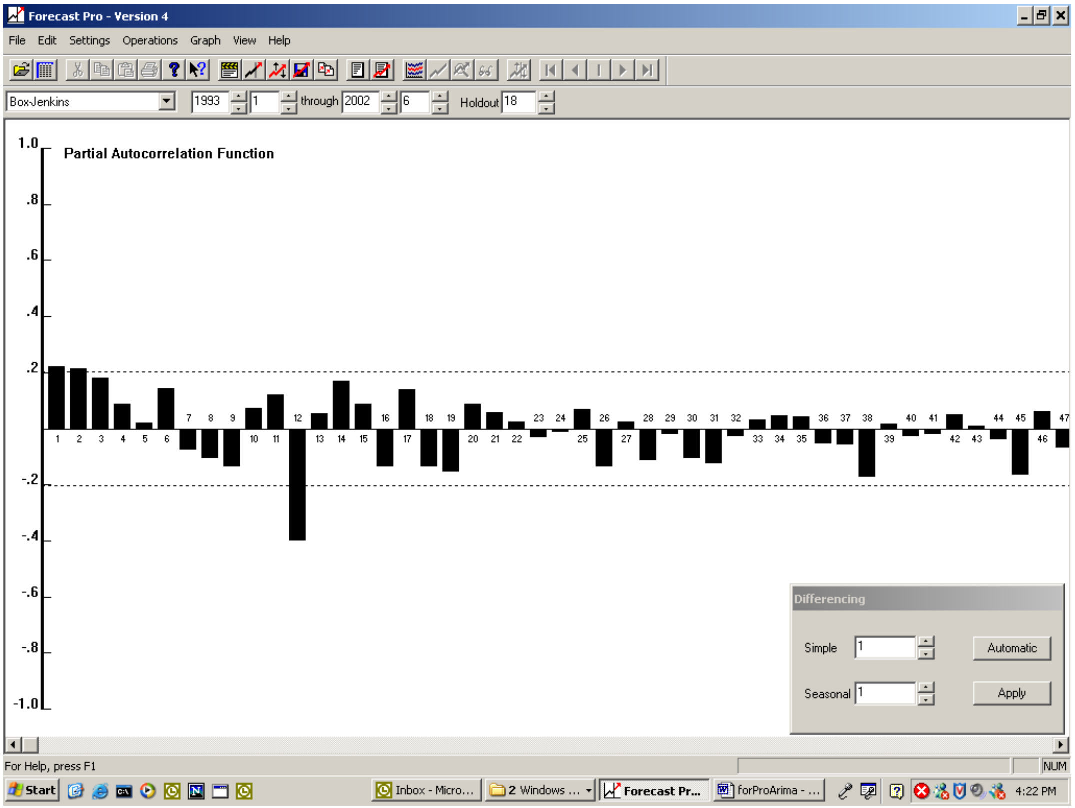
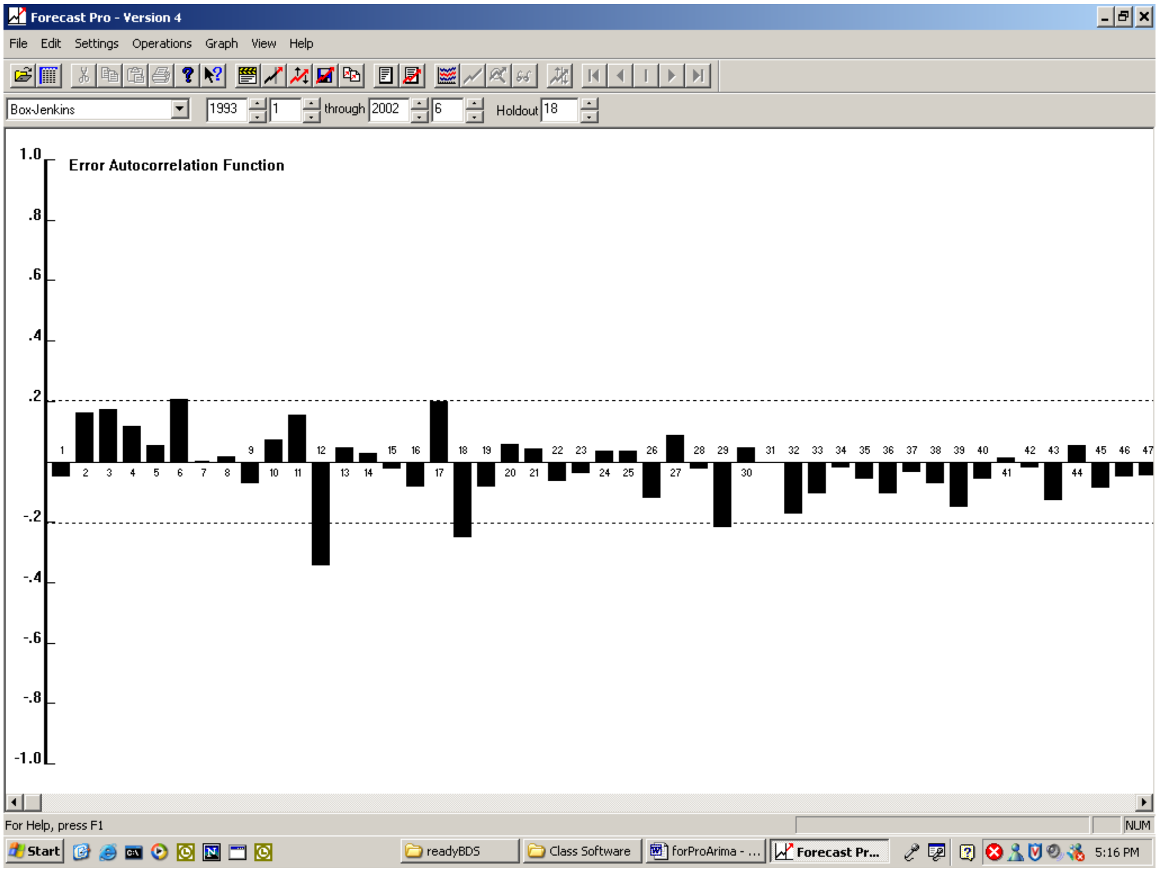


Figure VI-H: Error PACFs for ARIMA (1,1,0)*(0,1,0)



Fifth Model: ARIMA(1,1,1)*(0,1,0)

It appears that by taking the moving average step, we have improved the BIC (from 5119 to 5044) as well as the forecast error (from 5025 to 4861). Both the R squared and the adjusted R squared remained quite good. The Durbin-Watson statistics also remained quite good at a level of 2.077.

The value of the coefficient a[1] went up but still remained less than one, and is still statistically significant. The value of the coefficient b[1] is also less than one and is statistically significant which justifies our use of the MA(1) procedure.

The pessimistic forecast of this model is better than the previous one. The forecast is now much closer to the actual except for the effect of the recessions during which the forecast is a bit overestimating the level of consumer credit.

Table VI-E: Statistics for Model ARIMA (1,1,1)*(0,1,0)

Term	Coefficient	Std. Error	t-Statistic	Significance

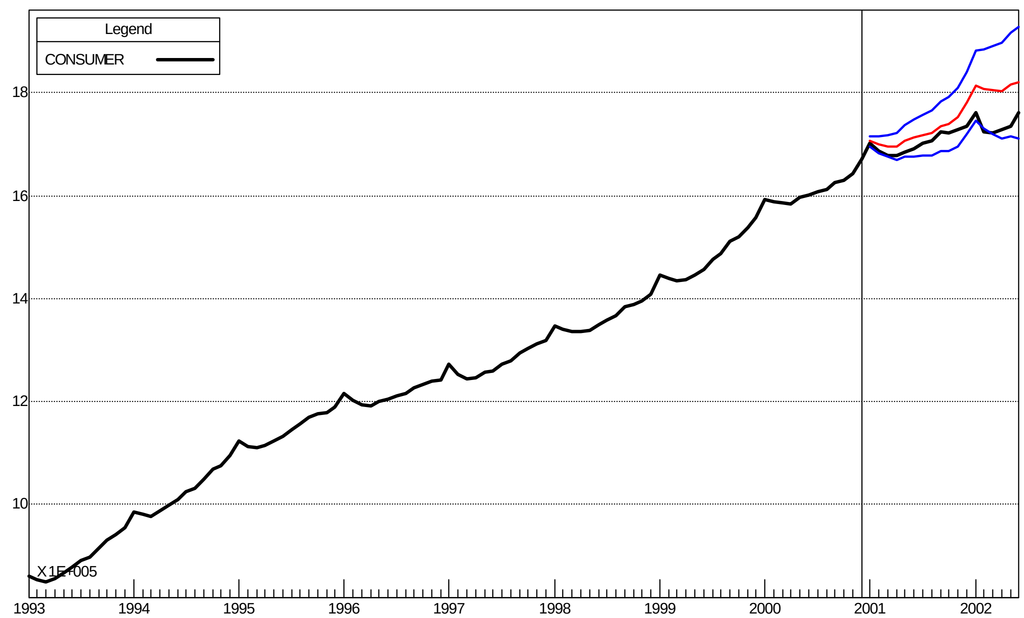
----

a[1]	0.8678	0.1178	7.3697	1.0000
b[1]	0.6794	0.1736	3.9131	0.9998

Within-Sample Statistics

Sample size 96	Number of parameters 2
Mean 1.25e+006	Standard deviation 2.24e+005
R-square 0.9995	Adjusted R-square 0.9995
Durbin-Watson 2.077	** Ljung-Box(18)=41.58 P=0.9987
Forecast error 4861	BIC 5044
MAPE 0.002681	RMSE 4810
MAD 3522	

Figure VI-I: Fit and forecast of ARIMA (1,1,1)*(0,1,0)



Sixth Model: ARIMA (1,1,1)*(0,1,1)

The sixth model turns out to be the best model that the expert selection system in Forecast-pro also came up with. The BIC value is now the lowest (4374), and the forecast error decreased significantly from 4861 to 4138. Both the R squared and the adjusted R squared remained quite good. The Durbin-Watson statistics also remained quite good at a level of 1.913.

The value of all the coefficients are less than one, and are still statistically significant, which justifies the additional step we have taken.

From Figure VI-J, we can see that even the pessimistic forecast of this model also tends to over-forecast the level of consumer credit, which could be explained by the fact that the model fails to take into account the cyclical effect in the economy.

The error PACFs still display a peak at lag 17, which is unexplainable so we chose to ignore it, Hence we conclude that have achieved white noise with the sixth model ARIMA (1,1,1)*(0,1,1). This model, however, does not outperform the decomposition model in forecasting, neither does it outperform Winters in fitting.

Table VI-F: Statistics for ARIMA (1,1,1)*(0,1,1)

Term	Coefficient	Std. Error	t-Statistic	Significance
a[1]	0.9036	0.0815	11.0845	1.0000
b[1]	0.6738	0.1471	4.5789	1.0000
B[12]	0.7663	0.0589	13.0181	1.0000

Within-Sample Statistics

Sample size 96	Number of parameters 3
Mean 1.25e+006	Standard deviation 2.24e+005
R-square 0.9997	Adjusted R-square 0.9997
Durbin-Watson 1.913	Ljung-Box(18)=21.2 P=0.7306
Forecast error 4138	BIC 4374
MAPE 0.002255	RMSE 4073
MAD 2954	

Figure VI-J: Fit and forecast of ARIMA (1,1,1)*(0,1,1)

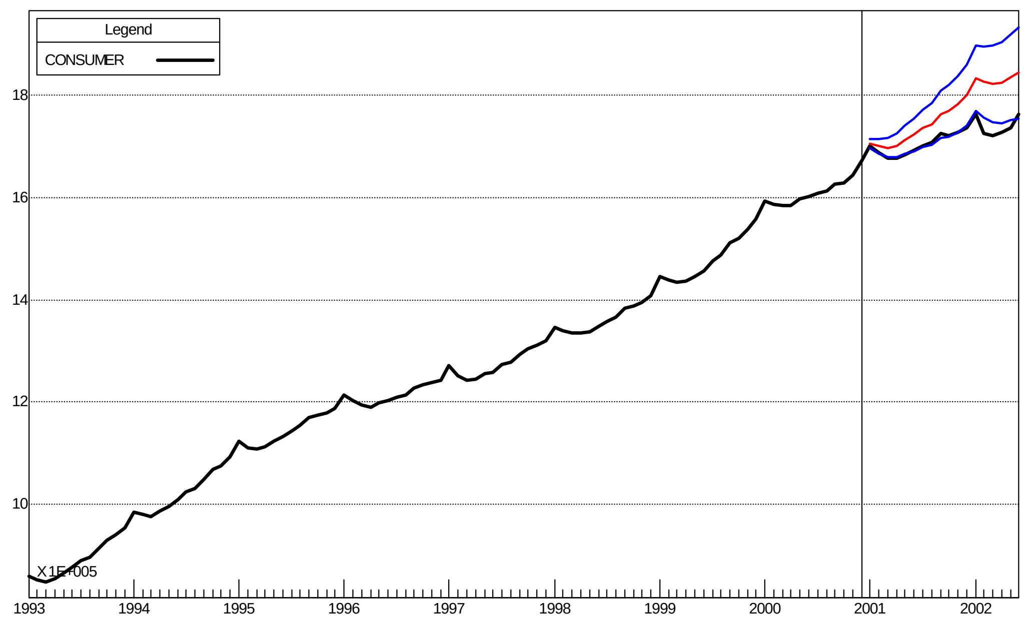
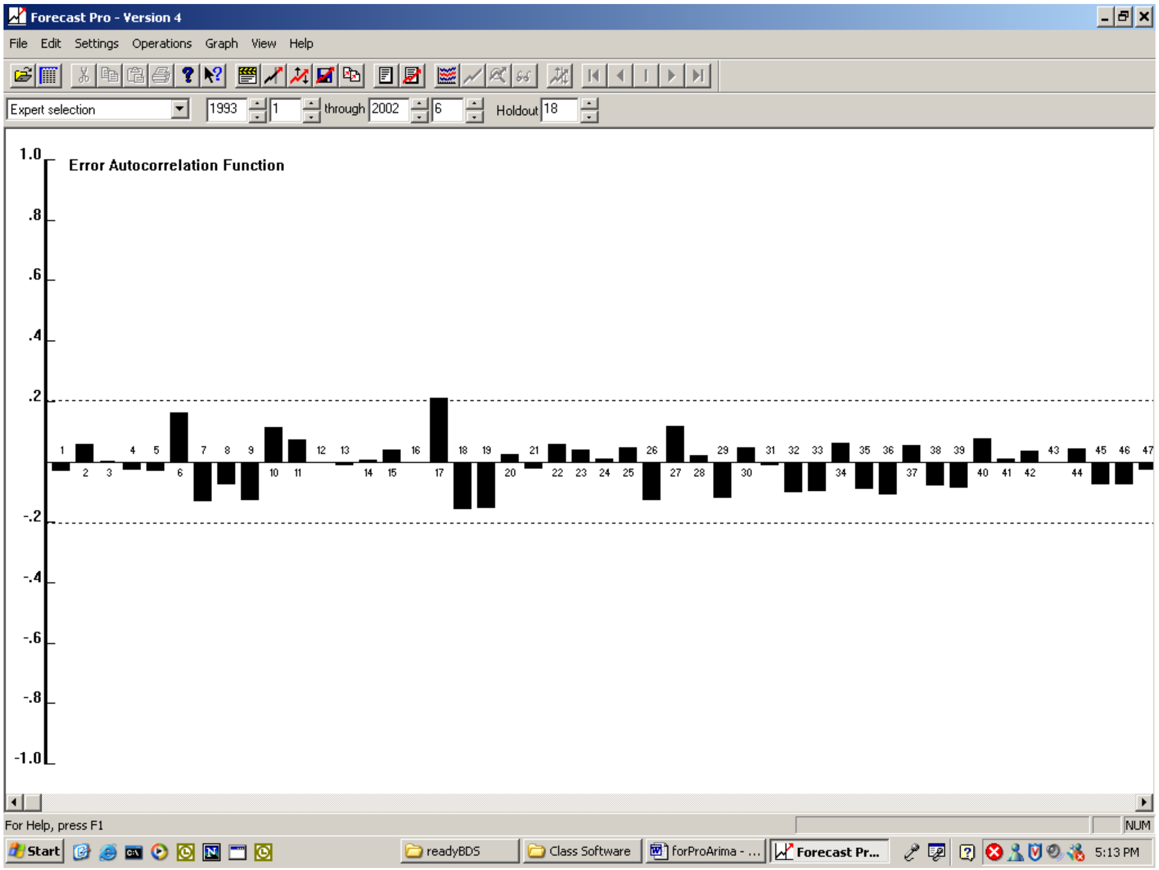


Figure VI-K: Error PACFs for ARIMA (1,1,1)*(0,1,1)



Estimation

The equation for ARIMA (1,1,1)*(0,1,1) is the following:

$Y_t = Y_{t-12} + (1 - \phi_1)\ (Y_{t-1} + Y_{t-13}) - \phi_1(Y_{t-2} + Y_{t-14}) + e_t - \theta_1 e_{t-1} - \theta_{12} e_{t-12} + \theta_1\theta_{12}\ e_{t-13}$

Where $\theta_1 = b[1] = 0.6738$
$\theta_{12} = B[12] = 0.7663$
and ϕ_1 is a[1] = 0.9036

$Y_t = Y_{t-12} + 0.0964(Y_{t-1} + Y_{t-13}) – 0.9036(Y_{t-2} + Y_{t-14}) + e_t - 0.6738e_{t-1} - 0.7663e_{t-12} + 0.5163e_{t-13}$

The coefficients of the error terms are less than one, which is a good thing in the sense that it minimizes the impact of the errors on the forecasted value. The model has an intuitive explanation: the forecasted value is equal to the value of 12 months ago plus some fraction of the difference between the value of last month and 12 months prior to last month, plus some negative fraction of the difference between the value of 2 months ago and 12 months prior to 2 months ago, plus the error terms.

Table VI-H: Custom ARIMA summary table

ARIMA	N	Mean	Std. Dev.	Level Stationarity	Variance Stationarity	White noise
(0,0,0)*(0,0,0)	96	1.25e+006	2.24e+005	No	Yes	No
(1,0,0)*(0,0,0)	96	1.25e+006	2.24e+005	No	Yes	No
(1,1,0)*(0,0,0)	96	1.25e+006	2.24e+005	No	Yes	No
(1,1,0)*(0,1,0)	96	1.25e+006	2.24e+005	No	Yes	No
(1,1,1)*(0,1,0)	96	1.25e+006	2.24e+005	No	Yes	No
(1,1,1)*(0,1,1)	96	1.25e+006	2.24e+005	Yes	Yes	Yes

VIII. Forecasting Performance

Table VII-A: Master Summary Table

	Method Prob.	Naive	Season. Naive	Decomp	Winters	ARIMA	M 9	M 12
FIT	***n***	95	84	96	84	96	96	96
	ME	8553	103027	-3.63	-83.58	19185510	20.61	175.62
	RSE	13,520	107,968	25,745	5,547	4,138	10,714	11,014
	MPE	0.006	0.080	-0.0005	-8.523^{E}-05	0	-0.00008	8.42
	MAPE	0.009	0.080	-0.019	0.003	0.002255	0.006314	0.0064
	R^2					0.9997		
	DW					1.913		
	***Q*-stat**					21.2 P=0.73		
FORECAST	***N***	18	18	18	18	18	18	18
	ME	43,364	110,176	9,365	-45,152	18,422,337	-37,699	-51,307
	RSE	64,120	145,619	22,579	70,041	61,484	46,141	62,903
	MPE	0.025	0.064	0.0055	-0.026	3780377858	-0.0218	-0.02974
	MAPE	0.025	0.064	0.011	-0.026	3780377858	0.0232	-0.031456
	R^2							
	DW							
	***Q*-stat**							

We learned that all statistics available must be considered when selecting a model, rather than just using one or two statistics. Most of the models selected have at least one statistic that compares favorably to the other models' or to the ideal value desired. For example, the BICs of some models are good but they do not do as well in forecasting.

As we worked through each model, the importance of adequately modeling the data seasonality and trend became more obvious. With each model we refined the method of estimating these components and produce increasingly accurate fits and forecasts. We found that both fit and forecast must be analyzed before selecting a model. This was particularly illustrated in the summary statistics of the Decomposition and ARIMA models.

Forecasts more than one year ahead may deteriorate if there is a significant cyclical change in the overall trend, either upward or downward. It is speculated that the trend of consumer credit may change significantly in the next year due to pessimistic expectations of the banks and financial institutions.

Table VII-B shows that the best model in fitting is Winters (lowest RSE of 4,138) but that same model does not perform well in forecasting. The best model in Forecasting turns out to be Decomposition (lowest RSE of 22,579). Strangely enough, decomposition was not a very good model in fitting (RSE = 25,745), which once again demonstrates that the best model in fitting is not necessarily the best model in forecasting especially when the forecasting period is subject to cyclical variations.

IX. Conclusions and Practical Significance

Even forecast-pro, one of the most powerful forecasting packages in the market failed to give an accurate or even close to accurate forecast of the consumer credit series. A less sophisticated method (decomposition) was able to forecast the series in a fairly good manner. That same method however, was not the best model in fitting the series. Conversely, the best model in fitting the data (Winters) was not very useful in forecasting the series. Hence, the best forecasting model is the following:

$$\hat{Y}_t = (862337.6 + 7991.38t)\, S_t$$

where t is the time period and S_t is the seasonal index for that time period

We assumed that growth of financial innovations is a continuous trend, and could be thought as an exogenous factor. Therefore it is argued that if it is the case that financial innovations are responsible for growth in consumer credit, the series can be accurately forecasted using univariate model. On the other hand, we found that one needs to be cautious with the univariate models that we examined, since they do not account for cyclical changes which seem to be important for forecasting consumer credit. Therefore, it could be concluded that we have further grounds in addition to economic theory to explore the impact of structural macroeconomic conditions for the level of consumer credit via employing multivariate forecasting models that would use some leading indicators to help us forecast the impact of the business cycle on consumer credit.

Thus, we can conclude that with the suggested importance of cyclical influences in the consumer credit series, one needs to be aware that using the historical data of the past years to accurately forecast future growth in consumer credit is not likely to be successful. Now, we have a further reason to suggest that we need to relate the consumer credit series to multiple independent variables such as structural macroeconomic conditions, as argued by the Levy Institute economists cited above.

X. References

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XI. Appendix

Table XI-A: Raw Data

Month	Total US Consumer Credit, Millions of $
Jan-93	792084
Feb-93	787232
Mar-93	782635
Apr-93	788703
May-93	787824
Jun-93	793332
Jul-93	798412
Aug-93	807900

Sep-93	816623
Oct-93	823101
Nov-93	833611
Dec-93	859011
Jan-94	852016
Feb-94	849501
Mar-94	855980
Apr-94	865740
May-94	876508
Jun-94	889523
Jul-94	895798
Aug-94	914850
Sep-94	929960
Oct-94	940507
Nov-94	954833
Dec-94	983933
Jan-95	980716
Feb-95	976109
Mar-95	986212
Apr-95	996675
May-95	1009335
Jun-95	1023803
Jul-95	1031361
Aug-95	1049005
Sep-95	1068387
Oct-95	1074531
Nov-95	1093705
Dec-95	1122828
Jan-96	1111605
Feb-96	1108966
Mar-96	1113174
Apr-96	1123195
May-96	1131855
Jun-96	1144476.58
Jul-96	1155221.48
Aug-96	1169174.93
Sep-96	1174791.52
Oct-96	1178475.53
Nov-96	1188736.84
Dec-96	1214096.33
Jan-97	1202548.65
Feb-97	1193843.9
Mar-97	1190153
Apr-97	1199755.11
May-97	1203940.94
Jun-97	1210047.7
Jul-97	1215047.54
Aug-97	1226571.74
Sep-97	1232925.94
Oct-97	1239194.74
Nov-97	1242179.38
Dec-97	1271622.75

Jan-98	1251922.16
Feb-98	1242531.11
Mar-98	1244803.36
Apr-98	1256493.79
May-98	1258847.13
Jun-98	1272841.29
Jul-98	1278761.11
Aug-98	1293249.99
Sep-98	1303621.69
Oct-98	1311666.09
Nov-98	1318989.38
Dec-98	1346595.83
Jan-99	1339958.88
Feb-99	1334932.82
Mar-99	1335342.72
Apr-99	1338553.31
May-99	1348162.85
Jun-99	1357783.64
Jul-99	1367045.43
Aug-99	1384585.45
Sep-99	1387429.83
Oct-99	1394445.1
Nov-99	1409068.16
Dec-99	1446127.06
Jan-00	1439427
Feb-00	1434051.68
Mar-00	1437026.03
Apr-00	1444909.32
May-00	1456159.38
Jun-00	1476465.41
Jul-00	1487090
Aug-00	1510693.62
Sep-00	1519640.13
Oct-00	1538612.44
Nov-00	1558172.21
Dec-00	1593115.8
Jan-01	1586957.69
Feb-01	1585129.18
Mar-01	1584373.13
Apr-01	1596412.68
May-01	1601824.36
Jun-01	1608182.72
Jul-01	1612054.97
Aug-01	1626198.38
Sep-01	1629285.68
Oct-01	1643374.07
Nov-01	1671608.87
Dec-01	1701855.59
Jan-02	1687002.91
Feb-02	1677718.42
Mar-02	1677195.83
Apr-02	1683644.44

May-02	1691993.07
Jun-02	1701250.5
Jul-02	1706654.59
Aug-02	1724225.03
Sep-02	1721954.5
Oct-02	1727410.97
Nov-02	1735540.27
Dec-02	1761967.92