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Forecasting for a Credit Loan from Households in South Korea*

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Abstract

Purpose – In this work, we examined the causal relationship between credit loans from households (CLH), loan collateralized with housing (LCH) and an interest of certificate of deposit (ICD) among others in South Korea. Furthermore, the optimal forecasts on the underlying model will be obtained and have the potential for applications in the economic field.

Research design, data, and methodology – A total of 31 realizations sampled from the 4th quarter in 2008 to the 4th quarter in 2016 was chosen for this research. To achieve the purpose of this study, a regression model with correlated errors was exploited. Furthermore, goodness-of-fit measures was used as tools of optimal model-construction.

Results – We found that by applying the regression model with errors component ARMA(1,5) to CLH, the steep and lasting rise can be expected over the next year, with moderate increase of LCH and ICD.

Conclusions – Based on 2017-2018 forecasts for CLH, the precipitous and lasting increase can be expected over the next two years, with gradual rise of two major explanatory variables. By affording the assumption that the feedback among variables can exist, we can, in the future, consider more generalized models such as vector autoregressive model and structural equation model, to name a few.

Keywords: Credit Loan for Households, Multiple Regression with Correlated Errors, Exponential Smoothing Method, Forecast.

JEL Classifications: B22, C22, C53, M21.

1. Introduction

Statistics Korea reported that household consumption spending decreased 0.5 percent on-year to an average some 2,700,000 won a month in 2016, showing the first decay since 2003. Bank of Korea reports households debt in South Korea came to a record of about 1,334 trillion won in the 4th quarter in 2016, which is 11.7 percent increase from a year earlier. Mortgages rose 2.1 trillion won month-over-month to some 536 trillion won in this February, and climbed 800 billion won from a month earthier.

In this paper, we examine a causal relationship between credit loan from households and several explanatory variables and get the predicted values based on the optimal both regression model with auto-correlated errors and exponential smoothing methods.

A brief outline for time series models will be, in section 2, introduced as well as goodness-of-fit statistics and in section 3, findings of multiple regression analysis with correlated errors, and forecasts for credit loan from households will be stated. Finally, concluding remarks and future work will be mentioned.

2. Review of Literature

Jeon and Lee (2013) verified existence of positive correlation and the long-term equilibrium relationship between housing prices and CLH by using a unit root test, cointegration test, causality test, and impulse response function. As a result, they found that, in terms of long-term equilibrium, the reduction of apartment prices adjusts to in a nationwide level, while the rise of LCH controls Gangnam and Gangbuk in Seoul. On the other hand, apartment prices affect LCH strongly in terms of short-term equilibrium. The positive relationship between apartment prices and LCH, in

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the long term, shows that increase of apartment prices leads the rise of LCH.

Hwang and Lee (2015) investigated profiles of households loan in South Korea and examined the influences of households loan on consumption and income using observations from 2003 to 2014. They found that both consumption and income are cointegrated with credit loan from households and also loan from households has significantly positive influences on consumption in the long-term and in the short-term as well.

Choi (2016) inferred determinants of household loans and evaluated effects of household loans on consumption by exploiting ordinary least square and quantile regression technique, respectively. As a result, larger housing incomes and more real assets induce more accumulated household loans and aggravation of household consumption.

Lee (2016) examined the affecting factors on households debt and found that persons who have less schooling year or women rather than men or the older or persons engaged in primary industry seem to be more vulnerable to the psychological burden of households debt.

Jeon and Lee (2016) examined a causal relation between asset prices and CLH by applying the vector autoregressive model and the housing lease on a deposit basis and stock price shocks greatly affect CLH in the long-run.

Ryoo and Jeon (2017) investigated the determinants of the selection for housing loans depending on both properties of rates and installment term based on the 5,636,802 realizations covering from 2010 to 2014. They found that higher need of fixed rate induces people to increase in housing price, while adjustable rate can be favored in case of rise of housing price and in case of maintaining longer term of a contract, in terms of housing loans.

3. Research Methodology

For the purpose of estimating the causal relationships between a dependent variable, a credit loan for households (CLH) and several independent variables such as an interest of certificate of deposit (ICD) and a loan collateralized with housing (LCH) and so forth.

The statistical analysis was performed by the IBM SPSS 23.0 software. Models applied to this works were multiple regression model with correlated errors, ARIMA model and exponential smoothing methods and also the statistical testing was made at the 5% level.

3.1. Main model under consideration

$$y_t = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \epsilon_t, \ t = 1,2,\cdots,n \tag{2.1}$$

where $\epsilon_t = \dfrac{\Theta_Q(B^s)\theta_q(B)}{\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D}\xi_t$

such that $\Theta_Q(B^s) = (1-\Theta_s B^s - \Theta_{2s}B^{2s} - \cdots - \Theta_{Qs}B^{Qs})$

$\Phi_P(B^s) = (1-\Phi_s B^s - \Phi_{2s}B^{2s} - \cdots - \Phi_{Ps}B^{Ps})$

$\theta_q(B) = (1-\theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$

$\phi_p(B) = (1-\phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$

and $\xi's$ are white noises.

(Anderson, 1971; Bianchi et al., 1998; Bowerman et al., 2005; Box et al., 1994; Brown, 1959; Fuller, 1976; Hamiltan, 1994; Jeong, 2010; Pankraz, 1983)

We choose the reasonable predictor variables among several considered variables by using STEPWISE procedure in IBM SPSS 23.0 (Wilkinson & Dallal, 1981). This method shows that at each step, predictor variables not in the formula which takes the smallest probability of F-value is entered, if that probability is sufficiently small and variables already in the equation are deleted if their probability of F-value is getting sufficiently large.

After constructing the optimal multiple regression model with correlated errors on given above, forecasts of explanatory variables under consideration can be produced in order to predict the response variable CLH.

In this case, taking into account the form of the trend and existence of seasonality of the considered time series, we can generate the forecasts of several regressors on the following four linear trend exponential smoothing methods:

3.2. Main exponential smoothing methods to forecast regressors

(Anderson, 1994; Archibald, 1990; Archibald & Koehler, 2003; Bartolomei & Sweet, 1989; Brown, 1963; Broze & Mélard, 1990; Gardner, 1985; Gardner, 2006; Jeong, 2009; Roberts, 1982; Rosas & Guerrero, 1994; Trigg & Leach, 1967; Winters, 1960)

While in single moving averages the past realizations are weighted equally, exponential smoothing allows exponentially decreasing weights as the realizations is older. Namely, recent realizations are assigned relatively more weight in predicting than the older realizations.

- Simple Exponential Smoothing method

It is used for forecasting a time series when there is no trend or seasonal pattern, but the mean (or level) of the time series is slowly changing over time. This is exploited for short-term prediction. The model supposes that observations fluctuate around a stationary mean (no specific trend. The forecast for the next period is

$$\hat{y}_{t+1} = \hat{y}_t + \alpha(y_t - \hat{y}_t)$$

where α is a smoothing parameter between 0 and 1.

- Holt's linear trend. This method is appropriate for the time series where there is a linear pattern and no seasonal variation, and it contains smoothing parameters (α, γ) of level and trend, respectively. The overall slope shows linearity and forecasts, with two smoothing parameters (α, γ).

• Brown's linear trend. This method is proper for the time series where there is a linear pattern and no seasonal variation, and it contains smoothing parameters α of trend. The overall slope shows exponential shape and forecasts, with one smoothing parameter α.

• Damped linear trend. This method is appropriate for the time series in which there is a linear trend with dying out and no seasonal variation, and it contains three smoothing parameters (α, γ, ϕ) of level, trend and damped trend, respectively. The overall slope shows linearity and forecasts, with three smoothing parameters (α, γ, ϕ).

3.3. Goodness-of-fit measures

(Chatfield, 1988; Chatfield, 1993; Chatfield, 1995; Chatfield, 1996; Chatfield, 1997; Chatfield, 2002; Hurcich & Tsai, 1990)

In order to perform the optimal modelling and to select predicted values of predictors, the following criteria can crucially be considered:

• Stationary R-squared. This measure is better than ordinary R-squared when a trend or seasonality in time series can be detected. If it is a negative value, then we can conclude that the baseline model is dominant to the model under consideration.

• R-squared. A statistic of the proportion of all variation in the time series accounted for by the model. This measure can be valid when the time series satisfy stationarity. A negative value of this measure means that the baseline model is dominant to the model under consideration, while a positive value means that the model under consideration is more suitable than the baseline one.

• Root Mean Square Error (RMSE). A statistic of how much a dependent time series changes from its model-predicted level.

• Mean Absolute Percentage Error (MAPE). This measure is not dependent on the units detected and be taken advantage of comparing the time series with different ones.

• Mean absolute error (MAE). A measure how much the time series fluctuate its model-predicted level.

• Maximum Absolute Percentage Error (MaxAPE). The biggest predicted error, depicted as a percentage. This measure is useful to estimate a worst situation for predicted values.

• Maximum Absolute Error (MaxAE). This measure is useful to estimate the worst-case scenario for predicted values.

• Normalized Bayesian Information Criterion (BIC). This statistic is a score focused on the MSE and covers a handicap for parameters in the underlying model under consideration and the length of the time series.

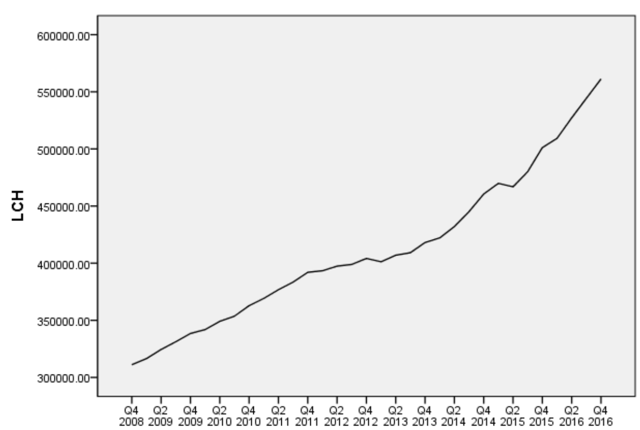
4. Descriptive Statistics and Discussion

Summary statistics of explanatory variables and a response variable for 33 realizations from the 4th quarter in 2008 to the 4th quarter in 2016, including arithmetic average, standard deviation, minimum and maximum, are shown in <Table 1>. Note that the variables LCH, ICD and CLH, under consideration in this work, are obtained from Korean Statistical Information Service (KOSIS) and Economic Statistical System (ECOS), respectively.

<Table 1> Summary statistics

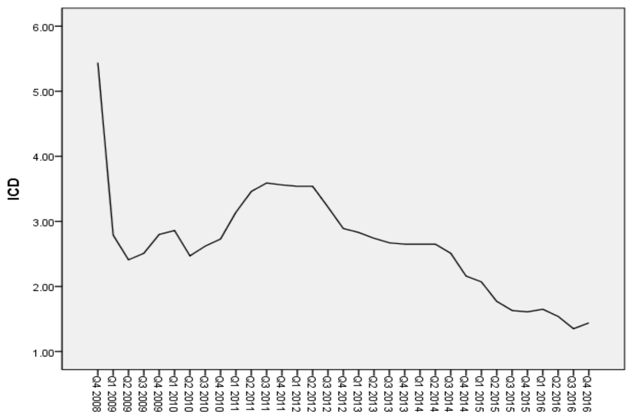
	N	Minimum	Maximum	Mean	Std. Deviation
LCH	33	311,158	561,262	412127.7	67146.8
ICD	33	1.35	5.44	2.651	.819
CLH	33	29,350	55,250	40515.8	6889.878

Note that we determine the final predictor variables such as an interest of certificate of deposit (ICD) and a loan collateralized with housing (LCH) after choosing the best subsets of predictors by using STEPWISE variable selection method.

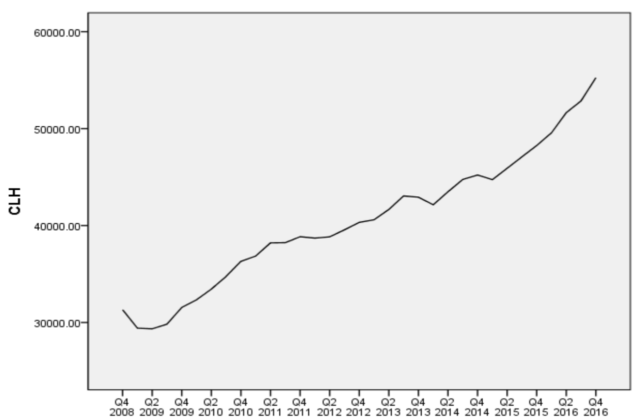


<Figure 1> Time-plot of LCH in South Korea

From both <Figure 1> and <Figure 3>, although the variance of these series appears to be constant through time, the mean seems to be non-stationary. Unlike the previous figures, a causal examination of <Figure 2> suggests that the series is stationary. The realizations seem to fluctuate around a fixed mean, and the variance seems to constant over time.



<Figure 2> Time-plot of ICD in South Korea



<Figure 3> Time-plot of CLH in South Korea

After fitting the linear regression model with predictors ln(LCH) and ICD, we can detect the suitable candidates of errors components such as MA(2), AR(5) and ARMA(1,5) based on both residual autocorrelation function (ACF) and residual partial autocorrelation function (PACF) (Akaike, 1970).

<Table 2> Optimal selection of errors component

Error component Statistics	MA(2)	AR(5)	ARMA (1,5)
Stationary R^2	.990	.992	**.993**
R^2	.990	.992	**.993**
RMSE	.018	**.016**	**.016**
MAPE	.132	**.115**	**.115**
MAE	.014	**.012**	**.012**
MaxAPE	.384	.299	**.283**
MaxAE	.041	.032	**.030**
Normalized BIC	-7.480	-7.735	**-7.762**
p-value of Box-Ljung	.188	.229	**.693**

The multiple linear regression with errors component ARMA(1,5) is dominant over the rest of two components in terms of the largest 'Stationary R^2', 'R^2' and the smallest the rest of six statistics such as RMSE etc.

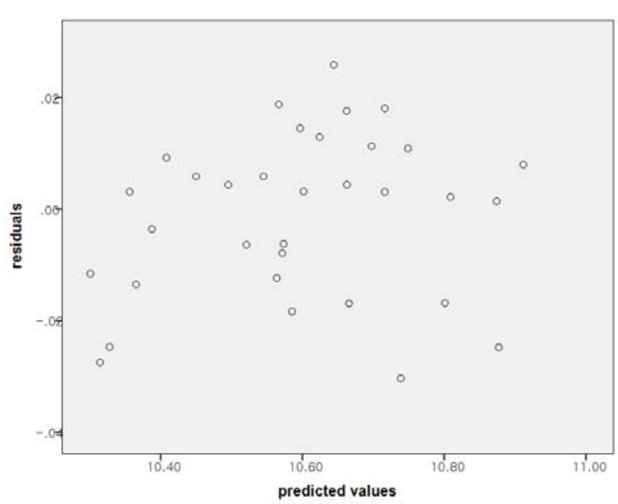
<Table 3> Testing of model adequacy for model (3.1)

Lag	Box-Ljung statistic		
	value	df	p-value
1	.384	1	.535
2	.446	2	.800
3	.673	3	.880
4	.675	4	.954
5	.675	5	.984
6	4.421	6	.620
7	4.449	7	.727
8	4.777	8	.781
9	5.972	9	.743
10	6.007	10	.815
11	6.683	11	.824
12	6.865	12	.866

<Table 3> shows that the multiple linear regression model with correlated errors ARMA(1,5) given below is satisfactory. Namely, none of p-values corresponding to Box-Ljung statistics is significant at the 5% significance level and also no specific patterns and relatively large residuals can be found from <Figure 4>, so that we can conclude that the linear regression model with correlated errors, (3.1), can satisfy optimality properties (Ljung & Box, 1978; Tsay & Tiao, 1984).

$$\ln(\widehat{CLH})_t = -4.506 + 1.163\ln(LCH)_t + 0.029\, ICD_t + \hat{\epsilon}_t$$

$$\text{where} \quad \hat{\epsilon}_t = \frac{(1-0.801\,B^5)}{(1-0.730\,B)}\hat{\xi}_t \tag{3.1}$$



<Figure 4> Residuals plot

Now, three linear trend exponential smoothing methods can be compared to obtain the optimal future values of each predictors. As a result, Holt's and damped linear trend method can be chosen for predictor variables ln(LCH) and ICD, respectively based on goodness-of-fit measures (see <Table 4> and <Table 5>).

<Table 4> Optimal model of a regressor ln(LCH)

Type Statistics	Holt	Brown	Damped
Stationary R^2	**.380**	.322	.044
R^2	**.995**	**.995**	**.995**
RMSE	**.011**	.012	**.011**
MAPE	**.062**	.069	**.062**
MAE	**.008**	.009	**.008**
MaxAPE	.222	.249	**.221**
MaxAE	**.029**	.033	**.029**
Normalized BIC	**-8.781**	-8.768	-8.642

<Table 5> Optimal model of a regressor ICD

Type Statistics	Holt	Brown	Damped
Stationary R^2	.038	.038	**.339**
R^2	.691	.691	**.752**
RMSE	.463	.455	**.421**
MAPE	9.437	9.433	**9.350**
MAE	**.223**	**.223**	.232
MaxAPE	94.19	94.19	**72.07**
MaxAE	2.27	2.27	**1.74**
Normalized BIC	-1.330	**-1.468**	-1.411

The optimal forecasts can be obtained as <Table 6> and <Table 7>, by fitting two linear trend exponential smoothing methods to regressors ln(LCH) and ICD, respectively.

<Table 6> Optimal forecasts of predictor ln(LCH)

Time period	Forecast	Time period	Forecast
Q1 2017	13.27	Q1 2018	13.38
Q2 2017	13.29	Q2 2018	13.41
Q3 2017	13.32	Q3 2018	13.44
Q4 2017	13.35	Q4 2018	13.47

<Table 7> Optimal forecasts of predictor ICD

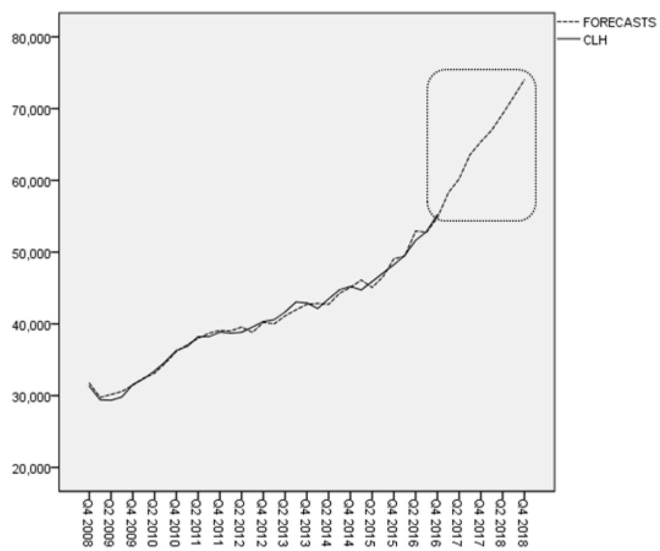
Time period	Forecast	Time period	Forecast
Q1 2017	1.51	Q1 2018	1.68
Q2 2017	1.57	Q2 2018	1.70
Q3 2017	1.62	Q3 2018	1.72
Q4 2017	1.65	Q4 2018	1.74

The optimal forecasts of the response variable CLH from the 1th quarter in 2017 to the 4th quarter in 2018 can be shown both in <Table 8> and in <Figure 5> (see rectangular box).

By applying the linear regression model with error component ARMA(1,5) to the response variable CLH, the steep and lasting increase can be expected over the whole months of 2018.

<Table 8> Optimal forecasts of CLH in South Korea from model (3.1)

Time	95% Lower Confidence Limit	Forecast	95% Upper Confidence Limit
Q1 2017	56,517.96	58,258.89	60,053.46
Q2 2017	58,005.05	60,223.03	62,525.82
Q3 2017	61,044.30	63,584.67	66,230.76
Q4 2017	62,681.73	65,398.18	68,232.36
Q1 2018	64,175.07	67,013.09	69,976.62
Q2 2018	66,106.82	69,269.94	72,584.40
Q3 2018	68,217.84	71,606.93	75,164.40
Q4 2018	70,457.80	74,025.23	77,773.28



<Figure 5> Optimal forecasts of CLH in South Korea from multiple regression model with corrected error component ARMA(1,5)

5. Concluding Remarks and Limitations

We may find a model to express a causal relationship among some economic variables and then evaluate this relationship or may forecast CLH. One of the important assumptions in the regression model is that the error disturbances are uncorrelated. Correlation in the error disturbances suggests that there exists extra information that has not been exploited in the model under consideration.

Based on the linear regression model under consideration, three options of correlated errors are considered: Moving Average of order 2, Autoregressive of order 5 and

Autoregressive Moving Average of order (1, 5).

The final regression model can include the correlated component ARMA(1, 5) by comparing the eight goodness-of-fit measures and Box-Ljung statistic at the same time. That is, ARMA(1, 5) shows strong superiority in terms of all goodness -of-fit statistics (having largest stationary R-squared, R-squared and smallest RMSE, MAPE, MAE, MAXPE, MAXAE and Normalized BIC).

First, loan collateralized with housing, one of the predictor variable chosen, has the predicted values 13.27, 13.29, 13.32, 13.35, 13.38, 13.41, 13.44 and 13.47, which are taken natural logarithm of loan collateralized with housing. These values are produced on Holt's linear trend by comparing the superiority of three exponential smoothing methods.

Second, interest of certificate of deposit, the other predictor variable, has the forecasts 1.51, 1.57, 1.62, 1.65, 1.68, 1.70, 1.72, and 1.74, which are obtained based on damped linear trend by similarly comparing the superiority of three exponential smoothing methods.

Third, the optimal forecasts of the response variable from the 1st quarter in 2017 to the 4th quarter in 2018 will be 58,259, 60,223, 63584, 65,398, 69,013, 69,270, 71,607 and 74,025. We can find out the steep and persisting increase of credit loan from households can be expected over the next two years, with moderate increase of two predictor variables.

Considering 2017-2018 forecasts for credit loan from households, we will produce the useful information for reforming financial conditions and related policies to stabilize national economy.

Policy makers should be more active in implementing expansionary fiscal policy, which needs to be coupled with structural reform and deregulation to increase employment as fundamental way to boost consumption and also measures to stir up consumption need further review and elaboration. However, the conditions for climbing income are challenging, so that Korea authority has to act more aggressively to create jobs and evade the consumption crisis. We note that household loans performed by liquidity restriction may reduce household consumption and consider the crucial factors such as incomes, age and type of loan rate.

This research was analyzed by taking advantage of the multiple regression model with correlated errors, but the limitations lie in the fact that the underlying model was analyzed without considering feedbacks and cross correlations between variables. We may try to use the modified regression model by adding indispensable regressor(s) to the original one or may fit the transfer function model, as an alternative, with taking into account time-lagged relationships between regressors and a response variable (Pankratz, 1991).

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