Base Cash Flow Model Validation-ACB_USCB_Loan Floaters

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Model ID 1537

Part I

```
getwd()

## [1] "C:/Users/n311129/Desktop/ACB_USCB-1537/Working Files"

setwd("C:/Users/N311129/Desktop/ACB_USCB-1537/Working Files")

load(file="ACB_USCB.RData")
```

install.packages("forecast")

install.packages("rcompanion",destdir = .libPaths()) My alternative when downloaded packages goes to Temp folder

install.packages("psych")

install.packages("caret")

```
library(e1071)
library(forecast)

## Registered S3 method overwritten by 'xts':
##   method     from
##   as.zoo.xts zoo

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo

## Registered S3 methods overwritten by 'forecast':
##   method             from
##   fitted.fracdiff    fracdiff
##   residuals.fracdiff fracdiff

library(rcompanion)

##
## Attaching package: 'rcompanion'

## The following object is masked from 'package:forecast':
##
##     accuracy
```

```r
ACB_USCB <- read.csv(file="ACB_USCB.csv")
str(ACB_USCB)
```

```
## 'data.frame':    27 obs. of  28 variables:
##  $ tmo                          : Factor w/ 27 levels
"1/1/2016","1/1/2017",..: 1 10 13 16 18 20 22 24 26 4 ...
##  $ Integer_Adjustment           : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ LONG_TERM_LOAN_FLOATER_ACBD   : num  23.3 24.3 24.6 24.7 24.8 ...
##  $ LONG_TERM_LOAN_FLOATER_USCB   : num  20.8 21.3 21.3 22 22.2 ...
##  $ loans_ACB_USCB               : num  44.1 45.5 46 46.7 47 ...
##  $ loans_ACB_USCByoy            : num  23.4 26.2 22.4 21.9 20.8 ...
##  $ LongTermLn_Float_Totyoy      : num  21.6 24 21.9 22.5 20.3 ...
##  $ LONG_TERM_LOAN_FLOATER_USCByoy: num  10.77 12.79 8.62 8.02 4.57 ...
##  $ LONG_TERM_LOAN_FLOATER_ACBDyoy: num  37.4 40.9 37.6 37.5 40.3 ...
##  $ BAA_Spread                   : num  3.36 3.56 3.24 2.98 2.87 2.89 2.72
2.68 2.68 2.62 ...
##  $ mo_CFed_CapSpendIndex        : num  -17.98 -21.97 -8.16 -17.29 -26.42
...
##  $ CI_Loans                     : num  1960 1990 2031 2053 2066 ...
##  $ Actuals_CI_Loansyoy          : num  9.81 10.11 10.21 10.25 10.12 ...
##  $ CFed_CapSpendIndex           : num  NA -21.97 -8.16 NA -26.42 ...
##  $ tqu                          : Factor w/ 9 levels
"1/1/2016","1/1/2017",..: 1 1 1 6 6 6 8 8 8 4 ...
##  $ mo_bfi_nominalyoy            : num  -0.279 -0.942 -1.605 -1.526 -1.446
...
##  $ mo_bfi_realyoy               : num  0.826 -0.544 -1.913 -2.204 -2.494
...
##  $ dateBBBSpread                : Factor w/ 27 levels ""," 1/29/2016",..:
2 7 8 11 12 14 16 18 21 22 ...
##  $ BBBSpread_Bloomberg          : num  2.17 2.28 1.99 1.79 1.76 1.83 1.69
1.65 1.65 1.59 ...
##  $ tda                          : Factor w/ 27 levels "","1/29/2016",..:
2 13 14 17 18 20 22 24 27 5 ...
##  $ BBBSpread_MUB                : num  2.55 2.84 2.61 2.49 2.26 ...
##  $ MUBf_CI_Loansyoy             : num  9.86 10.16 10.35 10.45 10.3 ...
##  $ X_merge                      : Factor w/ 1 level "matched (3)": 1 1 1
1 1 1 1 1 1 1 ...
##  $ ICE1mL                       : num  0.425 0.44 0.437 0.436 0.469 ...
##  $ ICE3mL                       : num  0.613 0.633 0.629 0.637 0.686 ...
##  $ FedFundsEffective            : num  0.29 0.29 0.25 0.3 0.29 0.3 0.3
0.3 0.29 0.31 ...
##  $ SwapRate3mL_1y               : num  0.694 0.743 0.74 0.782 0.872 ...
##  $ futureRateHikeExpect_1y3m     : num  0.0809 0.1094 0.1114 0.1457 0.1857
...
```

```r
summary(ACB_USCB)
```

```
##         tmo     Integer_Adjustment LONG_TERM_LOAN_FLOATER_ACBD
##  1/1/2016 : 1   Min.   :0.0000     Min.   :21.46
##  1/1/2017 : 1   1st Qu.:0.0000     1st Qu.:24.74
```

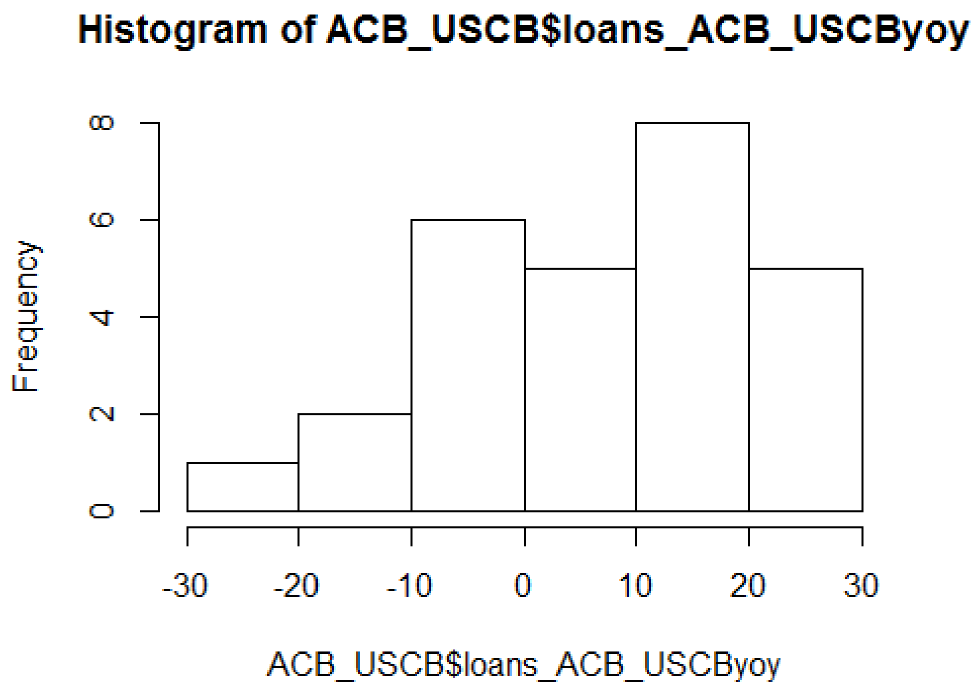
```
##  1/1/2018 : 1   Median :0.0000     Median :26.75
##  10/1/2016: 1   Mean   :0.3704     Mean   :25.99
##  10/1/2017: 1   3rd Qu.:1.0000     3rd Qu.:27.73
##  11/1/2016: 1   Max.   :1.0000     Max.   :28.90
##  (Other)  :21
##  LONG_TERM_LOAN_FLOATER_USCB loans_ACB_USCB  loans_ACB_USCByoy
##  Min.   :16.64               Min.   :38.10   Min.   :-20.512
##  1st Qu.:18.98               1st Qu.:45.48   1st Qu.: -3.625
##  Median :20.61               Median :46.76   Median :  5.167
##  Mean   :20.18               Mean   :46.17   Mean   :  6.219
##  3rd Qu.:21.67               3rd Qu.:47.92   3rd Qu.: 18.042
##  Max.   :22.32               Max.   :49.52   Max.   : 26.201
##
##  LongTermLn_Float_Totyoy LONG_TERM_LOAN_FLOATER_USCByoy
##  Min.   :-18.247         Min.   :-16.995
##  1st Qu.: -6.388         1st Qu.:-11.708
##  Median :  1.845         Median : -5.818
##  Mean   :  4.673         Mean   : -3.592
##  3rd Qu.: 18.508         3rd Qu.:  4.016
##  Max.   : 23.964         Max.   : 12.789
##
##  LONG_TERM_LOAN_FLOATER_ACBDyoy   BAA_Spread    mo_CFed_CapSpendIndex
##  Min.   :-23.039                Min.   :1.650   Min.   :-26.42
##  1st Qu.:  5.782                1st Qu.:2.085   1st Qu.:-21.25
##  Median : 14.794                Median :2.250   Median :-17.29
##  Mean   : 16.226                Mean   :2.406   Mean   :-15.97
##  3rd Qu.: 35.943                3rd Qu.:2.700   3rd Qu.:-11.66
##  Max.   : 41.839                Max.   :3.560   Max.   :  0.00
##
##     CI_Loans    Actuals_CI_Loansyoy CFed_CapSpendIndex        tqu
##  Min.   :1960   Min.   : 0.6301     Min.   :-26.42     1/1/2016 :3
##  1st Qu.:2066   1st Qu.: 1.7850     1st Qu.:-21.94     1/1/2017 :3
##  Median :2095   Median : 5.4950     Median :-15.87     1/1/2018 :3
##  Mean   :2083   Mean   : 5.3355     Mean   :-15.89     10/1/2016:3
##  3rd Qu.:2107   3rd Qu.: 8.9686     3rd Qu.:-10.32     10/1/2017:3
##  Max.   :2145   Max.   :10.2482     Max.   :  0.00     4/1/2016 :3
##                                     NA's   :9          (Other)  :9
##  mo_bfi_nominalyoy mo_bfi_realyoy      dateBBBSpread BBBSpread_Bloomberg
##  Min.   :-1.605    Min.   :-2.784             : 1    Min.   :1.230
##  1st Qu.:-0.989    1st Qu.:-1.695    1/29/2016: 1    1st Qu.:1.373
##  Median : 2.885    Median : 1.410    1/31/2017: 1    Median :1.520
##  Mean   : 2.733    Mean   : 1.254    1/31/2018: 1    Mean   :1.575
##  3rd Qu.: 5.866    3rd Qu.: 3.834    2/28/2017: 1    3rd Qu.:1.680
##  Max.   : 7.682    Max.   : 5.778    2/28/2018: 1    Max.   :2.280
##                                     (Other)   :21    NA's   :1
##          tda      BBBSpread_MUB   MUBf_CI_Loansyoy        X_merge
##            : 1   Min.   :1.081   Min.   : 0.8862   matched (3):27
##  1/29/2016 : 1   1st Qu.:1.643   1st Qu.: 2.1530
##  1/31/2017 : 1   Median :1.807   Median : 5.5462
##  1/31/2018 : 1   Mean   :1.896   Mean   : 5.5773
```

```
##  10/31/2016: 1   3rd Qu.:2.183   3rd Qu.: 9.1268
##  10/31/2017: 1   Max.   :2.844   Max.   :10.4546
##  (Other)   :21
##      ICE1mL           ICE3mL       FedFundsEffective SwapRate3mL_1y
##  Min.   :0.4250   Min.   :0.6126   Min.   :0.2500    Min.   :0.6755
##  1st Qu.:0.5104   1st Qu.:0.7992   1st Qu.:0.3000    1st Qu.:0.9087
##  Median :0.7889   Median :1.0640   Median :0.5700    Median :1.3565
##  Mean   :0.9256   Mean   :1.1363   Mean   :0.7215    Mean   :1.3087
##  3rd Qu.:1.2319   3rd Qu.:1.3258   3rd Qu.:1.0700    3rd Qu.:1.5124
##  Max.   :1.8831   Max.   :2.3117   Max.   :1.6700    Max.   :2.4200
##
##  futureRateHikeExpect_1y3m
##  Min.   :0.0214
##  1st Qu.:0.1104
##  Median :0.1579
##  Mean   :0.1724
##  3rd Qu.:0.2245
##  Max.   :0.3182
##
```

```
names(ACB_USCB)
```

```
##  [1] "tmo"                              "Integer_Adjustment"
##  [3] "LONG_TERM_LOAN_FLOATER_ACBD"      "LONG_TERM_LOAN_FLOATER_USCB"
##  [5] "loans_ACB_USCB"                   "loans_ACB_USCByoy"
##  [7] "LongTermLn_Float_Totyoy"          "LONG_TERM_LOAN_FLOATER_USCByoy"
##  [9] "LONG_TERM_LOAN_FLOATER_ACBDyoy" "BAA_Spread"
## [11] "mo_CFed_CapSpendIndex"            "CI_Loans"
## [13] "Actuals_CI_Loansyoy"              "CFed_CapSpendIndex"
## [15] "tqu"                              "mo_bfi_nominalyoy"
## [17] "mo_bfi_realyoy"                   "dateBBBSpread"
## [19] "BBBSpread_Bloomberg"              "tda"
## [21] "BBBSpread_MUB"                    "MUBf_CI_Loansyoy"
## [23] "X_merge"                          "ICE1mL"
## [25] "ICE3mL"                           "FedFundsEffective"
## [27] "SwapRate3mL_1y"                   "futureRateHikeExpect_1y3m"
```

```
hist(ACB_USCB$loans_ACB_USCByoy)
```



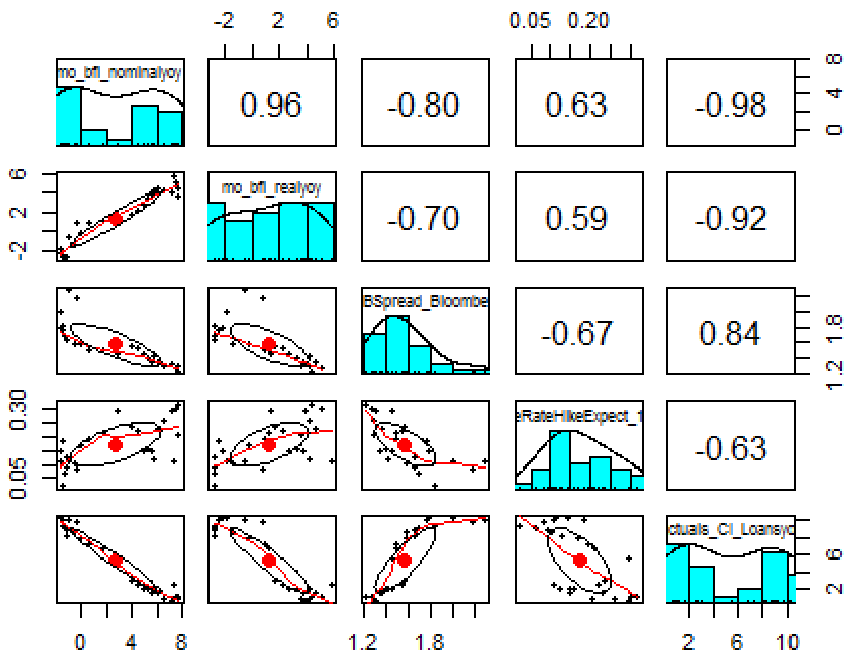
Correlation matrix By variables

```
library(psych)

##
## Attaching package: 'psych'

## The following object is masked from 'package:rcompanion':
##
##     phi

#pairs.panels(ACB_USCB)
source("https://raw.githubusercontent.com/briatte/ggcorr/master/ggcorr.R") # Here I'm using ggcorr as a stand alone function instead of via the GGally package.
#ggcorr(ACB_USCB,
#       label = TRUE,
 #      label_alpha = TRUE,
 #      hjust = 0.75,
  #     size = 3,
   #    low = "steelblue",
    #   mid = "white",
     #  high = "darkred")
```

The correlation of the MO selected variables

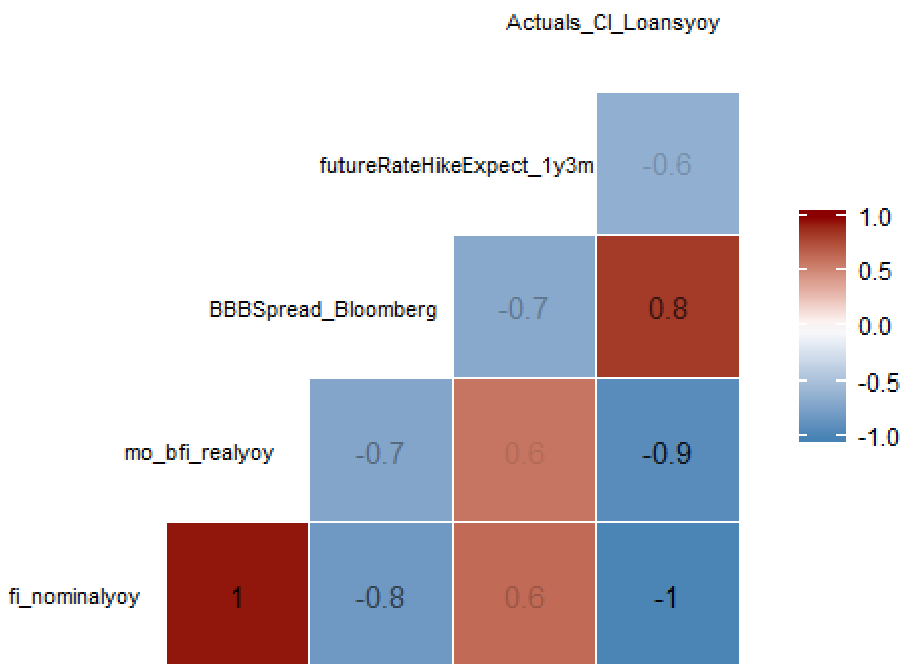
Test the correlation of the MO Selected variables in the data. This is possibly the rationale for the selected variables for this model

```
ACB_USCB.num=ACB_USCB[c("mo_bfi_nominalyoy","mo_bfi_realyoy","BBBSpread_Bloomberg","futureRateHikeExpect_1y3m","Actuals_CI_Loansyoy")]
pairs.panels(ACB_USCB.num)
```




```
ggcorr(ACB_USCB.num,
       label = TRUE,
       label_alpha = TRUE,
       hjust = 0.75,
       size = 3,
       low = "steelblue",
       mid = "white",
       high = "darkred")
```

```
##
## Attaching package: 'ggplot2'

## The following objects are masked from 'package:psych':
##
##     %+%, alpha
```



The visualization charts above shows that there's a very strong correlation between mo_bfi_nominalyoy and mo_bfi_realyoy (0.96), BBBSpread_Bloomberg and Actuals_CI_Loansyoy (0.84)

library(PerformanceAnalytics)

chart.Correlation(ACB_USCB.num, method = "pearson",histogram=(TRUE),phc = 16) I decided to use the chart above for a comparison of visualization but ignored it since there is no difference from the previous chart.

The Initial Model

Model 1. Build the model with all the MO provided Variables for ACB_USCB

```
ACB_USCB_Model<-lm(loans_ACB_USCByoy ~ mo_bfi_nominalyoy + mo_bfi_realyoy +
BBBSpread_Bloomberg + futureRateHikeExpect_1y3m + Actuals_CI_Loansyoy,data =
ACB_USCB)
summary(ACB_USCB_Model)

##
## Call:
## lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy + mo_bfi_realyoy +
##     BBBSpread_Bloomberg + futureRateHikeExpect_1y3m + Actuals_CI_Loansyoy,
##     data = ACB_USCB)
##
## Residuals:
##     Min       1Q   Median       3Q      Max
```

```
## -5.3272 -1.2746  0.1848  1.4274  4.4408
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  7.3985     7.9360   0.932 0.362314
## mo_bfi_nominalyoy           -5.1768     1.1893  -4.353 0.000308 ***
## mo_bfi_realyoy               0.9512     0.7083   1.343 0.194311
## BBBSpread_Bloomberg         15.1715     3.9893   3.803 0.001115 **
## futureRateHikeExpect_1y3m   -8.7538    10.2222  -0.856 0.401948
## Actuals_CI_Loansyoy         -1.8937     0.9127  -2.075 0.051132 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.517 on 20 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.9694, Adjusted R-squared:  0.9618
## F-statistic: 126.8 on 5 and 20 DF,  p-value: 1.947e-14
```

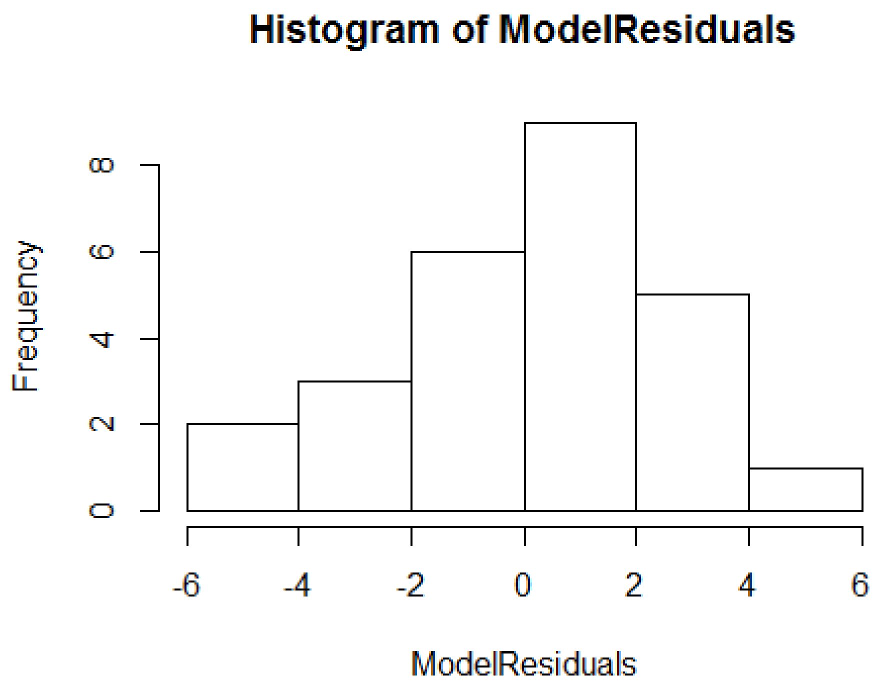
Analysis of Variance for Model 1

```
anova(ACB_USCB_Model)
```

```
## Analysis of Variance Table
##
## Response: loans_ACB_USCByoy
##                           Df Sum Sq Mean Sq  F value    Pr(>F)
## mo_bfi_nominalyoy          1 3831.0  3831.0 604.4897 < 2.2e-16 ***
## mo_bfi_realyoy             1   43.1    43.1   6.8015 0.0168339 *
## BBBSpread_Bloomberg        1   95.3    95.3  15.0383 0.0009358 ***
## futureRateHikeExpect_1y3m  1   20.9    20.9   3.3054 0.0840642 .
## Actuals_CI_Loansyoy        1   27.3    27.3   4.3045 0.0511316 .
## Residuals                 20  126.8     6.3
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

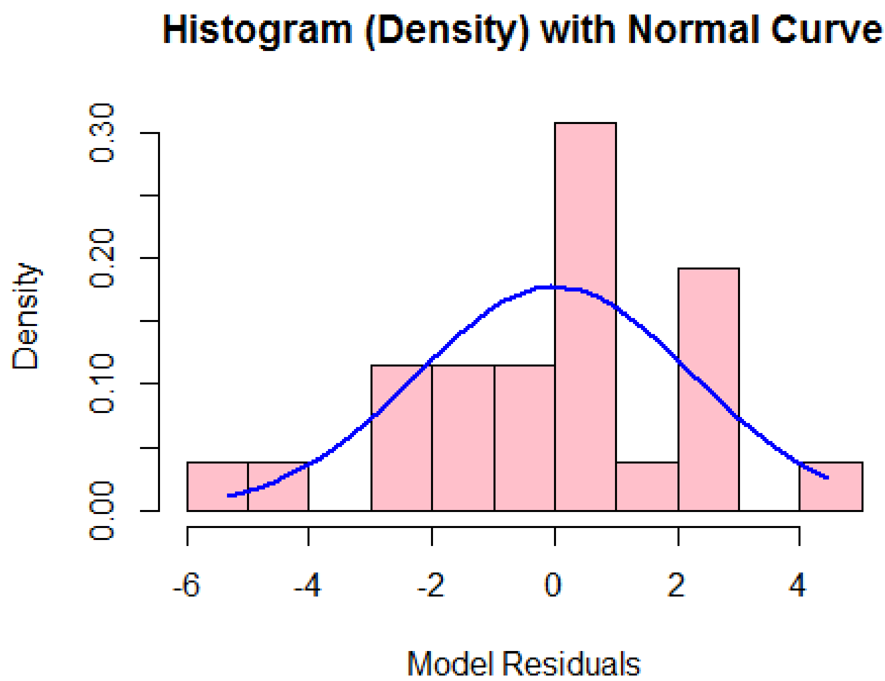
Ploting the residuals

```
ModelResiduals = residuals(ACB_USCB_Model)
hist(ModelResiduals)
```



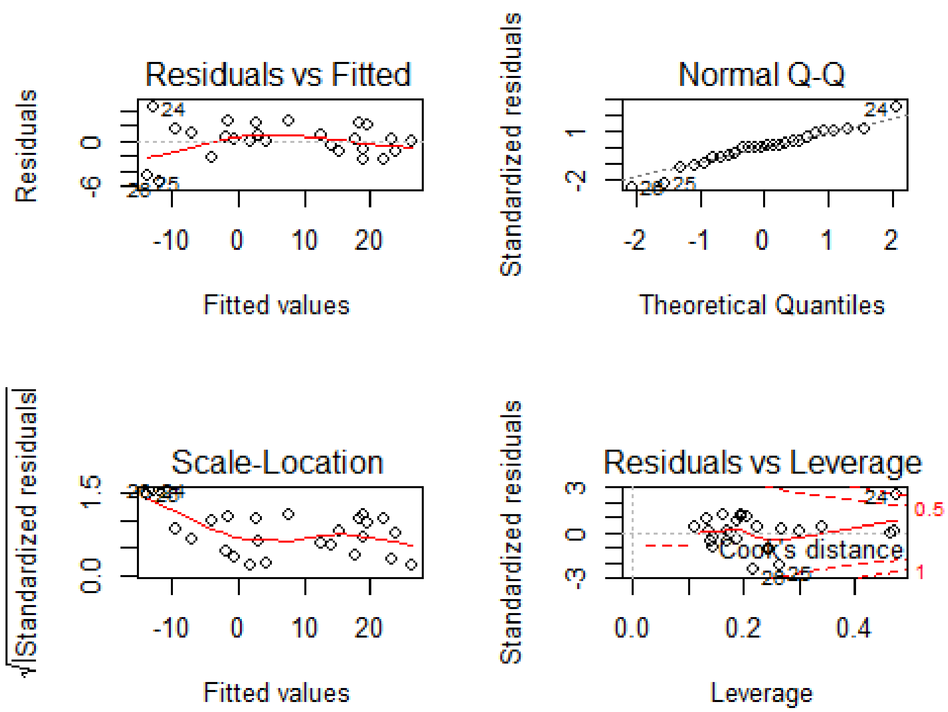
This chart shows that the Model's Residuals are Normally Distributed.

```
Residual_Distribution <- hist(ModelResiduals, breaks=12, col="Pink",
xlab="Model Residuals", main="Histogram (Density) with Normal Curve",
freq=FALSE)
xfit <- seq(min(ModelResiduals), max(ModelResiduals), length=40)
yfit_density <- dnorm(xfit, mean=mean(ModelResiduals), sd=sd(ModelResiduals))
lines(xfit, yfit_density, col="blue", lwd=2)
```



The Diagnostic plots provide checks for heteroscedasticity, normality, and influential observations. Plotting the model shows that the residuals have constant variance when plotted against fitted values(Residuals Vs Fitted graph); and the residuals and fitted values are uncorrelated. From the Normal Q-Q graph, the residuals from the regression model are approximately normally distributed

```
par(mfrow=c(2,2))
plot(ACB_USCB_Model)
```



Variable Selection

To Determine the best explanatory variables for the model using Step-wise regression in both direction (Step Forward and Step Backward).

```
stepMod <- step(ACB_USCB_Model, scope = list(ACB_USCB_Model), direction =
"both", trace = 0, steps = 1000)  # perform step-wise algorithm
shortlistedVars <- names(unlist(stepMod[[1]])) # get the shortlisted
variable.
shortlistedVars <- shortlistedVars[!shortlistedVars %in% "(Intercept)"]  #
remove intercept
print(shortlistedVars) # The following variables were selected from the step-
wise method to be significant "mo_bfi_nominalyoy"   "BBBSpread_Bloomberg"
"Actuals_CI_Loansyoy"

## [1] "mo_bfi_nominalyoy"   "BBBSpread_Bloomberg" "Actuals_CI_Loansyoy"
```

Using secondary method to identify variable importance

```
library(caret)

## Loading required package: lattice

varImp(ACB_USCB_Model)

##                             Overall
## mo_bfi_nominalyoy         4.3529128
## mo_bfi_realyoy            1.3430127
## BBBSpread_Bloomberg       3.8030695
```

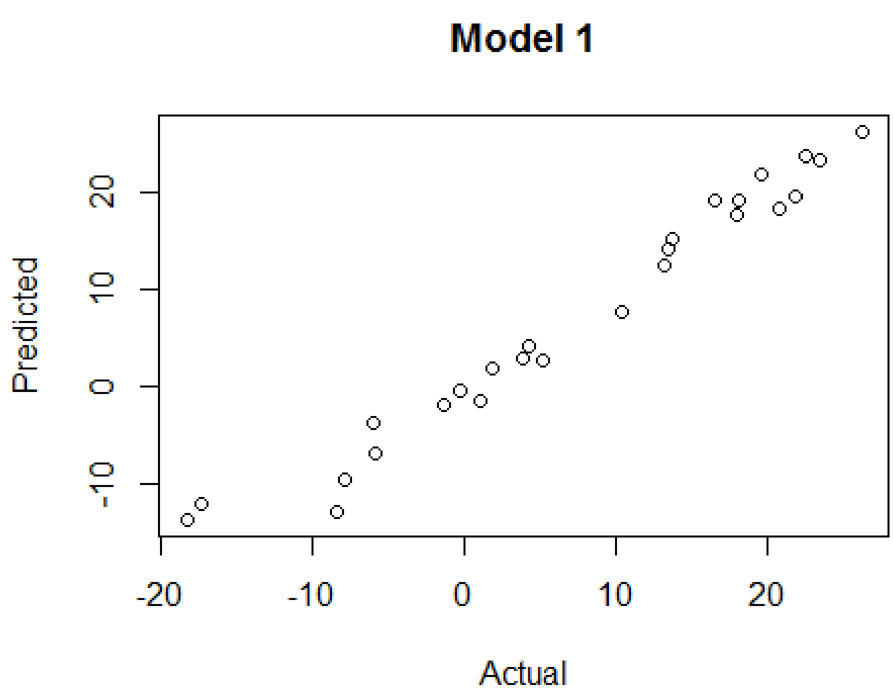
```
## futureRateHikeExpect_1y3m 0.8563506
## Actuals_CI_Loansyoy       2.0747321
```

```r
summary(influence.measures(ACB_USCB_Model))
```

```
## Potentially influential observations of
##   lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy + mo_bfi_realyoy +
BBBSpread_Bloomberg + futureRateHikeExpect_1y3m + Actuals_CI_Loansyoy,
data = ACB_USCB) :
##
##    dfb.1_  dfb.m_bf_n dfb.m_bf_r dfb.BBBS dfb.fRHE dfb.A_CI dffit
## 1  -0.03    0.01       0.03       0.02    -0.02     0.02     0.07
## 2   0.01    0.00       0.00      -0.02     0.00     0.00    -0.02
## 12  0.15   -0.15       0.18      -0.11     0.04    -0.04     0.23
## 15  0.00   -0.01      -0.01       0.02     0.02    -0.02     0.03
## 24 -1.29_*  2.34_*    -1.62_*    -0.26    -1.13_*   1.69_*   2.69_*
##    cov.r   cook.d hat
## 1   2.57_*  0.00   0.47
## 2   2.54_*  0.00   0.46
## 12  2.01_*  0.01   0.34
## 15  1.95_*  0.00   0.30
## 24  0.31    0.90   0.48
```

Model performance

```r
accuracy(list(ACB_USCB_Model),plotit=TRUE, digits=3)
```



```
## $Models
##   Call
## 1 "lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy + mo_bfi_realyoy + "
##
## $Fit.criteria
##   Min.max.accuracy  MAE   MAPE  MSE RMSE NRMSE.mean NRMSE.median
## 1            0.979 1.67 0.0396 4.88 2.21      0.305        0.285
##   NRMSE.mean.accuracy NRMSE.median.accuracy Efron.r.squared CV.prcnt
## 1               0.695                 0.715           0.969     30.5
```

Additional Model

Model 2. With the Selected variables

```
ACB_USCB_Model_2<-lm(loans_ACB_USCByoy ~ mo_bfi_nominalyoy +
BBBSpread_Bloomberg + Actuals_CI_Loansyoy,data = ACB_USCB)
summary(ACB_USCB_Model_2) # There is no significant difference in the R-
Squared value from the first model.
```

```
##
## Call:
## lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy + BBBSpread_Bloomberg +
##     Actuals_CI_Loansyoy, data = ACB_USCB)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.4895 -1.1965  0.1678  1.6757  3.6537
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)           1.4809     6.9382   0.213   0.8329
## mo_bfi_nominalyoy    -4.5512     0.8299  -5.484 1.64e-05 ***
## BBBSpread_Bloomberg  18.0087     3.4954   5.152 3.65e-05 ***
## Actuals_CI_Loansyoy  -2.0134     0.8337  -2.415   0.0245 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.539 on 22 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.9658, Adjusted R-squared:  0.9611
## F-statistic: 206.9 on 3 and 22 DF,  p-value: 2.877e-16
```

Analysis of Variance for Model 2

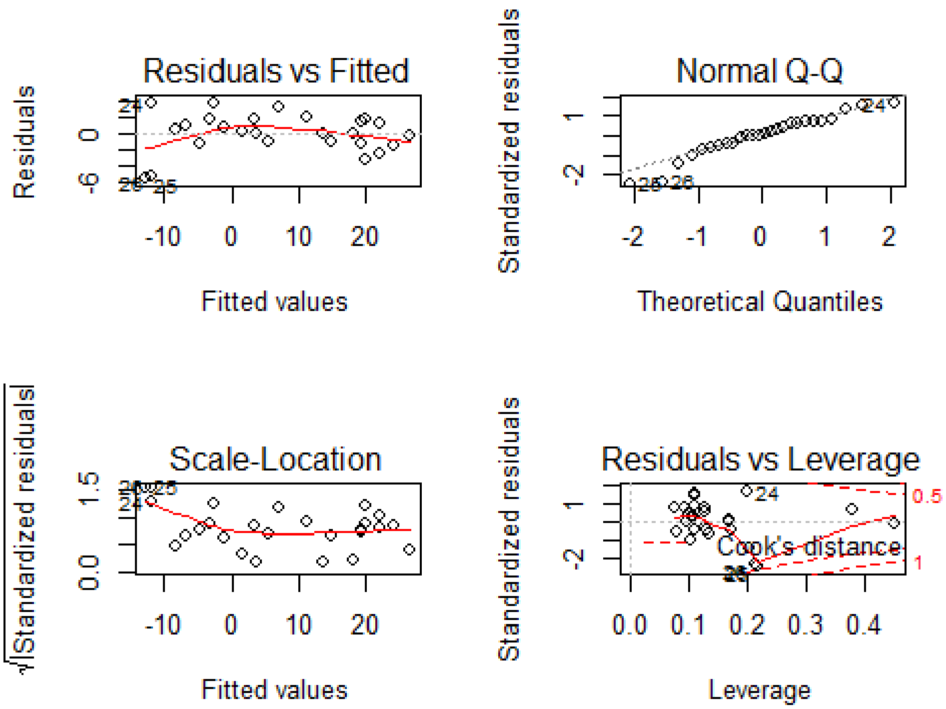
```
anova(ACB_USCB_Model_2)
```

```
## Analysis of Variance Table
##
## Response: loans_ACB_USCByoy
##                     Df Sum Sq Mean Sq  F value    Pr(>F)
## mo_bfi_nominalyoy    1 3831.0  3831.0 594.1197 < 2.2e-16 ***
## BBBSpread_Bloomberg  1  133.9   133.9  20.7687 0.0001547 ***
```

```
## Actuals_CI_Loansyoy  1   37.6    37.6   5.8327 0.0244875 *
## Residuals           22  141.9     6.4
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

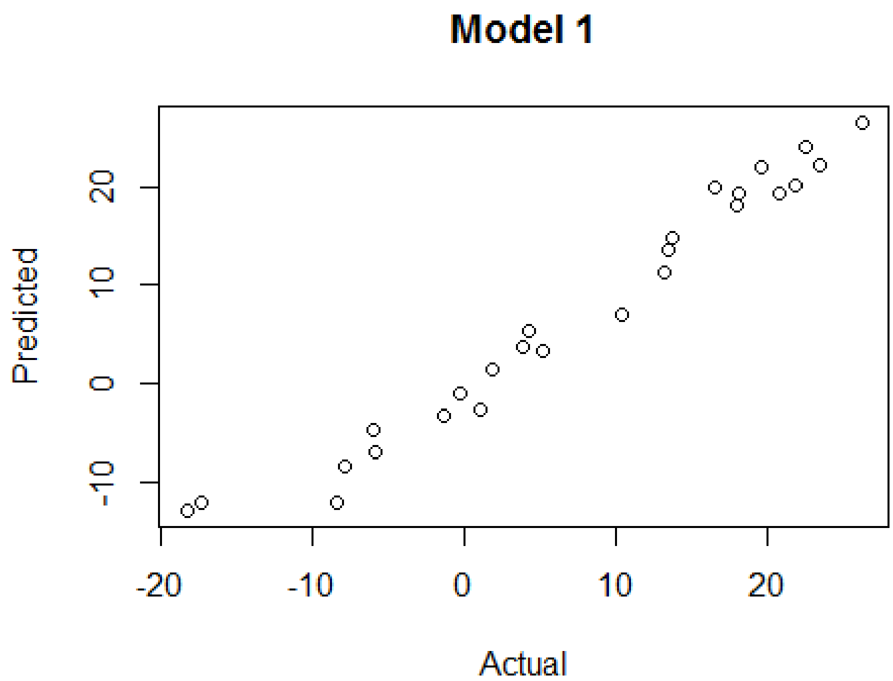
Plotting the model

```
par(mfrow=c(2,2))
plot(ACB_USCB_Model_2)
```



Model Performance

```
accuracy(list(ACB_USCB_Model_2),plotit=TRUE, digits=3)
```




```
## $Models
##   Call
## 1 "lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy +
BBBSpread_Bloomberg + "
##
## $Fit.criteria
##   Min.max.accuracy  MAE    MAPE  MSE RMSE NRMSE.mean NRMSE.median
## 1             1.07 1.81 -0.0567 5.46 2.34      0.322        0.301
##   NRMSE.mean.accuracy NRMSE.median.accuracy Efron.r.squared CV.prcnt
## 1               0.678                 0.699           0.966     32.2
```

Ceating a train and test data sets

The following code splits 70% of the data selected randomly into training set and the remaining 30% sample into test data set.

```
ACB = sort(sample(nrow(ACB_USCB), nrow(ACB_USCB)*.7))
Train_ACB<-ACB_USCB[ACB,]
Test_ACB<-ACB_USCB[-ACB,]
```

Build Model 3 on the train data set

```
ACB_USCB_Model_3<-lm(loans_ACB_USCByoy ~ mo_bfi_nominalyoy +
BBBSpread_Bloomberg + Actuals_CI_Loansyoy,data = Train_ACB)
summary(ACB_USCB_Model_3)

##
## Call:
```

```
## lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy + BBBSpread_Bloomberg +
##     Actuals_CI_Loansyoy, data = Train_ACB)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.1775 -2.4203  0.2847  2.2145  3.4935
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)           15.086      8.697   1.735 0.106447
## mo_bfi_nominalyoy     -6.513      1.140  -5.713 7.14e-05 ***
## BBBSpread_Bloomberg   18.308      3.950   4.635 0.000467 ***
## Actuals_CI_Loansyoy   -3.620      1.125  -3.218 0.006733 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.508 on 13 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.9728, Adjusted R-squared:  0.9665
## F-statistic: 155.1 on 3 and 13 DF,  p-value: 1.997e-10
```

Analysis of Variance for Model 3

```
anova(ACB_USCB_Model_3)
```

```
## Analysis of Variance Table
##
## Response: loans_ACB_USCByoy
##                     Df  Sum Sq Mean Sq F value    Pr(>F)
## mo_bfi_nominalyoy    1 2784.04 2784.04 442.504 2.007e-11 ***
## BBBSpread_Bloomberg  1   78.08   78.08  12.410  0.003746 **
## Actuals_CI_Loansyoy  1   65.14   65.14  10.354  0.006733 **
## Residuals           13   81.79    6.29
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

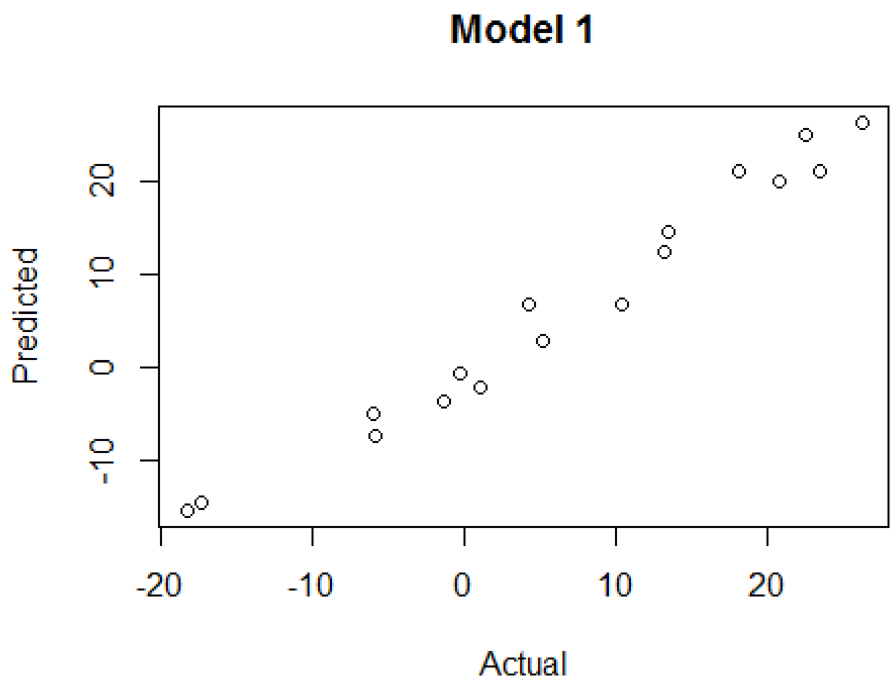
Predicting ACB_USCB Loan on the test data set

```
Pred_Loan <- predict(ACB_USCB_Model_3, Test_ACB)
```

Model Performance

Obtain the Accuracy for 3 Models

```
accuracy(list(ACB_USCB_Model_3),plotit=TRUE, digits=3)
```




```
## $Models
##   Call
## 1 "lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy +
BBBSpread_Bloomberg + "
##
## $Fit.criteria
##   Min.max.accuracy  MAE   MAPE  MSE RMSE NRMSE.mean NRMSE.median
## 1            0.961 1.92 0.0597 4.81 2.19      0.341        0.424
##   NRMSE.mean.accuracy NRMSE.median.accuracy Efron.r.squared CV.prcnt
## 1               0.659                 0.576           0.973     34.1
```

Creating models using each of the Explanatory Variable on the Train Dataset

Model 4

Analysis of Variance for Model 4 without Caret

```
ACB_USCB_Model_4<-lm(loans_ACB_USCByoy ~ mo_bfi_nominalyoy,data = Train_ACB)
summary(ACB_USCB_Model_4)

##
## Call:
## lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy, data = Train_ACB)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.9557 -3.5221 -0.2713  3.8210  6.1608
##
```

```
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)           17.4998     1.3812   12.67 9.33e-10 ***
## mo_bfi_nominalyoy     -4.0941     0.3038  -13.48 3.76e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.324 on 16 degrees of freedom
## Multiple R-squared:  0.919,  Adjusted R-squared:  0.914
## F-statistic: 181.6 on 1 and 16 DF,  p-value: 3.761e-10
```

```
anova(ACB_USCB_Model_4)
```

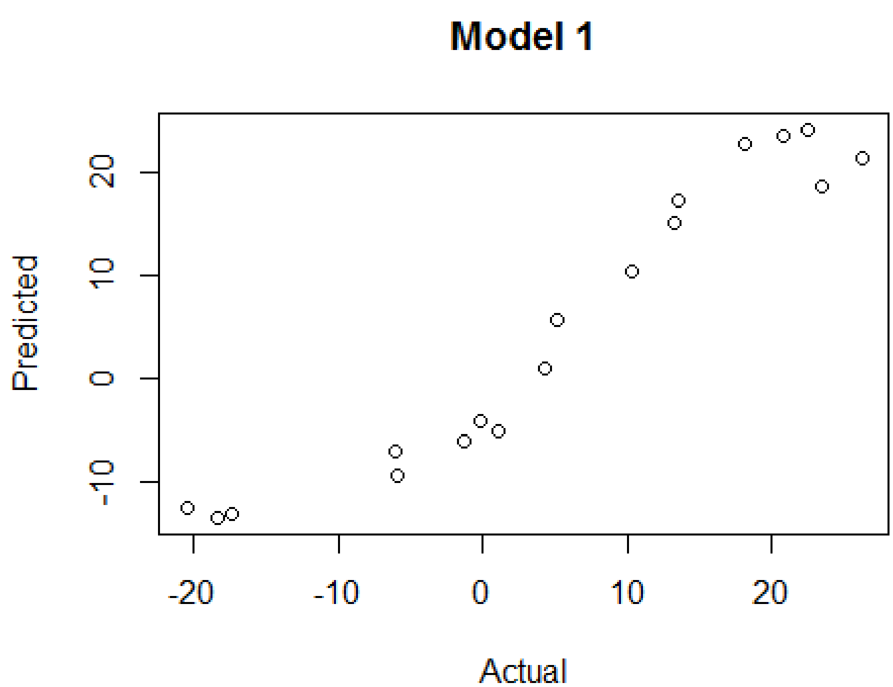
```
## Analysis of Variance Table
##
## Response: loans_ACB_USCByoy
##                      Df Sum Sq Mean Sq F value    Pr(>F)
## mo_bfi_nominalyoy     1 3395.5  3395.5  181.64 3.761e-10 ***
## Residuals            16  299.1    18.7
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Predicting

```
Pred_Loan <- predict(ACB_USCB_Model_4, Test_ACB)
```

Model performance

```
accuracy(list(ACB_USCB_Model_4),plotit=TRUE, digits=3)
```



```
## $Models
##   Call
## 1 "lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy, data = Train_ACB)"
##
## $Fit.criteria
##   Min.max.accuracy  MAE   MAPE  MSE RMSE NRMSE.mean NRMSE.median
## 1             1.92 3.57 -0.887 16.6 4.08      0.826        0.861
##   NRMSE.mean.accuracy NRMSE.median.accuracy Efron.r.squared CV.prcnt
## 1               0.174                 0.139           0.919     82.6
```

Model 5

Analysis of Variance for Model 5 without Caret

```
ACB_USCB_Model_5<-lm(loans_ACB_USCByoy ~ BBBSpread_Bloomberg,data =
Train_ACB)
summary(ACB_USCB_Model_5)
```

```
##
## Call:
## lm(formula = loans_ACB_USCByoy ~ BBBSpread_Bloomberg, data = Train_ACB)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.8439  -3.9984  -0.1552   6.9134   9.8029
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          -54.614      8.875  -6.153 1.85e-05 ***
## BBBSpread_Bloomberg   38.694      5.526   7.002 4.27e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.855 on 15 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.7657, Adjusted R-squared:  0.7501
## F-statistic: 49.03 on 1 and 15 DF,  p-value: 4.266e-06
```

```
anova(ACB_USCB_Model_5)
```

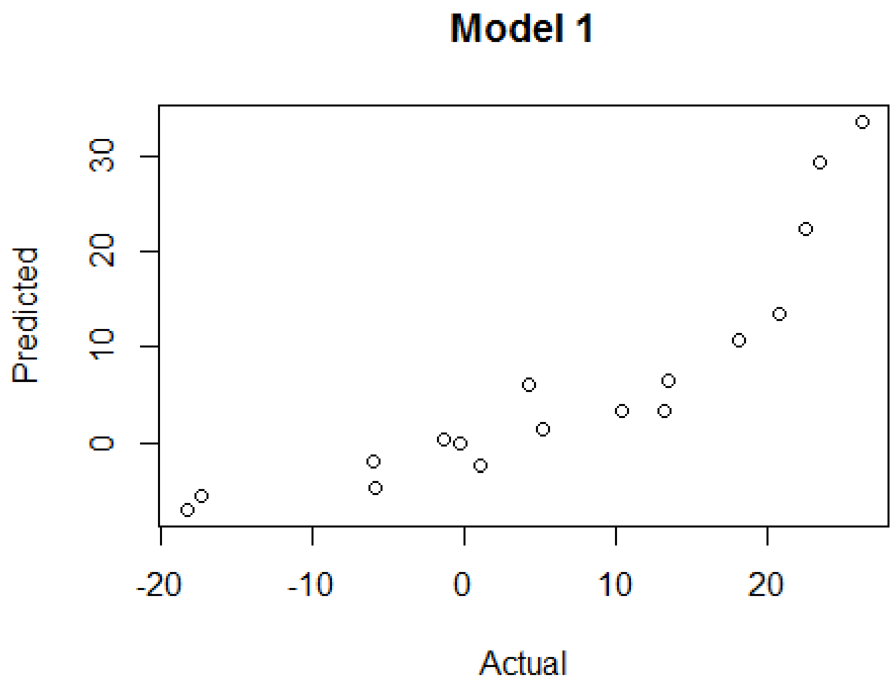
```
## Analysis of Variance Table
##
## Response: loans_ACB_USCByoy
##                     Df  Sum Sq Mean Sq F value    Pr(>F)
## BBBSpread_Bloomberg  1 2304.12  2304.1  49.028 4.266e-06 ***
## Residuals           15  704.93    47.0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Predicting

```
Pred_Loan <- predict(ACB_USCB_Model_5, Test_ACB)
```

Model Performance

```
accuracy(list(ACB_USCB_Model_5),plotit=TRUE, digits=3)
```




```
## $Models
##   Call
## 1 "lm(formula = loans_ACB_USCByoy ~ BBBSpread_Bloomberg, data =
Train_ACB)"
##
## $Fit.criteria
##   Min.max.accuracy  MAE  MAPE  MSE RMSE NRMSE.mean NRMSE.median
## 1            0.789 5.34 0.204 41.5 6.44          1         1.25
##   NRMSE.mean.accuracy NRMSE.median.accuracy Efron.r.squared CV.prcnt
## 1            -0.00126                -0.246           0.766      100
```

Model 6

```
ACB_USCB_Model_6<-lm(loans_ACB_USCByoy ~ Actuals_CI_Loansyoy,data =
Train_ACB)
summary(ACB_USCB_Model_6)
```

```
##
## Call:
## lm(formula = loans_ACB_USCByoy ~ Actuals_CI_Loansyoy, data = Train_ACB)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.1082  -1.7072   0.2866   4.1894   8.8715
##
```

```
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -13.6418     2.5888  -5.269 7.63e-05 ***
## Actuals_CI_Loansyoy   3.6086     0.4117   8.766 1.66e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.309 on 16 degrees of freedom
## Multiple R-squared:  0.8277, Adjusted R-squared:  0.8169
## F-statistic: 76.84 on 1 and 16 DF,  p-value: 1.661e-07
```

```
anova(ACB_USCB_Model_6)
```

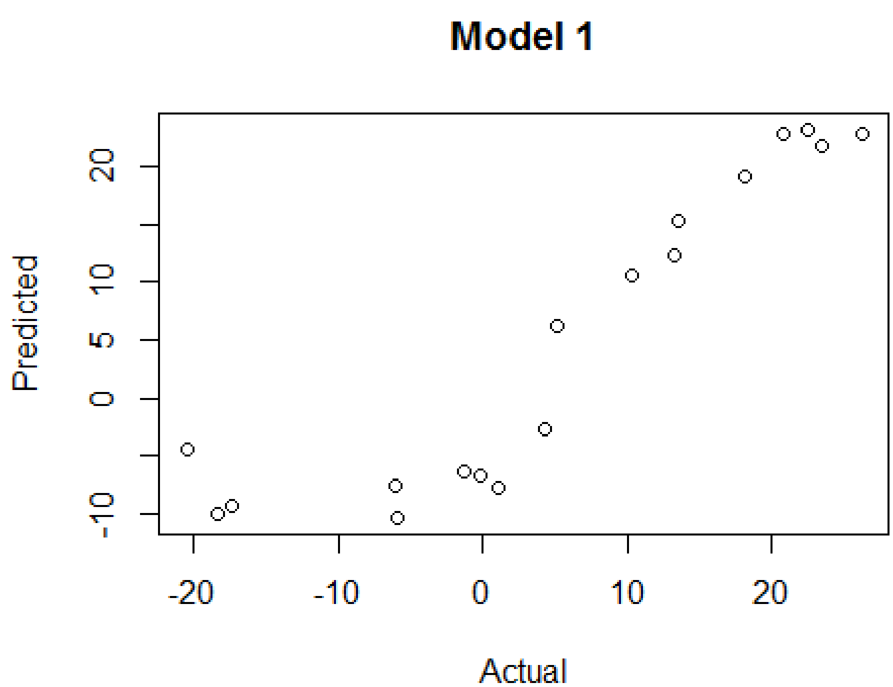
```
## Analysis of Variance Table
##
## Response: loans_ACB_USCByoy
##                     Df  Sum Sq Mean Sq F value    Pr(>F)
## Actuals_CI_Loansyoy  1 3057.89  3057.9  76.837 1.661e-07 ***
## Residuals           16  636.75    39.8
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Predicting

```
Pred_Loan <- predict(ACB_USCB_Model_6, Test_ACB)
```

Model Performance

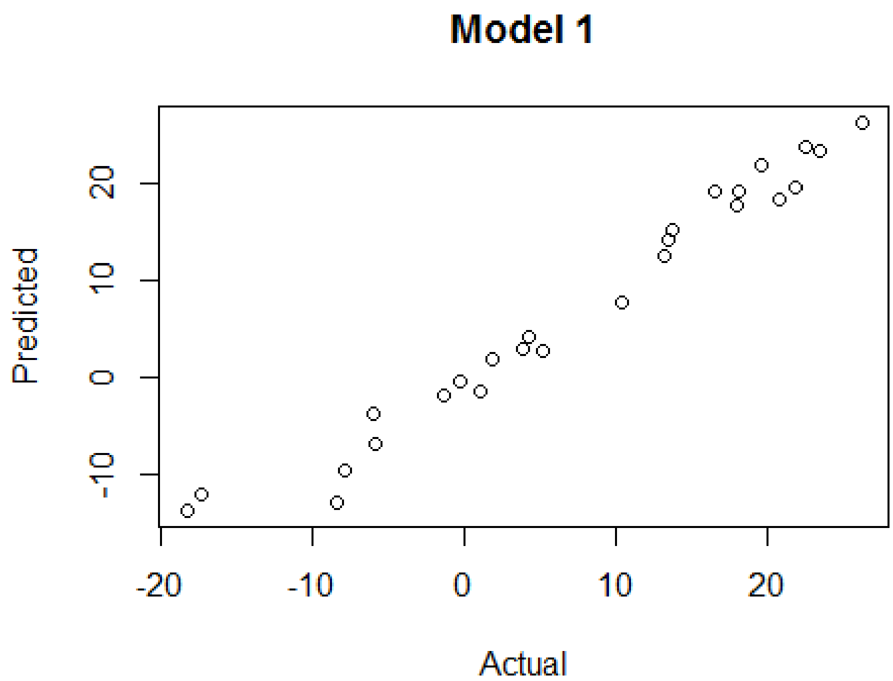
```
accuracy(list(ACB_USCB_Model_6),plotit=TRUE, digits=3)
```

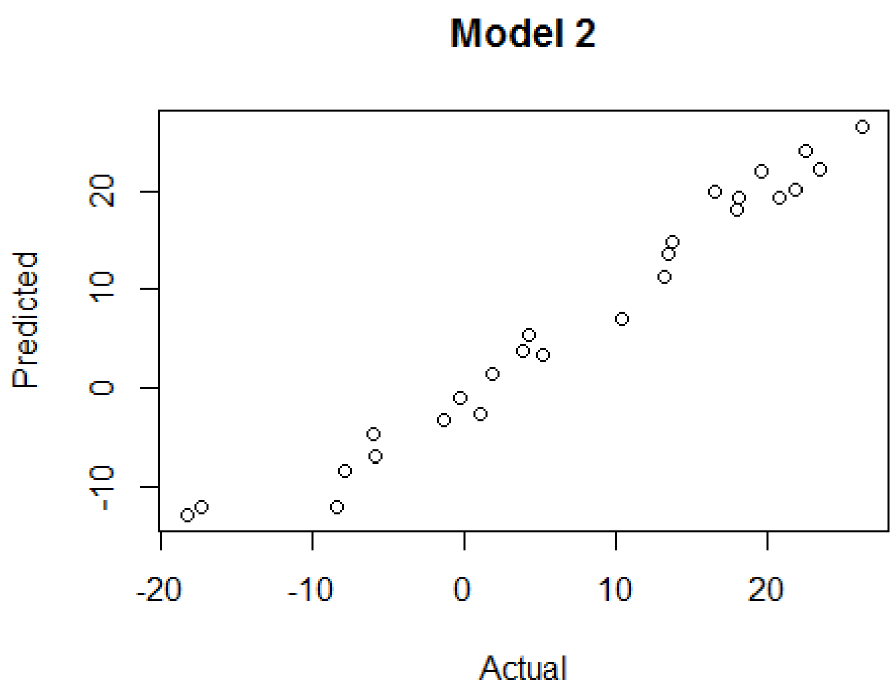


```
## $Models
##   Call
## 1 "lm(formula = loans_ACB_USCByoy ~ Actuals_CI_Loansyoy, data =
Train_ACB)"
##
## $Fit.criteria
##   Min.max.accuracy  MAE  MAPE  MSE RMSE NRMSE.mean NRMSE.median
## 1             2.68 4.39 -1.48 35.4 5.95       1.21         1.26
##   NRMSE.mean.accuracy NRMSE.median.accuracy Efron.r.squared CV.prcnt
## 1              -0.205                -0.256           0.828      121
```

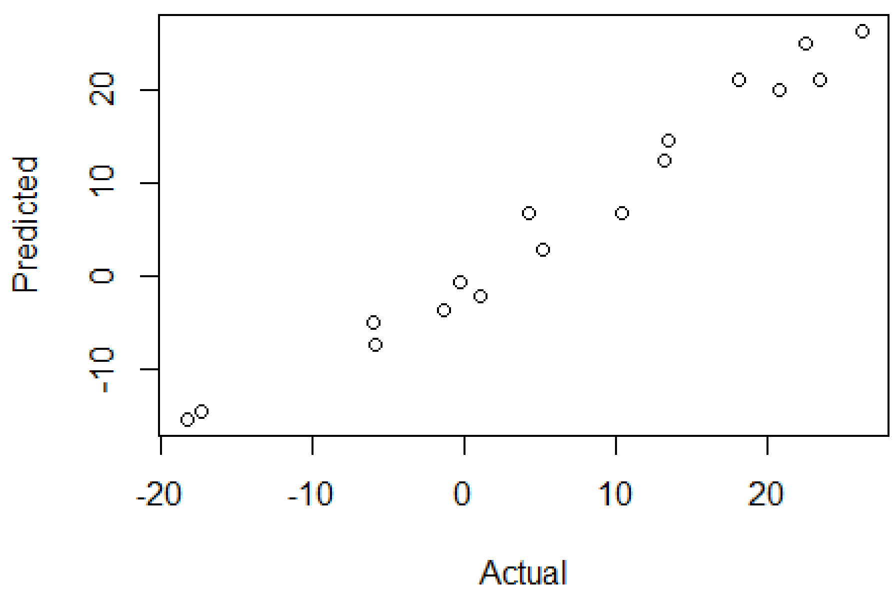
Plot All Models to determine the Best Fit

```
accuracy(list(ACB_USCB_Model,ACB_USCB_Model_2,ACB_USCB_Model_3,
ACB_USCB_Model_4, ACB_USCB_Model_5,ACB_USCB_Model_6),plotit=TRUE, digits=3)
```

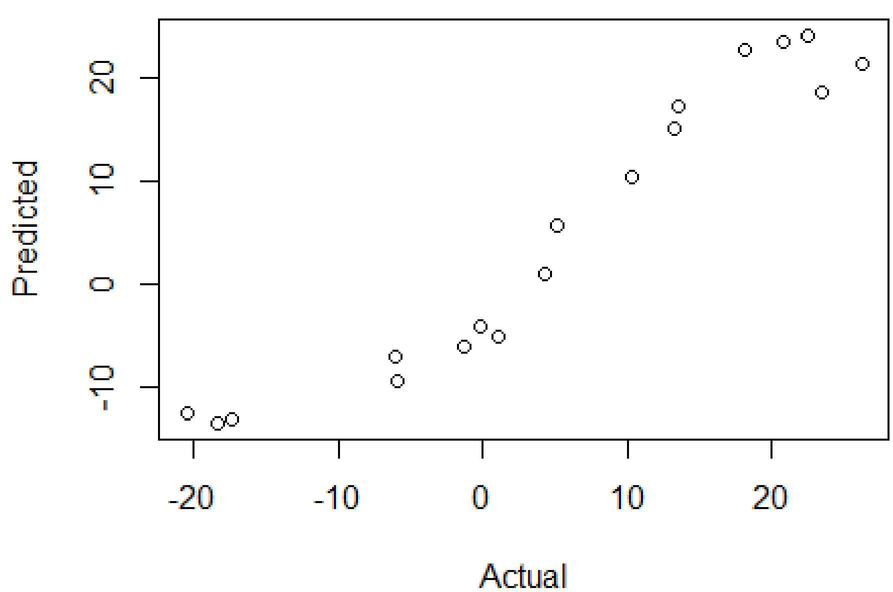

Model 1
Predicted
Actual
-20
-10
0
10
20

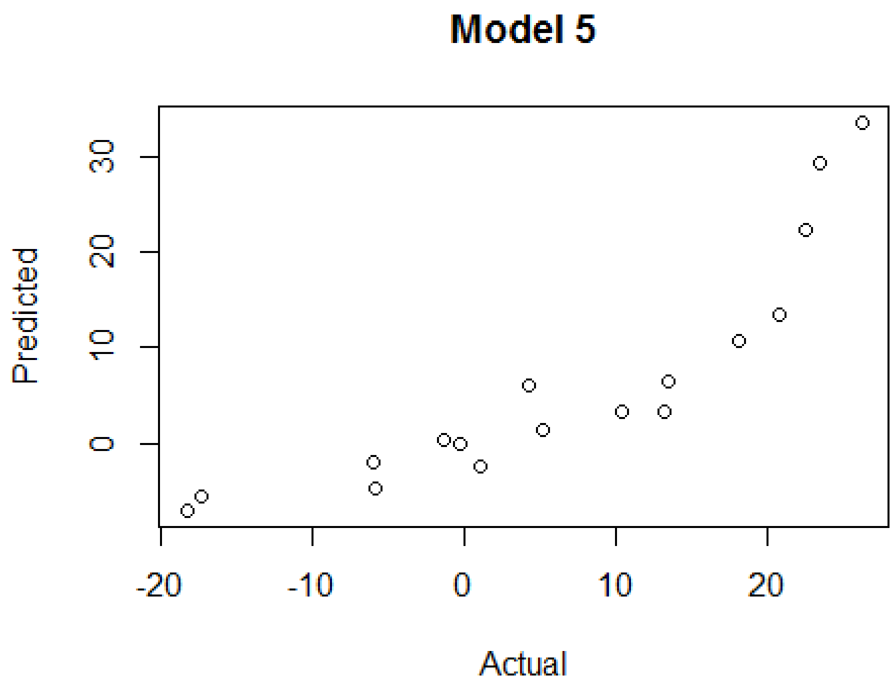

Model 2
Predicted
Actual
-20
-10
0
10
20

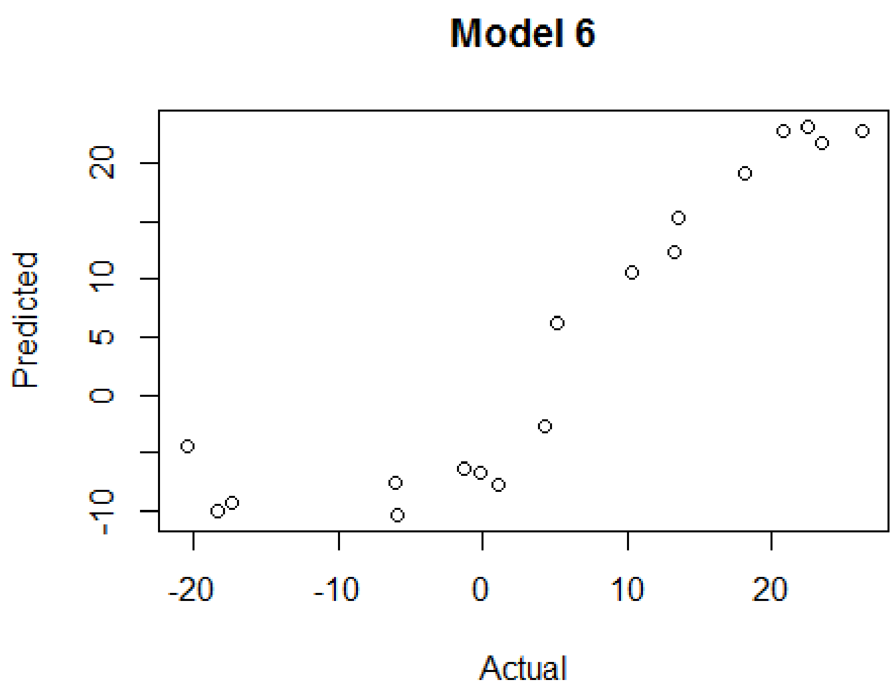
Model 3



Model 4








```
## $Models
##   Call
## 1 "lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy + mo_bfi_realyoy + "
## 2 "lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy +
```

```
BBBSpread_Bloomberg + "
## 3 "lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy +
BBBSpread_Bloomberg + "
## 4 "lm(formula = loans_ACB_USCByoy ~ mo_bfi_nominalyoy, data = Train_ACB)"
## 5 "lm(formula = loans_ACB_USCByoy ~ BBBSpread_Bloomberg, data =
Train_ACB)"
## 6 "lm(formula = loans_ACB_USCByoy ~ Actuals_CI_Loansyoy, data =
Train_ACB)"
##
## $Fit.criteria
##   Min.max.accuracy  MAE    MAPE   MSE RMSE NRMSE.mean NRMSE.median
## 1            0.979 1.67  0.0396  4.88 2.21      0.305        0.285
## 2            1.070 1.81 -0.0567  5.46 2.34      0.322        0.301
## 3            0.961 1.92  0.0597  4.81 2.19      0.341        0.424
## 4            1.920 3.57 -0.8870 16.60 4.08      0.826        0.861
## 5            0.789 5.34  0.2040 41.50 6.44      1.000        1.250
## 6            2.680 4.39 -1.4800 35.40 5.95      1.210        1.260
##   NRMSE.mean.accuracy NRMSE.median.accuracy Efron.r.squared CV.prcnt
## 1             0.69500                 0.715           0.969     30.5
## 2             0.67800                 0.699           0.966     32.2
## 3             0.65900                 0.576           0.973     34.1
## 4             0.17400                 0.139           0.919     82.6
## 5            -0.00126                -0.246           0.766    100.0
## 6            -0.20500                -0.256           0.828    121.0
```

End————————————————————————————————————-End

Part II

Cross Validation of Models using Caret Package

This process uses an accelerated cross-validation which produces predicted R-Squared without the need for train and test dataset TrainControl for cross validation using k=10

```
Control <- trainControl(method = "cv", number = 10)
```

Model 3a

```
ACB_USCB_Model_3a<-train(loans_ACB_USCByoy ~ mo_bfi_nominalyoy +
BBBSpread_Bloomberg + Actuals_CI_Loansyoy,data = ACB_USCB,trControl =
Control, method ="lm",na.action = na.pass)
summary(ACB_USCB_Model_3a)

##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.4895 -1.1965  0.1678  1.6757  3.6537
##
```

```
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)           1.4809     6.9382   0.213   0.8329
## mo_bfi_nominalyoy    -4.5512     0.8299  -5.484 1.64e-05 ***
## BBBSpread_Bloomberg  18.0087     3.4954   5.152 3.65e-05 ***
## Actuals_CI_Loansyoy  -2.0134     0.8337  -2.415   0.0245 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.539 on 22 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.9658, Adjusted R-squared:  0.9611
## F-statistic: 206.9 on 3 and 22 DF,  p-value: 2.877e-16
```

```
ACB_USCB_Model_3a
```

```
## Linear Regression
##
## 27 samples
##  3 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 25, 25, 24, 25, 24, 24, ...
## Resampling results:
##
##   RMSE      Rsquared   MAE
##   2.624957  0.9952288  2.181335
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```
ACB_USCB_Model_3a$resample
```

```
##         RMSE  Rsquared      MAE Resample
## 1  3.2557154 1.0000000 2.951728   Fold01
## 2  2.3819388 1.0000000 2.381155   Fold02
## 3  2.6467325 0.9934861 1.726761   Fold03
## 4  2.0382756 1.0000000 1.729267   Fold04
## 5  0.7776663 1.0000000 0.574585   Fold05
## 6  4.2326854 0.9997859 3.237115   Fold06
## 7  1.4532372 0.9999999 1.178243   Fold07
## 8  3.5558508 0.9769953 3.464816   Fold08
## 9  1.8893559 0.9999824 1.849620   Fold09
## 10 4.0181094 0.9820380 2.720059   Fold10
```

Model 4a

```
ACB_USCB_Model_4a<-train(loans_ACB_USCByoy ~ mo_bfi_nominalyoy,data =
ACB_USCB,trControl = Control, method ="lm",na.action = na.pass)
summary(ACB_USCB_Model_4a)
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -9.789 -2.328 -0.013  3.208  6.468
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)        16.2686     1.0010   16.25 8.47e-15 ***
## mo_bfi_nominalyoy  -3.6767     0.2255  -16.30 7.85e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.099 on 25 degrees of freedom
## Multiple R-squared:  0.914,  Adjusted R-squared:  0.9106
## F-statistic: 265.9 on 1 and 25 DF,  p-value: 7.852e-15
```

```
ACB_USCB_Model_4a
```

```
## Linear Regression
##
## 27 samples
##  1 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 24, 24, 25, 25, 24, 25, ...
## Resampling results:
##
##   RMSE      Rsquared   MAE
##   3.972969  0.9612636  3.424184
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```
ACB_USCB_Model_4a$resample
```

```
##        RMSE  Rsquared      MAE Resample
## 1  4.485539 0.8524042 3.866315   Fold01
## 2  2.032897 0.9998777 1.654723   Fold02
## 3  5.573341 1.0000000 5.447099   Fold03
## 4  3.590691 1.0000000 3.349958   Fold04
## 5  4.103683 0.9666074 3.441588   Fold05
## 6  2.249341 1.0000000 1.733784   Fold06
## 7  2.062009 0.9909311 1.806241   Fold07
## 8  4.559775 0.8970237 3.742566   Fold08
## 9  4.277722 0.9077615 3.488965   Fold09
## 10 6.794688 0.9980302 5.710600   Fold10
```

Model 5a

```
ACB_USCB_Model_5a<-train(loans_ACB_USCByoy ~ BBBSpread_Bloomberg,data =
ACB_USCB,trControl = Control, method ="lm",na.action = na.pass)

## Warning in nominalTrainWorkflow(x = x, y = y, wts = weights, info =
## trainInfo, : There were missing values in resampled performance measures.

summary(ACB_USCB_Model_5a)

##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.7865  -3.4616  -0.6017   5.8275   9.1122
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          -58.803      7.393  -7.954 3.50e-08 ***
## BBBSpread_Bloomberg   41.947      4.630   9.060 3.26e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.251 on 24 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.7738, Adjusted R-squared:  0.7643
## F-statistic: 82.08 on 1 and 24 DF,  p-value: 3.26e-09

ACB_USCB_Model_5a

## Linear Regression
##
## 27 samples
##  1 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 24, 25, 24, 25, 25, 24, ...
## Resampling results:
##
##   RMSE      Rsquared   MAE
##   6.145407  0.9276754  5.450438
##
## Tuning parameter 'intercept' was held constant at a value of TRUE

ACB_USCB_Model_5a$resample

##         RMSE  Rsquared       MAE Resample
## 1  10.389086 0.8251298  8.369468   Fold01
## 2   3.486616 1.0000000  2.873631   Fold02
```

```
## 3  11.639151 0.9986621 10.095541   Fold03
## 4   2.032480        NA  2.032480   Fold04
## 5   6.512833 1.0000000  6.510185   Fold05
## 6   5.364040 0.9885023  4.881442   Fold06
## 7   5.693209 0.9902524  5.313993   Fold07
## 8   5.286673 0.7637330  4.957723   Fold08
## 9   7.053950 0.7832332  5.615018   Fold09
## 10  3.996030 0.9995661  3.854898   Fold10
```

Model 6a

```
ACB_USCB_Model_6a<-train(loans_ACB_USCByoy ~ Actuals_CI_Loansyoy,data =
ACB_USCB,trControl = Control, method ="lm",na.action = na.pass)
summary(ACB_USCB_Model_6a)

##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -17.4411  -1.1339   0.2046   3.1432   7.2911
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -11.6399     1.8786  -6.196 1.76e-06 ***
## Actuals_CI_Loansyoy   3.3473     0.2896  11.558 1.60e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.551 on 25 degrees of freedom
## Multiple R-squared:  0.8424, Adjusted R-squared:  0.836
## F-statistic: 133.6 on 1 and 25 DF,  p-value: 1.6e-11

ACB_USCB_Model_6a

## Linear Regression
##
## 27 samples
##  1 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 25, 24, 24, 25, 24, 24, ...
## Resampling results:
##
##   RMSE      Rsquared   MAE
##   5.099097  0.9229526  4.164146
##
## Tuning parameter 'intercept' was held constant at a value of TRUE

ACB_USCB_Model_6a$resample
```

```
##          RMSE  Rsquared       MAE Resample
## 1   7.154004 1.0000000  7.136340   Fold01
## 2   4.670153 0.9998352  3.212964   Fold02
## 3   6.606997 0.9506203  4.870749   Fold03
## 4   1.242836 1.0000000  1.150840   Fold04
## 5   4.296654 0.9724654  3.366468   Fold05
## 6   6.204306 0.4401831  4.579013   Fold06
## 7   2.756850 0.9399448  2.143316   Fold07
## 8   2.237107 0.9966309  1.930326   Fold08
## 9  13.228675 1.0000000 11.206127   Fold09
## 10  2.593390 0.9298462  2.045321   Fold10
```

Combined results from the Cross validation

```
ACB_USCB_Model_3a

## Linear Regression
##
## 27 samples
##  3 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 25, 25, 24, 25, 24, 24, ...
## Resampling results:
##
##   RMSE      Rsquared   MAE
##   2.624957  0.9952288  2.181335
##
## Tuning parameter 'intercept' was held constant at a value of TRUE

ACB_USCB_Model_4a

## Linear Regression
##
## 27 samples
##  1 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 24, 24, 25, 25, 24, 25, ...
## Resampling results:
##
##   RMSE      Rsquared   MAE
##   3.972969  0.9612636  3.424184
##
## Tuning parameter 'intercept' was held constant at a value of TRUE

ACB_USCB_Model_5a

## Linear Regression
##
```

```
## 27 samples
##  1 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 24, 25, 24, 25, 25, 24, ...
## Resampling results:
##
##   RMSE      Rsquared   MAE
##   6.145407  0.9276754  5.450438
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

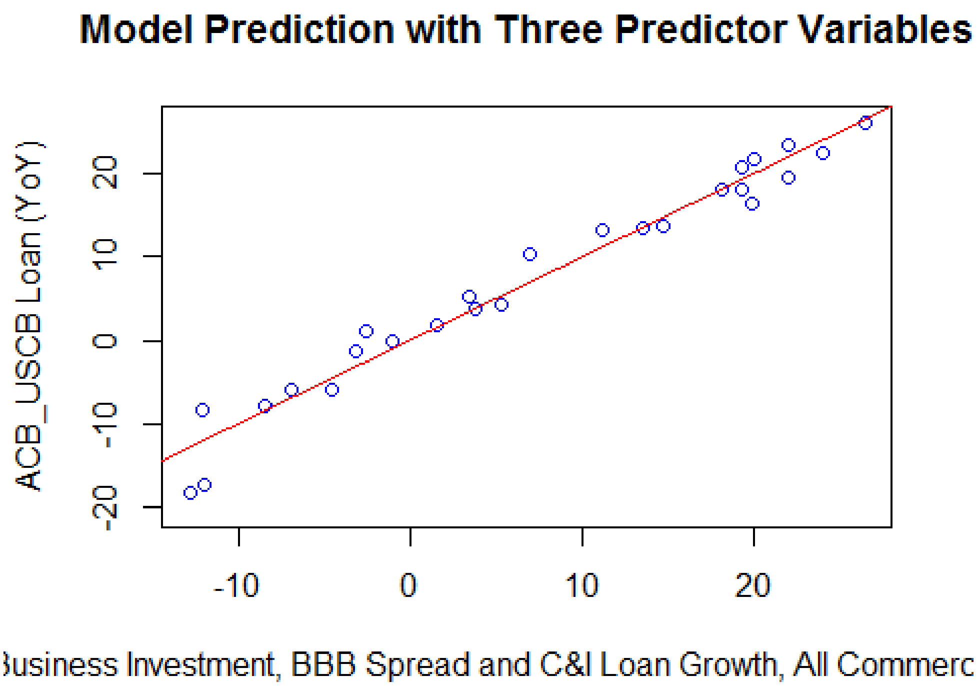
```
ACB_USCB_Model_6a
```

```
## Linear Regression
##
## 27 samples
##  1 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 25, 24, 24, 25, 24, 24, ...
## Resampling results:
##
##   RMSE      Rsquared   MAE
##   5.099097  0.9229526  4.164146
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

Plot All Models to determine the Best Fit

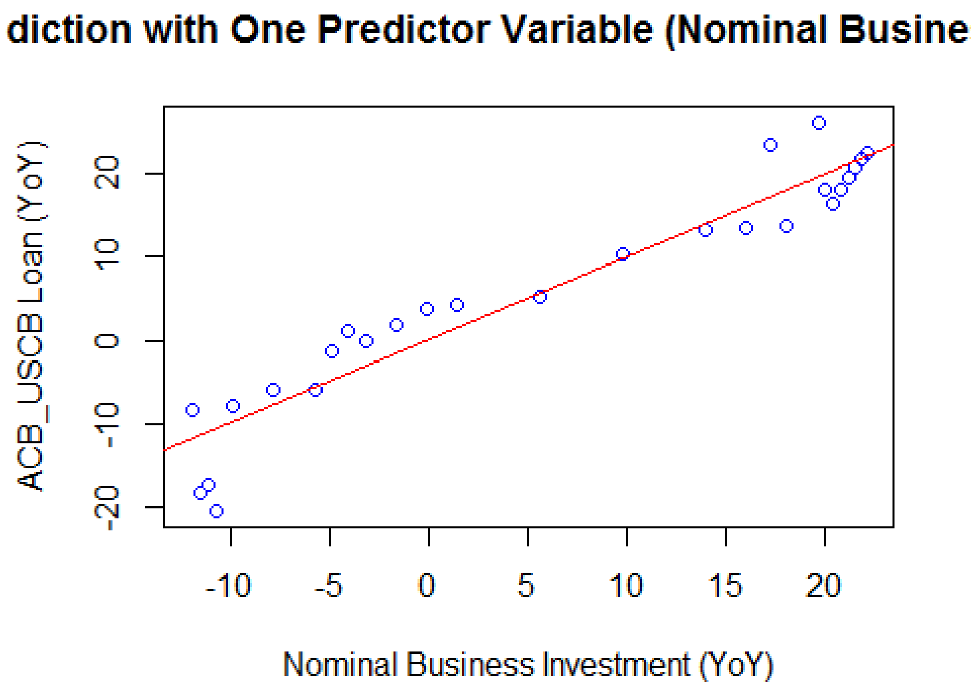
Model Prediction with Three Predictor Variables

```
plot(predict(ACB_USCB_Model_3a),ACB_USCB$loans_ACB_USCByoy,
     xlab = "Nominal Business Investment, BBB Spread and C&I Loan Growth, All 
Commercial Banks (YoY)", ylab = "ACB_USCB Loan (YoY)", main = "Model 
Prediction with Three Predictor Variables", col ="blue")
abline(a=0, b=1, col= "red")
```



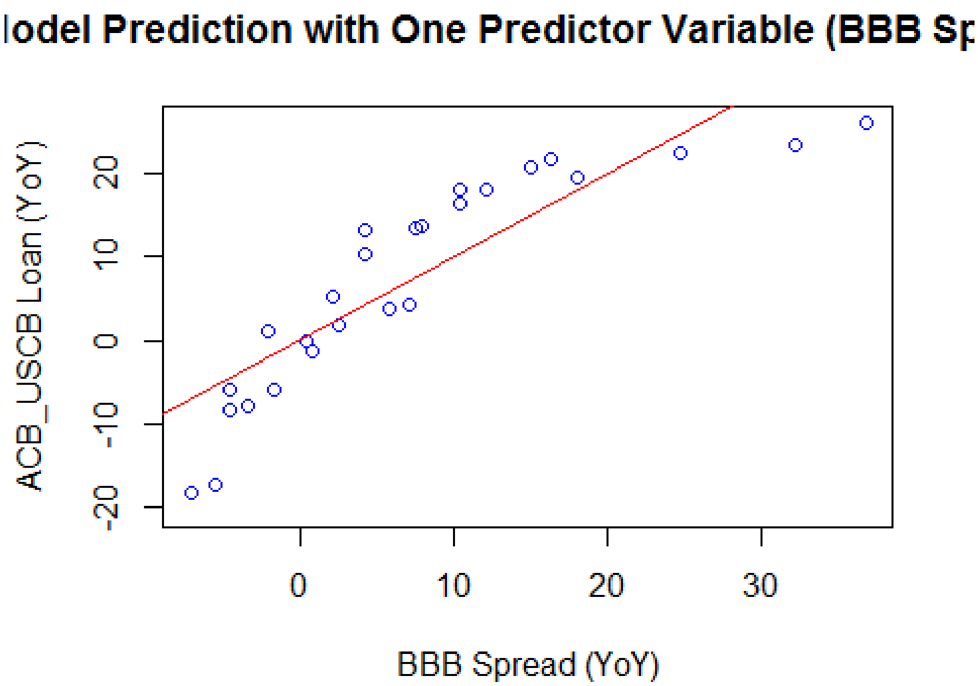
Model Prediction with One Predictor Variable (Nominal Business Investment)

```
plot(predict(ACB_USCB_Model_4a),ACB_USCB$loans_ACB_USCByoy,
     xlab = "Nominal Business Investment (YoY)", ylab = "ACB_USCB Loan
(YoY)", main = "Model Prediction with One Predictor Variable (Nominal
Business Investment)", col ="blue")
abline(a=0, b=1, col= "red")
```



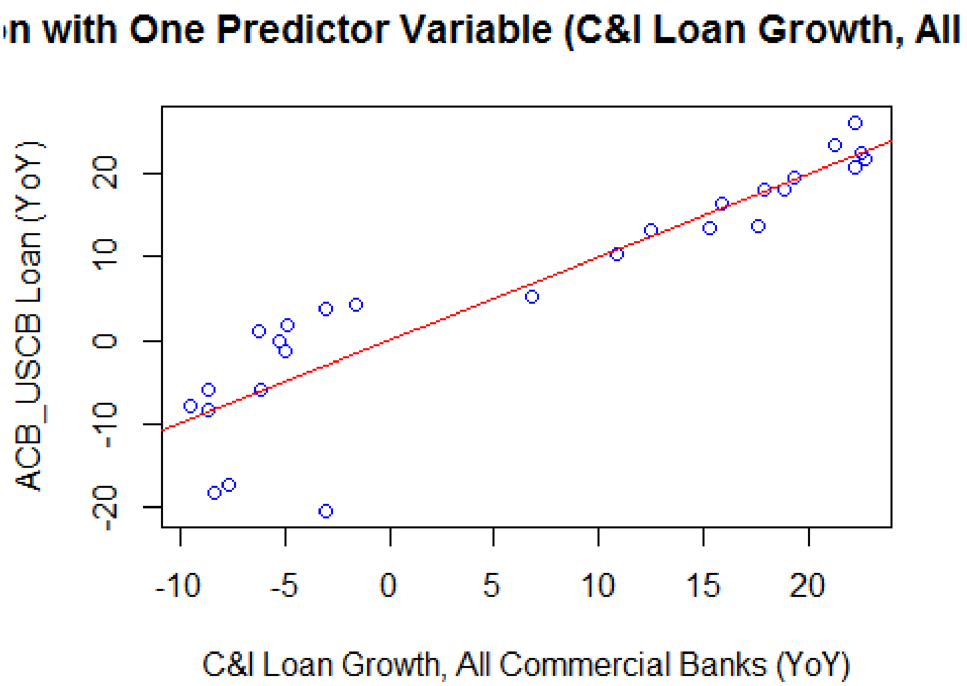
Model Prediction with One Predictor Variable (BBB Spread)

```
plot(predict(ACB_USCB_Model_5a),ACB_USCB$loans_ACB_USCByoy,
     xlab = "BBB Spread (YoY)", ylab = "ACB_USCB Loan (YoY)", main = "Model
Prediction with One Predictor Variable (BBB Spread)", col ="blue")
abline(a=0, b=1, col= "red")
```



Model Prediction with One Predictor Variable (C&I Loan Growth, All Commercial Banks)

```
plot(predict(ACB_USCB_Model_6a),ACB_USCB$loans_ACB_USCByoy,
     xlab = "C&I Loan Growth, All Commercial Banks (YoY)", ylab = "ACB_USCB
Loan (YoY)", main = "Model Prediction with One Predictor Variable (C&I Loan
Growth, All Commercial Banks)", col ="blue")
abline(a=0, b=1, col= "red")
```



Conclusion

Historical data on the explanatory variable C&I Loans comes from the FRED database, variable BUSLOANSNSA. Future values of C&I Loans comes from the output of Moody's Economic Model. The response variable ACB+USCB Long-Term Loans Floaters comes from Treasury Data Mart (TDM). According to the information provided in the model documentation, the data requirements are forecasts for aggregate C&I loans, and historical data on ACB+USCB loan balances.

The forecasts of the ACB+USCB Long-Term Loans Floaters will feed into existing model which was previously validated and used for daily base cashflow. Unacceptable model performance for this model is defined as three (3) consecutive months of yoy growth forecast errors larger than 10 percentage (10%) points. When this situation happens, the model overlays will be circulated and notification will be sent to stakeholders. Adjusting the model for optimal performance is permissible even if the model is not experiencing unacceptable performance.

The response variable for the model is the Long-Term Loan Floaters year-to-year (yoy) growth, combined ACB + USCB lines of business denoted as (loans_ACB_USCByoy). The final model was selected based on the ability of a particular variable to forecast the growth of ACB and USCB loans. The following variables were considered as possible explanatory variables during the development of the model: - mo_bfi_nominalyoy (Nominal Business Investment) - mo_bfi_realyoy (Real Business Investment) - BBBSpread_Bloomberg (BBB Spread) - futureRateHikeExpect_1y3m (Rate of Hike Expected) - Actuals_CI_Loansyoy (All US Commercial Banks)

The flowing variables are selected as candidate variables for the model based on the following rationale: - Real Business Investment- Loans for C&I purposes may be expected to increase as corporate customers require funds to increase investment. - BBB Spread- As bond issuance becomes cheaper; it becomes a competing source of funds to be used by corporate customers. They will rely on loans for funding less as bond spread shrinks. - C&I All US Commercial Bank - The corporate customers under ACB take out loans for C&I purposes. General trends in C&I loan usage at all commercial banks should be reflected in our sample of C&I loan customers. - FutureRateHikeExpect_1y3m (Rate of Hike Expected) - As rates are expected to increase we expect customers will slow their loan origination.

The level of importance for the variables are lsied below.

```
                          Overall
```

mo_bfi_nominalyoy 4.3529128 mo_bfi_realyoy 1.3430127 BBBSpread_Bloomberg 3.8030695 futureRateHikeExpect_1y3m 0.8563506 Actuals_CI_Loansyoy 2.0747321

I performed a correlation test for the variables using Pearson correlation. The visualization charts above shows that there is a very strong correlation between mo_bfi_nominalyoy and mo_bfi_realyoy (0.96), BBBSpread_Bloomberg and Actuals_CI_Loansyoy (0.84).

End————————————————————————————————-End