Business Statistics with R: Payday Loan study case

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Problem Description

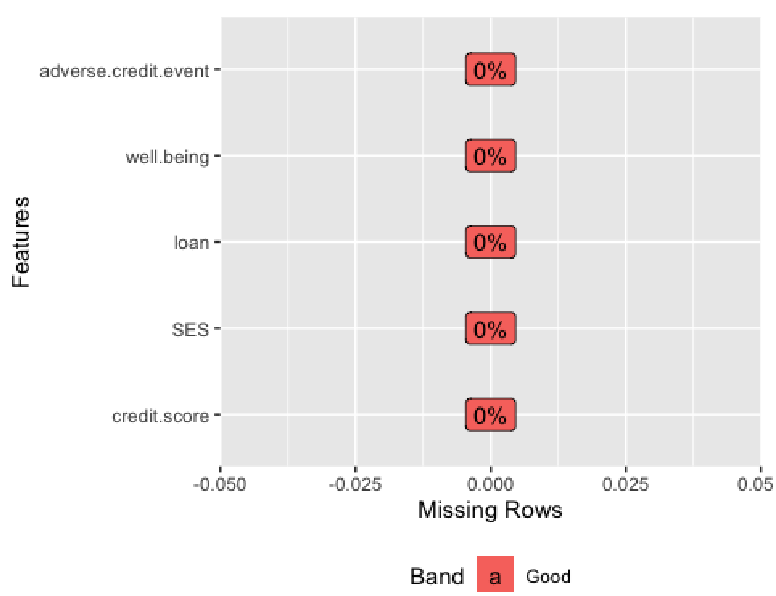
A financial conduct regulator needs to investigate the effect of payday loans. A dataset of a survey from 5,000 customers where they reported their well-being and a measure of their socio-economic status linked to their credit file is available.

Two questions arose:

1. Does receiving a payday loan change well-being? If so, how much?

2. Does taking payday loan makes people more or less likely to experience an adverse credit event?

```r
rm(list=ls())
library(tidyverse)
library(DataExplorer)
library(emmeans)
library(gridExtra) # for grid.arrange()
library(gmodels)
library(MASS)
options(width=100)

# --------- import data
payday <- read.csv('payday.csv')

# --------- variable check
payday$credit.score <- as.numeric(payday$credit.score)
payday$SES <- as.numeric(payday$SES)
payday$well.being <- as.numeric(payday$well.being)
#payday$adverse.credit.event <- factor(payday$adverse.credit.event, levels =
c(0,1), labels = c("no adverse", "adverse"))
payday$id <- NULL

view(payday)
str(payday)

## 'data.frame':    5000 obs. of  5 variables:
##  $ credit.score        : num  590 440 470 480 570 550 550 580 540 560 ...
##  $ SES                 : num  16 14 13 14 18 17 15 18 16 14 ...
##  $ loan                : int  1 0 0 0 1 1 1 1 1 1 ...
##  $ well.being          : num  5 4 3 2 7 7 4 7 5 6 ...
##  $ adverse.credit.event: int  0 1 0 1 0 0 1 0 0 1 ...

plot_missing(payday)
```



Data Dictionary

Variable	Description
id	Customer ID
credit.score	Customer's credit score [400 to 600]
SES	People's socio-economic status, with higher scores indicating higer status [1 to 26]
loan	A dummy variable indicating whether or not people were given the payday loan [0: no or 1: yes]
well.being	Customer's self-reported well-being on a 1-7 scale, with 7 being the highest well-being [1 to 7]
adverse.credit.event	A dummy indicating whether there was an adverse credit event in the next year [0: no or 1: yes]

Does receiving a payday loan change well-being? If so, how much?

Yes, loan significantly affects well-being by a decrease of .132 in well-being score if one receives payday loan, 95% CI[(-.242) – (-.022)], and no decrease otherwise, given SES and credit score held constant.

Individually, loan, SES, and credit score have significant effect and a positive correlation when used as a predictor of well-being. Put it simply, as one increases, well-being increases too. However, well-being is best explained by using the combination of loan, credit.score, and SES as predictors using a multiple regression model, R^2 = .694. Figure 1 describes how each predictor changes well-being when used together.

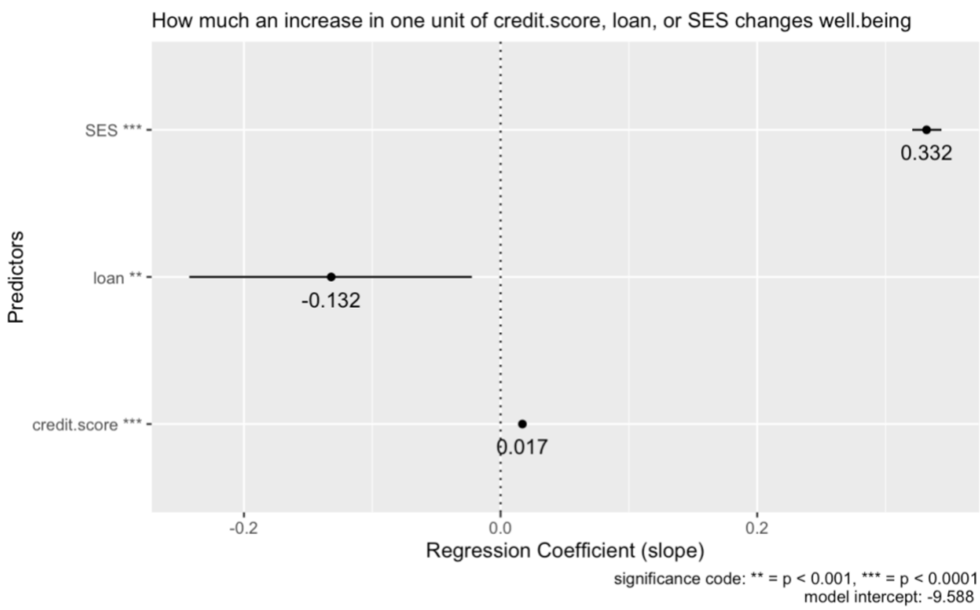


Figure 1. Regression coefficient of credit score, loan, and SES to describe the change in well-being per each unit increase.

Relative to other predictors, although still significant, loan has the least significant effect towards well-being, $F(1{,}4996) = 7.456, p = .006$. This is expected since loan and credit.score are highly correlated, R^2 = .494, whilst credit score can explain well-being better than loan, R^2 = .494 and R^2 = .354 respectively. Thus, making the model shifts its attention more to credit score than loan when it comes to predicting well-being.

As for the magnitude of change, holding credit.score and SES constant, one unit increase on loan variable predicts a decrease of .132 unit of well-being 95% CI[(-.242) – (-.022)]. Such change is significant, $t(4996) = -2.359, p < .001$.

Does taking payday loan makes people more or less likely to experience an adverse credit event?

Those taking payday loan are less likely to experience adverse credit event. And Social Economic Status does not have a significant effect on adverse credit event nor on the relationship loan has with adverse credit event.

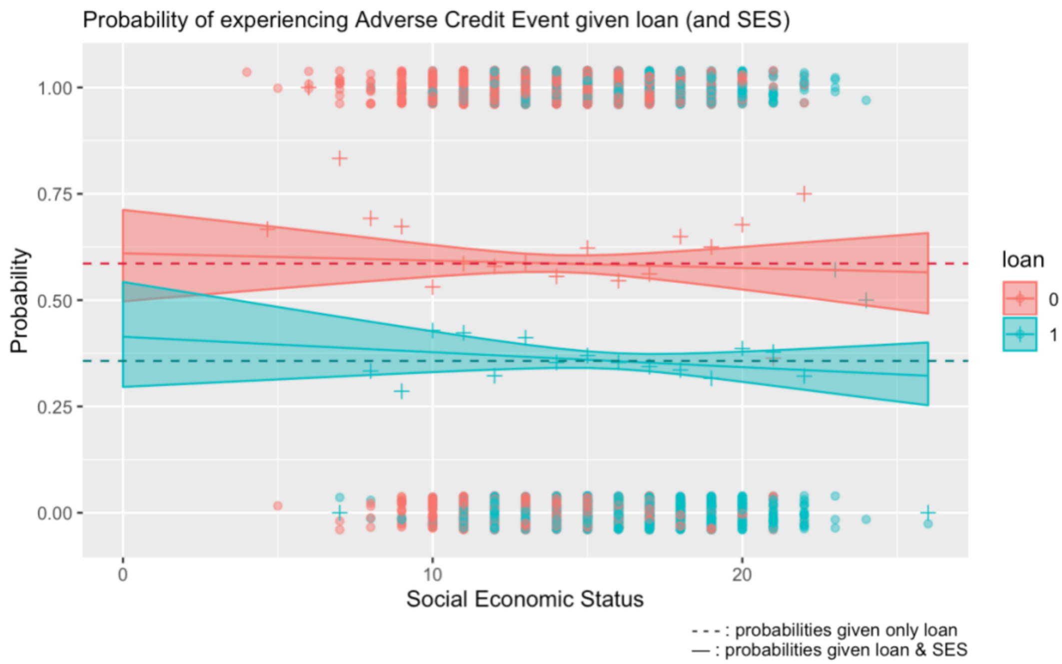


Figure 2.
A comparison of probability estimate on adverse credit event given loan (and SES)

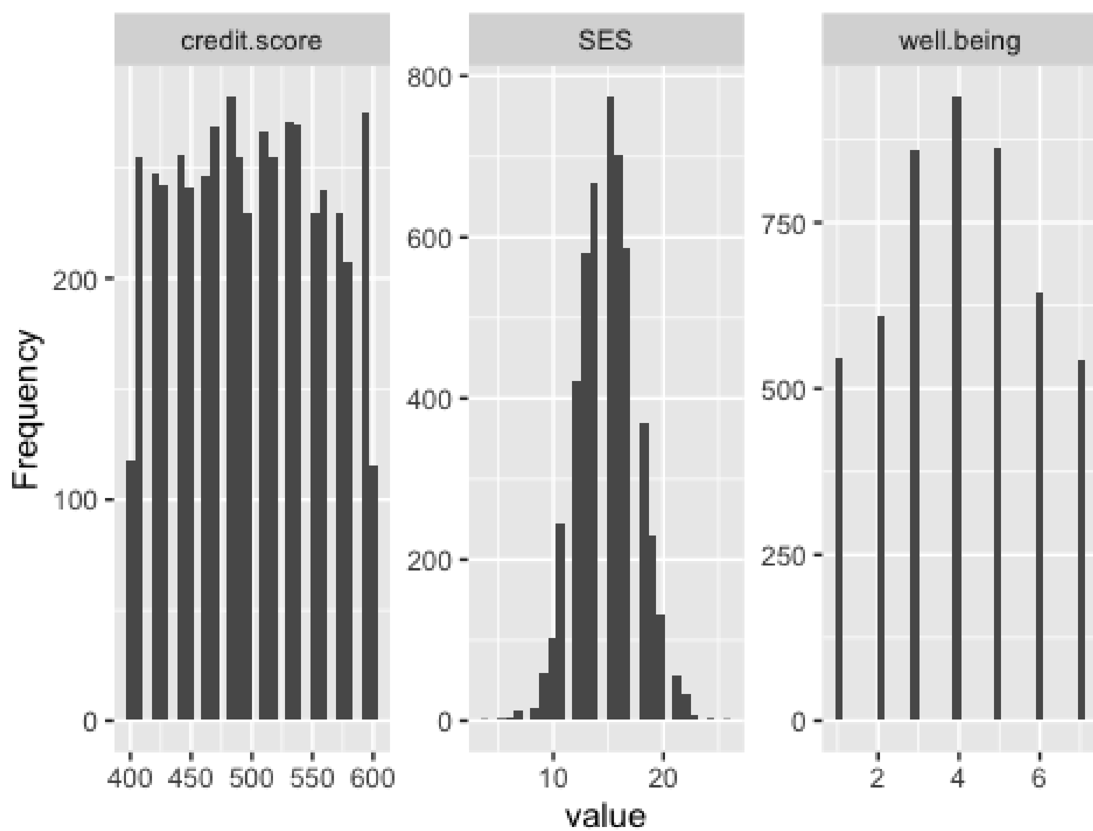
Figure 2 describes the difference in probability of experiencing adverse credit event (ACE) when receiving a loan and a comparison of how insignificant SES affect the probabilities as SES increases. The dashed line is the probability estimate for ACE given a loan or not (without SES), the dots describes the individuals who either experienced ACE or not, the +s are the proportion of ACE in each SES rank, while the line and ribbon are the fit of a logistic regression model and its 95% CI given SES.

The effects of loan on ACE is significant, $\chi^2(4998)=6644.6$, $p<.0001$. In contrast, SES has almost no effect on ACE, $\chi^2(4997)=6643.7$, $p=.339$ nor on the relationship loan has with ACE, $\chi^2(4996)=6643.6$, $p=.339$.

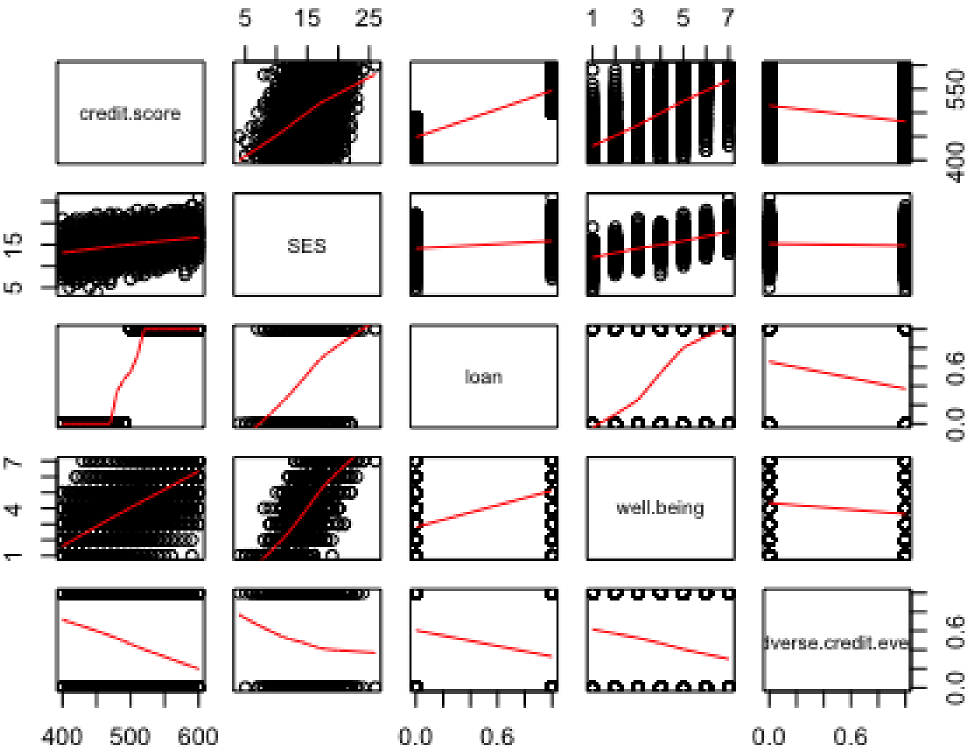
The probability of those taking payday loan to experience ACE, .357 95% CI[.339 – .376], is lower than those who do not, .586 95% CI[.566 – .606], about an absolute .229 change in probability.

In-depth Analysis

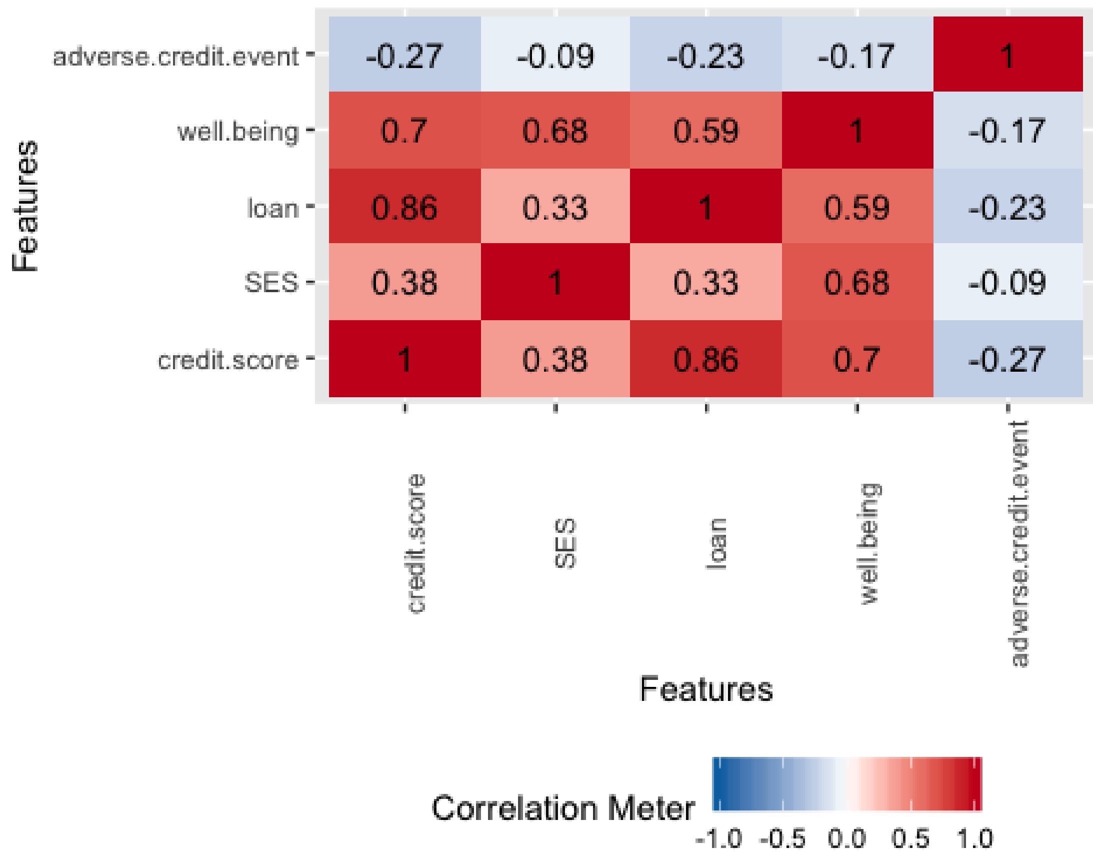
```
# --------- Exploratory Data Analysis

summary(payday)

##   credit.score        SES           loan           well.being     
adverse.credit.event
##  Min.   :400.0   Min.   : 4   Min.   :0.0000   Min.   :1.000   Min.   
:0.0000  
##  1st Qu.:450.0   1st Qu.:13   1st Qu.:0.0000   1st Qu.:3.000   1st 
Qu.:0.0000  
##  Median :500.0   Median :15   Median :1.0000   Median :4.000   Median 
:0.0000  
##  Mean   :499.3   Mean   :15   Mean   :0.5178   Mean   :4.011   Mean   
:0.4674  
##  3rd Qu.:550.0   3rd Qu.:17   3rd Qu.:1.0000   3rd Qu.:5.000   3rd 
Qu.:1.0000  
##  Max.   :600.0   Max.   :26   Max.   :1.0000   Max.   :7.000   Max.   
:1.0000

plot_histogram(payday)
```



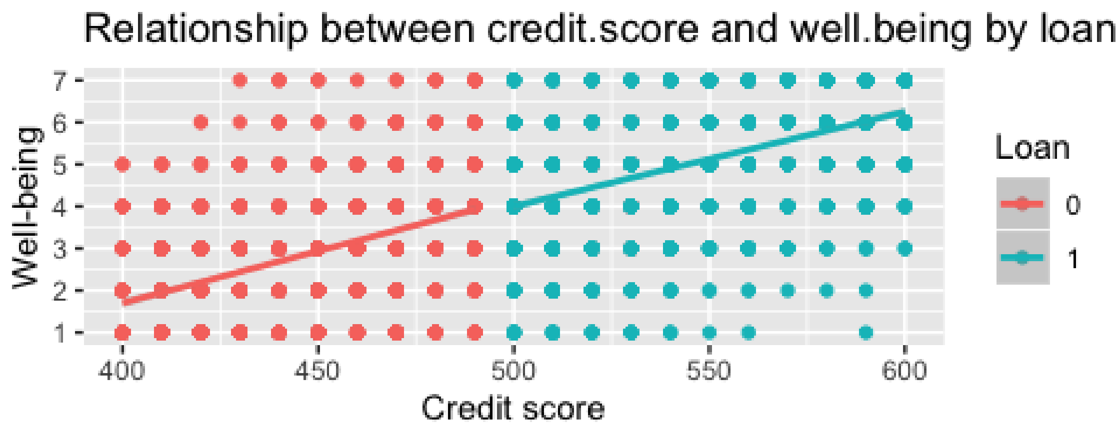

```
pairs(payday, panel=panel.smooth)
```




```
plot_correlation(payday)
```




```
grid.arrange(
    ggplot(payday, aes(y=well.being,
x=credit.score,colour=as.factor(payday$loan))) + geom_point(mapping =
aes(colour=as.factor(payday$loan))) + scale_y_continuous(breaks = 1:7)
+labs(x="Credit score", y="Well-being",title="Relationship between
credit.score and well.being by loan",col="Loan") + geom_smooth(method=lm),

    ggplot(payday, aes(y=well.being, x=SES,colour=as.factor(payday$loan))) +
geom_jitter() +scale_y_continuous(breaks = 1:7)+ labs(x="Social Economic
Status", y="Well-being",title="Relationship between SES and well.being by
loan",col="Loan") +geom_smooth(method=lm))
```




```
#  --------- Compute R^2 among variables to understand the multicoliniarity.
round((cor(payday))^2, digits = 3)

##                        credit.score   SES  loan well.being
adverse.credit.event
## credit.score                  1.000 0.148 0.743      0.494
0.071
## SES                           0.148 1.000 0.108      0.467
0.008
## loan                          0.743 0.108 1.000      0.354
0.053
## well.being                    0.494 0.467 0.354      1.000
0.030
## adverse.credit.event          0.071 0.008 0.053      0.030
1.000
```

loan and `credit.score` has relatively high correlation with each other ($R^2 = .743$), . However, `credit.score` ($R^2 = .494$) can explain well.being better than loan ($R^2 = .354$). Therefore, it is within expectation that `credit.score` might be a more significant independant variable than loan in a multiple regression for well.being.

```
# --------- Linear regression on bivariate
LM_loan <- lm(well.being~ loan, data=payday)
```

```r
LM_credit.score <- lm(well.being~ credit.score, data=payday)
LM_ses <- lm(well.being~ SES, data=payday)

# --------- Multiple regression models for well.being
LM_credit.loan <- lm(well.being~ credit.score + loan, data=payday) # model1,
without SES
LM_credit.loan.ses <- lm(well.being ~ credit.score + loan + SES ,
data=payday)  # model2, including SES
```

`LM_credit.loan` has loan and credit.score as independent variables for well.being. While, `LM_credit.loan.ses` in addition to what `LM_credit.loan` has, SES is added.

```r
# --------- NHST whether the variables are significant in a bivariate setup
anova(LM_loan)

## Analysis of Variance Table
##
## Response: well.being
##             Df  Sum Sq Mean Sq F value    Pr(>F)
## loan         1  5852.6  5852.6  2738.6 < 2.2e-16 ***
## Residuals 4998 10680.9     2.1
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(LM_credit.score)

## Analysis of Variance Table
##
## Response: well.being
##                Df Sum Sq Mean Sq F value    Pr(>F)
## credit.score    1 8163.1  8163.1  4874.3 < 2.2e-16 ***
## Residuals    4998 8370.3     1.7
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(LM_ses)

## Analysis of Variance Table
##
## Response: well.being
##             Df Sum Sq Mean Sq F value    Pr(>F)
## SES          1 7722.4  7722.4  4380.5 < 2.2e-16 ***
## Residuals 4998 8811.0     1.8
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# --------- NHST whether the variance differ between multiple regression
model with and without SES
#H0: LM_credit.loan == LM_credit.loan.ses ; HA: LM_credit.loan !=
LM_credit.loan.ses
anova(LM_credit.loan, LM_credit.loan.ses)
```

```
## Analysis of Variance Table
##
## Model 1: well.being ~ credit.score + loan
## Model 2: well.being ~ credit.score + loan + SES
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1   4997 8362.8
## 2   4996 5053.0  1    3309.8 3272.5 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# --------- NHST the significance of the variables
# For each variable... H0: model with variable == model without variable ; HA: model with variable != model without variable
anova(LM_credit.loan.ses)
```

```
## Analysis of Variance Table
##
## Response: well.being
##                Df Sum Sq Mean Sq   F value    Pr(>F)
## credit.score    1 8163.1  8163.1 8071.0331 < 2.2e-16 ***
## loan            1    7.5     7.5    7.4561  0.006344 **
## SES             1 3309.8  3309.8 3272.4871 < 2.2e-16 ***
## Residuals    4996 5053.0     1.0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

All bivariate LMs has significant effect on `well.being`, but when put together, the significance of loan shifts to `credit.score`. This comes back again to the fact that `credit.score` and `loan` are highly correlated. But `credit.score` still have the upperhand when it comes to predicting `well.being`.

The `LM_credit.loan.ses` fits significantly better, F=3272.5 and p < .0001, with an increase of 0.2 in R^2 and a decrease in 3309 of RSS compared to `LM_credit.loan`. We can say that adding `SES` explains an additional 20% of the variance in well being and it is statistically significant.

All independent variables in `LM_credit.loan.ses` are significant, but compared to `credit.score` and `credit.score`, loan is the least significant, p=.006.

```
# --------- the equation for wellbeing
summary(LM_credit.loan.ses)
```

```
##
## Call:
## lm(formula = well.being ~ credit.score + loan + SES, data = payday)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.8283 -0.6951  0.0084  0.6656  3.7784
##
## Coefficients:
```

```
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -9.5881336  0.2233281 -42.933   <2e-16 ***
## credit.score  0.0173921  0.0005017  34.667   <2e-16 ***
## loan         -0.1324966  0.0561764  -2.359   0.0184 *
## SES           0.3322207  0.0058075  57.206   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.006 on 4996 degrees of freedom
## Multiple R-squared:  0.6944, Adjusted R-squared:  0.6942
## F-statistic:  3784 on 3 and 4996 DF,  p-value: < 2.2e-16
```

```
cbind(coef(LM_credit.loan.ses), confint(LM_credit.loan.ses)) #Confidence
interval of the estimate
```

```
##                                  2.5 %      97.5 %
## (Intercept)  -9.58813364 -10.02595471 -9.15031256
## credit.score  0.01739205   0.01640852  0.01837558
## loan         -0.13249660  -0.24262709 -0.02236611
## SES           0.33222068   0.32083547  0.34360589
```

well.being can be explained through the following equation: $\widehat{well.being} = -9.588 + 0.017 \times credit.score - 0.132 \times loan + 0.332 \times SES$

As for the magnitude of change, holding credit.score and SES constant, one unit increase on loan variable predicts a decrease of .132 units on well.being 95% CI[(-.242) – (-.022)]. Such change is significant, $t(4996) = -2.359, p < .001$.

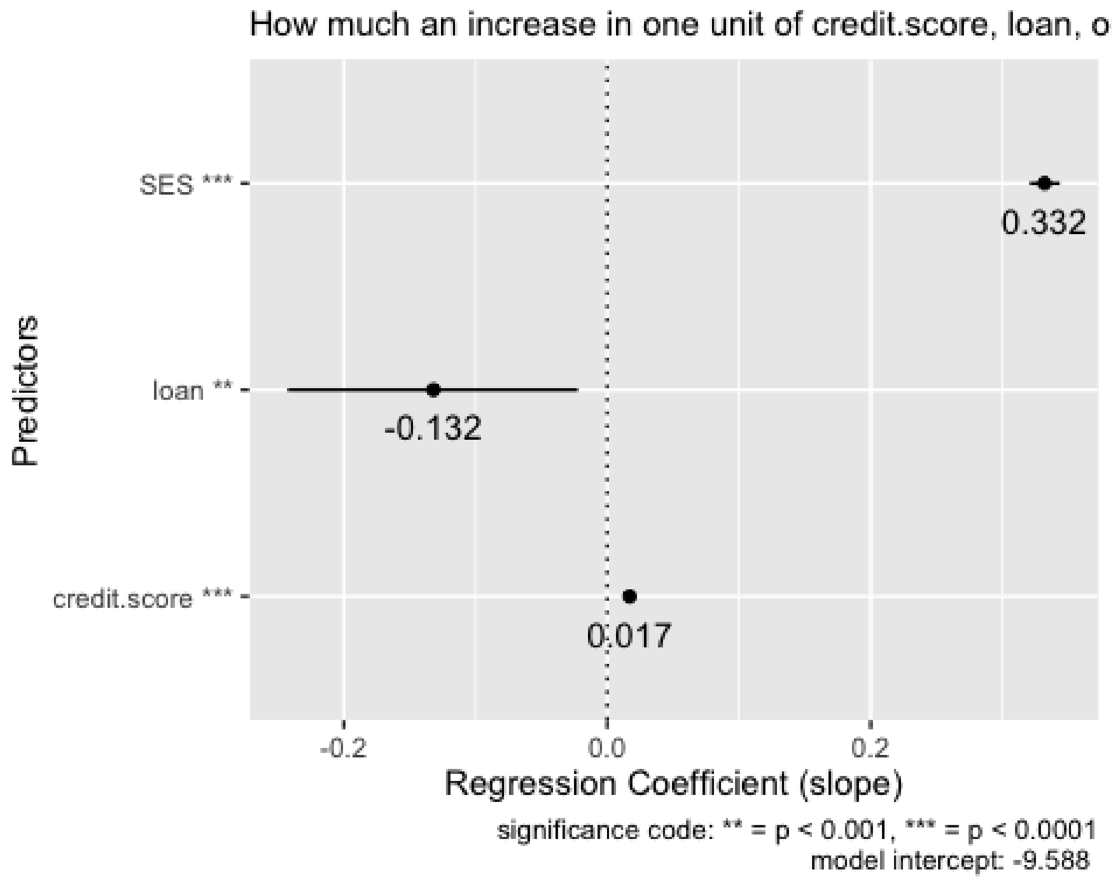
The negative coefficient of loan can be explained by the multiple colinearity with credit.score, the binary input, and the constraint of 7 scales of well.being. Simply put, loan balances credit.score's impact by going to the opposite direction when loan == 1.

```
# --------- plot prep
df_coeff <- as.data.frame(cbind(coef(LM_credit.loan.ses),
confint(LM_credit.loan.ses)))
df_coeff <- mutate(df_coeff, id = rownames(df_coeff))
df_coeff <- anti_join(df_coeff, subset(df_coeff, id=='(Intercept)'))
```

```
## Joining, by = c("V1", "2.5 %", "97.5 %", "id")
```

```
df_coeff <- df_coeff %>%
  mutate(V1 = round(V1,digits = 3))

df_coeff$id[df_coeff$id == "credit.score"] <- "credit.score ***"
df_coeff$id[df_coeff$id == "loan"] <- "loan **"
df_coeff$id[df_coeff$id == "SES"] <- "SES ***"

# --------- plotting
ggplot(df_coeff , aes(y=as.factor(id), x=V1)) +
  geom_point() + geom_text(aes(label=V1),hjust=0.5, vjust=2) +
  labs(x="Regression Coefficient (slope)", y="Predictors",subtitle="How much
```

```
an increase in one unit of credit.score, loan, or SES changes well.being",
caption = "significance code: ** = p < 0.001, *** = p < 0.0001\n model
intercept: -9.588 " ) +
  geom_segment(aes(x=`2.5 %`,xend=`97.5 %`,y=as.factor(id),yend=as.factor(id)
)) +
  geom_vline(xintercept = 0, linetype='dotted')
```



```
# --------- Exploratory Data Analysis
mu <- payday %>%
    group_by(adverse.credit.event) %>%
    summarise(mean=mean(credit.score))

ggplot(payday, aes(x=credit.score, color=as.factor(adverse.credit.event),
fill=as.factor(adverse.credit.event))) +
  geom_histogram(alpha =0.5, position="dodge", bins = 50)+
  geom_density(alpha=0.6)+
  geom_vline(data=mu, aes(xintercept=mean,
color=as.factor(adverse.credit.event)),linetype="dashed")+
  geom_vline(xintercept = 500, colour="#990000", linetype="longdash")+
  scale_color_manual(values=c("#999999", "#E69F00", "#56B4E9"))+
```

```
  scale_fill_manual(values=c("#999999", "#E69F00", "#56B4E9"))+
  theme(legend.position="top")
```


```
# --------- Build logistic regression model
adverse.by.loan.ses <- glm(adverse.credit.event~loan*SES , family=binomial,
data=payday)
adverse.by.loan <- glm(adverse.credit.event~loan, family=binomial,
data=payday)

summary(adverse.by.loan.ses)

##
## Call:
## glm(formula = adverse.credit.event ~ loan * SES, family = binomial,
##     data = payday)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3567  -0.9561  -0.9214   1.0392   1.4914
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) 0.447556   0.234026   1.912   0.0558 .
```

```
## loan        -0.795326   0.353494  -2.250   0.0245 *
## SES         -0.007080   0.016331  -0.434   0.6646
## loan:SES    -0.008152   0.023251  -0.351   0.7259
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6910.2  on 4999  degrees of freedom
## Residual deviance: 6643.6  on 4996  degrees of freedom
## AIC: 6651.6
##
## Number of Fisher Scoring iterations: 4
```

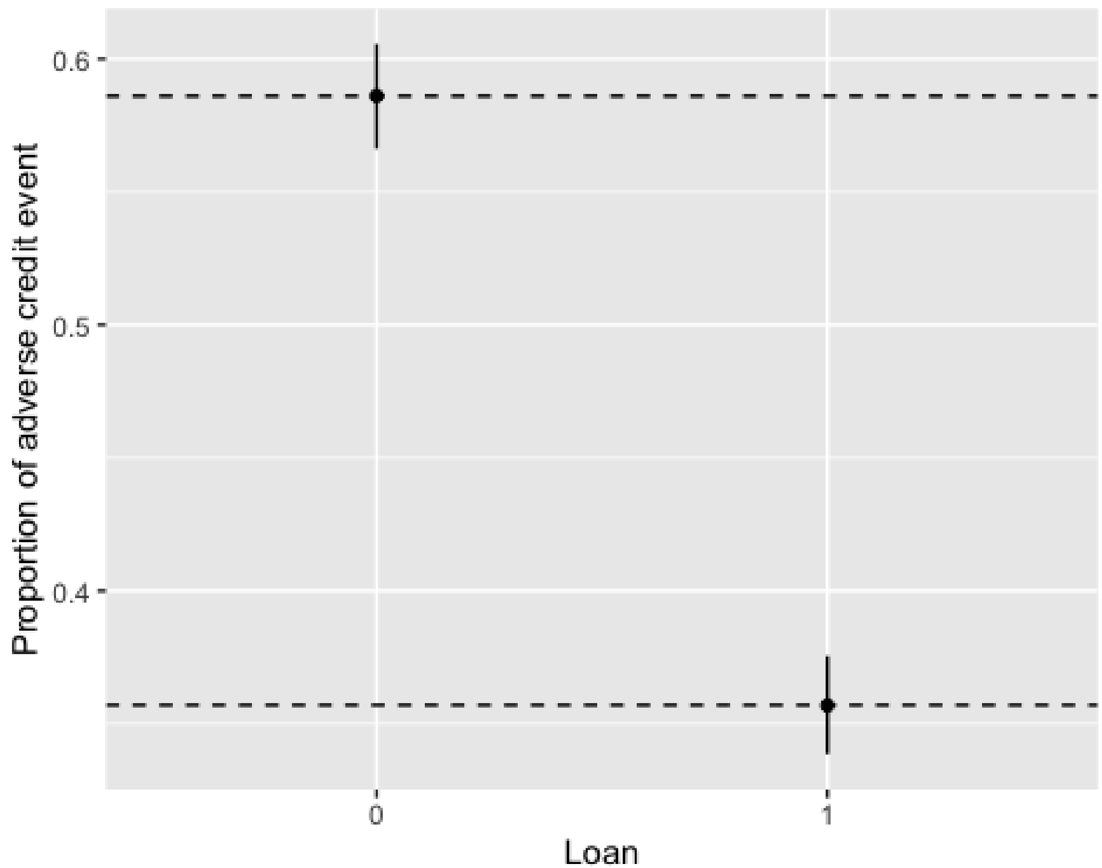
```
summary(adverse.by.loan)
```

```
##
## Call:
## glm(formula = adverse.credit.event ~ loan, family = binomial,
##     data = payday)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3282  -0.9396  -0.9396   1.0338   1.4355
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.34772    0.04135   8.409   <2e-16 ***
## loan        -0.93659    0.05825 -16.080   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6910.2  on 4999  degrees of freedom
## Residual deviance: 6644.6  on 4998  degrees of freedom
## AIC: 6648.6
##
## Number of Fisher Scoring iterations: 4
```

```
# --------- Get the probability of adverse credit event by loan and its
estimation
adverse.by.loan.emm <- emmeans(adverse.by.loan, ~loan, type="response")
confint(adverse.by.loan.emm)
```

```
##  loan  prob      SE  df asymp.LCL asymp.UCL
##     0 0.586 0.01003 Inf     0.566     0.606
##     1 0.357 0.00942 Inf     0.339     0.376
##
## Confidence level used: 0.95
## Intervals are back-transformed from the logit scale
```

```r
# --------- Plot the probabilities
ggplot(summary(adverse.by.loan.emm), aes(x=as.factor(loan), y=prob,
ymin=asymp.LCL, ymax=asymp.UCL)) + geom_point() + geom_linerange() +
labs(x="Loan", y="Proportion of adverse credit event")  +
  geom_hline(yintercept = 0.586, lty=2) +
  geom_hline(yintercept = 0.357, lty=2)
```

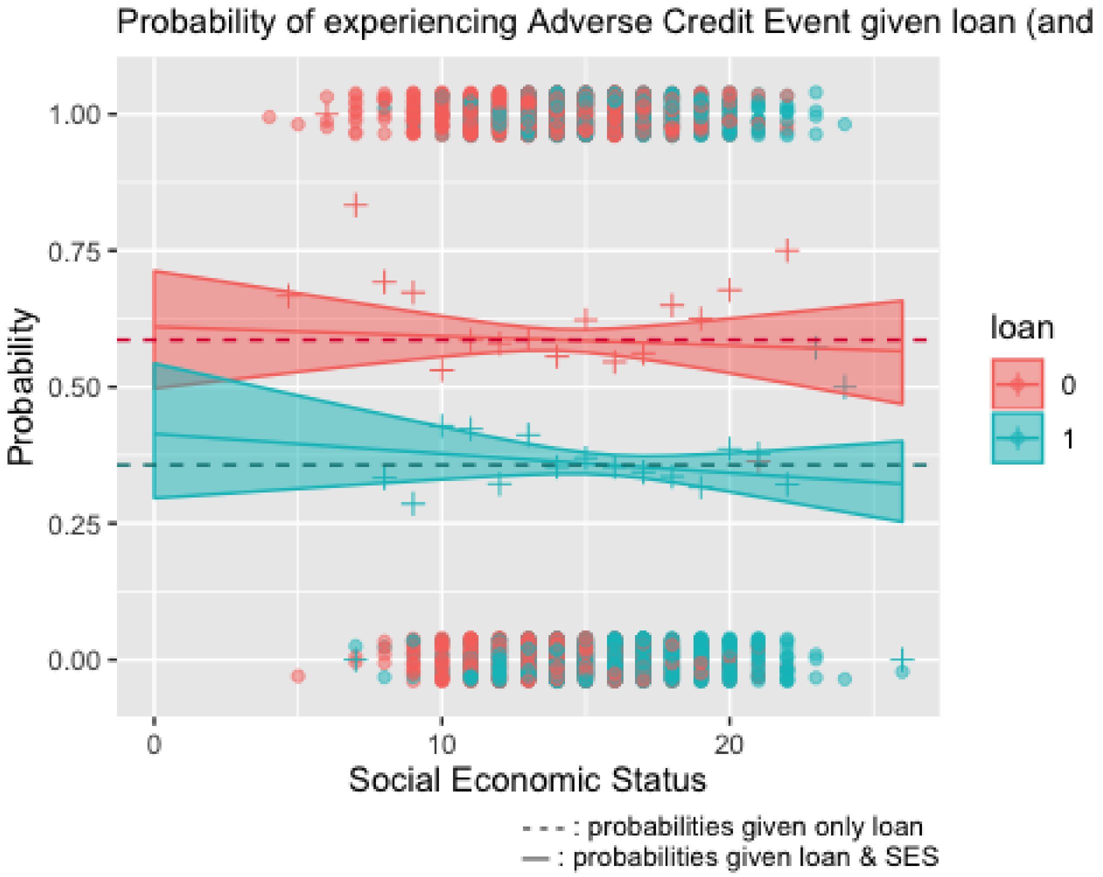



```r
# --------- Prove that SES is insignificant for explaining
adverse.credit.event
anova(adverse.by.loan.ses, test="Chisq")

## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: adverse.credit.event
##
## Terms added sequentially (first to last)
##
##
##         Df Deviance Resid. Df Resid. Dev Pr(>Chi)
## NULL                     4999     6910.2
## loan     1  265.597      4998     6644.6   <2e-16 ***
```

```
## SES       1    0.913      4997     6643.7   0.3394
## loan:SES  1    0.123      4996     6643.6   0.7259
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

A change of probability of ACE between receiving a loan and not receiving one is about an absolute 22.9%. Additionally, SES has almost no effect on ACE, $\chi^2(4997)$=6643.7, p=.339 nor on the relationship loan has with ACE, $\chi^2(4996)$=6643.6, p=.339.

```
# --------- Plot Prep
adverse.by.loan.ses.emm <- emmeans(adverse.by.loan.ses, ~loan*SES,
at=list(SES=seq(0,26,1)), type="response")
ses.unique<- unique(payday$SES)
payday_t <- payday %>%
  mutate(SES.deciles=cut(SES, breaks=ses.unique, include.lowest=TRUE))

payday_t.loan.ses <- payday_t %>%
  group_by(SES.deciles,loan) %>%
  summarise(Proportion.adverse=mean(adverse.credit.event),
decile.mean.ses=mean(SES))

payday_t$loan <- as.factor(payday_t$loan)
payday_t.loan.ses$loan <- as.factor(payday_t.loan.ses$loan)



sum_adverse.by.loan.ses.emm <-
as.data.frame(summary(adverse.by.loan.ses.emm))
sum_adverse.by.loan.ses.emm$loan <-
as.factor(sum_adverse.by.loan.ses.emm$loan)

# --------- Plotting mainplot
ggplot(sum_adverse.by.loan.ses.emm, aes(x=SES, col=loan, fill=loan,y=prob,
ymin=asymp.LCL, ymax=asymp.UCL)) +
    geom_jitter(data=payday_t, mapping=aes(y=adverse.credit.event, x=SES,
col=loan,ymin=NULL, ymax=NULL), height=0.04, width=0, alpha=0.5) +
    geom_point(data=payday_t.loan.ses, mapping=aes(y=Proportion.adverse,
x=decile.mean.ses, col=loan, ymin=NULL, ymax=NULL), size=2, shape=3) +
    geom_ribbon(alpha = 0.5) +
    geom_line() +
    labs(x="Social Economic Status", y="Probability", caption="- - - :
probabilities given only loan  \n  — : probabilities given loan & SES",
subtitle = "Probability of experiencing Adverse Credit Event given loan (and
SES)" ) +
  ylim(-0.05,1.05) +
  geom_hline(yintercept = 0.586, lty=2, color='#DC143C') +
  geom_hline(yintercept = 0.357, lty=2, color='#008080')
```


Probability of experiencing Adverse Credit Event given loan (and S
1.00
0.75
0.50
0.25
0.00
Probability
0
10
20
Social Economic Status
loan
0
1
- - - : probabilities given only loan
— : probabilities given loan & SES