

Econ-UB Assignment 2

Shalem Sumanthiran - sps9893

Theory: Simulating OVB

Question 1

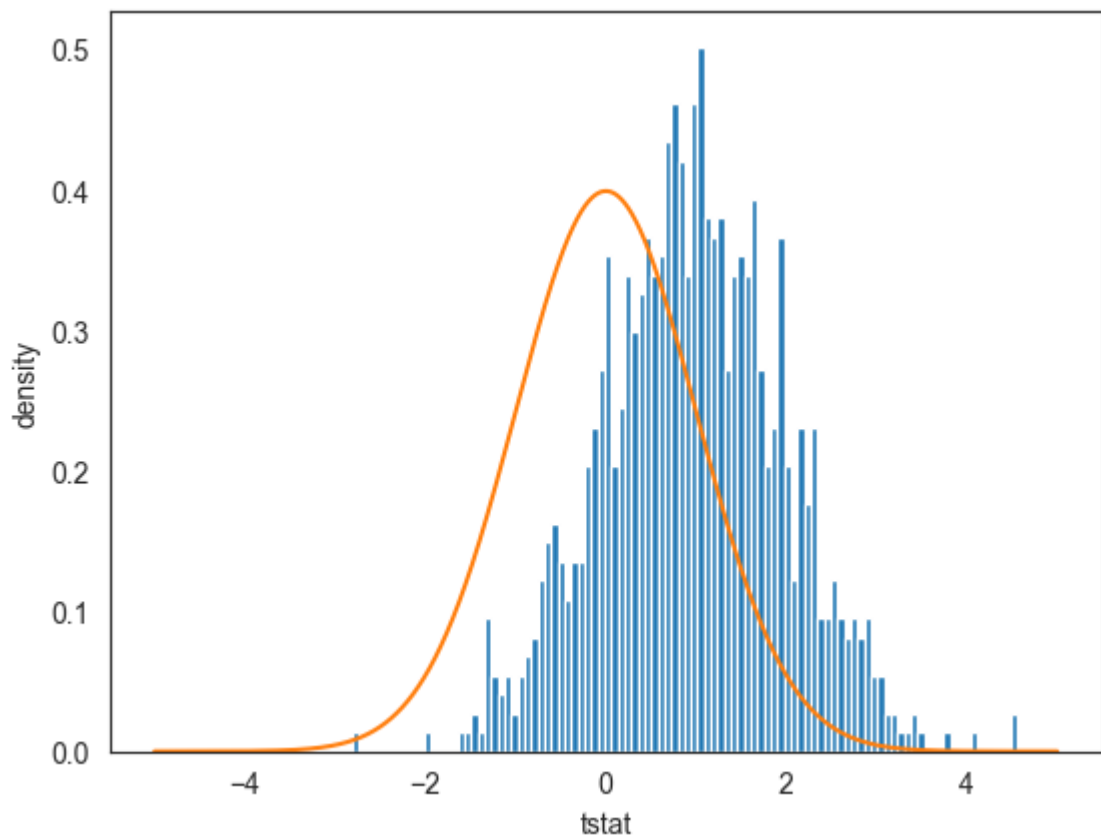
```
In [ ]: import numpy as np
import scipy.stats as sp
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import statsmodels.formula.api as smf
import statsmodels.api as sm
sns.set_style('white')

N=500
B=1000
beta1=[]
tstat=[]

np.random.seed(1)
for b in range(B):
    x1=np.random.normal(0,1,N)
    x2=0.1*x1+np.random.normal(0,1,N)
    y=1.1*x1+0.5*x2+np.random.normal(0,1,N)
    rho=np.corrcoef(x1,y)
    model = sm.OLS(y, x1)
    result = model.fit()

    beta1.append(result.params[0])
    tstat.append((beta1[b]-1.1)/(result.bse[0])) # store the beta_hat

myhist=plt.hist(tstat,bins=100, density=True)
x_axis = np.arange(-5, 5, 0.001)
mynorm=plt.plot(x_axis, sp.norm.pdf(x_axis,0,1)) # Mean = 0, SD = 1
plt.xlabel('tstat')
plt.ylabel('density')
plt.show()
```



Omitted variable bias occurs under two conditions:

1. Z is a determinant of Y (i.e. Z is part of u)
2. Z is correlated with the regressor X

In this model, we observe Omitted Variable bias. The simulated X_2 is defined using X_1 , which implies that Y_i is determined by the error term. Therefore, we can conclude that there is Omitted Variable bias as both conditions are satisfied. This is also seen in the graph, as the histogram does not align with the normal distribution.

Empirical

Question 2

```
In [ ]: import pandas as pd
from scipy.stats import kurtosis, skew

var_names = ["Credit_Score", "First_Payment_date", "First_Time_Homebuyer", "Maturi",
"MSA", "Mortgage_Insurance_Percentage", "Number_Units", "Occupancy_Status", "CLTV",
"DTI", "UPB", "LTV", "Interest_Rate", "Channel", "Prepayment_Penalty",
"Amortization_Type", "State", "Property_Type", "Postal_Code", "Sequence_Number",
"Purpose", "Loan_Term", "Number_Borrowers", "Seller_Name", "Servicer_Name",
"Super_Conforming", "Pre-HARP_Loan", "Program_Indicator", "HARP_Indicator",
"Valuation_Method", "Interest_Only", "Insurance_cancellation"]

mysample = pd.read_table("C:/Users/shale/Downloads/sample_2022/sample_orig_2022.

for column in var_names:
    mysample = mysample[mysample[column] != 9999]
```

```
mysample['UPB'] = mysample['UPB'].div(1000)

figure, (ax0, ax1, ax2) = plt.subplots(nrows=3, ncols=1, figsize=(8, 10))

ax0.hist(mysample['DTI'], bins=50, color='skyblue', edgecolor='black')
ax0.set_title('Histogram of DTI')
ax0.set_xlabel('DTI Values')

ax1.hist(mysample['UPB'], bins=50, color='lightcoral', edgecolor='black')
ax1.set_title('Histogram of UPB (in $1,000)')
ax1.set_xlabel('UPB (in $1,000)')

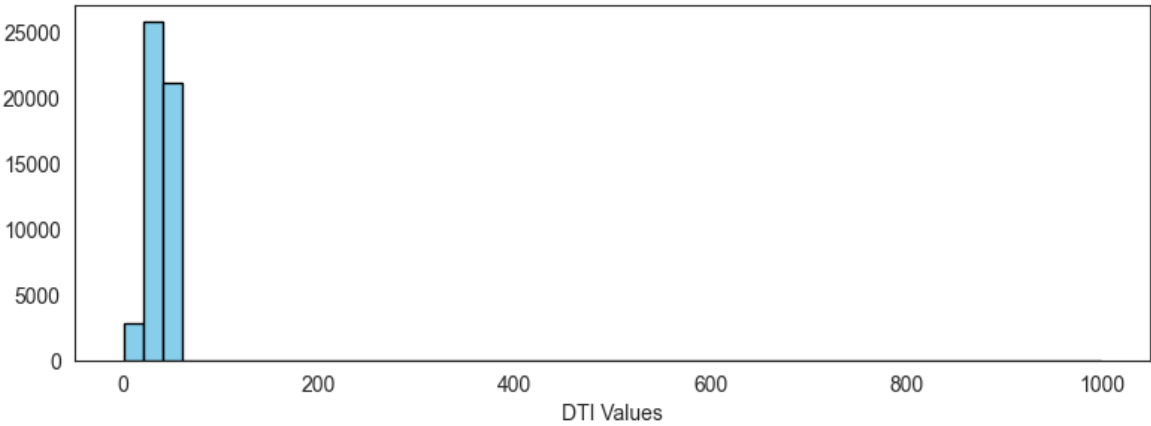
ax2.hist(mysample['LTV'], bins=50, color='lightgreen', edgecolor='black')
ax2.set_title('Histogram of LTV')
ax2.set_xlabel('LTV Values')

plt.suptitle('Distribution of DTI, UPB (in $1,000), and LTV')
plt.tight_layout()
plt.show()

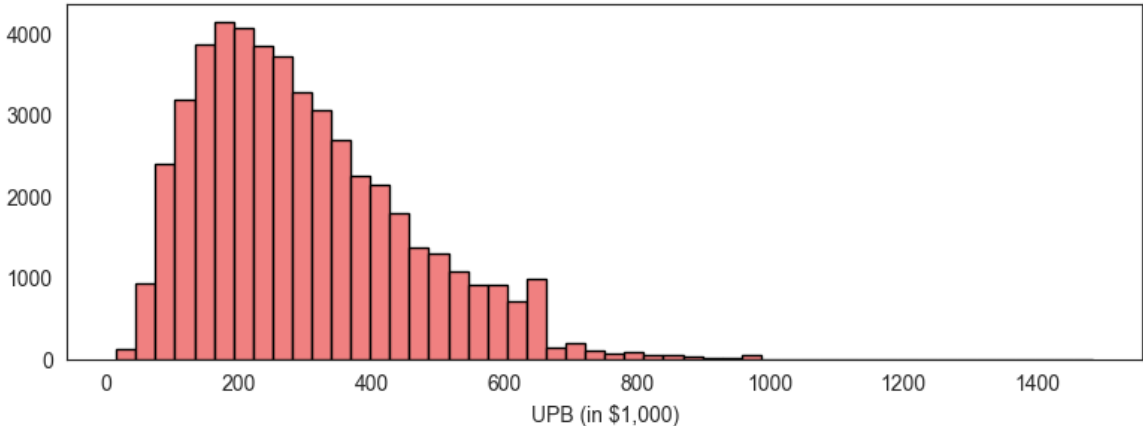
distribution_characteristics = mysample[['DTI', 'UPB', 'LTV']].describe()
distribution_characteristics.loc['kurtosis'] = [kurtosis(mysample['DTI']), kurtosis(mysample['UPB']), kurtosis(mysample['LTV'])]
distribution_characteristics.loc['skewness'] = [skew(mysample['DTI']), skew(mysample['UPB']), skew(mysample['LTV'])]

print(distribution_characteristics)
```

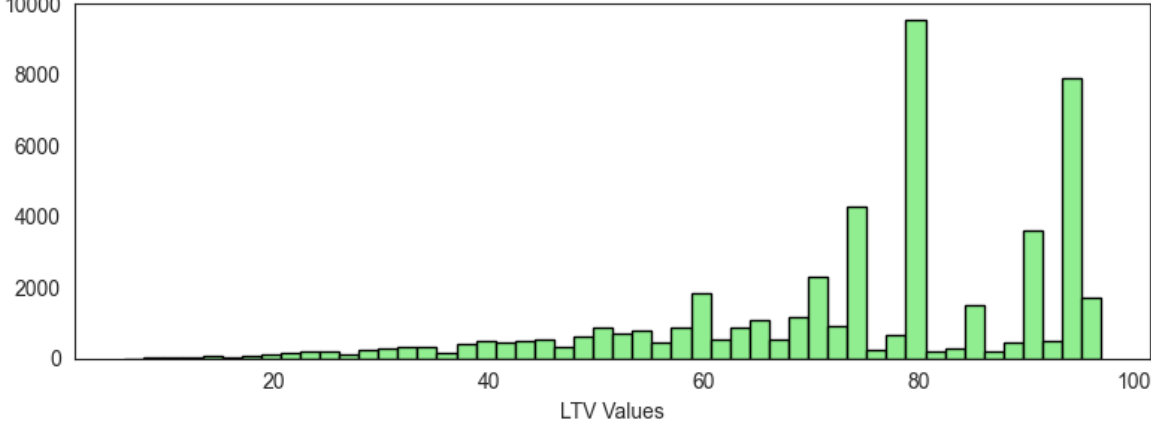
Distribution of DTI, UPB (in \$1,000), and LTV
Histogram of DTI



Histogram of UPB (in \$1,000)



Histogram of LTV



	DTI	UPB	LTV
count	49983.000000	49983.000000	49983.000000
mean	37.097773	299.661985	74.070624
std	15.225280	159.957928	18.483965
min	1.000000	16.000000	6.000000
25%	31.000000	176.000000	64.000000
50%	39.000000	270.000000	80.000000
75%	44.000000	394.000000	90.000000
max	999.000000	1485.000000	97.000000
kurtosis	2547.419542	0.741601	0.360242
skewness	40.205618	0.895555	-0.920109

The distribution characteristics above along with the histograms indicate the following:

For DTI - The distribution is right-skewed, indicating more observations relatively less than the mean, with one outlier of 999 given that the mean is 37.09 For UPB - The

distribution is right-skewed, indicating more observations relatively less than the mean. For LTV - The distribution is left-skewed, indicating more observations relatively greater than the mean.

All other characteristics are displayed in the table above.

Based on economic reasoning, the variables should be pricing factors that determine the interest rate of the loan, based on the following:

Debt-to-Income Ratio (DTI): DTI is a measure of the borrower's ability to manage debt payments in relation to their income. A high DTI indicates that a borrower has a significant portion of their income allocated to debt payments. Borrowers with lower DTIs may get lower interest rates because they are considered lower risk.

Unpaid Principal Balance (UPB): The UPB represents the outstanding balance of the loan, which decreases over time as the borrower makes payments. Therefore it may indicate a lower ability to repay the loan on the part of the borrower if they have significant outstanding balance, signalling a higher risk.

Loan-to-Value Ratio (LTV): LTV measures the ratio of the loan amount to the appraised value of the collateral. Higher LTVs imply that the borrower is financing a larger portion of the purchase price, which can be considered riskier.

Question 3

```
In [ ]: correlation_matrix = mysample[['Credit_Score', 'DTI', 'UPB', 'LTV']].corr()
print(correlation_matrix)
```

	Credit_Score	DTI	UPB	LTV
Credit_Score	1.000000	-0.052572	0.149520	0.062062
DTI	-0.052572	1.000000	0.070790	0.060250
UPB	0.149520	0.070790	1.000000	0.259811
LTV	0.062062	0.060250	0.259811	1.000000

There is unlikely to be a great risk of multicollinearity in the data, as we can see above that the respective correlations between each variable are relatively small (below 0.26 for any of them), therefore it should not be difficult to determine the individual effect of each independent variable on the dependent variable.

Question 4

```
In [ ]: import statsmodels.formula.api as smf
results = smf.ols('Interest_Rate ~ Credit_Score + DTI + UPB + LTV', data=mysamp1)
print(results.summary())
```

OLS Regression Results

=====						
Dep. Variable:	Interest_Rate	R-squared:	0.047			
Model:	OLS	Adj. R-squared:	0.047			
Method:	Least Squares	F-statistic:	531.0			
Date:	Thu, 19 Oct 2023	Prob (F-statistic):	0.00			
Time:	13:55:01	Log-Likelihood:	-79920.			
No. Observations:	49983	AIC:	1.599e+05			
Df Residuals:	49978	BIC:	1.599e+05			
Df Model:	4					
Covariance Type:	HC3					
=====						
	coef	std err	z	P> z	[0.025	0.975]

Intercept	5.0205	0.105	48.002	0.000	4.816	5.226
Credit_Score	-0.0013	0.000	-10.637	0.000	-0.002	-0.001
DTI	0.0044	0.001	3.878	0.000	0.002	0.007
UPB	-0.0005	3.59e-05	-15.229	0.000	-0.001	-0.000
LTV	0.0138	0.000	43.273	0.000	0.013	0.014
=====						
Omnibus:	2140.979	Durbin-Watson:	0.397			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	912.298			
Skew:	-0.049	Prob(JB):	7.89e-199			
Kurtosis:	2.345	Cond. No.	1.35e+04			
=====						

Notes:

[1] Standard Errors are heteroscedasticity robust (HC3)

[2] The condition number is large, 1.35e+04. This might indicate that there are strong multicollinearity or other numerical problems.

The coefficient of the credit score indicates that when the Credit Score changes by one unit, the Interest Rate reduces by 0.0013 units on average ceteris paribus.

The coefficients of DTI, and LTV have the expected signs of being positive as per the earlier discussion of the expected impact of the variables, however the UPB variable has a negative sign which was not expected, which may indicate something wrong with the model or a need to analyze more carefully our expectations.

The impact of all variables are statistically significant at a 5% level, which indicates that the variables will have an impact on Interest Rate more than 95 times out of 100 if we were to repeat the regression with different samples.

```
In [ ]: results2 = smf.ols('Interest_Rate ~ Credit_Score', data=mysample).fit(cov_type='
print(results2.summary())
```

OLS Regression Results

Dep. Variable:	Interest_Rate	R-squared:	0.002			
Model:	OLS	Adj. R-squared:	0.002			
Method:	Least Squares	F-statistic:	119.5			
Date:	Thu, 19 Oct 2023	Prob (F-statistic):	8.72e-28			
Time:	13:55:01	Log-Likelihood:	-81058.			
No. Observations:	49983	AIC:	1.621e+05			
Df Residuals:	49981	BIC:	1.621e+05			
Df Model:	1					
Covariance Type:	HC3					
=====						
	coef	std err	z	P> z	[0.025	0.975]

Intercept	6.0532	0.089	68.023	0.000	5.879	6.228
Credit_Score	-0.0013	0.000	-10.932	0.000	-0.002	-0.001
=====						
Omnibus:	2954.745	Durbin-Watson:	0.359			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1173.635			
Skew:	-0.113	Prob(JB):	1.41e-255			
Kurtosis:	2.284	Cond. No.	1.20e+04			
=====						

Notes:

[1] Standard Errors are heteroscedasticity robust (HC3)

[2] The condition number is large, 1.2e+04. This might indicate that there are strong multicollinearity or other numerical problems.

As seen above, the R squared of the model with only Credit Score is 0.002 while the R squared of the model with all the variables is 0.047, indicating that the model with the higher R-squared value explains more of the variation of the data, making it more accurate.

The coefficient estimate of Credit Score did not change significantly when looking at the standard error of the effect of the variable on Interest Rate. In addition, the effect is similar as well.

Question 5

```
In [ ]: # Define the null hypothesis
hypothesis = '(DTI = 0, UPB = 0, LTV = 0)'

# Perform the Wald test for joint hypothesis
wald_test = results.wald_test(hypothesis)

# Get the test statistic and p-value
test_statistic = wald_test.statistic
p_value = wald_test.pvalue

# Define the significance level
alpha = 0.05

# Check if the joint hypothesis is rejected at the 5% significance level
if p_value < alpha:
    print("Reject the joint hypothesis at the 5% significance level.")
else:
    print("Fail to reject the joint hypothesis at the 5% significance level.")
```

```
# Print the test statistic and p-value  
print("Test Statistic:", test_statistic)  
print("P-Value:", p_value)
```

Reject the joint hypothesis at the 5% significance level.

Test Statistic: [[2008.28904245]]

P-Value: 0.0

```
C:\Users\shale\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2  
kfra8p0\LocalCache\local-packages\Python311\site-packages\statsmodels\base\model.  
py:1906: FutureWarning: The behavior of wald_test will change after 0.14 to retur  
ning scalar test statistic values. To get the future behavior now, set scalar to  
True. To silence this message while retaining the legacy behavior, set scalar to  
False.  
warnings.warn(  

```

Therefore we reject the joint hypothesis at the 5% significance level, indicating that our restricted and unrestricted models are different to each other.

Question 6

```
In [ ]: results3 = smf.ols('Interest_Rate ~ Credit_Score + DTI + UPB + LTV + State', dat  
print(results3.summary())
```


OLS Regression Results

```

=====
Dep. Variable:          Interest_Rate    R-squared:                0.049
Model:                  OLS              Adj. R-squared:           0.048
Method:                 Least Squares    F-statistic:              39.49
Date:                  Thu, 19 Oct 2023  Prob (F-statistic):      0.00
Time:                  13:55:01          Log-Likelihood:           -79856.
No. Observations:      49983            AIC:                     1.598e+05
Df Residuals:          49925            BIC:                     1.603e+05
Df Model:              57
Covariance Type:       HC3
=====

```

	coef	std err	z	P> z	[0.025	0.975]
Intercept	4.8252	0.164	29.471	0.000	4.504	5.146
State[T.AL]	0.2007	0.135	1.488	0.137	-0.064	0.465
State[T.AR]	0.1244	0.142	0.875	0.381	-0.154	0.403
State[T.AZ]	0.1758	0.130	1.356	0.175	-0.078	0.430
State[T.CA]	0.1425	0.128	1.114	0.265	-0.108	0.393
State[T.CO]	0.1957	0.131	1.497	0.134	-0.060	0.452
State[T.CT]	0.1899	0.136	1.393	0.164	-0.077	0.457
State[T.DC]	0.1308	0.191	0.687	0.492	-0.243	0.504
State[T.DE]	0.2244	0.146	1.535	0.125	-0.062	0.511
State[T.FL]	0.2096	0.128	1.644	0.100	-0.040	0.460
State[T.GA]	0.2155	0.129	1.670	0.095	-0.037	0.468
State[T.GU]	-0.6965	0.748	-0.931	0.352	-2.163	0.770
State[T.HI]	0.0178	0.172	0.104	0.918	-0.320	0.356
State[T.IA]	0.0682	0.139	0.491	0.623	-0.204	0.340
State[T.ID]	0.3286	0.140	2.344	0.019	0.054	0.603
State[T.IL]	0.2480	0.129	1.921	0.055	-0.005	0.501
State[T.IN]	0.3651	0.131	2.792	0.005	0.109	0.621
State[T.KS]	0.2276	0.141	1.611	0.107	-0.049	0.504
State[T.KY]	0.2693	0.135	1.989	0.047	0.004	0.535
State[T.LA]	0.2875	0.137	2.099	0.036	0.019	0.556
State[T.MA]	0.1470	0.134	1.101	0.271	-0.115	0.409
State[T.MD]	0.0912	0.132	0.692	0.489	-0.167	0.350
State[T.ME]	0.1913	0.150	1.274	0.203	-0.103	0.486
State[T.MI]	0.3349	0.130	2.581	0.010	0.081	0.589
State[T.MN]	0.1879	0.131	1.438	0.150	-0.068	0.444
State[T.MO]	0.2695	0.132	2.048	0.041	0.012	0.527
State[T.MS]	0.1062	0.155	0.683	0.495	-0.199	0.411
State[T.MT]	0.3506	0.155	2.258	0.024	0.046	0.655
State[T.NC]	0.1532	0.129	1.184	0.236	-0.100	0.407
State[T.ND]	-0.0592	0.178	-0.332	0.740	-0.409	0.290
State[T.NE]	0.1454	0.147	0.989	0.323	-0.143	0.434
State[T.NH]	0.4129	0.148	2.796	0.005	0.123	0.702
State[T.NJ]	0.1673	0.131	1.278	0.201	-0.089	0.424
State[T.NM]	0.2931	0.148	1.986	0.047	0.004	0.582
State[T.NV]	0.1331	0.135	0.983	0.326	-0.132	0.399
State[T.NY]	0.1586	0.130	1.224	0.221	-0.095	0.413
State[T.OH]	0.2606	0.129	2.016	0.044	0.007	0.514
State[T.OK]	0.2561	0.137	1.869	0.062	-0.013	0.525
State[T.OR]	0.2265	0.133	1.700	0.089	-0.035	0.488
State[T.PA]	0.2185	0.129	1.692	0.091	-0.035	0.472
State[T.PR]	-0.8364	1.063	-0.787	0.432	-2.920	1.248
State[T.RI]	0.1071	0.169	0.634	0.526	-0.224	0.438
State[T.SC]	0.1823	0.132	1.384	0.166	-0.076	0.440
State[T.SD]	0.1111	0.165	0.672	0.502	-0.213	0.435
State[T.TN]	0.2021	0.131	1.547	0.122	-0.054	0.458
State[T.TX]	0.1848	0.127	1.451	0.147	-0.065	0.435

State[T.UT]	0.1714	0.133	1.287	0.198	-0.090	0.432
State[T.VA]	0.1539	0.130	1.181	0.238	-0.102	0.409
State[T.VI]	-0.5079	0.946	-0.537	0.591	-2.362	1.346
State[T.VT]	0.0956	0.174	0.550	0.582	-0.245	0.436
State[T.WA]	0.1947	0.131	1.489	0.137	-0.062	0.451
State[T.WI]	0.2018	0.134	1.507	0.132	-0.061	0.464
State[T.WV]	0.1121	0.161	0.698	0.485	-0.203	0.427
State[T.WY]	0.1148	0.172	0.668	0.504	-0.222	0.452
Credit_Score	-0.0013	0.000	-10.690	0.000	-0.002	-0.001
DTI	0.0045	0.001	3.862	0.000	0.002	0.007
UPB	-0.0004	4.01e-05	-11.208	0.000	-0.001	-0.000
LTV	0.0134	0.000	39.714	0.000	0.013	0.014

```
=====
Omnibus:                2045.484    Durbin-Watson:                0.400
Prob(Omnibus):          0.000    Jarque-Bera (JB):            888.226
Skew:                   -0.051    Prob(JB):                    1.33e-193
Kurtosis:               2.355    Cond. No.                    1.49e+05
=====
```

Notes:

[1] Standard Errors are heteroscedasticity robust (HC3)

[2] The condition number is large, 1.49e+05. This might indicate that there are strong multicollinearity or other numerical problems.

The state GA and IL have statistically significant positive coefficients at the 10% significance level, indicating that because the loans originate from those states, the Interest Rate will increase by 0.2155 and 0.2480 respectively on average ceteris paribus.

The inclusion of state did not change the impact of Credit Score on Interest Rate significantly, as the standard errors and coefficient are still the same.

Question 7

```
In [ ]: mysample['Log_Credit_Score'] = np.log(mysample['Credit_Score'])
        mysample['sqr_LTV'] = np.square(mysample['LTV'])

        results4 = smf.ols('Interest_Rate ~ Log_Credit_Score + DTI + UPB + State + sqr_L
        print(results4.summary())
```

OLS Regression Results

Dep. Variable:	Interest_Rate	R-squared:	0.055
Model:	OLS	Adj. R-squared:	0.053
Method:	Least Squares	F-statistic:	46.91
Date:	Thu, 19 Oct 2023	Prob (F-statistic):	0.00
Time:	13:55:02	Log-Likelihood:	-79717.
No. Observations:	49983	AIC:	1.596e+05
Df Residuals:	49925	BIC:	1.601e+05
Df Model:	57		
Covariance Type:	HC3		

	coef	std err	z	P> z	[0.025	0.9
Intercept	11.0304	0.601	18.344	0.000	9.852	12.
State[T.AL]	0.2085	0.134	1.555	0.120	-0.054	0.
State[T.AR]	0.1362	0.141	0.964	0.335	-0.141	0.
State[T.AZ]	0.1850	0.129	1.437	0.151	-0.067	0.
State[T.CA]	0.1501	0.127	1.181	0.238	-0.099	0.
State[T.CO]	0.2043	0.130	1.574	0.115	-0.050	0.
State[T.CT]	0.1966	0.135	1.452	0.147	-0.069	0.
State[T.DC]	0.1246	0.189	0.660	0.509	-0.245	0.
State[T.DE]	0.2314	0.145	1.593	0.111	-0.053	0.
State[T.FL]	0.2198	0.127	1.736	0.083	-0.028	0.
State[T.GA]	0.2219	0.128	1.731	0.083	-0.029	0.
State[T.GU]	-0.6432	0.749	-0.859	0.390	-2.111	0.
State[T.HI]	0.0239	0.172	0.139	0.889	-0.313	0.
State[T.IA]	0.0692	0.138	0.502	0.616	-0.201	0.
State[T.ID]	0.3356	0.139	2.409	0.016	0.063	0.
State[T.IL]	0.2496	0.128	1.947	0.052	-0.002	0.
State[T.IN]	0.3665	0.130	2.823	0.005	0.112	0.
State[T.KS]	0.2295	0.140	1.635	0.102	-0.046	0.
State[T.KY]	0.2718	0.135	2.021	0.043	0.008	0.
State[T.LA]	0.2915	0.136	2.141	0.032	0.025	0.
State[T.MA]	0.1533	0.133	1.155	0.248	-0.107	0.
State[T.MD]	0.0928	0.131	0.709	0.478	-0.164	0.

349						
State[T.ME]	0.1964	0.149	1.315	0.188	-0.096	0.
489						
State[T.MI]	0.3351	0.129	2.600	0.009	0.083	0.
588						
State[T.MN]	0.1869	0.130	1.441	0.150	-0.067	0.
441						
State[T.MO]	0.2733	0.131	2.091	0.037	0.017	0.
529						
State[T.MS]	0.1200	0.154	0.777	0.437	-0.183	0.
423						
State[T.MT]	0.3494	0.155	2.259	0.024	0.046	0.
653						
State[T.NC]	0.1605	0.129	1.249	0.212	-0.091	0.
412						
State[T.ND]	-0.0653	0.177	-0.369	0.712	-0.412	0.
282						
State[T.NE]	0.1468	0.146	1.004	0.315	-0.140	0.
433						
State[T.NH]	0.4199	0.147	2.861	0.004	0.132	0.
708						
State[T.NJ]	0.1779	0.130	1.368	0.171	-0.077	0.
433						
State[T.NM]	0.3055	0.147	2.083	0.037	0.018	0.
593						
State[T.NV]	0.1397	0.135	1.039	0.299	-0.124	0.
403						
State[T.NY]	0.1656	0.129	1.287	0.198	-0.087	0.
418						
State[T.OH]	0.2638	0.128	2.055	0.040	0.012	0.
515						
State[T.OK]	0.2581	0.136	1.895	0.058	-0.009	0.
525						
State[T.OR]	0.2300	0.132	1.738	0.082	-0.029	0.
489						
State[T.PA]	0.2223	0.128	1.733	0.083	-0.029	0.
474						
State[T.PR]	-0.8089	1.067	-0.758	0.448	-2.899	1.
282						
State[T.RI]	0.1187	0.168	0.706	0.480	-0.211	0.
448						
State[T.SC]	0.1901	0.131	1.454	0.146	-0.066	0.
446						
State[T.SD]	0.1149	0.165	0.698	0.485	-0.208	0.
438						
State[T.TN]	0.2117	0.130	1.632	0.103	-0.043	0.
466						
State[T.TX]	0.1917	0.127	1.515	0.130	-0.056	0.
440						
State[T.UT]	0.1778	0.132	1.344	0.179	-0.081	0.
437						
State[T.VA]	0.1587	0.129	1.226	0.220	-0.095	0.
412						
State[T.VI]	-0.5815	0.995	-0.585	0.559	-2.531	1.
368						
State[T.VT]	0.1115	0.173	0.646	0.518	-0.227	0.
450						
State[T.WA]	0.2000	0.130	1.540	0.124	-0.055	0.
455						
State[T.WI]	0.2045	0.133	1.538	0.124	-0.056	0.

465						
State[T.WV]	0.1130	0.160	0.707	0.480	-0.200	0.
426						
State[T.WY]	0.1181	0.171	0.690	0.490	-0.218	0.
454						
Log_Credit_Score	-1.0300	0.088	-11.707	0.000	-1.202	-0.
858						
DTI	0.0044	0.001	3.888	0.000	0.002	0.
007						
UPB	-0.0004	3.98e-05	-11.232	0.000	-0.001	-0.
000						
sqr_LTV	0.0001	2.42e-06	44.179	0.000	0.000	0.
000						
=====						
Omnibus:	2033.639	Durbin-Watson:	0.410			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	881.034			
Skew:	-0.044	Prob(JB):	4.85e-192			
Kurtosis:	2.356	Cond. No.	1.17e+06			
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Notes:

[1] Standard Errors are heteroscedasticity robust (HC3)

[2] The condition number is large, 1.17e+06. This might indicate that there are strong multicollinearity or other numerical problems.

The effect of the log of credit score on interest rate indicates that for each percentage change in the Credit Score, the Interest Rate reduces by 1.0300/1000.

The effect of the square of the LTV on Interest Rate is difficult to interpret accurately as it is not linear and depends on the individual values of LTV.

We should use this model as opposed to the previous one as the adjusted R-squared indicates that this model explains the variability in the data better as 0.053 > 0.048.