Unraveling the Determinants of Credit Card Debt Delinquency Rates

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Abstract

The primary inquiry of this econometric study revolves around the determinants influencing the delinquency rate on credit card loans. The delinquency rate is a financial term used to describe the percentage of loans within a financial institution's loan portfolio that are late or have missed payments. This paper uses time series data to research and build linear regression to answer the question of what factors and how they influence it. The outcome of research suggests the main factors that increase delinquency rates on credit cards are the interest rate on credit card plans, financial conditions in the markets, periods of recession, and the unemployment rate after a certain level. On the other hand, factors that have a negative effect on delinquency rates on credit cards are the amount of spending with credit cards, the federal fund effective rate, and the unemployment rate at lower levels, especially during the COVID-19 pandemic.

Introduction

The delinquency rate on credit card loans is affected by the many various factors in the economy like household spending behavior, the economic state of the country, central bank monetary policy, and random social shocks like the pandemic. This paper uses different independent variables to explain how these various factors determine the level of delinquency rate in different conditions.

Time series data and variables that capture spending behavior are households' personal saving rates and the amount of spending with credit cards in the US. The economic state of the US and its effect is captured in variables like the unemployment rate, financial condition index, GDP, and the recession periods. Central bank monetary policy is symbolized by the federal funds effective rate and interest rate on credit card plans that are influenced by central bank policy. Additionally model captures some effects of the COVID-19 pandemic that significantly influenced the US economy.

Data Description

Data collection was sourced exclusively from the Federal Reserve Economic Data (FRED) website, focusing solely on the United States. Additionally, as the model has continuous data it was broken down into quarters starting from the 3rd quarter of 2000 till the 2nd quarter of 2023.

Dependent variable in the model (variable has continuous data):
DELRATE = Delinquency Rate on Credit Card Loans, All Commercial Banks (Percent, Seasonally Adjusted)

Independent variables in the model (all variables have continuous data):
CCINTREST = Commercial Bank Interest Rate on Credit Card Plans, All Accounts (Percent, Not Seasonally Adjusted)
CCAMOUN = Consumer Loans: Credit Cards and Other Revolving Plans, All Commercial Banks (Billions of U.S. Dollars, Seasonally Adjusted)
PSAVERATE = Personal Saving Rate (Percent, Seasonally Adjusted)
FEDFUNDS = Federal Funds Effective Rate (Percent, Not Seasonally Adjusted)
UNRATE = Unemployment Rate (Percent, Seasonally Adjusted)
UNRATE_UNRATE = Squared Unemployment Rate
FINCONINDEX = Chicago Fed National Financial Conditions Index (Index, Not Seasonally Adjusted)
GDP = Real Gross Domestic Product (Billions of Chained 2017 Dollars, Seasonally Adjusted)

Dummy independent variable:

RECES = NBER based Recession Indicators for the United States from the Peak through the Trough (dummy variable, 1 if quarter of recession and 0 otherwise)

covid = dummy variable takes value 1 starting from the first quarter of 2020 when covid started and holds 1 value till the last quarter in the data, otherwise before the covid period has value 0

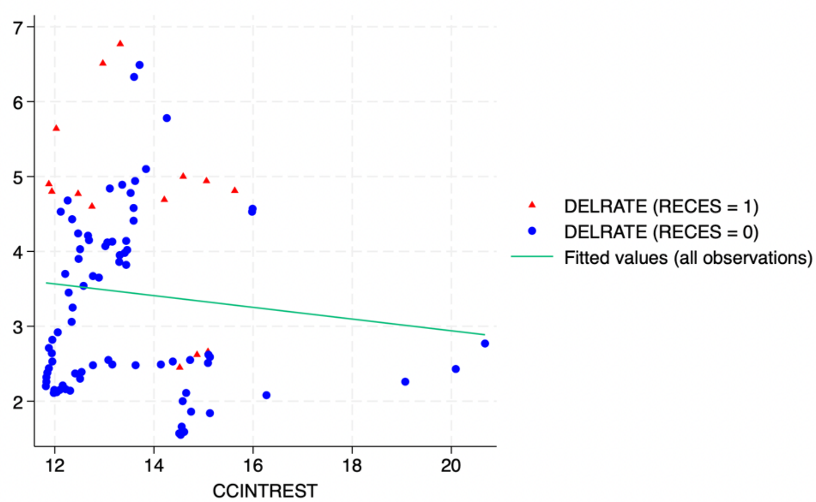
Dummy interaction variable:

UNRATE_covid = interaction term of a dummy variable covid and a continuous variable UNRATE

Descriptive Statistics

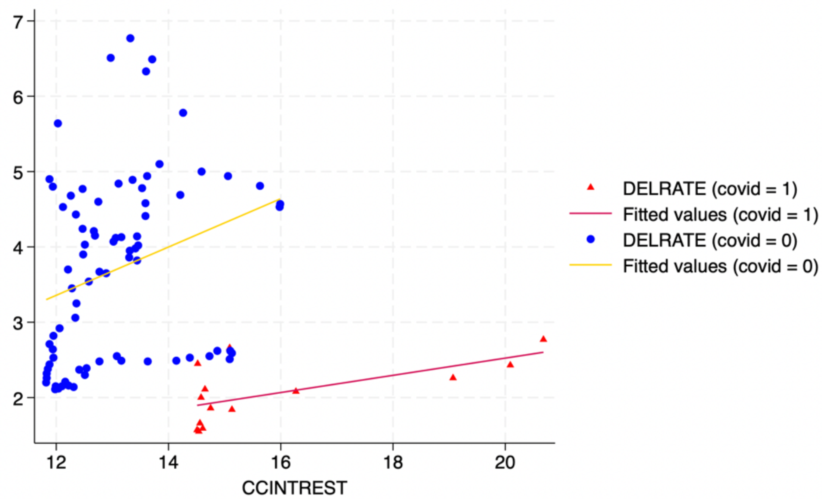
Variable	Obs	Mean	Std. Dev.	Min	Max
daten	92	18946.946	2438.219	14792	23101
UNRATE	92	5.848	1.964	3.5	12.967
CCAMOUNT	92	535.989	227.888	217.137	985.266
CCINTREST	92	13.5	1.665	11.82	20.68
RECES	92	.152	.361	0	1
DELRATE	92	3.449	1.287	1.55	6.77
PSAVERATE	92	5.798	3.201	1.8	24.367
FINCONINDEX	92	-.359	.521	-.8	2.613
FEDFUNDS	92	1.618	1.814	.06	6.52
time	92	46.5	26.702	1	92
GDP	92	17773.253	2310.627	14145.312	22225.35
covid	92	.152	.361	0	1
UNRATE UNRATE	92	38.017	27.581	12.25	168.134
UNRATE covid	92	.82	2.199	0	12.967

All my indepenst variables have 92 observations. From these variables, covid, UNARATE_UNRATE, and UNRATE covid were generated by me. Additionally, we can see a significantly higher standard deviation and overall staticky values for variables that are not originally measured in percent, such variables are CCAMOUNT and GDP. Additionally, squared UNRATE has noticeably higher values.



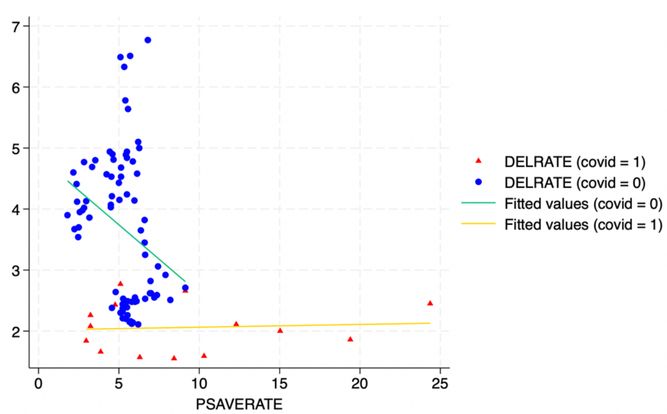
(1.1) Scatterplot with credit card interest rate (X-axis) versus delinquency rate (Y-axis), differentiated by recession dummy variable.

The dummy variable of recession helps to highlight the times when the recession was present and show that DELRATE was significantly higher during decreasing economic periods. However, against the theory, this best-fit line for this scatterplot suggests that there is a negative relationship between CCINTREST and DELRATE. This is caused by several outliers that we have in our data that were caused by the Covid period so we will create another scatter plot that separates observations during the Covid pandemic from the rest.

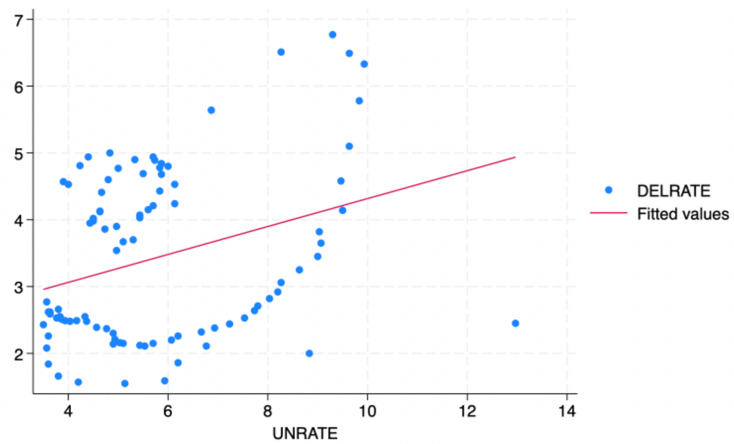


(1.2) Scatterplot with credit card interest rate (X-axis) versus delinquency rate (Y-axis), differentiated by the covid dummy variable.

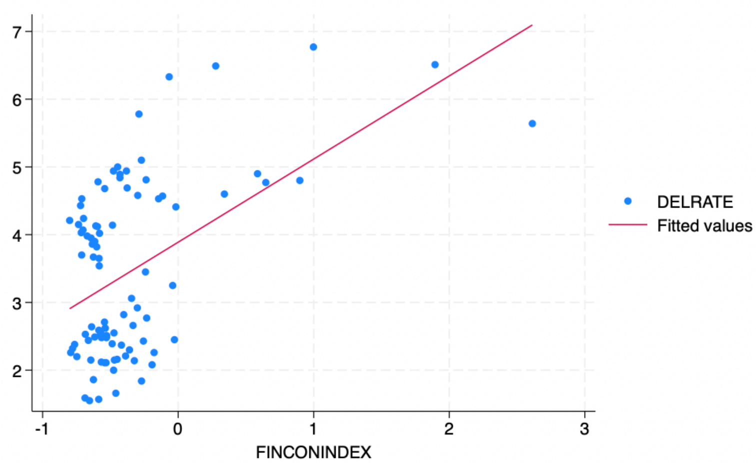
We separated observations from those that were before and after COVID and created separate best-fit lines for each group. Now we can see a positive relationship between CCINTREST and DELRATE which makes theoretically more sense and proves that higher interest rates on credit cards lead to higher delinquency rates on them.



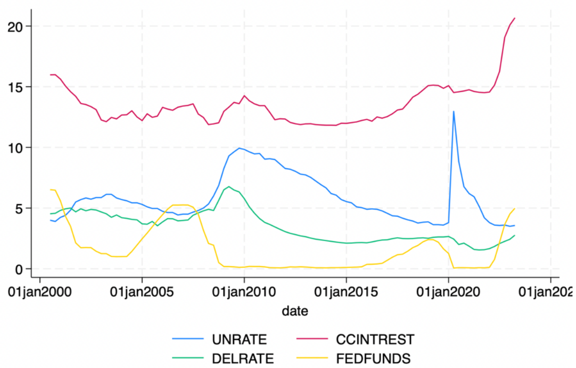
(1.3) Scatterplot with the personal saving rate (X-axis) versus delinquency rate (Y-axis) differentiated by the covid dummy variable.
The strong negative relationship between these two variables in time of no COVID is theoretically sound as if households save more the less probability they will be able to pay back their credit card debt. However, we can see a positive relationship in the time of COVID, which would influence our coefficient for the PSAVERATE effect on the dependent variable. Due to this slope of the regression line might be different for the control vs. treatment group, so it would make sense to consider the creation of a slope dummy variable.

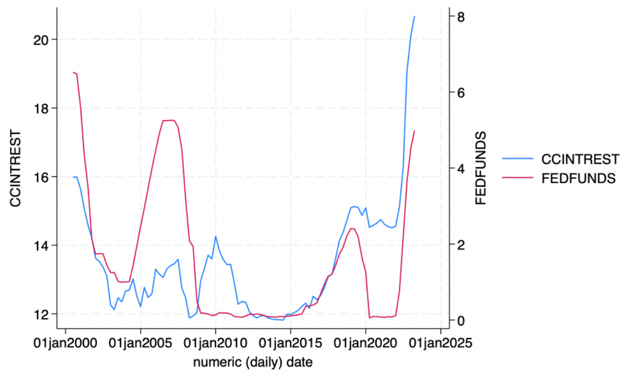


(1.3) Scatterplot with the unemployment rate (X-axis) versus delinquency rate (Y-axis).
The best-fit line suggests a positive relationship between two variables, which is theoretically sound, as if a household loses his jobs and income he is more likely not to be able to pay off his credit card debt. Additionally, on this scatter plot, we can see that the relationship might not be linear, due to this we should consider transforming our regression and using squared or logged variables.



(1.4) Scatterplot with the Chicago Fed National Financial Conditions Index rate (X-axis) versus delinquency rate (Y-axis). There is a strong positive relationship between these two variables, as when the Chicago Fed National Financial Conditions Index increases (which suggests tighter financial consciousness in the markets) the delinquency rate goes up as households will find it harder to be able to pay on their credit card debt in a tighter financial conscious in the markets.





(1.5 & 1.6) The time series graph illustrates how different rates in our model have changed through time. As movements in change are very similar and in the same direction, for example, at the second time series graph when FEDFUNDS rate increases the CCINTREST increases too. Due to this, we can suspect strong multicollinearity between these two variables.

Matrix of correlations

Variables	(1)	(2)	(3)
(1) FEDFUNDS	1.000		
(2) CCINTREST	0.443	1.000	
(3) UNRATE	-0.557	-0.333	1.000

Additionally, if we check the correlation between variables that we suspect to have high multicollinearity we would find a moderate level of correlation. For example, FEDFUNDS and CCINTREST have a correlation equal to 0.443 which is not extremely significant, FEDFUNDS and UNRATE have a correlation equal to -0.557 which is concerning but not extreme.

Empirical Model

$$DELRATE = -1.436 - 0.352 \times UNRATEi + 0.042 \times UNRATE\_UNRATEi - 0.007 \times CCAMOUNTi + 0.41 \times CCINTRESTi + 0.01 \times PSAVERATEi + 0.565 \times FINCONINDEXi - 0.164 \times FEDFUNDSi + 0 \times GDPi + 0.244 \times RECES - 0.286 \times UNRATE\_covidi$$

Statistical output for the linear regression model can be seen in the Results and Diagnostics part under Model IV.

The overall model has a high R^2 = 0.9474, which suggests that 94.74% of the variance in independent variables explained the variance in the dependent variable DELRATE.

Independent variables interpretation(in the braces are the coefficients of the variables) :

UNRATE (− 0.352) & UNRATE_UNRATE (0.042)

As UNARATE had a non-linear relationship with DELARET, the transformation was done to create UNRATE_UNRATE variable for the model to be more accurate and realistic.

DELRATE= − 0.352×UNRATEi + 0.042×UNRATE_UNRATEi

This output means that for higher values of UNRATE, a small change in UNRATE has a larger impact on DELRATE.

For example, at level UNRATE = 2% will have -0.184 effect on DELRATE, at level UNRATE = 3% effect will be 0.026, which proves that at the high levels change of UNARTE will have a more significant effect positive effect on DELRATE. As UNRATE continues to increase, the marginal effect of UNRATE on DELRATE becomes positive. This shift marks the transition from decreasing to increasing returns. Beyond a certain level of UNRATE, further increases in UNRATE lead to an increase in DELRATE.

To find the value of where UNRATE starts to have a positive impact on DELARET we need to find the derivative and equal it to zero.

$\frac{d\,DELATE}{d\,UNARATE} = -\,0.352 + 0.084 \times UNRATE = 0 \Rightarrow UNRATE = 4.19$

Due to this after UNRATE exceeds 4.19% it will start having a positive effect on DELRATE, which is more than twice the FED target of 2% U3.

UNRATE_covid (− 0.286)

This interaction term of a dummy variable captures the effect of UNRATE during the COVID-19 pandemic on DELRATE. During the COVID pandemic, the unemployment rate was affected significantly, and UNARTE peaked at 14.7% which was a historical high. This variable captures the negative effect of the coefficient − 0.286 and suggests that during the COVID period, the relationship between the unemployment rate and the delinquency rate changed. Specifically, for each one percent increase in the unemployment rate during the COVID period, the delinquency rate decreases by an additional 0.286 percentage points compared to non-COVID times, holding other variables constant. This can be explained by a fiscal policy that the US government took during a pandemic and the low-interest rates that we aimed to support the economy which helped households to inverse personal savings and decrease the chance of not being able to pay back their credit card loans.

Additionally, as UNARATE had a non-linear relationship with DELARET the value of where UNRATE starts to have a positive impact on DELARET has changed during covid too and we need to find the derivative and equal it to zero to see a new impact during covid.

DELRATE= $-$ 0.352×UNRATEi + 0.042×UNRATE_UNRATEi $-$ 0.286×UNRATE_covidi

$\frac{d\, DELATE}{d\, UNARATE}$ = $-$ 0.352 + 0.084×UNRATE $-$ 0.286 = 0 => UNRATE = 7.59

We can conclude that during the covid the level of UNRATE would have started having a positive effect on DELRATE only after exceeding 7.59%.

CCAMOUNT (-0.007)

The coefficient of -0.007 suggests that one unit increase (1 billion dollars) in the amount of spending with credit cards decreases DELRATE by 0.007%, holding other variables constant. This goes against expectation, as theoretically, it would make sense more that higher credit card spending would be followed by a high chance of people not being able to pay back.

CCINTREST (0.4)

The coefficient of 0.4 suggests that one unit increase (1%) in the credit card interest rates increases DELRATE by 0.4%, holding other variables constant. This is theoretically sound as higher interest rates for loans mean a higher probability that households might fail to pay back their loans, especially when banks can change interest rates periodically which can expose credit card users if no change in behavior occurs.

PSAVERATE (0.01)

The coefficient of 0.01 suggests that one unit increase (1%) in the personal saving increases DELRATE by 0.01%, holding other variables constant. This goes against expectation, as the assumption was that higher personal savings would have a negative effect on DELRATE, as it would mean that households with savings can use that money to pay back on credit card loans on time. However, it is important to note that this variable is statistically insignificant in our model, due to which it is likely that the model has the wrong effect. Additionally in the first model before any transformation PSAVERATE coefficient was $-$ 0.084 which suggested a negative relationship and was satisfied with the assumption.

FINCONINDEX (0.565)

The coefficient of 0.565 suggests that one unit increase (1 value of the index) in the Chicago Fed National Financial Conditions Index increases DELRATE by 0.565%, holding other variables constant. This is theoretically sound, as positive values of the FINCONINDEX indicate financial conditions that are tighter than average, while negative values indicate financial conditions that are looser than average. Due to this tighter financial conditions in the markets have a significant positive effect on DELRATE.

FEDFUNDS (-0.164)
The coefficient of 0.164 suggests that one unit increase (1%) in the Federal Funds Effective Rate decreases DELRATE by 0.164%, holding other variables constant. This goes against expectation, as the assumption was that higher FED interest rates lead to tighter financial conditions in the lowen markets and further have a positive effect on DELRATE. However, it also could be seen that financial conditions in the lowen markets in the longer run can decrease the initiative of using credit cards and decrease the chances of people failing to pay off their loans.

GDP (0)
The coefficient of 0 suggests that GDP does not influence DELRATE in any direction.

RECES (0.244)
The dummy variable coefficient suggests that in quarters of recession, the DELRATE goes up by 0.244%. This is theoretically sound as during harder economic times people might more often fail on their loan payments. It is important to note that variable RECES has low significance due to a high p-value, so there is a high probability that its coefficient is not accurate and we can not accept it being significant for our model.

Results and Diagnostics

I. My first regression gave the output of the following equation:
DELRATE = 3.228 + 0.18×UNRATEi − 0.003×CCAMOUNTi + 0.298×CCINTRESTi + 0.199×RECESi − 0.084×PSAVERATEi + 0.702×FINCONINDEXi − 0.097×FEDFUNDSi − 0×GDPi

Linear regression

DELRATE	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
UNRATE	.18	.042	4.28	0	.096	.263	***
CCAMOUNT	-.003	.001	-4.62	0	-.005	-.002	***
CCINTREST	.298	.044	6.83	0	.211	.385	***
RECES	.199	.182	1.09	.278	-.164	.561	
PSAVERATE	-.084	.021	-4.05	0	-.126	-.043	***
FINCONINDEX	.702	.128	5.48	0	.447	.956	***
FEDFUNDS	-.097	.049	-1.95	.054	-.195	.002	*
GDP	0	0	-1.64	.105	0	0	
Constant	3.228	1.186	2.72	.008	.87	5.587	***

Mean dependent var	3.449	SD dependent var	1.287
R-squared	0.891	Number of obs	92
F-test	84.569	Prob > F	0.000
Akaike crit. (AIC)	120.809	Bayesian crit. (BIC)	143.505

*** *p*<.01, ** *p*<.05, * *p*<.1

Adj. R^2_1 = 0.8802.

R^2 = 0.891 which is quite a high result that suggests 89.1% of the variance in the dependent variable (DELRATE) can be explained by variance in all independent variables in our model. This model only partly matched my theoretical expectations. But as I expected UNRATE, CCINTREST, FINCONINDEX, and RECES had positive effects on the dependent variable while PSAVERATE had negative which matches with economic theory. However, the coefficients of variables CCAMOUNT, FEDFUNDS, and GDP are not as I expected.
CCAMOUNT coefficient is -0.003 which would mean that this variable holds little negative weight in our regression. Additionally, I assumed that higher spending with credit cards would cause more people to miss their credit card debt payments which will cause DELRATE to increase, however, we get the opposite effect in our model.
GDP coefficient is very close to 0 which might mean this variable does not belong in the equation and we might consider later omitting it.
FEDFUNDS coefficient is -0.097 which would mean that this variable holds relatively little negative weight in our regression. Additionally, I assumed that higher FED interest rates which can be seen as a signal of tighter economic conditions and credit market, would cause DELRATE to increase, however, the effect is the opposite. This might be caused by the delayed effect that FED interest rates have on the economy. For example, if we look at graph 1.5 we can see that FEDFUNDS peak before any other rate, which suggests that the effect is delayed.
Additionally, we got high p-values for variables RECES and GDP which suggests that they are not significant in our regression and we probably won't be able to reject the null hypothesis of them being equal to zero. We see one more reason to conclude that GDP does not belong in regression, on the other hand we should try to improve the level of significance and t-score for RECES. Another variable that has a high p-value is FEDFUNDS due to which we can reject the null hypothesis only with 90% confidence. These results might be misleading as we still have a high probability of wrong specification and the presence of multicollinearity and auto-correlation in the model which violates classical linear regression model assumptions and calculates wrong variance with t-statistic.
Joint significance test for model:

H_0: UNRATE = CCAMOUNT = RECES = CCINTREST = PSAVERATE = FINCONINDEX = = FEDFUNDS = GDP = 0

H_a: UNRATE or/and CCAMOUNT or/and RECES or/and CCINTREST or/and PSAVERATE or/andFINCONINDEX or/and FEDFUNDS or/and GDP ≠ 0

F-test(8, 83) = 84.569; Fc = 2.06 => F-test > Fc => reject the null hypothesis and accept the alternative hypothesis of our variables being jointly significant

II. Model after adding a dummy variable of covid:

DELRATE = −3.72 + 0.212×UNRATE$_i$ − 0.006×CCAMOUNT$_i$ + 0.29×RECES$_i$ + 0.503×CCINTREST$_i$ − 0.053×PSAVERATE$_i$ + 0.589×FINCONINDEX$_i$ − 0.185×FEDFUNDS$_i$ + 0×GDP$_i$ − 1.447851×covid$_i$

Linear regression

DELRATE	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
UNRATE	.212	.034	6.31	0	.145	.279	***
CCAMOUNT	-.006	.001	-8.69	0	-.008	-.005	***
RECES	.29	.146	1.99	.05	0	.579	**
CCINTREST	.503	.045	11.08	0	.413	.594	***
PSAVERATE	-.053	.017	-3.09	.003	-.087	-.019	***
FINCONINDEX	.589	.103	5.71	0	.384	.794	***
FEDFUNDS	-.185	.041	-4.48	0	-.267	-.103	***
GDP	0	0	2.62	.01	0	0	**
covid	-1.448	.207	-7.01	0	-1.859	-1.037	***
Constant	-3.72	1.369	-2.72	.008	-6.443	-.997	***

Mean dependent var	3.449	SD dependent var	1.287
R-squared	0.932	Number of obs	92
F-test	124.192	Prob > F	0.000
Akaike crit. (AIC)	79.638	Bayesian crit. (BIC)	104.856

**** p<.01, ** p<.05, * p<.1*

Adj. $R^2$2 = 0.9317

Adjusted R^2 has increased by 0.0515 after adding the dummy variable covid which suggests that the exoplanetary power of our model has improved quite significantly. Additionally, the significance of our variables (RECES , GDP) has increased as t-values rose and p-values are less than and equal to 0.05. However, the GDP’s coefficient still has stayed close to zero. Additionally, we see some changes in values for all coefficients in our model.

III. Model after adding a squared UNRATE, changing the covid dummy variable to dummy interaction term variable of UNRATE and covid:

$$DELRATE = -1.436 - 0.352\times UNRATE_i + 0.042\times UNRATE\_UNRATE_i - 0.007\times CCAMOUNT_i + 0.4\times CCINTREST_i + 0.01\times PSAVERATE_i + 0.565\times FINCONINDEX_i - 0.164\times FEDFUNDS_i + 0\times GDP_i + 0.244\times RECES - 0.286\times UNRATE\_covid_i$$

Linear regression

DELRATE	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
UNRATE	-.352	.152	-2.32	.023	-.655	-.05	**
UNRATE_UNRATE	.042	.01	4.15	0	.022	.062	***
CCAMOUNT	-.007	.001	-10.79	0	-.008	-.006	***
CCINTREST	.41	.035	11.88	0	.341	.479	***
FINCONINDEX	.565	.092	6.12	0	.381	.749	***
PSAVERATE	.015	.019	0.75	.453	-.024	.053	
FEDFUNDS	-.164	.038	-4.29	0	-.24	-.088	***
GDP	0	0	3.54	.001	0	0	***
RECES	.244	.132	1.84	.069	-.02	.507	*
UNRATE_covid	-.286	.033	-8.75	0	-.351	-.221	***
Constant	-1.436	1.336	-1.07	.286	-4.095	1.223	

Mean dependent var	3.449	SD dependent var	1.287
R-squared	0.947	Number of obs	92
F-test	145.918	Prob > F	0.000
Akaike crit. (AIC)	57.527	Bayesian crit. (BIC)	85.267

*** *p*<.01, ** *p*<.05, * *p*<.1

Adj. $R^2{}_3 = 0.9409$

Adjusted R^2 has increased again, this time by 0.0092, which is a sign that our model has improved. Also in this model, several changes were made in terms of independent variables, we replaced the covid dummy variable with the UNRATE times covid dummy variable which created a dummy interaction term variable. I believe this dummy interaction term is more theoretically sound and helps to dive deeper into what effect covid had on unemployment and therefore on delinquency rate. Additionally, as was noted in scatterplot 1.3 UNRATE has non non-linear shape so it was squared to be more correct. The dummy variable RECES lost some of its significance as the p-value increased for it.

Variance inflation factor

	VIF	1/VIF
UNRATE	82.892	.012
UNRATE UNRATE	72.458	.014
GDP	21.395	.047
CCAMOUNT	20.162	.05
UNRATE covid	4.802	.208
FEDFUNDS	4.477	.223
PSAVERATE	3.554	.281
CCINTREST	3.071	.326
FINCONINDEX	2.151	.465
RECES	2.123	.471
Mean VIF	21.708	.

The last model has a strong sign of multicollinearity as mean VIF = 21.708 which suggests that on a mean the variances of the coefficients in our model are 21.708 times larger than they should be. Specfcily this is caused by several factors. The model has a very high VIF for UNRATE and squared UNRATE, which is caused by the transformation that we did to deal with the non-linear relationship of UNRATE and DELRATE. Also, GDP and CCAMOUNT have both high VIFs of above 20 which suggest multicollinearity in these variables. This is caused by a very high correlation between these two variables which is equal to 0.943. Due to this, it would be correct to consider once more omitting GDP as it innately had a small weight in our model and caused high VIF values that suggest multicollinearity.

Matrix of correlations

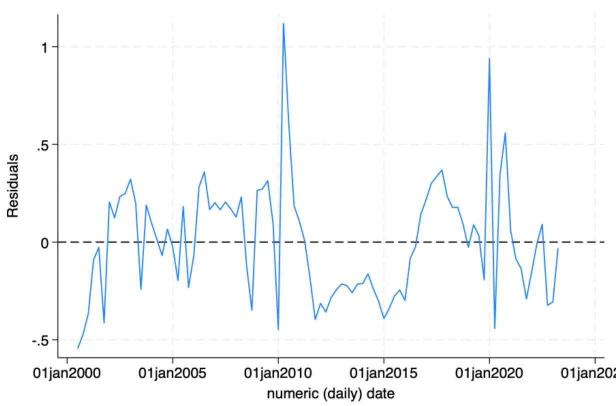
Variables	(1)	(2)
(1) GDP	1.000	
(2)	0.943	1.000
CCAMOUNT		

After omitting GDP the high VIF values could be seen only for UNRATE and squared UNRATE, which means that GDP was causing additional multiclonarty. However, for this project's purposes, I will keep the GDP variable and not omit it.

Variance inflation factor

	VIF	1/VIF
UNRATE	82.546	.012
UNRATE	72.281	.014
UNRATE		
FEDFUNDS	4.476	.223
CCAMOUNT	3.564	.281
PSAVERATE	3.281	.305
UNRATE	2.96	.338
covid		
CCINTREST	2.836	.353
RECES	2.041	.49
	1.914	.522
FINCONINDE		
X		
Mean VIF	19.544	.

Testing for autocorrelation model III :



(1.7) Time series plot of the residuals from model III. The positive values of the error term are somewhat clustered together, and the negative values are too, so we can suspect autocorrelation is present in our model and the error term is not truly random.

Durbin–Watson d-statistic(11, 92) = 0
Durbin–Watson test suggests that we have perfect positive autocorrelation in our model. We can not reject the null hypothesis of no autocorrelation as d-stat < d-L = 1.5.

IV. Estimate model 3 regression using Newey-West Robust Standard Errors:
DELRATE = − 1.436 − 0.352×UNRATEi + 0.042×UNRATE_UNRATEi − 0.007×CCAMOUNTi + 0.41×CCINTRESTi + 0.01×PSAVERATEi + 0.565×FINCONINDEXi − 0.164×FEDFUNDSi + 0×GDPi + 0.244×RECES − 0.286×UNRATE_covidi

Linear regression

DELRATE	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
UNRATE	-.352	.156	-2.26	.026	-.662	-.043	**
UNRATE_UNRATE	.042	.011	3.89	0	.021	.064	***
CCAMOUNT	-.007	.001	-8.28	0	-.009	-.005	***
CCINTREST	.41	.035	11.55	0	.339	.481	***
FINCONINDEX	.565	.102	5.54	0	.362	.768	***
PSAVERATE	.015	.014	1.08	.285	-.012	.041	
FEDFUNDS	-.164	.035	-4.72	0	-.233	-.095	***
GDP	0	0	2.78	.007	0	0	***
RECES	.244	.165	1.47	.145	-.086	.573	
UNRATE_covid	-.286	.032	-8.88	0	-.35	-.222	***
Constant	-1.436	1.512	-0.95	.345	-4.444	1.571	
Mean dependent var		3.449	SD dependent var			1.287	
R-squared		0.947	Number of obs			92	
F-test		161.969	Prob > F			0.000	
Akaike crit. (AIC)		57.527	Bayesian crit. (BIC)			85.267	

*** *p*<.01, ** *p*<.05, * *p*<.1

After we run Robust Standard Errors method the coefficients stayed the same, but, t-stata increased and p-values decreased for variables UNRATE, PSAVERATE, GDP, and RECES. This method allowed us to keep the same coefficients and recalculate the correct variance estimates that take into account error term correlation between each other. However, some variables still have low significance. PSAVEARTE has a low t-stat and high p-value which suggests that it is not statistically significant and we can not reject the null hypothesis of its coefficient being equal to zero. The same situation is with the dummy variable RECES which has t-stat = 1.47 and t critical value = 1.65 for a 10% level of significance, due to which t-stat is smaller than its critical value and we can not reject the null hypothesis of coefficient being equal to zero. Additionally, standard errors were recalculated and have increased.

Conclusion

The research output concludes that the main factors that drive delinquency rates on credit card loans are the interest rates on credit card plans, financial conditions in the markets, and periods of recession. Additionally, it was found that the unemployment rate plays a very important role in determining households' ability to pay on their credit card loans. The unemployment rate has a negative effect on the delinquency rate as long as it is below 4.19% after which it has an increasing positive effect. However, the situation changed during the COVID pandemic when as marginal effect of the unemployment delinquency rate became positive only after exceeding the 7.59% level of unemployment. The research indicates that both credit card spending and the federal fund's effective rate have a modestly negative impact on the dependent variable.

Further research that could improve the understanding of what determines delinquency rates on credit card loans should dive deeper into the analysis of effects of the social and economic shocks like the COVID-19 pandemic and times of recession. Additionally, explore more patterns in a household's change of behavior, maybe even by using cross-sectional data.

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