ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue IX, September 2025

Modeling the Impact of Macroeconomic Variables on Personal Loan Applications and Approvals Before and During the COVID-19 Pandemic

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DOI: https://doi.org/10.51583/IJLTEMAS.2025.1409000030

Received: 29 Aug 2025; Accepted: 05 Sep 2025; Published: 01 October

Abstract: This study investigates the association between personal loan applications and approvals and macroeconomic variables, including bank interest rates, the consumer price index (CPI), and employment and unemployment figures, both prior to and during the COVID-19 pandemic. Data spanning January 2018 to June 2022, were utilized for the analysis. Two analytical techniques were employed: the correlation matrix and the multiple linear regression model. The correlation analysis revealed strong relationships between the CPI and employment figures, as well as between interest rates and unemployment, in their association with both loan applications and approvals. Results from the regression model indicated that bank interest rates and employment status significantly influenced personal loan applications, regardless of the pandemic context. With respect to loan approvals, the findings demonstrated that bank interest rates, unemployment, and the CPI exerted significant effects, particularly in regions severely affected by COVID-19. These results highlight the critical role of macroeconomic conditions in shaping lending behavior and provide insights into the interaction between financial markets and economic shocks.

Keywords: Personal loan; consumer price index; correlation; COVID-19; pandemic; multiple linear regression; employment rate; bank interest.

I. Introduction

Providers of financial goods have observed the impact of the Covid-19 outbreak on consumer behaviour. During this time, there has been a significant shift toward online operations due to restrictions on freedom of movement and the risk to consumer health. Interpersonal trust and social media use have a positive and significant impact on e-commerce application usage. Market size, consumer capacity, and commercial infrastructure all demonstrated positive effects, albeit to variable degrees. However, market intensity did not have a statistically meaningful impact. The study by Valdivino et al. (2025) suggests that the use of e-commerce applications in Latin America is due to a combination of individual and systemic factors. Access to e-commerce applications is governed by commercial infrastructure and economic competence, but consumer adoption is directly influenced by interpersonal trust and social media activity.

In Malaysia, the ratio of household debt to disposable income stands at 140.4%, significantly higher than 105.3% in Singapore, 123.3% in the United States, and 52.7% in Thailand, making Malaysia one of the highest globally in this metric. This indicates that Malaysian households, on average, borrow an amount equivalent to 1.4 times their annual income (Ismail et al., 2018). The early months of 2020 saw food shortages driving inflation, while disruptions in production and consumption across various industries created temporary

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bottlenecks in the supply chain, leading to significant innovations in supply chain management. The need for pandemic containment further compelled individuals to save and seek alternative income sources (Oindrila Chakraborty, 2022).

The "buy now, pay later" trend has led to increased credit card usage among Malaysian Generation Y (Gen Y). Research shows that knowledge of credit cards and self-efficacy are negatively associated with credit card misuse among Gen Y in Malaysia, while attitudes toward credit cards, materialism, and social norms are positively correlated with misuse (Zainudin et al., 2019). To address these challenges, Uriawan et al. (2019) proposed a collateral-light peer-to-peer personal lending platform. The trustworthiness of borrowers emerges as a critical predictor of on-time payments, with reputation and interpersonal relationships serving as key factors in assessing borrower reliability.

The COVID-19 pandemic has significantly hindered banks' capacity to meet credit demand and provide liquidity and funding. Global lockdowns and border restrictions have aimed to reduce health-related expenses and ensure public safety (Najaf et al., 2022). Kamarudin et al. (2021) explores the pricing of goods and services across various sub-sectors, with a particular focus on essential items needed by all consumers. Throughout the pandemic, prices generally declined, although the consumer price index (CPI) for food increased, reflecting similar trends in health and education sectors (Kamarudin et al., 2021). Sales of consumer durable goods rose during the pandemic, driven by consumer preferences and disposable incomes. However, these trends are expected to diminish as public health concerns are addressed, and the U.S. economy reopens (Tauber & Van Zandweghe, 2021). Gur (2024) implied Long Short-Term Memory (LSTM), MARS, XGBoost, and hybrid approaches like LSTM-MARS and LSTM-XGBoost, to enhance the forecasting accuracy of the US CPI and found that variables such as past values of the CPI, oil prices, and gross domestic product (GDP) significantly influence CPI.

The pandemic has also led to increased loan delinquency, attributed to high interest rates and business failures. Consequently, banks may find their relevance challenged, with their credit culture and lending variables becoming more critical in the context of priority sector lending (Kumar Tiwari & Bapat, 2020). Interestingly, rising oil prices and new COVID-19 cases have positively influenced the Saudi banking index, despite the impacts of lockdowns and interest rate cuts (Assous & Al-Najjar, 2021). Study from Narvekar & Guha (2021), enhanced bankruptcy prediction research by employing machine learning techniques, particularly XGBoost, on a quarterly dataset of financial ratios from U.S. public firms (1970 – 2019) and applies this model to forecast a substantial rise in bankruptcy rates in the second half of 2020 due to COVID-19 lockdowns, suggesting that the levels may not significantly exceed those of 2010.

A large data set on COVID-19 relief policy loans in Taiwan was used to examine the correlations between the speed of loan approval for individual applicants and their demographic characteristics, credit data, banking relationships, and the corporate social responsibility of the lending banks by Kung et al. in 2024. The influence of lending bank characteristics on the financial inclusion of applicants with poor credit was also analyzed. Evidence was found that the prioritization of individuals in need enabled the policy to be implemented in a manner that facilitated the rapid disbursement of loans, thereby substantially promoting financial inclusion (Kung et al., 2024).

The primary objectives of this research are to compare the effects of bank interest rates, employment status, and the consumer price index on the likelihood of approval for personal loans from Bank Negara Malaysia, both before and during the COVID-19 pandemic. This will be achieved using correlation methods and multiple linear regression models.

II. Methodology

Multiple regression analysis can be looked upon as an extension of straight-line regression analysis which involves only one independent variable, to the situation in which more than one independent variable must be considered (David G. Kleinbaum, 2014). The general multiple regression model can be represented by the following equation:

$$y_i = \beta_0 + \beta_1 X_1 + \ \beta_2 X_2 + \ldots \quad \ldots + \ \beta_n X_n + \ \varepsilon_i \qquad (1)$$

where

$X_1 \ to \ X_n$ are independent variables

$\beta_0, \beta_1, \beta_2 \ , \ldots\ldots, \beta_n$ are regression coefficients

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y is the predicted value of the dependent variable

ε is the is the model's random error (residual) term (how much variation there is in predicted y).

The model takes from $y = x_i^{\mathrm{T}}\beta + \varepsilon_i$. Where $^{\mathrm{T}}$ denotes the transpose, so that $x_i^{\mathrm{T}}\beta$ is the inner product between vectors x_i^{T} and β. Often these n equations are stacked together and written in matrix notation as:

$$y = X\beta + \varepsilon. \tag{2}$$

where

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

$$X = \begin{bmatrix} x_1^{\mathrm{T}} \\ x_2^{\mathrm{T}} \\ \vdots \\ x_n^{\mathrm{T}} \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1p} \\ 1 & x_{21} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{np} \end{bmatrix}$$

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{bmatrix}$$

$$\varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}.$$

The p-values help determine whether the associations observed in your sample are present in the larger population. To apply regression analysis, a model must be fitted and validated. Examine then the regression coefficients and p-values using. Low p-values indicate statistical significance for the independent variable (typically 0.05). The coefficients represent the average change in the dependent variable when the independent variable (IV) is altered by one unit, while the other IVs remain unchanged (Forst, 2017).

2.1. Correlation Coefficient

Correlation coefficient provides a measure of how two random variables are linearly associated in a sample and has properties closely related to those of straight-line regression. Sample correlation coefficient,

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{(n\sum x^2 - (\sum \varkappa)^2)(n\sum y^2 - (\sum y)^2}}. \tag{3}$$

Least-square estimate of the slope of fitted regression line,

$$r = \frac{Sx}{Sy}\ \hat{\beta}. \tag{4}$$

The relationship becomes more positive as r becomes more positive. This implies that, when r is close to 1, a person with a high value for one variable will likely have a high value for the other variable, and a person with a low value for one variable will likely have a low value for the other variable. The squared correlation coefficient or coefficient of determination r^2 measures the strength of the linear relationship between the dependent variable Y and the independent variable X. The closer r^2 is to 1, the stronger the linear relationship; the closer r^2 is to 0, the weaker the linear relationship.

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2.2. ANOVA

To summarize the results of a multiple regression analysis, the analysis of variance (ANOVA) technique is often employed. The specific form of an ANOVA table may differ, however, depending on how the contributions of the independent variables are to be regarded (individually or collectively).

$$\text{Coefficient of determination, } r^2 = \frac{SSY - SSE}{SSY}. \quad (5)$$

Regression sums of squares,

$$(SSY - SSE) = \sum_{i=1}^{\infty} \left(\hat{Y}i - \bar{Y}\right)^2. \quad (6)$$

Total unexplained variation = Variation due to regression + Residual variation after regression.

$$\sum_{i=1}^{\infty} (Yi - Y)^2 = \sum_{i=1}^{\infty} (\hat{Y}i - Y)^2 + \sum_{i=1}^{\infty} (Y_i - \hat{Y}i)^2 \quad (7)$$

Sum of squares = Regression sums of squares + Residual sum of squares. The test is used to check if there is a linear relationship between the dependence variable and at least one of the predictor variables. The hypotheses are shown below:

$$H_0 = \beta_0 = \beta_1 = \cdots = \beta_n = 0$$

$$H_1 = \beta_k \neq 0 \ for \ at \ least \ one \ k$$

The H_0 will be rejected if the calculated F value is bigger than $F_{\alpha,k,(n-(k+1))}$. Rejection of H_0 implies that the regression coefficient differs from zero. That is at least one predictor variable is significant. The significance F value showed in the ANOVA table can also compare with the significance level, α value. If the significance value *F* is smaller than α, then the null hypothesis can be rejected. The way of testing H_0 is equivalent to using the two-sided t test. This is so because, for v degrees of freedom,

$$F_{1,v} = T_v^2 \quad (8)$$

So

$$F_{1,v,1-\alpha} = t_{v,1-\alpha/2}^2 \quad (9)$$

The expression states that the $100(1-\alpha)\%$ point of the *F* distribution with 1 and v degree of freedom is the same as the square of the $100(1-\alpha/2)\%$ point of the *t* distribution with v degree of freedom. The calculation of the ANOVA is explained in Table 1 below.

Table 1. The calculation of every value generated in ANOVA table.

Source	Degree of freedom, DF	Sum of Squares, SS	Mean Square, MS	*F*-value
Model (Regression)	k	$SSY - SSE$	$\frac{SS \text{ Regression}}{DF \text{ Regression}}$	$\frac{MS \text{ Regression}}{MS \text{ Residual}}$
Error (Residual)	$n-k-1$	SSE	$\frac{SSE}{DF \text{ Residual}}$	
Corrected Total	$n-1$	SSY		

where k is the number of parameters, n is the number of data, SSY is the total sum of squares, and SSE is the sum of squares

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due to error.

2.3. t-test

When employing a multiple linear regression model to ascertain whether a linear relationship exists between the response and predictor variables, the t-test is utilized to determine the statistical significance of the various regression coefficients. The hypothesis statements to test the significance of a particular regression coefficient, β_p

$$H_0 = \beta_p = 0$$

$$H_1 = \beta_p \neq 0.$$

The test statistics for this test are based on *t* distribution:

$$T = \frac{\hat{B}_p}{S_{\hat{\beta}_p}} \tag{10}$$

where $\hat{B}_p$ is the corresponding estimated coefficient and $S_{\hat{\beta}_p}$ is the estimate of the standard error, both are produced by standard regression programs. H_0 will be rejected if the t-test lies outside the acceptance region:

- $|T| > t_{n-p-2,1-\frac{\alpha}{2}}$ (two-sided test; $H_{A:}\ \beta_p \neq 0$) Test for linearity
- $T > t_{n-p-2,1-\alpha}$ (right-tailed test: $H_{A:}\ \beta_p > 0$) Test for a positive slope
- $T > t_{n-p-2,1-\alpha}$ (left-tailed test; $H_{A:}\ \beta_p < 0$) Test for a negative slope

Rejection H_0 implies that the β_p is significant to the model. Besides, we can also draw the conclusion from p-value. If the p-value is smaller than the significance level, $\alpha = 0.05$, the null hypothesis is rejected. Hence, we have sufficient evidence to conclude that the variable is significantly contributing to the model.

III. Results and Discussion

In this study, the data is obtained from Bank Negara Malaysia (BNM) website except for COVID-19 cases, where the data is obtained from Kementerian Kesihatan Malaysia (KKM) website. The personal loan data consists of the number of applications and number of approvals from BNM as the dependent variable and 5 independent variables which are interest rate, employed number, unemployed number, CPI and COVID-19 cases. The definition of the labels used in this study is listed in Table 2.

Table 2. The response (dependent variables) and explanatory variables (independent variables) used in this study.

Labels	**Definitions**
Response Variable	
$\boldsymbol{Y_1}$	Personal loan approvals
$\boldsymbol{Y_2}$	Personal loan applications
Continuous Explanatory Variables	
Interest	BNM personal loan interest
Employed	Monthly record: Malaysians get employment
Unemployed	Monthly record: Malaysian loss of job or retirement
CPI	Monthly record: Consumer Price Index

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COVID-19	Monthly new confirmed cases of COVID-19 in Malaysia

The personal loan applied and approved will be studied to see the relation between these two variables with interest rate, employed and unemployed number, CPI and COVID-19 cases. The monthly data for all these variables is recorded monthly. The plots for loan applied and approved can be shown below.

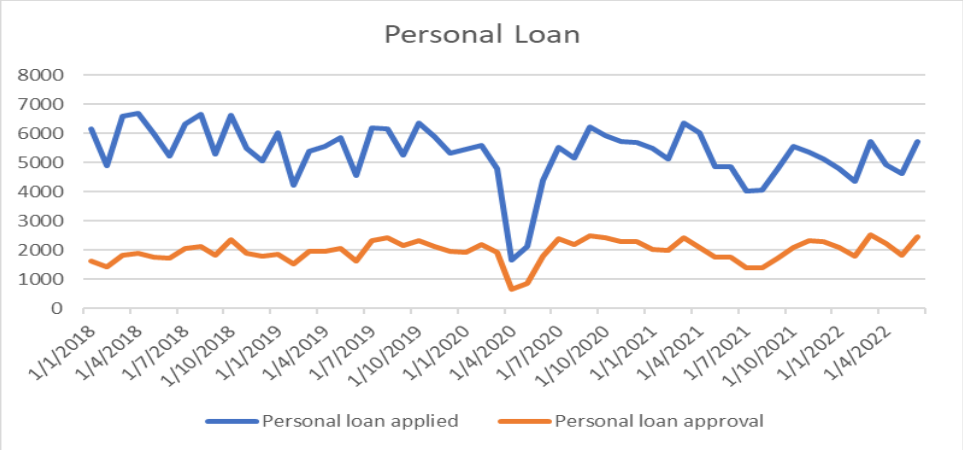


Figure 2. Time series plot of personal loan applied, and personal loan approved.

The graph in Figure 1 above displays the number of banks applied and approved personal loans in Malaysia. It is apparent that the loan applied reduces during the early stages of COVID-19, but it returns to normal after July 2020. The loan applied has a larger decrement than the loan granted. This is understandable given that the quantity of applications has been reduced throughout this period. Loans applied vary more than loans approved. It is it is apparent banks have targeted figures when issuing loans every month. The descriptive statistics of the response variables which are the personal loan applied and approved is shown in Table 3.

Table 3. Descriptive statistics of the response variables; personal loan application and personal loan approval.

	Loan Application	**Loan Approval**
Mean	5330.7671	1965.8020
Standard Error	131.2442	51.2939
Median	5467.5455	1985.6375
Mode	-	-
Standard Deviation	964.4442	376.9317
Sample Variance	930152.5655	142077.5060
Kurtosis	4.5269	2.3005
Skewness	1.6369	-1.1509
Range	5044.6490	1868.4230
Maximum	6701.1560	2528.0170
Minimum	1656.5070	659.5940
Sum	287861.4210	106153.3080
Count	54	54

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Based on descriptive statistics in Table 3, the mean value shows that the loan approved is about 37% from the loan applied. The standard deviation values show that the loan applied has larger value compared to loan approved which means that the loan application is more divergent compared to loan approved. It can be supported by the minimum value and the maximum value of these two variables. The difference between the minimum and maximum number for loan applied is larger than loan approved. As for the other variables, the descriptive statistics can be shown in Table 4 below.

Table 4. Descriptive statistics of the explanatory variables; unemployment rate, employment rate, bank interest, CPI and COVID-19 cases.

	Unemployment	Employment	Bank Interest	CPI	COVID-19
Mean	625.2859	15213.0309	6.1716	121.8463	136323.162
Standard Error	15.3248	41.6598	0.0873	0.2728	31271.0331
Median	620.5685	15201.6000	6.2613	121.4000	62085
Standard Deviation	112.6140	306.1358	0.6416	2.0049	190214.268
Sample Variance	12681.9186	93719.1276	0.4117	4.0195	3.62E+10
Kurtosis	-1.7193	0.0752	-1.9334	0.7270	3.6430
Skewness	0.2334	0.5558	0.0112	0.6825	2.0554
Range	321.3000	1265.8000	1.4325	9.8000	762952
Maximum	826.1000	14670.5000	6.9221	127.4000	763289
Minimum	504.8000	15936.3000	5.4896	117.6000	337
Sum	33765.4380	821503.6680	333.2669	6579.7000	5043957
Count	54	54	54	54	37

This table presents descriptive statistics for Unemployment, Employment, Bank Interest, CPI, and COVID-19 cases. Unemployment has a mean of 625.29 and moderate variability, while Employment is much higher, averaging 15,213 with a wider range, indicating more fluctuation in the employed population. Bank Interest rates are stable, with a low standard deviation around a 6.17% average. CPI shows modest variation with a mean of 121.85, suggesting relative price stability. COVID-19 has a high mean; 136,323 and extreme variability, shown by a large standard deviation; 190,214.27 and range; 762,952, reflecting the impact of the pandemic. The skewness and kurtosis values indicate that COVID-19 data is positively skewed and has heavy tails, whereas Bank Interest and Unemployment data are more symmetric and flatter. To observe the relationship between all variables, the correlation matrix will be utilized. The correlation between every conceivable pair of variables is shown by the correlation matrix. It is an effective tool for finding and visualizing trends in the data provided as well as for summarizing huge datasets. The correlation matrix for the personal loan applied and approved is shown in Figure 2 below.

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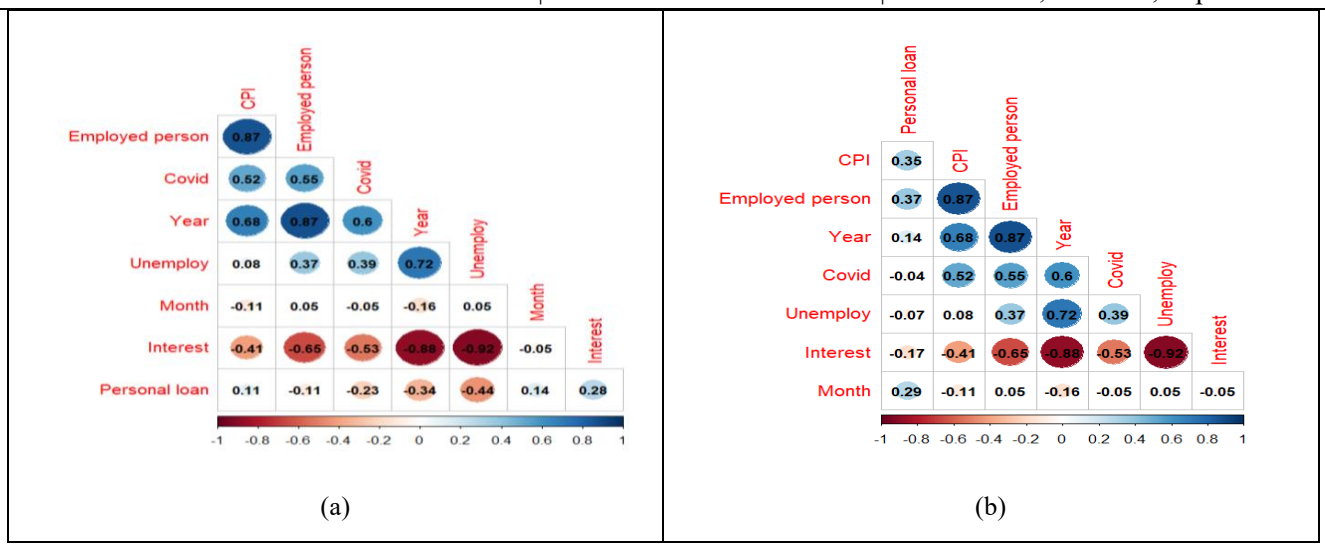


Figure 2. The correlation matrix for (a) personal loan applied and (b) personal loan approved.

Figure 2 above is a correlation matrix visualized with a heatmap and correlation coefficients, showing the relationships between personal loan applied and different economic and social factors. CPI and employment number have a correlation value of 0.87 which indicates a strong positive correlation between CPI and employment. Interest and unemployment have a correlation value of -0.92 and this is a very strong negative correlation, suggesting that as interest rates increase, unemployment tends to decrease, or vice versa. Interest and CPI have -0.88 as correlation value. This indicates, as interest rates increase, CPI tends to decrease. COVID and Employed Person has a correlation of 0.55 which indicates there is a moderate positive correlation between COVID-19 and employment, which could imply that employment trends were impacted during the COVID-19 period. Interest and COVID have a correlation of -0.65 which indicates a negative relationship between interest rates and COVID-19. Some factors, like personal loans, have weaker correlations with other variables, suggesting that they are less directly related to the primary economic factors here.

The correlation matrix in Figure 2 above shows the relationships between personal loans approved with various economic and social variables, with values indicating the strength and direction of their correlations. The strongest positive correlation is between CPI and employed person at 0.87, suggesting that as CPI increases, employment also tends to increase. There is also a strong positive correlation between the year's and employed number, which is 0.87 indicating a trend of increasing employment over time. Additionally, Interest shows a strong negative correlation with unemployed (-0.92), suggesting that higher interest rates are associated with lower unemployment rates. Interest also has a negative relationship with CPI; -0.88, indicating that higher interest rates tend to coincide with lower CPI values. Other correlations, like those between personal loan and CPI and between employed person and COVID, are moderate, while some relationships, such as month with other variables, show weaker correlations, suggesting little direct relationship. The color coding, with blue representing positive correlations and red representing negative ones, helps visually highlight these relationships.

After checking the correlation between each variable, the loan applied, and loan approved will be fit with Multiple Linear Regression (MLR) model. MLR can describe relationships between variables by fitting a line to the observed data. Regression allows you to estimate how a dependent variable changes as the independent variables' changes. The analysis of the MLR model is described in Table 5 below.

Table 5. MLR model output for personal loan applied.

Regression Statistic	
Multiple R	0.7104
R Square	0.5046

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Adjusted R Square	0.4530
Standard Error	713.2979
Observations	54

ANOVA					
	Degree of Freedom	**SS**	**MS**	**F**	**Significance F**
Regression	5	24875977.85	4975195.5703	9.7784	1.731E-06
Residual	48	24422108.12	508793.9192		
Total	53	49298085.97			

	Coefficients	**Standard Error**	**t Stat**	***p*-value**	**Lower 95%**	**Upper 95%**
Intercept	74988.07	18844.0067	3.9794	0.0002	37099.661	112876.49
Interest	-3756.2	786.5869	-4.7754	1.72E-05	-5337.772	-2174.69
CPI	44.753	129.7651	0.3449	0.7317	-216.1565	305.66
Employed	-2.5801	0.8533	-3.0236	0.0040	-4.2958	-0.864
Unemployed	-20.093	3.9280	-5.1156	5.43E-06	-27.9916	-12.196
COVID	-0.0013	0.0007	-1.8308	0.0733	-0.0028	0.0001

According to the results shown in Table 5, the multiple R value or the correlation coefficient, r of 0.7104 indicates that the relationship between the loan applied and the other variables such as interest, CPI, employment, unemployment, and COVID-19 is quite strong, and the R square or coefficient of determination, r^2 gives a value of 0.5046. This value indicates that 50.46% of the amount of variation in independent variables can be attributed to the number of loans applied, with the remaining 49.54% due to other, unexplained factors. Although the r^2 is not very strong, we could not make the conclusion that there is no linear relationship between the loan applied and the independent variables since the results from the ANOVA table, we reject the null hypothesis of no linear relationship since Significance F value is less than 0.05.

This low percentage might be caused by the p-value of the coefficients where CPI and COVID have values greater than 0.05, indicating that these two factors do not have an influence on the loan applied. If the MLR wants to be used as a modelling purpose, these variables could be removed and variables could be analyzed again in order to increase the R square value. The MLR model for the accepted loan can be shown in Table 6 below.

Table 6. MLR model output for personal loan approved.

Regression Statistic	
Multiple R	0.7198
R Square	0.5180
Adjusted R Square	0.4678

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Standard Error	274.9676
Observations	54

ANOVA					
	Degree of Freedom	**SS**	**MS**	**F**	**Significance F**
Regression	5	3900962.85	780192.5703	10.3190	9.275E-07
Residual	48	3629144.97	75607.1868		
Total	53	7530107.82			

	Coefficients	**Standard Error**	**t Stat**	***p*-value**	**Lower 95%**	**Upper 95%**
Intercept	25649.68	7264.1338	3.5310	0.0009	11044.160	40255.19
Interest	-1553.94	303.2196	-5.1248	5.26E-06	-2163.605	-944.28
CPI	-106.77	50.0229	-2.1343	0.0379	-207.344	-6.188
Employed	0.2632	0.3289	0.8000	0.4276	-0.3982	0.924
Unemployed	-8.0371	1.5142	-5.3079	2.80E-06	-11.0816	-4.992
COVID	-0.0007	0.0003	-2.6274	0.0115	-0.0013	-0.0002

The results are quite similar with the previous analysis of the loan applied especially on the Multiple R and R square, but looking at the p-value of the coefficients, only employed variable shows value larger than 0.05 which means that this variable does not has any significant effect on the loan approval. The MLR fitting from Table 5 and Table 6 shows that, even though the r and r^2 between loan applied and loan approval has quite similar values, the independent variables that affect the dependent variable are different.

IV. Conclusions

Based on the correlation matrix in Figure 2, it shows that the personal loan applied, and approval does not have a strong relationship with all the variables because most of the values are close to 0. However, using the MLR, the Multiple R and ANOVA has proved that there is a linear relationship between personal loan applied and personal loan approved with interest, CPI, employment, unemployment, and COVID-19. However, for certain variables such as CPI and COVID-19 with personal loan applied and employment rate with loan approved, it could be confirmed that these variables have no significant relationship with the selected dependent variables since both correlation matrix and MLR results give similar findings.

Both correlation matrix and MLR have their own advantages. Correlation matrix observes the relationship for each of the variables. Although the dependent variables (loan applied and loan approved) show no relationship with the independent variables, it gives information about other relationships such as employment number and CPI, unemployment number and interest rate, have strong relationships for both personal loans applied, and personal loan approved. MLR allows researchers to assess the model's variation as well as the relative contribution of each independent variable to overall variance.

In conclusion, there is a linear relationship between parameters such as interest rate, employment, and unemployment with loan applied, and the number of personal loan applications is unaffected by COVID-19 situations. However, different conditions for personal loan approval, such as CPI, interest rates, unemployment, and COVID-19 cases, have an impact on bank loan approvals.

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Other than that, for both applied and approved personal loans, employment statistics and interest rates have a very significant relationship, which is similar to unemployment numbers and CPI.

Acknowledgments

We would like to thank Bank Negara Malaysia and Kementerian Kesihatan Malaysia for giving access to the data used in this study.

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