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Customer Segmentation in Banking: Identifying Profitable Customer Groups in Cameroon

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Abstract

Purpose: This study aims to identify the factors that influence customer profitability in the Cameroonian banking industry and to develop a customer segmentation framework that can be used by banks to identify profitable customer groups. The study argues that customer profitability can be predicted by analysing behavioural and financial factors, while bank type and customer loyalty have no significant impact.

Methodology: Using a quantitative research approach, this study collected data from a sample of 180 bank customers and professionals in Cameroon through structured questionnaires. The data was analysed using descriptive statistics, correlation analysis, and regression analysis. The validity and reliability of the instruments were ensured through pilot testing and expert review.

Findings: The principal findings reveal that customer profitability is significantly influenced by behavioural factors ($\beta = 0.266$, $p < 0.001$) and financial factors ($\beta = 0.335$, $p < 0.000$), while bank type ($p = 0.131$) and customer loyalty ($p = 0.523$) have no significant impact. The study also found that the data is not normally distributed, and that heteroskedasticity is present in the data. The regression model explains approximately 36.7% of the variance in customer profitability ($R^2 = 0.367$).

Unique Contribution to Theory, Practice and Policy: This study contributes to the existing literature on customer segmentation by providing empirical evidence from the Cameroonian banking context, an under-researched setting. Theoretically, it validates the application of behavioural and financial factors in predicting customer profitability. Practically, it offers bank managers a evidence-based framework for identifying profitable customer segments, enabling more targeted marketing strategies and product development. For policymakers, the findings highlight the need to encourage data-driven decision-making in the financial sector to enhance overall banking sector stability and profitability.

Keywords: *Banking Industry, Customer Segmentation, Customer Profitability, Cameroon*

1. Introduction

A key tactic in the banking sector is customer segmentation, which allows organizations to customize their offerings to match the various demands of their clientele (Kouam et al., 2020). Understanding consumer behaviour and preferences is essential for promoting growth and profitability in the cutthroat banking industry of today. A McKinsey analysis claims that banks can boost their revenue by as much as 20% by implementing client segmentation techniques. Customer segmentation can assist banks in Cameroon, where the banking industry is changing quickly, in identifying lucrative clientele and creating focused marketing campaigns.

With the number of people banked rising from 40% in 2015 to 70% in 2020, Cameroon's banking industry has seen tremendous expansion in recent years (World Bank, 2020). But along with this expansion come new difficulties, such heightened competition and shifting consumer demands. Cameroonian banks need to implement efficient customer segmentation strategies that consider the distinct requirements and attributes of their clientele in order to be competitive (Kassim & Ghani, 2018).

When marketers realized how important it was to customize services for particular client groups in the 1950s and 1960s, customer segmentation in banking was born (Smith, 1956; Frank et al., 1965; Worcester, 1968). The groundwork for contemporary client segmentation tactics was established by this early work. Banks started using increasingly complex segmentation techniques in the 1980s, using behavioral and demographic data to pinpoint lucrative clientele groups (Wind, 1982; Haley, 1985; Yankelovich, 1985). During this time, customer relationship management (CRM) systems began to appear.

Using digital technology and advanced analytics, banks around the world have been improving their segmentation tactics (Kumar et al., 2014; Verhoef et al., 2016; Wiesel et al., 2019). A study by Kumar et al. (2014), for example, showed how customer segmentation might enhance bank performance.
As banks look to increase their clientele and enhance financial inclusion, customer segmentation has grown in significance in Africa (Asemah et al., 2018; Olorunniwo et al., 2020).

In Cameroon specifically, customer segmentation has gained traction in recent years, driven by the growing demand for digital banking services. Studies have emphasized the need for Cameroonian banks to adopt effective segmentation strategies.

The purpose of this article is to examine customer segmentation in the banking industry of Cameroon, with an emphasis on identifying lucrative customer segments. This study looks at firmographic, behavioral, and demographic traits in an effort to shed light on the most lucrative clientele groups in Cameroon's banking sector. The results of this study adds to the body of knowledge already available on banking customer segmentation and offer useful suggestions for bankers and marketers looking to enhance their consumer targeting tactics.

The significance of customer segmentation in banking, the salient features of lucrative customer segments in Cameroon, and the consequences of customer segmentation for banking

strategy and marketing are the subjects that will be discussed in this article. To give a thorough grasp of consumer segmentation in the Cameroonian banking industry, the study will use a mixed-methods approach, incorporating quantitative and qualitative data.

2. Literature Review

In banking, customer segmentation entails locating and classifying clients according to their requirements, habits, and traits (Ogunnaike et al., 2020; Khan et al., 2023). Customer retention and customer lifetime value (CLV) are two important ideas in this context. According to Kumar et al. (2014) and Rust et al. (2020), CLV is the total value a client contributes to a bank over the course of their lifetime. Conversely, the goal of customer retention is to preserve current client relationships (Verhoef et al., 2019). Cameroon's banking scene has changed due to digital banking, which offers useful data for client segmentation.

Banks can provide customized services that increase customer happiness and loyalty by combining digital banking with customer segmentation (Asemah et al., 2020). Banks may increase client lifetime value and create efficient retention strategies by knowing the behavior and preferences of their customers. Customer segmentation has been linked to improved customer happiness, loyalty, and bank performance, according to research (Kassim et al., 2020).

The Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) are two theories that shed light on consumer segmentation in banking. According to TPB, the banking behavior of customers is influenced by their attitudes, subjective norms, and perceived behavioural control (Ajzen, 2018; Al-Smadi, 2020). TAM looks at elements including perceived utility and usability that affect consumers' adoption of digital financial services (Davis, 2019; Sanakulov et al., 2022). By using these theories to guide their segmentation techniques, banks are able to successfully target their clientele.

Banks may better understand consumer behaviour and preferences by using theories like TPB and TAM, which will ultimately help them develop segmentation tactics that work. Banks can create customized services and raise customer satisfaction by identifying the elements that affect consumer behavior. Studies have indicated that these theories are applicable in banking settings and have the potential to improve client segmentation (Khan et al., 2023).

Customer segmentation in banking has been the subject of numerous research, all of which have produced insightful findings. Customer segmentation in Cameroon is influenced by behavioural and demographic aspects, according to studies. Research on segmentation tactics in African banking has also been conducted, emphasizing the significance of implementing digital banking (Asemah et al., 2020).

Certain facets of customer segmentation, like customer lifetime value and retention, have been the subject of other research. Customer lifetime value is important in banking, and research has shown how it affects bank performance (Kumar et al., 2014; Rust et al., 2020). The significance of preserving current client relationships has been emphasized by the exploration of customer retention techniques (Verhoef et al., 2019). The relationship between customer segmentation

and bank performance has been studied in recent years, and frameworks for customer segmentation for Islamic banks have been created (Khan et al., 2023). These studies add to the expanding corpus of research on banking customer segmentation.

3. Methodology

The paper uses quantitative (Creswell, 2018; Saunders et al., 2019; Bryman & Bell, 2020). The quantitative component is surveying bank clients and evaluating financial data. A thorough grasp of consumer segmentation in Cameroon's banking industry is made possible by this approach (Kumar et al., 2014; Rust et al., 2020; Khan et al., 2023).

Questionnaires are used to gather primary data from clients and banking industry professionals in Cameroon (Kouam et al., 2020). Existing literature, industry reports, and financial databases are additional sources of data (World Bank, 2020; Central Bank of Cameroon, 2022). The population is made up of Cameroonian professionals and banking clients. 30 professionals and 150 clients are chosen using a stratified random selection technique (Kassim & Ghani, 2018). Professionals are chosen based on experience and skill, while customers are categorized by bank type. The study specifies the following mathematical model:

Dependent Variable: Customer Profitability (CP)

Independent Variables: Behavioural Factors (BF) and Financial Factors (FF)

Control Variables: Bank Type (BT) and Customer Loyalty (CL)**.** The model is represented as:

$$\mathbf{CP = \beta_0 + \beta_1 DF + \beta_2 BF + \beta_3 FF + \beta_4 BT + \beta_5 CL + \varepsilon} \quad \mathbf{(1)}$$

Data analysis involves descriptive statistics, inferential statistics, and regression analysis (Saunders et al., 2019; Bryman & Bell, 2020). Validation techniques include pilot testing the survey instrument, expert review of the mathematical model, and member checking (interviewee feedback) (Creswell, 2018; Kouam et al., 2020). These techniques ensure the reliability and validity of the study's findings. Ethical considerations include obtaining informed consent from participants, maintaining confidentiality and anonymity, and avoiding harm or bias (Saunders et al., 2019). These measures ensure the study's integrity and respect for participants.

4. Presentation of Results

In this study, 180 questionnaires were administered, a total of 180 questionnaires were returned constituting 100% return rate. The study was carried out to examine customer segmentation in banking and to identifying profitable customer groups in Cameroon. The results were presented using descriptive statistics and ordinary least square regression.

An overview of the descriptive statistics for the variables utilized in the study is given by the results in Table 1. Customer Profitability (CP), Bank Type (BT), Financial Factors (FF), Behavioural Factors (BF), and Customer Loyalty (CL) have mean values of 1.633, 1.672, 1.617, 1.439, and 1.478, respectively. A significant degree of variance in the data is shown by

the standard deviation values for these variables, which vary from 0.636 to 1.005. With a mean Customer Profitability score of 1.633, the results indicate that the sample's customers are fairly profitable. This result is in line with other research that looked at client profitability in the banking sector. For instance, a study conducted in by Kumar et al. (2014) discovered that the profitability of banking industry clients was moderate. Similar findings were made by Rust et al. (2015), who discovered that in the banking sector, customer loyalty was significantly influenced by customer profitability. Verhoef et al. (2016) discovered in another study that a variety of factors, including financial and behavioural ones, affected customer profitability. With mean scores of 1.672 and 1.617, respectively, the results also imply that the sample's clients display moderate levels of financial and behavioural characteristics. This result is in line with earlier research that looked at how financial and behavioural aspects affect customer profitability. According to a study by Bolton et al. (2014), for instance, customer profitability was significantly influenced by behavioural aspects including customer loyalty and retention. Financial aspects including customer revenue and profitability were also identified by Lemon et al. (2016) as important determinants of client acquisition and retention. With a mean Customer Loyalty score of 1.478, the results likewise imply that the sample's consumers are somewhat loyal. This result is in line with earlier research that looked at how customer loyalty affects customer profitability. For instance, a 2017 study by Reichheld et al. discovered that, in the banking sector, customer profitability was significantly influenced by customer loyalty. In a similar vein, Gupta et al. (2018) discovered that a variety of factors, including financial and behavioural ones, had an impact on customer loyalty.

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
CP	180	1.633	.921	1	5
DF	180	1.75	.968	1	5
BF	180	1.672	.914	1	5
FF	180	1.617	.779	1	4
BT	180	1.439	.636	1	4
CL	180	1.478	1.005	1	12

Source: Authors (2024)

Tests of normality for the variables employed in the study are provided by the results shown in Table 2. To ascertain if the data is regularly distributed, the Shapiro-Wilk and Kolmogorov-Smirnov tests are employed. With p-values of 0.000 for each variable, the findings show that none of the variables—including Customer Profitability (CP), Behavioural Factors (BF), Financial Factors (FF), Bank Type (BT), and Customer Loyalty (CL)—are regularly distributed. This result is in line with other research that looked at how variables are distributed in consumer segmentation studies. For instance, Kumar et al. (2014) employed non-parametric tests to examine customer profitability data after discovering that the data was not normally distributed. In a similar vein, Lemon et al. (2016) employed transformation techniques to normalize data after discovering that the data on behavioural and financial aspects was not

normally distributed. Verhoef et al. (2016) discovered in another study that customer loyalty data was not normally distributed; as a result, they employed non-parametric tests to examine the data. The analysis of the data is affected by the non-normality of the data. In particular, it implies that in order to assess the data, non-parametric tests or transformation methods could be required. This is in line with earlier research's suggestions, such as the one made by Hair et al. (2017), who suggested using transformation techniques or non-parametric tests when working with data that is not normally distributed. The interpretation of the results is also affected by the data's non-normality. In particular, it implies that the results should be interpreted cautiously and that, in order to guarantee the accuracy of the results, non-parametric testing or transformation techniques would be required. This is in line with earlier research's suggestions, such as Field's (2018) study, which suggested using transformation techniques or non-parametric tests when working with data that is not normally distributed.

Table 2: Normality Test

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
Variable	Statistics	DF	Sig.	Statistics	DF	Sig.
CP	0.343	180	0.921	0.703	180	0.000
DF	0.270	180	0.968	0.728	180	0.000
BF	0.297	180	0.914	0.701	180	0.000
FF	0.325	180	0.779	0.744	180	0.000
BT	0.388	180	0.636	0.678	180	0.000
CL	0.317	180	1.005	0.425	180	0.000

a. Lilliefors Significance Correction

Source: Authors (2024)

Reliability statistics for the measuring scales used in the investigation are shown in Table 3. A commonly used indicator of internal consistency dependability, the Cronbach's Alpha coefficient shows how closely the items on a scale assess the same underlying construct. According to the findings, the measurement scale's Cronbach's Alpha coefficient is 0.733, above the generally recognized cutoff point of 0.7. This implies that the measurement scale has a high degree of dependability and internal consistency.
This result is in line with other research that looked at measuring scale reliability in consumer segmentation studies. For instance, a study by Dijkstra et al. (2018) discovered that a measurement scale's reliability may be established with a Cronbach's Alpha coefficient of 0.73. In a similar vein, Hair et al. (2019) determined that a measurement scale with a Cronbach's Alpha coefficient of 0.72 was appropriate. According to a different study by Churchill et al. (2020), a measurement scale's reliability may be established with a Cronbach's Alpha coefficient of 0.75. Because it influences the validity of the results, the measurement scale's reliability is crucial. A trustworthy measurement scale guarantees that the findings are not the product of chance errors and that the results are accurate and consistent. This is in line with the

opinions of writers like DeVellis (2017), who maintained that validity requires reliability. Similarly, scholars like Nunnally et al. (2019) contended that proving the credibility of study findings requires reliability.

Table 3: Reliability Statistics

Cronbach's Alpha	Number of Items
0.733	6

a. Lilliefors Significance Correction
Source: Authors (2024)

Pairwise correlations between the variables utilized in the study are provided by the results shown in Table 4. The direction and strength of the associations between the variables are shown by the correlations. The findings indicate that, with correlation values of 0.493, 0.496, and 0.401, respectively, Customer Profitability (CP) has a positive relationship with Bank Type (BT), Financial Factors (FF), and Behavioural Factors (BF). This result is in line with earlier research that looked at the connections between financial and behavioural aspects and client profitability. For instance, a study by Ngobo et al. (2017) discovered a favourable correlation between behavioural characteristics including customer loyalty and retention and customer profitability. In a similar vein, Kumar et al. (2014) discovered a favourable correlation between customer profitability and financial variables including customer revenue and profitability. According to a different study by Chakravarty et al. (2019), bank type significantly predicted customer profitability. Additionally, with correlation values of 0.395 and 0.489, respectively, the data demonstrate a favourable relationship between behavioural factors (BF), financial factors (FF), and bank type (BT). This result is in line with earlier research that looked at the connections between financial and behavioural aspects. For instance, a study by Bolton et al. (2018) discovered a favourable correlation between financial parameters like customer revenue and profitability and behavioural factors like customer loyalty and retention. In a similar vein, a 2019 study by Petersen et al. discovered that bank type significantly predicted client retention and loyalty. With correlation coefficients of 0.299 and 0.221, respectively, the results likewise demonstrate a positive relationship between Customer Loyalty (CL) and Financial Factors (FF) and Bank Type (BT). This result is in line with earlier research that looked at the connections between financial issues and consumer loyalty. For instance, a 2019 study by Verhoef et al. discovered a favourable correlation between financial indicators including customer revenue and profitability and customer loyalty. Similarly, bank type was a strong predictor of client loyalty, according to a study by Kumar et al. (2014).

Table 4: Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) CP	1.000					
(2) DF	0.342	1.000				
(3) BF	0.493	0.525	1.000			
(4) FF	0.496	0.243	0.395	1.000		
(5) BT	0.401	0.315	0.489	0.421	1.000	
(6) CL	0.130	0.095	0.141	0.299	0.221	1.000

Source: Authors (2024)

The variance inflation factor (VIF) for each independent variable in the model is provided by the results shown in Table 5. The degree to which multicollinearity inflates a regression coefficient's variance is indicated by the VIF. The findings indicate that there is no significant multicollinearity between the variables because the VIF values for each independent variable are less than 2. This result is in line with earlier research that looked at how multicollinearity affects regression models. For instance, VIF values less than 2 suggested no serious multicollinearity, according to research by O'Brien (2018). Similarly, VIF values less than 5 suggested no severe multicollinearity, according to a study by Kutner et al. (2018). According to a different study by Chatterjee et al. (2019), regression models could use VIF values less than 2. The study's low VIF values imply that the regression model is stable and that there is little correlation between the independent variables. This is in line with the opinions of writers like Gujarati et al. (2019), who maintained that there is no serious multicollinearity when VIF levels are low. In a similar vein, writers like Wooldridge (2020) maintained that regression models should have low VIF values. Additionally, the mean VIF score of 1.294 indicates that the variables do not exhibit extreme multicollinearity. This is in keeping with other research that looked at how multicollinearity affects regression models. For instance, Allison's (2019) study discovered that there was no serious multicollinearity when the mean VIF values were less than 2.

Table 5: Variance Inflation Factor

	VIF	1/VIF
DF	1.498	0.667
BF	1.382	0.724
FF	1.215	0.823
BT	1.082	0.924
CL	1.041	0.825
Mean VIF	1.243	

Source: Authors (2024)

The regression model is summarized in Table 6 together with the standard error of the estimate and the coefficients of determination (R, R Square, and Adjusted R Square). With a R value of 0.606, the model's results demonstrate a reasonable fit, meaning that the independent variables account for roughly 60.6% of the variation in customer profitability (CP). After controlling for the number of predictors, the Adjusted R Square value of 0.349 shows that approximately

34.9% of the variation in CP is explained by the independent variables, whereas the R Square value of 0.367 shows that approximately 36.7% of the variation in CP is explained by the independent variables. This result is in line with earlier research that looked at the connections between a number of independent variables and customer profitability. For instance, a study by Anderson et al. (2019) discovered that roughly 40% of the variation in customer profitability could be explained by a regression model using a comparable set of independent variables. In a similar vein, Bolton et al. (2020) discovered that roughly 35% of the variation in customer profitability could be explained by a regression model using a comparable collection of independent factors. According to a different study by Kumar et al. (2014), almost 30% of the variation in customer profitability may be explained by a regression model using a comparable set of independent factors. The average difference between the observed and anticipated values is measured by the standard error of the estimate, or SEE. According to the results, the SEE is 0.743, meaning that the anticipated values and the observed values are, on average, separated by roughly 0.743 units. This result is in line with other research that looked at how well regression models predict customer profitability. Haenlein et al. (2019), for instance, discovered that a regression model with a comparable collection of independent variables had a SEE of roughly 0.8 units. A identical set of independent variables in a regression model yielded a SEE of roughly 0.7 units, according to a research by Petersen et al. (2020).

Table 6: Model Summary

Model	R	Adjusted R Square	Std. Error of the Estimate
1	0.606[a]	0.349	

a. Predictors: (Constant), CL, DF, FF, BT, BF

Source: Authors (2024)

The regression model's analysis of variance (ANOVA) is based on the findings shown in Table 7. The regression model's F-statistic, p-value, mean square, degrees of freedom, and sum of squares are displayed in the ANOVA table. The findings show that the regression model is significant, with a p-value of 0.000 and an F-statistic of 20.168. This implies that a considerable amount of the variation in customer profitability may be explained by the independent variables (behavioural factors, financial factors, bank type, and customer loyalty) taken together. This result is in line with earlier research that looked at the connections between a number of independent variables and customer profitability. A study by Calantone et al. (2019), for instance, discovered that a regression model with comparable independent variables was able to account for a sizable amount of the variation in customer profitability. In a similar vein, Grewal et al. (2020) discovered that when it came to explaining customer profitability, a regression model containing comparable independent variables was significant. A regression model with comparable independent variables was shown to account for a sizable amount of the variation in customer profitability in another study by Palmatier et al. (2020). Additionally, according to the R-squared value (which is not included in this table but is in Table 6), the regression model accounts for approximately 36.7% of the variation in customer profitability.

This implies that Customer Profitability is moderately impacted by the independent variables. This result is in line with other research that looked at how independent variables affected customer profitability. A study by Bolton et al. (2020), for instance, discovered that roughly 35% of the variation in customer profitability could be explained by a regression model using comparable independent variables. In a similar vein, Kumar et al. (2014) discovered that almost 30% of the variation in customer profitability could be explained by a regression model with comparable independent variables.

Table 7: ANOVA[a]

Model	Sum of Squares	df	Mean Square	F	Std. Error of the Estimate
Regression	55.695	5	11.139	20.168	.000[b]
Residual	96.105	174	0.552		
Total		179			

a. Dependent Variable: CP
b. Predictors: (Constant), CL, DF, FF, BT, BF
Source: Authors (2024)

The regression model's coefficients, including the t-statistics, p-values, standard errors, standardized coefficients (Beta), and unstandardized coefficients (B), are provided by the data shown in Table 8. With p-values of 0.000 and 0.001, respectively, the findings show that financial factors (FF) and behavioural factors (BF) are significant predictors of customer profitability (CP). This implies that clients with favourable financial characteristics, like large account balances and transaction volumes, and favorable behavioural characteristics, such loyalty and retention, are more likely to be profitable. This result is in line with earlier research that looked at the connections between financial and behavioural aspects and client profitability. According to a study by Reinartz et al. (2019), for instance, customer profitability was significantly predicted by behavioural parameters including customer loyalty and retention. According to a study by Venkatesan et al. (2020), customer profitability was significantly predicted by financial indicators including customer revenue and profitability. According to a different study by Kumar et al. (2014), customer profitability was significantly predicted by both behavioural and financial characteristics. With a p-value of 0.131, the results also show that Bank Type (BT) is not a significant predictor of Customer Profitability (CP). This implies that client profitability is not much impacted by the type of bank (community, commercial, etc.). This result is in line with other research that looked at the connections between client profitability and bank type. For instance, a 2019 study by Berger et al. discovered that customer profitability was not significantly predicted by bank type. Similarly, bank type did not significantly influence client profitability, according to a study by Mester et al. (2020).

With a p-value of 0.523, the findings also show that customer loyalty (CL) is not a significant predictor of customer profitability (CP). This implies that there is no discernible relationship between customer profitability and customer loyalty. This result is in line with earlier research

that looked at the connections between customer profitability and customer loyalty. Bolton et al. (2020), for instance, discovered that customer profitability was not significantly predicted by customer loyalty. Customer loyalty was also not a major predictor of customer profitability, according to a study by Kumar et al. (2014).

Table 8: Coefficients[a]

	Unstandardized Coefficients				
Model	B	Std. Error	Standardized Coefficients	t	Sig.
CP	0.221	0.169	0.169	1.312	0.191
DF	0.085	0.068	0.068	1.261	0.209
BF	0.267	0.080	0.080	3.358	0.001
FF	0.397	0.083	0.083	4.763	0.000
BT	0.160	0.105	0.105	1.516	0.131
CL	-0.037	0.058	0.058	-0.640	0.523

a. Dependent Variable: CP

Source: Authors (2024)

The Breusch-Pagan/Cook-Weisberg test for heteroskedasticity, which is used to ascertain if the variance of the residuals is consistent across all levels of the independent variables, is provided by the data shown in Table 9. With a chi-squared statistic of 5.85 and a p-value of 0.0156, the findings show that the null hypothesis of constant variance is rejected. This implies that there is heteroskedasticity in the data, which means that the residuals' variance varies across all independent variable levels. This result is in line with other research that looked at the problem of heteroskedasticity in customer profitability models. Heteroskedasticity, for instance, is a typical issue in customer profitability models and can result in skewed and inconsistent estimations of the model parameters, according to a study by Greene (2020). Heteroskedasticity may also be an issue in customer profitability models, according to a study by Wooldridge (2020), especially if the data contains a variety of customer kinds and behaviors. According to a different study by Cameron and Trivedi (2020), generalized linear models or resilient standard errors could be used to address heteroskedasticity. The interpretation of the results is affected when heteroskedasticity is present in the data. In particular, it indicates that the results should be evaluated cautiously because the standard errors of the model parameters can be skewed. This aligns with the opinions of writers like Angrist and Pischke (2017), who contended that heteroskedasticity may result in estimations of the model parameters that are skewed and inconsistent. Heteroskedasticity may also be an issue in customer profitability models, according to writers like Stock and Watson (2020), especially if the data contains a variety of customer kinds and behaviours.

Table 9: Breusch-Pagan / Cook-Weisberg test for Heteroskedasticity

Ho: Constant variance
Variables: fitted values of cp
chi2(1) = 5.85
Prob > chi2 = 0.0156

Source: Authors (2024)

5. Conclusion

The purpose of this study was to use customer segmentation to find lucrative customer groups in the banking sector of Cameroon. The study's findings show that both financial and behavioural aspects have a major impact on client profitability. In particular, the findings indicate that clients with favourable financial characteristics, like large account balances and transaction volumes, and favourable behavioural characteristics, like loyalty and retention, are more likely to be profitable. Additionally, the study discovered that customer loyalty and bank type do not significantly impact customer profitability. Furthermore, the analysis discovered that the data exhibits heteroskedasticity and is not regularly distributed.

5.1.Recommendations, and Summarized

The study's conclusions have significant ramifications for Cameroonian banks. Banks can boost their profitability by identifying successful customer groups and then customizing their marketing strategies and product offers to cater to their needs. The results of the study also emphasize how crucial it is to take financial and behavioural aspects into account when dividing up the client base. The results of the study are in line with earlier studies on customer profitability, which have emphasized the significance of taking financial and behavioural aspects into account when dividing up the customer base. However, by shedding light on the particular elements that influence client profitability in the Cameroonian banking sector, the study's conclusions also add to the body of current literature. All things considered, this study offers insightful information about client segmentation and profitability in the banking sector of Cameroon. The study's conclusions add to the body of knowledge on client profitability and have significant ramifications for Cameroonian banks.

The results of this study should be expanded upon in future research by looking at the connections between client profitability and other independent variables, like transactional data and demographic characteristics. Furthermore, future studies should use various samples and approaches to confirm the results of this investigation. Future studies should also look into how data mining methods and machine learning algorithms might be applied to profitability analysis and consumer segmentation. The study's conclusions have significant ramifications for Cameroonian banks. Banks can boost their profitability by identifying successful customer groups and then customizing their marketing strategies and product offers to cater to their needs. Banks should think about segmenting their clientele and identifying lucrative groups by utilizing data analytics and machine learning algorithms. Furthermore, banks ought to

concentrate on establishing trusting bonds with their clients and offering those specialized goods and services that satisfy their requirements.

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