

FGP Loyalty Program

MARK3054

Marketing Analytics Report



Endeavour Consulting

Client: Jennifer (Loyalty Program Manager at FGP)

Team: Judy Choi (z5257298), Emily Cong (z5309522), Ayra Islam (z5255744), Capri Maher (z5317323), Hanlin Wei (z5237511)

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Executive Summary

This report will provide insights to guide the expansion of the FGP Loyalty program and to pre-empt predicaments existing amongst merchant members. A range of analytical tools were used to identify the most valuable customers to the loyalty program, predict customer retention and manage customers accordingly. The report recommends the following actions:

1. Allocate more resources to target City A and G

Redeeming customers add more value to the loyalty program than non-redeeming customers. Customers in City A and G department are most likely to redeem FGP's program loyalty points. It is recommended to increase the investment budget in both cities, and invest more budget in marketing campaigns and establish more store outlets in both cities. Within both market segments, it is encouraged to target customers identified as Race 1 to establish an efficient market expansion strategy with less investment resources.

2. Concrete marketing efforts towards improving the satisfaction of customers who own a credit card

Given the positive correlation between customers who own credit cards and a higher customer value - measured through customer satisfaction and Net Promoter Score (NPS), FGP should prioritise this group of customers and target marketing activity towards them. This could involve partnerships with credit card companies or exclusive promotions, all of which seek to maximise overall profitability and customer value.

3. Promote points redemption to drive engagement, particularly targeting grocery customers

While FGP customers are aggregating significant points through their purchases at each of the three chains, there is a lack of redemption activity. Comparing average Net Promoter Scores (NPS), there is a significant uplift amongst redeeming customers, hence making this a priority suggestion for Jennifer to adopt. As grocery customers have shown no record of redeeming their points, this particular merchant can be targeted.

Introduction

The FGP Customer Loyalty Program operates in Asia and comprises three different merchants: Fast Food Chain (F), Grocery Store Chain (G) and Petrol Station Chain (P). Loyalty programs are an effective marketing tool to build stronger attitudes towards a brand and increase customer loyalty. However, beyond these benefits, loyalty programs provide access to consumer information and trends, offering companies the ability to accurately target specific consumer segments and counteract churn (Berman, 2006). This ensures that programs such as FGP can build an enhanced customer experience which is crucial in gaining a competitive advantage within a highly saturated market to maximise revenue (Manning and Czarnecki, 2016).

Managerial Problem

How to estimate the value of a customer in the loyalty program, predict if a customer will churn, and manage the customers accordingly?

Research Design

To assist Jennifer, the loyalty program manager, this managerial problem must be dissected and examined from multiple perspectives of the program to develop a holistic solution. As such, the following research questions have been created:

1. What customer factors are most valuable to the FGP loyalty program?

Objective: To understand qualitatively the value of customers through analysing which demographic-based and behavioural-based characteristics of customers correlated in having a higher Net Promoter Score.

2. How can we estimate the customer's lifetime value and is it related to merchants of the program?

Objective: To understand quantitatively the value of customers through calculating CLR (Customer Lifetime Revenue) as a measurement of economic value generated by customers.

3. Do customers that redeem their points add more value to the program than customers who do not, and do similarities exist between these customers?

Objective: To explore the commonalities between customers who are point redeemers and non-redeemers through Recency Frequency Monetary Value Analysis to determine whether redeeming customers are more valuable to the FGP loyalty program.

4. What factors influence customer churn and retention, and how can FGP manage customers accordingly?

Objective: To analyse customer factors which are influential to their churn and retention utilising a binary logistic regression.

Results & Findings

Research Question 1

What customer factors are most valuable to the FGP loyalty program?

Overview

It is important to examine the relationship value that customers have in the FGP loyalty program through an analysis of the Net Promoter Score and explore whether correlations are present between specific characteristics. Beyond the monetary value of a customer within an economic landscape, the tendency of loyal customers to promote the FGP program at their own willingness is a powerful driver for acquiring new customers. This is beneficial for the program as the client must recognise the immense marketing costs behind the acquisition of each new customer through advertising and other promotions which make it difficult to grow profitably (Mackintosh, 2015). As Reichheld (2003) suggested “the only path to profitable growth may lie in a company’s ability to get its loyal customers to become, in effect, its marketing department”. It is thus essential for clients like Jennifer to understand which customer characteristics demonstrate such loyalty to effectively take advantage of word-of-mouth marketing and utilise NPS to predict economic growth. As such, it could be concluded that NPS was an appropriate variable to measure the relationship value of a customer.

Methodology

Multiple linear regression was conducted as an appropriate analytical test to determine if relationships between NPS (the dependent variable) and various customer characteristics (the independent variables) were present. Observable characteristics of customers included demographics whilst behavioural characteristics described the customers who owned products and services which may affect their interaction with the FGP loyalty program. For this test, the following demographic (D) characteristics and behavioural (B) characteristics were examined:

- Gender (D)
- OwnCar (B)
- HomeCity (D)
- Race (D)
- OwnCreditCard (B)
- BirthYear (D)

It is important to note that HomeCity and BirthYear were omitted in the final model as the intercorrelation between these variables (CityA – CityG, BirthYear 1934-99) was unacceptable (multicollinearity existed) and would result in unreliable findings.

When running the multiple linear regression, if the p-value was less than 0.05 and t-value was greater than 1.96 and less than -1.96, the model rejected the null hypothesis that there was no difference in NPS between different customer characteristics. This methodology was kept consistent when running all the models.

Results

The results of the multiple linear regression showed that the model was statistically significant as the p-value was less than $2.2e-16$ and the model also explained the differences in NPS at a level of 14.39% (Adjusted R-Square = 0.1439). As shown in Appendix 1.1, the results confirmed that there was no difference in NPS for all demographic characteristics (ie. race, birth year and home city) apart from **gender** which presented a significance of $< 2e-16$. Conversely, both behavioural characteristics (ie. owning a car, owning a credit card) revealed to have a significant difference between NPS ($p = 5.34e-08$ and $p = 0.00215$, respectively). The correlation between these independent variables were further tested and confirmed that multicollinearity did not occur (see Appendix 1.2 & Appendix 1.3).

Variables	Coefficients	P-Value
Intercept	5.1260	$< 2e-16$ ***
Gender_F	1.8427	$< 2e-16$ ***
OwnCar (Y)	-0.6193	$5.34e-08$ ***
OwnCreditCard (Y)	0.3468	0.00215 **

As shown by the table above, the model explained a positive relationship between NPS and female (1.8427) and NPS and Credit Card owners (0.3468) whilst there was a negative relationship between NPS and Car owners (-0.6193). The model's output presented two distinct findings; (1) females that were credit card owners were more likely to promote the FGP loyalty program and (2) car owners exhibited lower NPS than customers who did not own cars.

Predictions & Recommendations

Based on the two key insights gained from the test results, FGP should direct more marketing resources towards females who own credit cards and reduce existing marketing efforts which target car owners.

Noting the magnitude of the Gender_F coefficient, Jennifer should consider incorporating unique value offerings inclusive of its female customers through promotions such as 'Mother's Day specials' or double loyalty points when purchasing female sanitary goods. Additionally, Jennifer can consider establishing partnerships with major credit card companies such as Mastercard or American Express to capitalise on these customers. Conversely, Jennifer should seek to cut back its marketing efforts towards car owners through dissolving partnerships with car dealerships and brands or reducing promotional activities within the petrol station chain of the FGP program.

Limitations

There are two main limitations presented when running the multiple linear regression model. Firstly, **multicollinearity** is present between independent variables impacting the accuracy and reliability of the coefficient results. Additionally, as the model does not account for all relevant variables such as employment or education level due to the limited dataset, **omitted-variable bias** occurs within the multiple linear regression model. This could be supported by the model's low Adjusted R-Square of 0.1439 suggesting that approximately 86% of variations in NPS could not be explained.

Research Question 2

How can we estimate the customer's lifetime value and is it related to merchants of the program?

Overview

This research question intends to measure customer value on an economic scale and explore how each firm's contribution to the FGP program through the examination of 3 firms' individual average Customer Lifetime Revenue (CLR).

Methodology

By taking discount rate and customer chum rate into consideration, the value of the customer would be measured from a long-term perspective. This question focuses on expressing customer value in economic scenes.

Due to missing data on acquisition costs and operating costs, this report examines CLR. The discount rate would be estimated as 10%. Also, by comparing the customer active status between 2015 and 2016, the resultant customer retention rate would be 75.1%.

Results

<u>Descriptive Statistics Means</u>				
	FastFood Company	Grocery Company	Petrol Company	FGP program
CLR mean	5.06	33.59	10.67	11.73

The CLR mean indicates the marginal value that each purchase brings to the overall customer CLR, it also demonstrates how each purchase contributes economic value to the FGP program from a long-term perspective. Based on the result, every purchase brings 11.73 CLR toward the general FGP program. Yet, the CLR mean between the 3 companies varied. The fast-food company has the lowest score (5.06) among the 3 companies, and it is below the general FGP program CLR mean (11.73). The grocery company has the highest CLR mean (33.59), and it is almost three times higher than the overall CLR mean (11.73). The Petrol company has the medium CLR mean (10.57) among the 3 companies and the result is close to the general CLR mean (11.73). The result suggests that each firm's sales have a different marginal value on the FGP program through CLR mean test. Grocery has the largest portion of single sales CLR value among the FGP program, in comparison the fast-food company has the lowest contribution.

Limitations

This research is based on a limited dataset without customer acquisition cost and serving cost, CLR was implemented to replace CLV. Given the missing data, the accuracy of CLR was compromised. Also, the discount rate was assumed to be 10% based on convention rules. However, the discount rate may be varied across global pandemics. Since the central bank needs to issue more money against the economy's decline, which would result in the depreciation of currency. Also, this research is based on economic perspective, the CLR test fails to examine each merchant's customer's engagement in the FGP program. The customer engagement would also be seen as a valuable tribute in the evaluation of customer value, and research question 3 would focus on this segment.

Research Question 3

Do customers that redeem their points add more value to the program than customers who do not, and do similarities exist between these customers?

Overview

This question aims to identify any significant commonalities and/or differences that exist between redeeming and non-redeeming customers and whether those who do redeem add

more value to the program. It was hypothesised that redeeming customers will be of greater value to the FGP loyalty program than non-redeeming, and this analysis allowed for a greater understanding of the similar characteristics possessed by these valuable customers.

Methodology/Results

To determine significant insights to pursue, descriptive statistics were used to compare mean level of satisfaction and net promoter scores of redeeming and non-redeeming customers:

<u>Descriptive Statistics Means</u>					
	Sat_Program	Sat_FastFood	Sat_Petrol	Sat_Grocery	NetPromoter
Redeeming	7.93	8.54	8.21	6.60	8.00
Non-redeeming	7.10	6.87	8.05	6.80	5.44

This suggests that a higher NPS of 8 exists for redeeming customers versus 5.44 for non-redeeming customers. Since NPS is amongst the defining criteria for a valuable customer, this implies that redeeming customers add more value than non-redeeming.

Recency Frequency Monetary Value Analysis

An RFM analysis was conducted to further understand any similarities and differences between redeeming and non-redeeming customers to reveal the purchasing behaviour of the most valuable customers. The data was categorised into recency of latest purchase, frequency of purchases since initial purchase and the amount spent since the initial purchase.

The customers were divided into ‘redeemed’ and ‘not redeemed’, showing that out of 1,995 customers, only 393 had redeemed (Appendix 2.1). Recency was determined by calculating the time since each customer made their last purchase, Frequency was found via the number of times each customer completed a purchase in 2015 and the Monetary value was calculated using the total sales amount for each customer. From this it was discovered that non-redeeming customers had a higher mean sales amount of \$26.58 compared to redeeming customers at \$24.

To conduct this analysis, an RFM scale of 1-3 (lowest to highest) was used for ‘redeeming’ and ‘non-redeeming’ customers. The scores were calculated by dividing the range for each

metric into 3 clusters of which a 1, 2 or 3 was applied to. For the ‘redeeming’ category with a range of 1-283, a score of 1 was given for 1-94, 2 for 95-188 and 3 for 189-283.

<u>RFM Analysis Mean Scores</u>				
	Recency	Frequency	Monetary	RFM
Redeeming	2.02	3.00	1	6
Non-redeeming	2.05	1.11	1	4

Whilst the maximum possible RFM score is 9, redeeming customers average score was 6 which was higher than non-redeeming customers at a score of 4 indicating that customers who redeem points add more value to FGP than those who do not. With non-redeeming customers being below average in this score, it suggests that Jennifer could focus on this area by introducing promotions to incentivise point redemptions or targeting marketing efforts at non-redeeming customers in order to increase this score and improve the value they add.

Further descriptive statistics based on home city, race and redeem firm were analysed on the 393 redeeming customers who are currently the more ‘valuable’ customer segment in order to further understand the similarities and identify any trends that FGP could capitalise on for more effective marketing strategies. 101 redeeming customers resided in CITY A and 109 in City G (Appendix 2.2), suggesting that these are major cities and should be geographical areas for FGP to focus on. A significant 263 of the redeemed customers were of race 1, followed by 98 of race 2 and 32 labelled Other (Appendix 2.3). Of all 393 redeeming customers, zero customers redeemed at Grocery Stores whilst a majority of 311 redeemed points from Fast Food, followed by 82 from Petrol firms. Of the 311 Fast Food redeeming customers, 108 lived in City A and 218 were of Race 1.

Predictions & Recommendations

This analysis implies that there are many similarities between redeeming customers, with the most valuable being of race 1, living in City A or G and redeeming from Fast Food and Petrol firms. Thus, these areas should be of focus for Jennifer when planning marketing efforts or expansion strategies for the growth of the loyalty program.

Limitations

Results may not be an accurate representation of the subset due to the significant difference in the number of customers that redeem versus the 1,602 that did not redeem.

Research Question 4

What factors contribute to customer churn and retention levels, and how does this inform FGP's management of customers?

Overview

Analysing customer churn is key to understanding the performance of FGP Loyalty Program. Customer churn is defined by the percentage reduction in active customers each year. In this dataset, only 75.13% of active customers in 2015 were still active in 2016, indicating a 24.87% churn rate. In efforts to maximise customer value and retain a robust customer base, statistical/quantitative analysis into the factors which drive customer churn is required.

Methodology

From the full dataset inclusive of all active customers in 2015, a binary logistic regression was performed with Act_16 as the dependent variable to facilitate analysis of the relationship between retention and other factors. A selection of independent variables indicative of a range of demographic and psychographic characteristics of FGP's customer base allowed for informative insights into the significance of different contributing factors, ranging from customer satisfaction across each of the three merchants (Sat_Petrol, Sat_Grocery and Sat_FastFood) to other factors such as car and credit card ownership (Car, CCard). The use of this analytical method aligns with the categorical and binary nature of Act_16 as a variable, with the results output containing three measures of success - goodness of fit through McFadden's R², significance and impact of model coefficients and predictive accuracy.

Results

Binary Logistic Regression Model

$$\log_e\left(\frac{p}{1-p}\right) = -8.31487 + 0.70825\text{Sat_Petrol} + 0.37710\text{Sat_FastFood} + 0.17298\text{NetPromoter} + 0.28425\text{Car} + 0.43337\text{CCard}.$$

R² and coefficients

Overall, the model achieves a McFadden's R² score of 0.1926 and a predictive accuracy of 88.47%. Since an ideal McFadden R² score lies between 0.2 and 0.4, the first score indicates that the model is moderately strong. Furthermore, the high predictive score implies that the combination of selected variables explains most variation in retention rate. This makes the

model suitable for use. The table below displays coefficient figures corresponding to each variable included in the model.

	Intercept	Sat_Petrol	Sat_FastFood	NetPromoter	Car	CCard
Coefficients	-8.31784	0.70825	0.37710	0.17298	0.28425	0.43337

From first glance, all independent variables (excluding the intercept) have positive correlations with Act_16. This means that all variables increase the probability that a customer will remain active in 2016.

As shown in Appendix 3.1, the probability variables Sat_Petrol, Sat_FastFood, NetPromoter, and CCard have an insignificant relationship with retention is extremely low. However, a weak relationship was identified between retention rate and Car.

Predictions & Recommendations

To further assess the output, calculations of predictive accuracy can be conducted to estimate retention probability following the principle below:

$$P(\text{retention}) = 1 - P(\text{churn})$$

$$P(\text{churn}) = \frac{1}{1 + e^{\log_e\left(\frac{p}{1-p}\right)}}$$

Probabilities of churn and retention were calculated between two group types. The first group consisted of car and credit owners, who are highly satisfied with petrol and fast food merchants, and have a high NPS score. The second group was the inverse of the first group. As evident below, those who fall in the indicative customer segment had 93.4% probability of retention while those with the inverse had an overwhelming 99.7% of churn.

Exhibit 4.1

Sat_Petrol	Sat_FastFood	NetPromoter	Ccard	Car	Probability of retention	Probability of churn
8	8	9	1	1	0.933539159	0.066460841
2	2	2	0	0	0.003023808	0.996976192

Moving forward, the recommendation is to maximise customer satisfaction scores in petrol and fast food sectors. Within this subset of customers, customers with both cards only should be targeted. This is because Act_16 has a stronger relationship with credit card owners, then

car owners. Finally, it is recommended to optimise NPS, higher NPS is associated with a higher retention rate, as shown above in Exhibit 4.1.

Limitations

The model has a low McFadden's R^2 score, and the model suffers from omitted variable bias. Through a closer examination of the variables, more variables could be included in the model such as service ratings and income. Finally, a binary regression model is made under the assumption that there was a straight line relationship between all variables and dependent variables. However, this assumption might not be true for the given dataset.

Recommendations

Based on the previous data analysis, several recommendations would be made from FGP program management and business expansion perspectives.

1. Allocate more resources to target City A and G

To enhance program resource efficiency, Jennifer should allocate limited resources to the most profitable segments. Given the Q3 analysis model result, City A and G's redeeming customers have a higher possibility to redeem the FGP program points (see Appendix 3.1). Furthermore, Q3 also identified the positive relationship between customers' RFM value with the frequencies of redeeming points. The frequencies of redeeming FGP points indicate customers' engagement with the program, considering the varied satisfaction mean score between redeeming customers with non-redeeming customers in the Q3 model. Therefore, it would be ideal to increase the investment budget in the City A and G region. Jennifer should consider expanding the FGP program in 2 cities, by investing more budget in marketing campaigns and establishing more store outlets. Also, Jennifer should target Race 1 as the FGP program's primary customers group in City A and G. According to Q3's analysis, 67% of redeeming customers could be identified as Race 1. By targeting Race 1 as a market penetration segment, Jennifer would be able to establish an efficient market expansion strategy with less investment resources.

2. Concrete marketing efforts towards improving the satisfaction of customers who own a credit card

Through the binary logistic model, Q4 identifies the positive relationship between the satisfaction rate of the independent variable “customer owns a credit card” and NPS score. Customer satisfaction and NPS are more likely to have greater scores if the customer owns a credit card. To further support the point "Customers who have higher satisfaction and an NPS score are more valuable", the calculation of predictive accuracy was conducted in Q4. As the results in both Q1 & Q4 suggest, the credit card customer segments have greater retention rates and are more loyal to the FGP program. It indicates customers with this demographic characteristic would be more valuable (loyal) to the FGP program, in comparison to other segments that tend to have lower satisfaction scores and lower retention rates. Jennifer should consider this customer as the FGP program's alternate target customer group.

Based on this objective, Jennifer would conduct a marketing campaign that highlights using credit cards for refilling, dining, or shopping would receive extra redemption points for FGP program users. Jennifer can leverage customers who have credit cards by forming partnerships with credit card companies such as MasterCard or American Express. These credit card companies can also benefit from the partnership through customer acquisition, which would help the company increase market share and further suppress competitors, especially in the oligopoly credit card industry. Through the partnership, Jennifer would be able to implement promotions such as a 10% discount rate when retailers use the selected credit cards. These benefits will incentivize customers to participate in the purchase and redemption process, which will further increase the frequency and amount of each purchase. This marketing promotion intends to maximise the FGP program's profitability, given that most consumers own a credit card.

3. Promote points redemption to drive engagement, particularly targeting grocery customers

In assessing customer engagement, the dataset explores both purchase and redemption records of its active customers. A key recommendation moving forward would be for FGP to more closely analyse redemption data and encourage higher redemption rates across merchants. Beyond earning points as they purchase at fast food, grocery and petrol merchants, records show that only 393 out of the 1995 total unique customers have redeemed points at all, and if so, this has been limited to the fast food and petrol merchants. Right now, less than 20% of customers are redeeming their points, and given the discrepancy between the average net promoter score (NPS) of redeeming and non-redeeming customers (8 and 5.44 respectively),

it is highly advised for FGP to drive an uplift in redemption in order to subsequently raise customer satisfaction. Specifically, points redemption at the grocery merchant is especially worth exploring as there are currently no records of redemption there, while a large portion of customers are indeed earning points for their purchases at the merchant.

Reference List

Berman, B. (2006). Developing an effective customer loyalty program. *California management review*, 49(1), 123-148. [accessed 29 Mar 2022]
<https://journals.sagepub.com/doi/pdf/10.2307/41166374?casa_token=zGLOH0glDycAAAAA:-uQ5R7vCxvVRaf18xUDpWcW0G9EI7n64tY7QW6U-PLSPZVwtSLiUqjVAswF8PzBNLdiNYS_t5Jm3>

Mackintosh, D. (2015). Net promoter scores: Monitoring practice performance. *In Practice*, 37(7), 370-372. [accessed 1 April 2022]
<<https://bvajournals-onlinelibrary-wiley-com.wwwproxy1.library.unsw.edu.au/doi/pdfdirect/10.1136/inp.h2645>>

Manning, H., & Czarnecki, D. (2016). Customer Experience Drives Revenue Growth, 2016. *Business case: The Customer experience ecosystem Playbook*. Forrester Research Inc, 7. [accessed 29 Mar 2022]
<<https://vkconsulting.gr/wp-content/uploads/Forrester-Customer-Experience-Drives-Revenue-Growth-21-June-2016.pdf>>

Reichheld, F. F. (2003). The one number you need to grow. *Harvard business review*, 81(12), 46-55. [accessed 1 April 2022]
<<https://hbr.org/2003/12/the-one-number-you-need-to-grow>>

Appendices

Appendix 1.1: Multiple Linear Regression Model Output

```
Call:
lm(formula = NetPromoter ~ factor(Gender_F) + factor(Race) +
    factor(OwnCar) + factor(OwnCreditCard), data = customer)

Residuals:
    Min       1Q   Median       3Q      Max
-5.7381 -1.7381 -0.1752  1.8248  5.5986

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)      5.2885     0.1936  27.313 < 2e-16 ***
factor(Gender_F)1  1.8317     0.1122  16.328 < 2e-16 ***
factor(Race)RACE1 -0.1133     0.1936  -0.585  0.55861
factor(Race)RACE2 -0.2680     0.1996  -1.343  0.17955
factor(OwnCar)Y    -0.6191     0.1135  -5.456 5.47e-08 ***
factor(OwnCreditCard)Y 0.3503     0.1138   3.077 0.00212 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.468 on 1989 degrees of freedom
Multiple R-squared:  0.1419,    Adjusted R-squared:  0.1397
F-statistic: 65.77 on 5 and 1989 DF,  p-value: < 2.2e-16
```

Appendix 1.2: Correlation Test (Multicollinearity)

```
> cor(customers[,c(16, 19:20)])
```

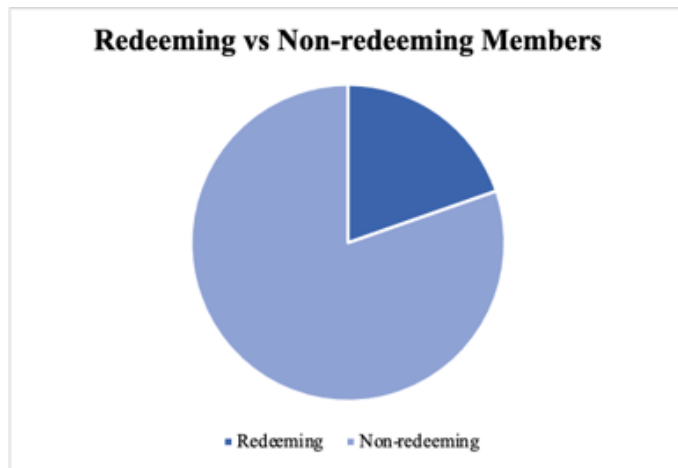
	Gender_F	Car	CCard
Gender_F	1.00000000	-0.1246429	-0.09931913
Car	-0.12464294	1.00000000	0.14597692
CCard	-0.09931913	0.1459769	1.00000000

Appendix 1.3: VIF

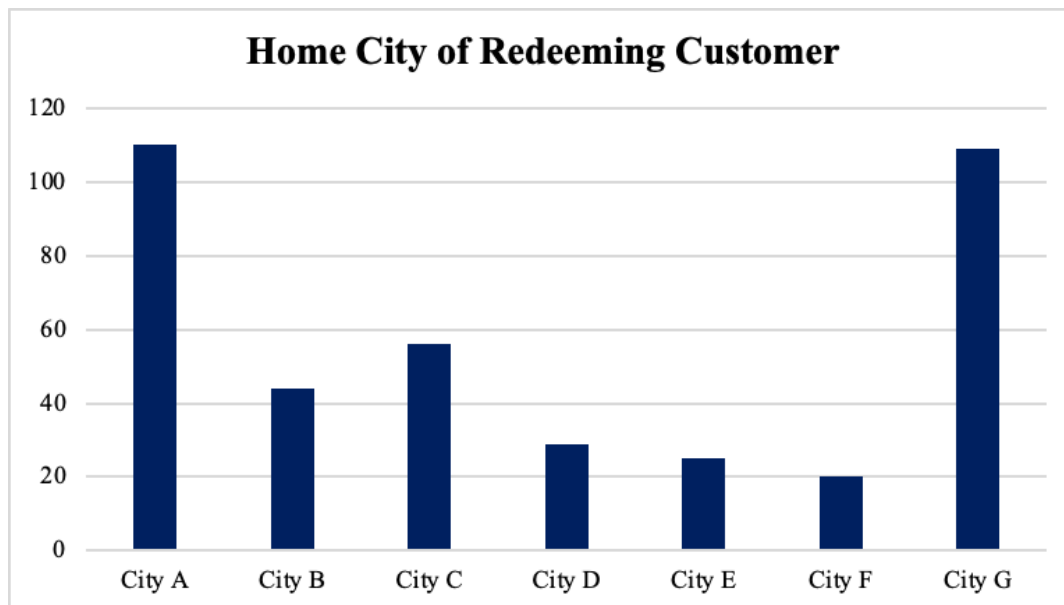
```
vif(fit2)
```

	Gender_F	as.factor(OwnCar)	as.factor(OwnCreditCard)
	1.022767	1.034727	1.028800

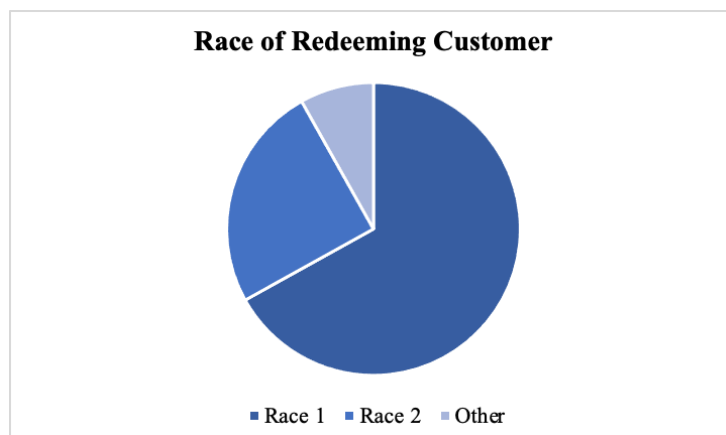
Appendix 2.1: Redeeming vs Non-redeeming Members Pie Chart



Appendix 2.2: Redeeming Customer Home City Bar Chart



Appendix 2.3: Redeeming Customer Race Pie Chart



Appendix 3.1: Predictive model for assessing customer retention rate

Variables	Coefficients	Standard Error	Z value	Probability coefficient is insignificant	Significance indicator
(Intercept)	-8.37381	0.66806	-12.534	< 2e-16	***
Sat_Petrol	0.70331	0.06517	10.792	< 2e-16	***
Sat_Grocery	0.01348	0.04862	0.277	0.781575	
Sat_FastFood	0.37922	0.04664	8.13	4.29E-16	***
NetPromoter	0.17152	0.02733	6.276	3.48E-10	***
CCard	0.43274	0.1208	3.582	0.000341	***
Car	0.28748	0.12353	2.327	0.019949	*