Influence of Socio-Demographic Determinants on Credit Cards Default Risk in Commercial Banks in Kenya

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Abstract: ***Commercial banks play a major role in economic growth and development through provision of credit. To achieve this, financial payment instruments such as credit cards are increasingly accepted and used in consumer credit market worldwide. However, credit card performance surveys shows that credit default is a major risk faced by commercial banks in Kenya. The risk attributable to credit card default leads to high effective borrowing rates and therefore increased cost of doing business. A study on influence of determinants of credit cards default is therefore necessary for mitigation against this risk and for the safety and soundness of the banking sector. This study therefore sought to investigate the influence of socio-demographic determinants of credit card default in commercial banks in Kenya. The study used secondary data containing socio-demographic details of credit card holders obtained from bank records. The data set was used to identify risk factors associated with a credit cardholder that had higher predictive power of credit card default. These risk factors were gender, marital status, age and educational level. Independent samples t-tests and Chi-Square tests were carried out to identify significant explanatory variables for default in credit cards. A Logistic regression model was then fitted to determine factors with high predictive power of default in credit card loans. Results show that age is a risk factor in credit cards default with younger cardholders having higher olds of defaulting compared to older cardholders. Male cardholders have equal likelihood of defaulting as female cardholders. Education level was found to be statistically insignificant to credit card default. The study therefore recommends creation of more awareness and sensitization to young cardholders on optimal and best industry practice in credit card usage.***

Keywords: Credit card, credit card default, consumer credit market, logistic model and logit transformation

1. Introduction

Globally, the development of credit card is probably the most significant phenomenon in the banking industry (Simiyu, Mumanyi, Naibei and Odondo ,2012). Since the first credit card was first issued in 1730. there has been a tremendous increase in use of plastic cards in the purchase of goods and services as corporate and individual consumers seek to avoid the inconvenience and risks of cash-based transactions, including fraud, robbery, and violence.

However, consumer debt is two-faced. On the one hand, the use of credit facilities in purchases can be mutually beneficial to both the buyer and the seller. For the retailer, it helps to promote sales, as buying on credit constitutes an enhancement of the buyer's purchasing power, thereby increasing demand, turnover, and, consequently, profitability (Olukunle and Simangaliso, 2012; Federal Reserve Bank of Chicago, 1997; Beal and McKeown, 2006; Leonard, 2008; Einzig, 1956). From the consumer perspective, availability of credit increases the purchase convenience and raises the level of consumption and welfare of the buyer, as he is able to buy and consume now at a level only feasible at a future higher level of income (Olukunle and Simangaliso, 2012; Chang and Hanna, 1992; Bernthal *et al.*, 2005; Kilborn, 2005).

At the national economic level, credit purchases can accelerate the pace of growth and development. First, the increase in spending has the effect of increasing the multiplier effect on income in addition to encouraging aggregate investment (Olukunle and Simangaliso, 2012). Increased income raises the level of expenditure further thus setting in motion a virtuous cycle of growth in consumption, investment, income, and development (Olukunle and Simangaliso, 2012). Debt also helps to sustain such growth by making it possible for consumers to resist the downward adjustment of their consumption during a fall of their income (Lee, 1964).

On the other hand, default in credit negatively affects the overall safety and soundness of the banking system and impacts negatively on the general performance of an economy (CBK, 2014). Credit default leads to high borrowing and lending rates. The high lending rates restrict access to credit and generally increase the cost of doing business (FSD-Kenya, 2013). Lending institutions respond to credit risk through credit rationing, higher interest rate, and shorter loan maturity. These in turn result in an inefficient allocation of credit, less efficient banking industry, slower economic growth and development (Muthoni, 2014; Wafula and Karumba, 2012; CBK, 2014).

In Kenya the need for consumer credit and use of credit cards as a financial payment instrument is projected to increase in future. The increased adoption of credit cards as major drivers of financial transactions and therefore economic growth requires in-depth understanding of the factors that may contribute to their credit default(Wafula & Karumba, 2012).

The New Basel Capital Accord (known as Basel II) is the latest initiative by the Bank of International Settlement (BIS)

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to regulate the global financial services industry. The key objective of Basel II is to enhance the safety and soundness of the banking system through vastly improved risk and capital management, tailored to each bank and banking group (Bolton, 2009). A possible mitigation to minimize credit risk and default is for individual banks to develop an accurate credit scoring model with high ability to discriminate between credit applicants with higher probabilities of default and those with lower probabilities of default (Marjo, 2010). Calibrated and validated correctly such a scoring model will prevent credit lenders from granting loan to "bad" customers and to avoid giving false rejection to "good" customers. The loans of customers with higher probabilities of default could then be priced higher than their counterparts with lower probabilities of default.

Consumer debt levels and non-business bankruptcy trends indicate that consumers are increasingly getting over-committed and overly-dependent on credit to supplement their consumption patterns (Olukunle and Simangaliso, 2012). Among the Organization for Economic Cooperation and Development (OECD) countries, the ratio of total household debt to income is reported to have risen from 80% or lower two decades ago, to at least 120% in Canada and Germany, more than 130% in Japan, and 180% in the Netherlands (Worthington, 2006). Most recent studies indicated that consumer over-indebtedness continued to increase at an alarming rate (Beder, 2009; Crotty, 2009). The high consumer debt levels create grounds for default.

Theoretical literature indicates that socio-demographic characteristics of a credit card holder can influence credit card default. For instance, Abdul-Muhmin and Umar (2007) finds that the tendency to revolve in credit cards is higher among males than females. Arminger *et al.*, (1997); Kocenda and Vojtek, (2009); Dunn and Kim (1999) argue that gender is a risk factor in credit card loans and that females default less frequently possibly because they are more risk averse. Agarwak et al (2009) indicates. This study is motivated by the default aspect of consumer credit. In this paper, we focus on socio-demographic attributes of a credit cardholder that are statistically significant with respect to credit cards default and draw inferences on their marginal effects on credit card default.

2. Research Design

The study adopted both correlational and descriptive survey designs. Descriptive design was used to generate explanatory variables of credit card default. Correlational design was used to establish significant relationships between socio-demographic characteristics of a cardholder and credit card default.

2.1 Target population, sampling design and data collection technique

The target population for the study were all the 18 commercial banks licensed by the Central Bank of Kenya (CBK) to issue credit cards. Eight banks however were excluded from the sampling frame as their requirements for credit cards application lacked more than 50% of the explanatory variables of interest for credit cards default. The remaining 10 banks in the sampling were stratified into three stratum; banks with international affiliation, banks in which government of Kenya has majority shareholding and private or family owned banks. A random sample of size 95 was generated and used for analysis. The entire data for the study were secondary data containing socio-demographic details of cardholders obtained from bank records.

2.2 Empirical model

In this study we used the logistic model that caters for categorical variables in a way roughly analogous to that in which ordinary linear regression model is used with continuous variables.

2.2.1 The logistic model

The logistic model is most appropriate for dichotomous data when the response variable can only take one out of two possible outcomes generally representing presence or absence of an attribute of interest. For credit card account holders, the possible outcomes are either payment or default in payment. According to Adem, Gichuhi and Otieno (2012), the concept of logistic model is based on Bernoulli and Binomial distributions which can be summarized as follows:

2.2.2 The Bernoulli Distribution

For a binary response variable y_i assuming only two values which for purpose of this study were y_i = 1 if the i[th] credit card holder defaulted and y_i = 0 if the account holder paid, y_i is a realization of a random variable Y_i that can take the values 1 and 0 with probabilities π_i and 1-π_i, respectively. The distribution Y_i is Bernoulli distribution with parameters π_i which can be written as

$$P\{Y_i = y_i\} = \pi_i^{y_i} (1-\pi_i)^{1-y_i} \qquad \text{.........(3.1)}$$

for y_i = 0,1.

The probability distribution function (pdf) of Y_i is then given by

$$P\{Y_i = y_i\} = \binom{n_i}{y_i} \pi_i^{y_i} (1-\pi_i)^{n_i - y_i} \qquad \text{...... (3.2)}$$

for y_i = 0,1,.....,n_i where $\pi_i^{y_i}(1-\pi_i)^{n_i-y_i}$ is the probability of obtaining y_i successes and $n_i - y_i$ failures. The mean and variance of Y_i is given by $u_i = n_i\pi_i$ and $\sigma_i^2 = n_i\pi_i(1-\pi_i)$ where n_i denotes the number of card holders in group *i* classified according to the variables of interest such as gender, age, marital status etc. y_i denotes the number of defaulters in group i.

2.2.3 The logistic function

The logistic function describes the mathematical form on which the logistic model is based. The logistic function f(z) is given by

$$f(z) = \frac{1}{1+e^{-z}} \qquad \text{.....................................(3.3)}$$

Where

$Z = \alpha + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \ldots\ldots + \beta_kX_k$

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x_1, x_2, x_3, ...x_k are a vector of observed covariates (independent variables) and α, β_1, β_2, β_3, ..., β_k are a vector of regression coefficients of the independent variables to be determined.

2.2.4 The Logistic Regression Model

Consider k independent observations y_1 , y_2 , ...y_k and where the i-th observation is a realization of a random variable Y_i. Assuming $Y_i \sim B(1, \pi_i)$ the logit of the probability π_i is the linear function of

$$\operatorname{logit}(\pi_i) = X'\beta \quad \text{..............................(3.7)}$$

where X_i are a vector of covariates and β_i are a vector of regression coefficients.

From equation 3.7 the odds for the ith unit are given by

$$\frac{\pi_i}{1-\pi_i} = \exp(X'_i\beta) \quad \text{........................(3.8)}$$

Solving for π_i in equation 3.8 gives

$$\pi_i = \frac{\exp(x'_i\beta)}{1+\exp(x'_i\beta)} \quad \text{........................(3.9)}$$

This can be re-written as

$$f(y) = \frac{e^z}{1+e^z} \quad \text{..............................(3.10)}$$

Where z is the logit of y defined as

$$z = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots \ldots \ldots + \beta_k x_k \quad \text{....(3.11)}$$

The socio-demographic variables of interest in our study were gender, age, marital status and education level of a cardholder.

Incorporating these variables in the logistic regression model defined above gave the general model for the study as

$$\pi_i = f(ag, ms, gd, ed) \quad \text{...................(3.12)}$$

Where

π_i = probability of default in credit card by the i-th cardholder

ag = socio-demographic factors, age

ms = socio-demographic factors, marital status

gd = socio-demographic factors, gender

ed = socio-demographic factors, education level

From equations 3.11 and 3.12

$$z = \alpha + \beta_1 ag + \beta_2 ms + \beta_3 gd + \beta_4 ed \quad \text{...............(3.13)}$$

2.5 Data Analysis

Both descriptive and inferential data analysis were carried out. Chi-square testing for independence of variables was carried out to identify if there were statistically significant associations between categorical variables (gender, marital status and education level) and default in credit cards. For the continuous variable ,age, independent samples t-tests were carried out to obtain the significance in the difference of means for the defaulted and non-defaulted groups under statistical investigation. To draw inferences about the influence on credit cards default by each variable of interest, a logistic regression model was fitted and run in SPSS 20. Marginal effects analysis for the effect of a unit change in the independent variable on credit card default was carried out using the odds ratio.

3. Findings

3.1 Influence of Gender on credit card default

From the results female cardholders had a lower default rate of 13.7% compared with male cardholders whose default rate was 27.4%. Also from the study results, 64.2% of sampled credit cardholders were male. These results are consistent with findings by Abdul-Muhmin and Umar (2007) that the tendency to revolve in credit cards is higher among males.

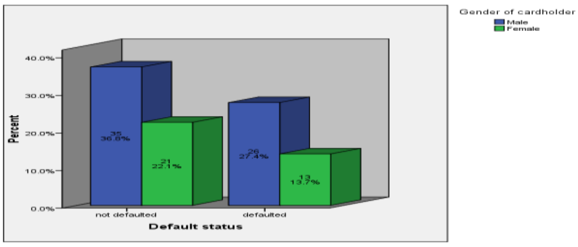

Figure 3.1: Default status by gender of credit cardholder

Despite the observed relatively higher default rate among male cardholders, the Chi-square results showed that there was no statistically significant relationship between gender and credit card default rate ($\chi 2 = 0.174$, $p = 0.677$, $\alpha = 0.05$) which implied that gender, taken alone did not influence default in credit card. These results vary with the findings of Arminger et al., (1997), Kocenda and Vojtek, (2009); Dunn and Kim (1999) that gender is a risk factor in loans and that females default less frequently possibly because they are more risk averse.

3.2 Influence of Age on credit card default

From group statistics of age of cardholders, the study results shows that the mean age of cardholders who defaulted was 44.18 years which was lower than that of non-defaulters which was 52.14 years.

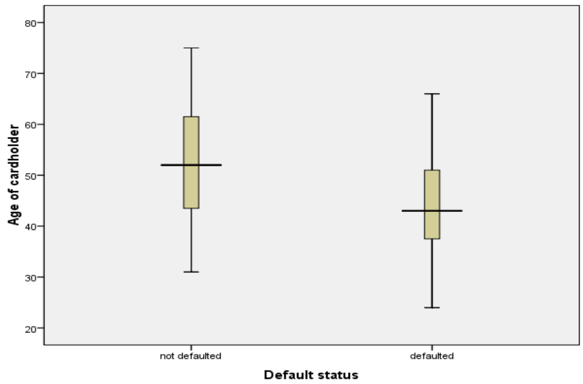

Figure 3.2: Default status by Age of cardholder

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The Levene's test of equivalence of variance (p = 0.854, α = 0.05) showed that the variance of the two groups, defaulted and non-defaulted are the same. However, the t-test for equality of means (p = 0.000, α = 0.05) indicated that there was statistically significant relationship at 5% level of significance between age of cardholder and credit card default. In particular, young cardholders had a higher default rate compared to older cardholders. These results are consistent with literature, Dunn and Kim (1999); Arminger et al. (1997) as well as Agarwal et al. (2009) that older borrowers are more risk averse and will therefore be less likely to default.

3.3 Influence of marital status on credit card default

Descriptively the study results show that there was lower default rate of 39.5% among married cardholders compared to cardholders in other marital status whose default rate was 47.4%. However, Chi-square testing shows there was no significant relationship between marital status and credit card default rate ($\chi2$ = 0.391, p = 0.531, α = 0.05) which implied that default in credit card was independent of marital status of the cardholder.

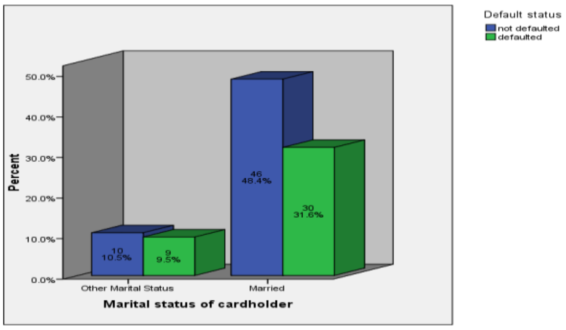

Figure 3.3: Default status by marital status of cardholder

This study result disagrees with the study by Agarwak *et al* (2009) which indicated that marital status can predict default rate on the basis that marital status should be seen to be a sign of responsibility, reliability or maturity of a borrower.

3.4 Influence of Education level on credit card default

On education level, the results showed that 16.8% of cardholders with university level education defaulted compared with 24.2% for cardholders with education level lower than university. These results are presented in Figure 4.4. Consistent with the findings of Steenackers and Goovaerts (1989) that customers who are highly-educated professionals were less likely to default on their credit cards, the current study similarly observed, albeit descriptively, a lower frequency in default for cardholders with university education relative to cardholders with lower than university education.

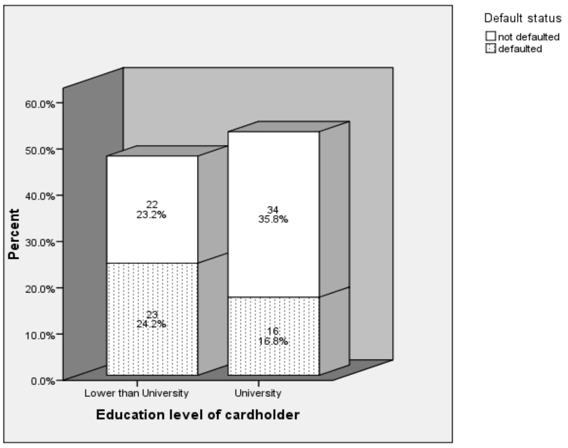

Figure 3.4: Default status by Education level of cardholder

However, Chi-Square tests results ($\chi2$ = 3.575, p = 0.059, α = 0.05) showed that education level of a cardholder is independent of credit card default.

4. Conclusions

A number of socio-demographic factors influence credit cards default. Among them, age has the highest influence and is statistically significant in credit cards default. While gender, marital status and education level also affect credit cards default, their influence is statistically insignificant. The research further shows that each of the socio-demographic factors have strategic significance to credit cards issuers and would be useful in mitigating credit cards default.

5. Future Scope

The current study used logistic regression to investigate the influence of socio-demographic, behavioral and economic determinants on credit cards default in commercial banks in Kenya. The focus of this study was to obtain a set of explanatory variables with highest predictive probabilities of default in credit cards as loan assets. As per the Basel II framework and requirements, future studies may address other components of expected loss for credit cards which includes; Loss Given Default (LGD), Exposure at Default (EAD) and Maturity of Exposures (M). Future studies could also explore use of other statistical techniques such multiple discriminant analysis model, linear probability model or the probit model.

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