# A Gendered Look at Savings Behavior among Nigerian Microsavers

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## Abstract

Well-designed financial products improve the overall financial health of users. The design of products is particularly important for low-income customers, for whom product design drives behavior. In this paper, we offer insights on low-income customers' savings behavior and on how they use their savings accounts. More specifically, we focus on detecting and measuring the effects of a set of explanatory variables on transaction amount. To do so, we use quantile regression (QR) and apply it to a novel dataset collected from a financial institution in Nigeria. The data show individual transactions made using the account over time, along with additional socioeconomic information on each customer. Using these data, we specify a model that incorporates customer age, account age, location, transaction type, gender, and seasonality effects, evaluating their correlation with transaction size. With the QR model, we are able to study the effect of the explanatory variables within each quantile of transaction amount instead of just showing trends on average. This is the first study to examine transaction size among low-income customers through a gender lens using QR. All of the variables incorporated in this model have a significant effect on transaction size. However, among all of the explanatory variables, the season in which a customer places a transaction (seasonality effect) has the largest impact on predicting transaction amounts.

***Keywords:*** *Financial Inclusion, Behavioral Finance, Savings, Quantile Regression, Nigeria*

## 1. Introduction

Savings mechanisms are widely considered to be effective strategies for building financial health. Savings support households in bearing difficult economic burdens such as unemployment or consumption shocks (Hubbard, Skinner, & Zeldes, 1995). Relative to individuals with middle and upper-middle income, low-income people have less stable employment and earnings and are more prone to experiencing income volatility. For low-income people, savings play a vital role (Barr & Blank, 2008; Sherraden & McBride, 2010), but the ability of low-income people to save is impacted by a number of factors.

Savings behavior is a broad topic, and each of its components is a research area of its own. Although savings behavior has received a significant amount of attention from researchers, there is a need for further studies and investigations. Detecting and measuring the effects of various factors impacting the amount a customer deposits or withdraws (transaction amount), especially among low-income individuals, is one area that requires more research. To address this issue and attempt to close this gap in the literature, this study focuses on the relationship between socioeconomic, demographic, and environmental factors and our variable of interest, which is transaction amount.

Most studies of savings behavior report their findings in terms of the effect of some explanatory factors on the variable of interest. Although insightful, such findings suffer from a problem of generalizability, because mean is not always an appropriate statistic for describing a distribution. In the following sections, we will explain in more detail why this holds true in many cases. For this study, we suggest quantile regression as the statistical model of use to address the problem of generalizability. The quantile regression method helps us to study the effects of the aforementioned factors on different quantiles of our variable of interest.

In this paper, we present new empirical evidence based on confidential de-identified data collected from a Nigerian FSP. This empirical evidence introduces a unique opportunity to investigate the effects of socioeconomic, demographic, and environmental factors and to relate them to transaction amount. Detecting and measuring the effect of factors influencing savings deposit and withdrawal amounts is particularly useful for product designers at financial institutions.

## 2. Literature Review

To detect variables that have an influence on savings behavior and more specifically on transaction amount, we did a deep dive into the literature. This gave us useful information about which explanatory variables have already been studied in the literature and showed us where the gaps are. Based on these findings, we chose the appropriate explanatory variables for our modeling task. Our literature review also provided good insights on influential factors affecting savings behavior. We will share the relevant insights here.

The literature on savings behavior reveals the diversity of researchers and research study approaches. An in-depth understanding of factors affecting savings behavior at the individual level among low-income people helps policymakers make informed decisions (Stuart &

Sherman, 2015). A wide variety of factors affect savings behavior, and while some of these factors are well studied in the literature, others require more investigation. To construct a framework for studying these factors and their effect on savings behavior, we divide the factors into three categories: macroeconomic and environmental, microeconomic, and institutional.

*Macroeconomic and environmental factors:* The macroeconomic factors driving savings behavior are many, but the most cited factors in the literature are negative interest rate, inflation, and natural disasters. A negative interest rate penalizes individuals who postpone their consumption. Those affected by a negative interest rate will theoretically prefer to buy goods now instead of saving their income (Aizenman, Cheung, & Ito, 2019). While the common assumption is that a high interest rate lowers private savings, Nabar (2011) studied China during the 2000s, when the country saw a decline in interest rates while household and individual savings grew. Inflation decreases purchasing power, lowers the standard of living, raises the interest rates, and erodes the value of earnings on savings accounts. Inflation adversely affects savings and is one of the main barriers for individuals who try to save for their future (O'Neill, 2015). Among the environmental factors affecting savings behavior, natural disasters play an important role. In general, natural disasters have a negative effect on economic growth. Surprisingly, the current empirical literature does not provide enough information on the channels through which natural disasters might affect economic growth and economic empowerment. Natural disasters can also have a significant effect on people’s financial behavior. Berlemann, Steinhardt, & Tutt (2015) reported that natural disasters can affect individual savings behavior due to medium-term or even long-term economic growth effects on the financial system. Apart from a few studies in this area, the impact of natural disasters on financial behavior and more specifically on savings behavior is not yet well studied.

*Microeconomic factors:* These refer to the more personal factors that impact individuals’ financial behavior. Modigliani & Brumberg (1954) argue that savings are determined by the individual life cycle. This approach is based on the life cycle hypothesis, which assumes that people attempt to adjust their consumption in response to life needs. When an individual has a low income, he/she borrows money, which usually occurs early in the life cycle stages. As people get older, they are able to save, and in later years, they spend down this balance. This hypothesis assumes that consumption is a function of long-term income, which is determined by a person’s status in the life cycle and aging process (Modigliani & Brumberg, 1954). Another individual-level factor that affects savings is financial literacy. People’s ability to save has a positive correlation to their level of understanding of financial concepts. Studies show that financial education programs can help improve saving and financial decision-making (Lusardi, A., 2008). Although low-income and poor people may not have enough information to make sound financial decisions, those who have social support networks to encourage and facilitate their savings habit tend to save more (Sherraden, 1991).

Hogarth & Anguelov (2003) studied the potential effects of goal setting on savings behavior. They found that helping people to identify a goal and encouraging them to save to reach that goal increases the probability that they will become savers. In other words, the shift from having no reason or goal for saving to having a clear reason and a goal increases the likelihood of developing a savings habit.

Whitaker, Bokemeiner, & Loveridge (2016) studied the effect of gender on savings behavior. They found that gender is a primary variable when explaining savings behavior. For example, Yuh & Hanna (2010) found that single female households are less likely to save compared to single male households. Women on average have lower levels of income and wealth and have less money to save. Women are also more risk averse and tend to make more conservative investment decisions (Fisher, 2015).

The last factor under this category is the effect of health insurance access on savings. Hogarth & Anguelov (2003) studied the effect that access to health insurance has on savings. They found that individuals who have health insurance were more likely to save compared to similar families without health insurance (Stuart & Sherman, 2015).

*Institutional factors:* According to the institutional theory of savings behavior, institutions play an important role in shaping their consumers' financial behavior (Beverly & Sherraden, 1999; Han & Sherraden, 2009). Karlan, Ratan, & Zinman (2014) found that transaction costs, lack of trust, and regulatory barriers could all adversely affect individuals' savings behavior. Other researchers cite additional factors such as access, security, incentives, information, facilitation, and expectations (Beverly, McBride, & Schreiner, 2003; Schreiner & Sherraden, 2006; Sherraden & Barr, 2005). Access refers to the level to which an individual can communicate with an institution. Studies show that having access to financial institutions has a positive correlation with savings balances. Incentive refers to financial and nonfinancial institutional factors that make savings more attractive (Sherraden & McBride, 2010). Facilitation is the extent to which a potential saver can benefit from all of the plans designed to make savings easy and to make it difficult to choose existing consumption at the expense of future consumption. Automatic payroll deduction is a common example of facilitation (Beverly & Sherraden, 1999; Sherraden & McBride, 2010). Given the right institutional context, individuals are more likely to save compared to those who lack facilitation. All of the factors explained above are shown in Table 1.

**Table 1. Influential Factors on Savings Behavior**

| Factor | Effects on Savings | I |
|---|---|---|
| Macroeconomic Factors | | |
| Higher inflation rate | Negative | O'Neill, 2015 |
| Interest rate | Significant | Aizenman et al., 2019; Nab |
| Financial crisis | Significant | Hendey et al., 2012 |
| Natural disasters | Significant | Berlemann et al., 2015 |
| Armed conflicts and political instability | Negative | Torres et al., 2019 |
| Microeconomic Factors | | |
| Higher level of education | Positive | Yuh & Hanna, 2010 |
| Higher financial literacy | Positive | Lusardi, 2008 |
| Income | Positive | Yuh & Hanna, 2010 |

| | | |
|---|---|---|
| Net worth | Positive | Yuh & Hanna, 2010 |
| House ownership | Positive | Yuh & Hanna, 2010 |
| Having health insurance | Positive | Yuh & Hanna, 2010; Hogar |
| Future income expectations | Positive | Yuh & Hanna, 2010 |
| Having clear reasons to save | Positive | Rha, Montalto, and Hanna, |
| Good credit record | Positive | Rha, Montalto, and Hanna, |
| Social network | Positive | Beverly et al., 2003 |
| Gender | Significant | Whitaker et al., 2013; Whit |
| Gender: Single male vs. single female households | Positive | Yuh et al., 2010 |
| Gender: Men typically have higher levels of income and wealth | Positive | Fisher, 2015 |
| Gender: Men are typically less risk averse, make riskier investments | Positive | Fisher, 2015 |
| Generation | Significant | Dirk et al., 2016 |
| Parental influence | Significant | Dirk et al., 2016 |
| Institutional Factors | | |
| Financial institution and institutional dimensions of savings such as: access, security, incentives, information, and facilitation | Significant | Beverly & Sherraden, 1999 Sherraden & Barr, 2005; Sc Han et al., 2009 |
| Lack of trust in financial institution | Negative | Karlan et al., 2014 |
| Higher transactional costs | Negative | Karlan et al., 2014 |
| Bank account ownership | Positive | Rha, Montalto, and Hanna, |
| | | |

*Factors flagged as "Significant" may have a negative or positive effect on savings based on the situation.

## 3. Problem Statement

Studying customers' financial behavior has different components. In this research, we focus on one aspect of financial behavior—transaction amount—and try to detect the factors that influence it. ("Transaction amount" and "transaction size" are used interchangeably in this paper.)

This research looks at this topic by bringing three perspectives together in a novel approach that:

- Studies this topic from a gender lens perspective to understand how a given set of factors can have a different effect on men's and women's transaction size
- Uses QR
- Studies seasonality effect on transaction size

## 4. Empirical Strategy

We divide our datasets into two groups: transactions placed by women and transactions placed by men. The female dataset contains 279,077 records and the male dataset contains 577,639 records. All of the transactions in both datasets were placed between July 2016 and July 2018. As explained earlier, the outcome variable is transaction amount, reported in Nigerian Naira. The explanatory variables we use in building the statistical model are customer age, location of the customers, transaction type, account age, average number of monthly transactions, and seasonality effect:

- Transaction size: Amount of credit or debit in Nigerian Naira
- Customer age: Age of customer at the time of the transaction
- Location: A binary variable denoting customers living in Lagos/Anambra with “1” and customers living in other parts of the country with “0”
- Transaction type: A binary variable showing deposit (credit) with “1” and withdrawal (debit) with “0”
- Account age: Time difference in months between account opening date and the start of our study (June 2016)
- Average number of monthly transactions: Total number of transactions a customer has placed between July 2016 and July 2018 divided by 25 (number of months between July 2016 and July 2018)
- Seasonality: A binary variable that takes “1” for dry season and “0” for rainy season[1]

Looking into the distribution of transaction amount among women (Figure 1) and men (Figure 2), we see that transaction amount has a right-skewed distribution that makes the mean of transaction amount larger than its median. Since the distribution of transaction amount among both men and women is highly skewed and bimodal, using the mean of transaction amount does not provide a complete understanding of how different factors have effects on transaction amount. Therefore, according to the language used earlier, we cannot generalize any findings that are based on mean.

As a result, QR is a well-suited model to use for the relationship between explanatory variables and the outcome variable: transaction size. Unlike models such as ordinary least squares (OLS) that are based on conditional expectation, QR can explain the effect of explanatory variables on different percentiles of the outcome variable. This model helps us to understand how different quantiles of the conditional distribution of the outcome variable vary with the explanatory variables.

[1] Nigeria has two main seasons: rainy and dry (Hamilton et al., 2019). The length of the rainy season in general decreases as we move from south to north. The rainy season in the south lasts from March to November, while it is shorter in the north, lasting only from May to September (Falola et al., 2019). In addition, during the dry season, the international (for tourism) and rural-urban migration in Nigeria improves the business environment for informal enterprises in cities (The World Bank, 2017). Harvests are taken to market during the dry season. Thus, the dry season may result in higher trade and economic activities in Nigeria.

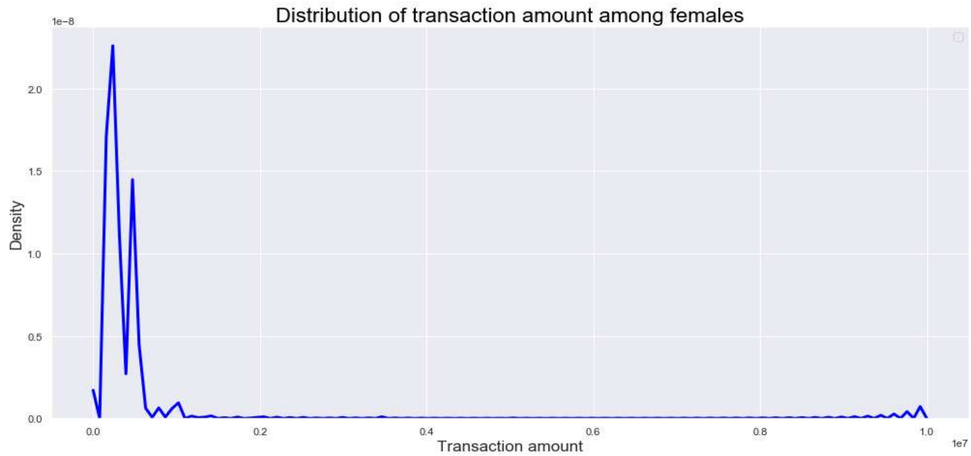


Figure 1. pdf of transaction amount among females


Figure 2. pdf of transaction amount among males

## 5. Mathematical Modeling and Terminology

Ordinary least squares regression (OLS) studies the relationship between a set of explanatory variables (regressors) and the outcome variable using conditional expectation of outcome variable given the regressors. This classic and most-used statistical approach captures the effects at the mean. However, OLS does not provide a complete picture of the relationship between regressors and the outcome variable. It assumes that regression coefficient effects are constant across the population. Here, we consider the fact that in many cases, we are not only interested in the average effects. If the question of interest is depicting the relationship between outcome variable ($Y$) and regressors ($X$s) at different points of the conditional distribution of $Y$, we can no longer use OLS regression. In this situation, QR can capture this conditional distribution at different quantiles. QR estimates the effect of a covariate on the full distribution of the dependent variable and accommodates for the heteroscedasticity. It allows slopes of the regression line to vary across different percentiles of the response variable and offers the flexibility to focus on specific segments. Furthermore, QR can show the differences in the signs (+/-) and magnitude of regression coefficients at different quantiles. Such a change in sign signals important aspects of the relationship between the explanatory and dependent variable (Hohl, 2009). In QR, the distribution of the outcome does not need to be strictly specified with certain parametric assumptions. This property makes QR create robust estimation when compared to OLS. The OLS model is highly sensitive to the existence of outliers. Outliers can lead to a poor fit. Unlike OLS, QR is less sensitive to outliers and can outperform OLS in such cases. All of these features have increased the applications of QR. The QR model is widely accepted and viewed as a critical extension and complement to OLS, specifically when OLS assumptions are violated (Huang, Hanze, Jiaqing, & Mengying, 2017; Baum, 2013; Koenker & Bassett, 1978).

Mathematically, the quantile regression can be expressed as equation 1 (Eq. 1), where $y_i$ denotes the value of the outcome variable at the $p^{th}$ percentile and $x_i$ is the vector of explanatory variables. $Q^p\ (y_i|x_i)$ is the conditional quantile function, $\beta_0$ is the constant, and $\beta_\theta$ is the vector of parameters specific to each percentile. Quantile regression minimizes the sum of the absolute residuals to fit a regression line for $p^{th}$ percentile.

$$Q^p(y_i|x_i) = \beta_0^p + \beta_\theta^p x^i \qquad \text{(Eq. 1)}$$

QR estimator for quantile $q$ minimizes the following objective function (Eq. 2) using simplex method:

$$\mathrm{Q}\ (\mathrm{B_q}) = \sum_{i:yi\geq xi'B}^{N} q|yi - xi'Bq\ | + \sum_{i:yi<xi'B}^{N}(1-q)|yi - xi'Bq| \qquad \text{(Eq. 2 )}$$

## 6. Empirical Results and Discussion

To build the QR model, we use the conditional quantile of the outcome variable at $10^{th}$, $25^{th}$, $50^{th}$ (median), $75^{th}$, and $90^{th}$ quantiles. Using a wide range of quantiles is necessary to understand how the effects of explanatory variables may vary along the conditional distribution of transaction amount. In addition, we build an OLS model using the same set of explanatory variables to have a point of comparison between OLS and QR estimates.

As explained earlier, we divide the dataset into two sub-datasets using customers' gender. Following the same approach, we build two different models, one for male and one for female customers. We could use and build only one model instead, then add gender and its interaction to it. However, the results are easier to read, understand, and interpret from a gender lens perspective if we use two separate models, one for each gender.

Tables 2 and 3 show the output of the model for female customers and male customers. The second column in both tables shows the results derived from fitting an OLS model. Each of these OLS coefficients shows how much increase/decrease we expect to see in the average transaction amount when the corresponding explanatory variable increases by one unit. The other columns show the effect of explanatory variables on each specified quantile of the outcome variable. After this briefing on the tables, we dig into model interpretation.

Customer age is the first explanatory variable shown in both tables. Looking into the second column and assessing the OLS coefficient, we see that on average, both male and female customers tend to make larger transactions as their age increases. For each one-year increase in age, we expect transactions placed by a female customer to get 47.29 NGN larger; controlling for other explanatory variables, the expected increase for her male counterpart would be 94.41 NGN.

Looking into the coefficient of age and its variation among male and female customers at different percentiles of the response variable shows that QR and OLS coefficients are significantly different. By looking into the coefficient of age at *q50* (median), we see that this coefficient is -6.29 for female and 1.19 for male customers. Comparison between values of these two coefficients with OLS coefficients shows that coefficients that are based on mean are much larger compared to those that are based on median. This significant difference denotes that conditional expectation (OLS) cannot provide the complete picture of the relationship between age and transaction size. Coefficients of age at *q90* show that the tendency to make very large transactions goes down as customers get older. This effect is three times larger for female customers compared to male customers. This can be an indication that young male customers are more involved in business activities that generate higher income. However, this statement needs further investigation and requires qualitative research, which is out of the scope of this study.

The second explanatory variable is geographical location. There are 36 states in Nigeria. Our dataset consists of customers coming from all of the states. Some states are hubs for business activities while some have slower businesses. Our partner FSP in this research told us that those customers who live in Lagos or Anambra are expected to have higher business activities. To understand and quantify the relationship between living in a business hub and the transaction amount customers place using their account, we create a binary variable that takes “1” if a customer lives in Lagos or Anambra and takes “0” otherwise. Based on OLS and QR outputs, we see that female and male customers living in Lagos or Anambra tend to place larger transactions on average. Female customers living in Lagos-Anambra tend to place transactions that are 416 NGN higher on average compared to female customers living in other states. Looking into male customers, we see that the individuals living in those two states tend to make transactions that are 2,037 NGN higher compared to their counterparts in other states. Comparing these numbers shows that male customers living in Lagos-Anambra tend to make transactions that are five times larger compared to female customers living in the same states. This gap can be an indication that men living in these two states are more involved in high-paying business activities compared to women in the same states. However, this statement requires more investigation in order to be fully confirmed. Taking into account both OLS and QR output, we can say that both female and male customers (except for *q90*) who live in Lagos or Anambra tend to make larger transactions compared to their counterparts living in other states.

The third explanatory variable is transaction type. Transaction type shows whether a transaction was either a deposit or a withdrawal. OLS and QR coefficients for this variable show that among both female and male customers, withdrawals are significantly larger than deposits (except for *q10*). This pattern shows that these accounts are not being used in a sustainable way. When withdrawal amounts tend to be larger than deposits, it means that customers who initially had some amount of money in their accounts (mostly an initial large deposit or an accredited loan) take that money out and do not fill their account at a comparable rate to their withdrawal. Therefore, after a relatively short period, these accounts end up with a very low balance. This finding is in line with what bank officers told our team regarding account usage. The bank's primary goal for opening these accounts was encouraging low-income customers to build savings. However, this result shows that this goal is not met for many of the account holders.

The fourth explanatory variable is account age. Based on OLS and QR coefficients, account age has a positive relationship with transaction amount for both male and female customers. This effect is very small and it is negligible for *q10*. However, it shows a positive increasing effect on other percentiles among both men and women.

The fifth explanatory variable, average number of transactions, shows that per one-year increase in the account age, female customers tend to make transactions that are larger by 235 NGN and male customers tend to make transactions that are larger by 222 NGN. In other words, customers who are more active tend to make larger transactions as well. By looking into QR, we see the same pattern. Therefore, there is a small segment of customers who are more active (higher number of transactions) and tend to make larger transactions as well. This segment of customers have a significant influence on the cash flow of this savings account.

The last explanatory variable is seasonality effect. This variable shows whether customers tend to make larger/smaller transactions based on the season. As explained earlier, most parts of Nigeria experience two seasons, dry and rainy. In the dry season, both male and female customers tend to make much larger transactions as compared to transactions in the rainy season. The seasonality effect differs across lower and higher percentiles of the outcome variable. As we move towards higher percentiles, this effect gets larger. Relative to the coefficients of other explanatory variables, the impact that seasonality has on transaction amounts is very large.

**Table 2: Model Output for OLS and Quantile Regression on Female Transactions**

| | **OLS** | **q10** | **q25** | **q50** | **q75** | **q90** |
|---|---|---|---|---|---|---|
| **Intercept** | 9,346 (49.35) | 500.00 (1.60E+15) | 1,441 (55.42) | 4,673.50 (187.8) | 15,47 (118.29) | 19,61 (94.09) |
| **Customer age** | 47.29 (7.86) | -0.00 (-.14) | 0.69 (2.06) | -6.29 (-12.35) | -43.87 (-31.42) | -111.46 (-21.66) |
| **Geographical location-Lagos/Anambra** | 416.45 (3.06) | -0.00 (0.01) | 163.74 (30.86) | 208.37 (22.16) | 281.90 (8.52) | -262.78 (-2.25) |
| **Transaction type-deposit** | -11215.06 (-50.34) | -0.00 (- 0.01) | -1,042.66 (-46) | -4,050.86 (-159.37) | -12,699.18 (-130.48) | -10,62 (-103.08) |
| **Account age** | 135.83 (21.43) | 0.00 (0.13) | 6.23 (41.38) | 15.31 (41.65) | 53.13 (30.01) | 175.92 (24.89) |
| **Average number of transactions** | 235.05 (21.51) | 0.00 (0) | 20.41 (43.04) | 83.13 (69.94) | 179.64 (62.68) | 370.91 (32.02) |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Seasonality effect-dry** | 2,312.20 (14.66) | 0.00 (0.19) | 102.39 (25.49) | 231.34 (26.32) | 877.88 (24.17) | 2,819.94 (26.75) |

*t* statistics in parentheses. All coefficients are statistically significant at $p < 0.001$.

**Table 3: Model Output for OLS and Quantile Regression on Male Transactions**

| | **OLS** | **q10** | **q25** | **q50** | **q75** | **q90** |
|---|---|---|---|---|---|---|
| **Intercept** | 8,107.90 (38.07) | 300.00 (5.10E+11) | 813.10 (46.42) | 3,399.01 (141.15) | 11,559.56 (104.01) | 14,991.74 (46.51) |
| **Customer age** | 94.41 (14.72) | 0.00 (1.94) | 3.19 (10.47) | 1.19 (1.71) | -15.15 (-10.73) | -31.99 (-4.04) |
| **Geographical location-Lagos/Anambra** | 2,037.38 (19.20) | 500.00 (3.10E+11) | 675.80 (21.78) | 731.15 (53.27) | 1,198.20 (34.6) | 998.97 (8.79) |
| **Transaction type-credit** | -11,337.59 (-70.11) | 200.00 (6.20E+11) | -165.36 (-11.20) | -2,858.93 (-139.34) | -9,498.72 (- 128.37) | -7,472.65 (-69.34) |
| **Account age** | 176.58 (34.37) | -0.00 (-1.38) | 7.39 (10.94) | 27.58 (40.70) | 83.47 (32.33) | 233.23 (27.45) |
| **Average number of transactions** | 222.06 (32.87) | 0.00 (0.96) | 13.08 (10.03) | 109.32 (70.47) | 248.44 (67.92) | 435.50 (55.82) |
| **Seasonality effect-dry** | 3,383.67 (27.95) | 0.00 (0.85) | 113.95 (10.10) | 477.98 (30.60) | 1,430.44 (34.92) | 3,878.22 (26.64) |

*t* statistics in parentheses. All coefficients are statistically significant at $p < 0.001$.

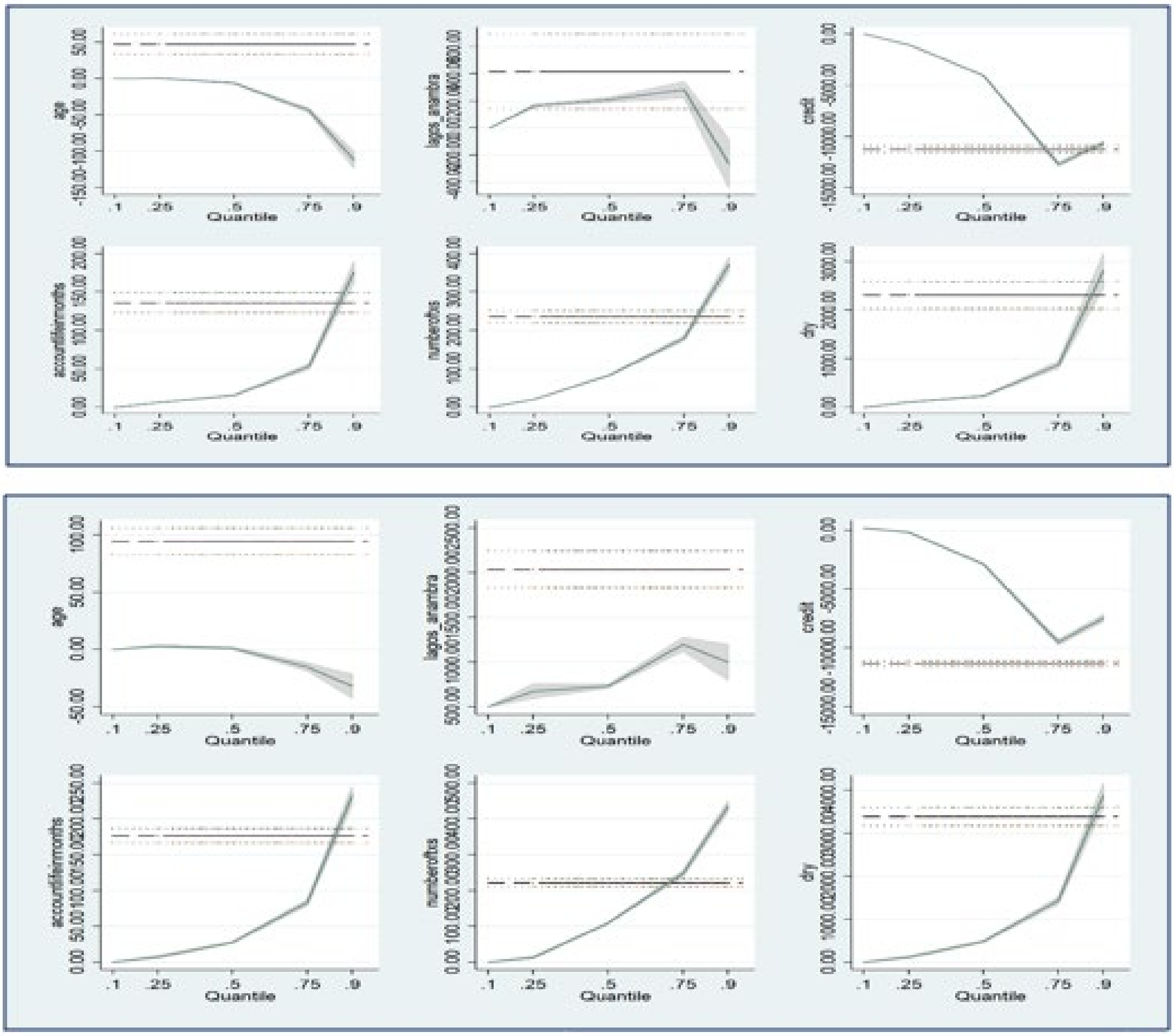


Figure 3. Quantile plots – The first set of plots (on the top) shows the QR coefficients for female customers, and the second set of plots (the one on the bottom) shows the QR coefficients for male customers.

## 7. Conclusion and Policy Recommendations

In this research, we investigated the effect of customer age, geographical location, transaction type, account age, financial activity rate (average number of transactions), and seasonality on the savings behavior of a group of microsaving account holders in Nigeria. Our empirical results are based on a novel data set collected from one of the largest banks in Nigeria. The result of this study has two key takeaways: 1) the study suggests how determinants of financial behavior at the mean can behave differently when compared to the median or other percentiles of the outcome variable and; 2) it shows how men and women may have different financial behaviors. This difference illustrates the necessity of studying the financial behavior of low-income customers through a gender-lens perspective.

Understanding the differences between men and women is crucial in developing services that are designed based on the needs and limitations of each gender. Traditionally, financial products and services have been designed based on men's financial needs. However, more studies should consider the similarities and differences between men's and women's financial needs, specifically among low-income populations.

The only way scholars can conduct this kind of research is by having access to gender-disaggregated datasets. However, many FSPs, banks, and government agencies do not collect those. This research shows the importance of gender-disaggregated datasets and the value they can bring to the world of financial inclusion.

Policy recommendations:

- Financial projections: Having a sound understanding of the effect that each variable has on transaction amount and how it varies between male and female customers helps FSPs to more accurately project their portfolio cash flows.
- Capital structure: Accurate projection of cash flows helps FSPs have a more accurate response and to know what percentage of their capital should be in equity and what percentage should be in credit.
- Detecting financial fraud: Taking the learnings from this model and applying them into a model for predicting each transaction value helps FSPs flag transactions that are significantly different from the expected amount that was estimated using the predictive model. These types of transactions can be flagged as suspicious and go under audit investigations.
- Bundled products: Many FSPs provide bundled products, such as a credit product that is bundled with mandatory savings or a credit product bundled with mandatory savings and insurance. In such cases, having a clear understanding of how customers with different profiles save and use their accounts can help FSPs to estimate and understand the performance of a bundled product before or during the roll-out phase for that product. As an example, we can think of the seasonality effect we detected during our analysis. Detecting seasonality effect on an optional (non-mandatory) savings program can be a sign of seasonality effect on income stream as well. If after further investigation, an FSP understands that the income level varies largely in different seasons, the FSP might need to consider designing a flexible loan repayment method instead of fixed and standardized loan installments. Seasonal occupations are among the cases in this category. The role of gender is another example. If an FSP sees a significant difference between the financial behavior of men and women, similar to what we saw in our study, it would need to consider this difference in the design of that specific bundled product.

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