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Markov Chain Analysis of Brand Switching Behavior among Instant Noodle Consumers in Nigeria

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ABSTRACT

The study used a discrete-time Markov chain (DTMC) to examine brand switching among consumers of three instant noodle brands (Indomie, Supreme, and Minimie) at Girei Modern Market, Girei Local Government Area, Adamawa State, Nigeria. A structured questionnaire was administered to 100 respondents recruited by convenience sampling, and their previous and most recent purchases were used to estimate a 3 × 3 transition probability matrix. An Anderson–Goodman chi-square test rejected the hypothesis that current brand choice is independent of the previous choice (χ^2 (4) = 14.27, p = 0.006), supporting the Markov specification. Market shares were projected over three purchase periods, and the long-run (steady-state) distribution was derived. Supreme retained the largest proportion of its own buyers (62.9%) and attracted the largest proportions of buyers leaving Minimie (38.2%) and Indomie (32.3%). The model predicts that Supreme's share rises from 35.0% to a steady-state value of 48.5%, while Indomie and Minimie settle at 27.5% and 24.0%, respectively. Bootstrap confidence intervals and a sensitivity analysis of the retention probabilities show that the exact equilibrium shares are imprecise at n = 100, but Supreme's leading position is robust. Product availability and price were the most frequently cited reasons for switching, and the pattern of reasons differed significantly across brands (χ^2 (10) = 44.97, p < 0.001). Because the data come from a single-market convenience sample, the results are an exploratory baseline for Girei rather than estimates for Adamawa State as a whole. The study shows that a Markov chain fitted to simple survey data gives fast-moving consumer goods (FMCG) firms in data-scarce markets a low-cost way to monitor and anticipate brand switching.

1. Introduction

The instant noodles category in the packaged food market is crowded and competitive. According to MetaTech Insights (2024), the global market was valued at USD 59.3 billion in 2024 and is projected to grow at a compound annual growth rate (CAGR) of about 5.7% to USD 109.1 billion by 2035, with instant noodles becoming a common household staple in developing countries. Other research firms report lower figures (Research and Markets, 2024), but all predict sustained growth driven by low prices and convenience. Because

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many firms offer comparable products at comparable prices, retaining current customers is central to a brand's success. In Nigeria, food and other necessities now take a larger share of household spending because of rising costs (Oladipo, 2025).

It is useful to separate two levels of explanation. At the macro level, food inflation, exchange-rate depreciation, and supply shocks change the conditions under which every brand in the category competes, raising production costs and squeezing household budgets. These conditions do not by themselves cause any individual switch. Switching happens at the micro level, when a consumer at the point of purchase responds to a brand-specific driver: a relative price difference, an empty shelf, a taste preference, a recommendation, or trust in a familiar name. Macroeconomic pressure matters because it changes the weight consumers place on these micro-level drivers, most notably price. This study measures the micro-level drivers directly and treats the inflationary environment as context.

A key component of this competitiveness is brand switching, which occurs when a customer switches from one brand to a rival in the same category. NielsenIQ's 2025 Consumer Outlook survey, as reported by Oladipo (2025), found that nearly six in ten Nigerian shoppers had switched brands in the previous year because of higher prices. Brand managers must foresee how switching will evolve over time and provide explanations for why it occurs because every lost client lowers the sales of an incumbent brand. Qualitative panels and focus groups can explain why people switch, but they are unable to forecast how it will affect market shares. The discrete-time Markov chain (DTMC), which treats each brand as a state and uses transition probabilities between states to indicate switching, is a logical choice among stochastic models that are more appropriate for that task. According to the approach, a customer's subsequent purchase is determined by their most recent purchase rather than their past purchases (Norris, 1997). Markov brand-switching studies typically make this first-order assumption (Kassa *et al.*, 2017). Additionally, the fundamental model has been expanded. In a hidden Markov model developed by Kumaraswamy and Bhatracharyulu (2023a), unseen factors influence switching and repeat purchases. Sowunmi *et al.* (2022) investigated the chicken feed brands used by professional egg producers in Nigeria using a Markov chain and logistic regression; 43.1% of producers switched brands because their favorite feed had become more costly. In order to determine competitive tactics for e-commerce platforms in Medan, Indonesia, Halim and Sitompul (2024) combined game theory with a Markov chain.

There is currently little quantitative research on brand switching in Nigeria's packaged food industry, and the evaluated literature did not contain any prior Markov chain studies on instant noodles in Nigeria. Using a DTMC fitted to primary data from Girei Modern Market, Girei Local Government Area, Adamawa State, this study fills that gap. The market is peri-urban; the majority of its patrons are young, and foot traffic indicates that they frequently purchase convenience food. The goals are to determine the primary causes of brand switching among consumers of instant noodles in the market; create and estimate a Markov chain transition probability matrix; forecast the brands' market shares three periods in advance; and ascertain the long-term market shares. This provides a quantitative explanation of the dynamics of brand switching in Nigeria's instant noodle industry, an area that has primarily received descriptive treatment up to this point. It demonstrates that a well-designed survey and a Markov chain may still be used to do a thorough analysis of a market without retail scanner-panel data. Additionally, it provides brand managers with actionable brand-specific data.

2. Literature Review

This section reviews the literature on which the study builds. Section 2.1 examines brand switching in fast-moving consumer goods and packaged food markets, with attention to evidence from Nigeria and other developing economies. Section 2.2 sets out the Markov chain framework, its first-order assumption, and its applications and extensions in consumer behavior research. Section 2.3 turns to

the instant noodle market, the macroeconomic pressures it faces in Nigeria, and the factors that earlier studies identify as drivers of switching, which informed the reasons recorded in the questionnaire.

2.1 Brand Switching in FMCG and Packaged Food Markets

In fast-moving consumer goods, switching is widespread since rival brands extensively advertise at the point of sale, several alternatives are available on the same shelf, and testing a different brand is inexpensive. A linear statistical model based on Dirichlet brand performance metrics, including market share, repeat rate, and the polarization index, along with a transition probability matrix, was used by Kumaraswamy and Bhatracharyulu (2023b) to model repeat buying and switching. Price has been the primary motivator for consumers to switch brands throughout Nigeria's recent inflation. NielsenIQ's 2025 Consumer Outlook survey also found that toothpaste, cooking oil, and laundry products recorded the highest levels of switching, while beverages and personal care retained stronger loyalty, which NielsenIQ attributed to consumers' emotional connection with those brands (Oladipo, 2025). One interpretation is that switching is highest where consumers see competing brands as close substitutes. Instant noodles, with several low-priced brands on the same shelf, appear to fit this description.

Using partial least squares structural equation modeling, Sunardi *et al.* (2023) estimated that 57% of growing-up milk customers in Java, Indonesia, switched brands. The biggest factor influencing switching was a bad past experience, primarily with defective products, which was followed by variety seeking, subpar product features, and discontent. As a result, packaged food loyalty appears to be conditional, and a bad product experience is frequently sufficient to drive customers away. Sowunmi *et al.* (2022) is the Nigerian study that most closely resembles the current one. Working with 145 commercial egg producers in southwest Nigeria, they discovered that the most frequent cause of moving feed brands was price increases and that switching was influenced by flock size, association membership, average feed prices, and distance to feed dealers. Their two-period design, which contrasted the brand in use at the moment with the brand used six months prior to the poll, is comparable to this one.

2.2 Markov Chain Models in Consumer Behavior Research

According to Anderson and Goodman (1957) and Norris (1997), a Markov chain is a discrete-state stochastic process with a single defining characteristic: the likelihood of progressing to a future state solely depends on the current state and not on how the process got there as in Eq. (1). Formally, with a finite state space S and a series of random variables $\{X_0, X_1, X_2 \ldots\}$

$$P(X_{t+1} = j \mid X_t = i,\ X_{t-1} = k, \ldots) = P(X_{t+1} = j \mid X_t = i) = P_{ij} \qquad (1)$$

where the one-step probability of switching from brand i to brand j is represented by P_{ij}. When it comes to purchases, the property implies that the brand that is selected next is determined by the brand that was purchased most recently rather than by the entire buy history. The majority of brand-switching applications adopt this first-order structure (Kassa *et al.*, 2017). Statistical tests for comparing it to higher-order alternatives and determining whether the transition probabilities remain constant over time are provided by Anderson and Goodman (1957).

The fundamental DTMC has been expanded in recent studies. In order to prevent consumers in the same observed state from acting in the same way, Kumaraswamy and Bhatracharyulu (2023a) created a hidden Markov model in which unobserved factors, such as purchasers' sentiments, drive repeat purchases and switches. In a subsequent study, the same authors developed a hidden Markov framework for how consumers evolve over time, integrated the Poisson and Weibull distributions to describe repeat purchases, and constructed the transition probability matrix using Dirichlet model parameters (Kumaraswamy & Bhatracharyulu, 2025).

Numerous industries are covered by applied studies. Four restaurant categories were modeled by Kassa *et al.* (2017) around Ethiopia's Bahir Dar Institute of Technology. According to their forecasts, the three restaurants were losing market share by the third month, while the fourth category—"other restaurants"—acted as an absorbing state and eventually captured the entire market as it lost no patrons. Halim and Sitompul (2024) investigated Shopee, Lazada, and Tokopedia in Medan, Indonesia. They used game theory to determine the optimal strategy for each pair of competitors across five marketing-mix factors: price, promotion, security, service, and product availability. They reported brand-switching probabilities of 0.469, 0.306, and 0.223 for the three platforms. Sowunmi *et al.* (2022) utilized the same approach to a farm input, and these studies also apply it to restaurants and online shopping. The closest precedent for Markov-based market-share prediction in Nigeria is their study on chicken feed, which included brands of inputs purchased by farmers. In this study, the approach is applied to a retail consumer good whose states are determined by the brand preferences of individual consumers.

The first-order assumption needs justification in a retail setting, because brand choice can depend on more than the last purchase. Consumers may build loyalty over several purchase occasions, and some deliberately alternate between brands out of variety seeking (McAlister & Pessemier, 1982); both behaviors imply that choice depends on purchases further back than the most recent one. Scanner-panel research nonetheless shows that recent purchases carry most of the predictive weight in frequently bought packaged goods: in the brand-choice model of Guadagni and Little (1983), loyalty is an exponentially weighted average of past purchases in which the latest purchase counts most. Instant noodles are cheap, low-involvement, and bought often, so habit and the most recent experience are likely to dominate the next choice. The first-order chain is also the only specification the present data can support. A second-order chain on three brands has 18 free transition parameters instead of 6 and requires each respondent's last three purchases, whereas this survey recorded two. The first-order model is therefore adopted as a parsimonious approximation; its dependence structure is tested in Section 4.4, and its limitations are set out in Section 4.9.

Markov chains also serve as building blocks in broader decision-analytic frameworks used in retail and supply chain analytics. Adding actions and rewards to a Markov chain produces a Markov decision process, in which a firm chooses among interventions such as price cuts, promotions, or restocking policies to maximize expected long-run returns (Puterman, 1994). Multi-criteria decision-making methods such as the analytic hierarchy process (Saaty, 1980) can weight the factors that drive switching, such as price, availability, and taste, and these weights can then indicate which transition probabilities a firm should try to change. Halim and Sitompul (2024) provide a hybrid example, combining Markov switching probabilities with game theory to select marketing strategies among competing platforms. The present study estimates the descriptive layer on which such frameworks rest: an empirical transition matrix and its long-run implications. The sensitivity analysis in Section 4.7 takes a first step toward decision use by showing how changes in each brand's retention probability would alter long-run market shares.

2.3 Noodle Market Dynamics and Switching Factors

The state of the economy affects the demand for instant noodles. According to Research and Markets (2024), the global market was estimated to be worth USD 25.3 billion in 2023 and is expected to rise at a compound annual growth rate (CAGR) of 3.9% to reach USD 33.0 billion by 2030. The primary factors driving this growth are urbanization, busy lives, and the need for convenient, reasonably priced food. This estimate is significantly less than the previously mentioned MetaTech Insights value. Although both sources anticipate continuous expansion, published market-size estimates fluctuate significantly amongst research organizations due to differences in how they define the industry and gather data. The category is directly impacted by Nigeria's economic circumstances. In June 2024, food inflation was 40.87% year over year (National Bureau of Statistics, 2024). According to Amare *et al.* (2025), the COVID-19 pandemic in 2020, the conflict in Ukraine in 2022, and

the fuel subsidy reform in 2023 are the three shocks responsible for the recent increases in food prices. Since wheat flour is used to make instant noodles, they report that wheat prices increased by 63.3% during these shocks. Demand is likely to become more price-sensitive and switching more frequent under such pressure. Five categories of factors are identified in the literature as being responsible for brand switching in this market:

(i) **Price and promotions**: Short-term discounts and price differences cause consumers to switch brands. Higher pricing was the most frequent excuse given by consumers for switching during Nigeria's recent inflation (Oladipo, 2025), and egg producers cited price as the primary justification for switching feed brands (Sowunmi *et al.*, 2022). Price and promotion are viewed as distinct strategic levers by Halim and Sitompul (2024).

(ii) **Product availability and distribution:** Customers take whatever is on the shelf when a favorite brand is unavailable, so distribution has a direct impact on loyalty. Halim and Sitompul (2024) listed product availability as one of the elements influencing competition between platforms, whereas Sowunmi *et al.* (2022) included the availability of a less expensive brand and the shortage of the chosen one as reasons producers changed feed.

(iii) **Taste, quality, and flavor:** Consumers are drawn to different brands by negative product experiences, subpar product features, and a need for variety (Sunardi *et al.*, 2023). Therefore, a unique flavor could help a company retain consumers who seek variety.

(iv) **Brand reputation and trust:** Even in situations when there is no price or availability benefit, a well-known brand reduces the perceived risk of a purchase, which works against switching (Kotler & Keller, 2016). According to 99% of Nigerian consumers surveyed by NielsenIQ in 2025, brand trust is very or somewhat significant (Oladipo, 2025).

(v) **Social suggestion and advertising:** Brand preference is influenced by social recommendations and advertisements. In a sample mostly composed of young social media users, Ehichoya and Omoregbe (2024) discovered that confidence in social media influencers was the strongest predictor of Nigerian FMCG consumers' purchase and switching intentions.

In this study, the Markov chain quantifies how these variables combine to create customer flows across companies and how those flows accumulate over time to form a route of market shares.

3. Methodology

This section describes how the data were collected and analyzed. Section 3.1 introduces the study area and research design, and Section 3.2 describes the questionnaire, the definition of a model period, and the sampling procedure and its precision. Section 3.3 formulates the Markov chain model, covering the estimation of transition probabilities, the projection of market shares, and the derivation of the steady-state distribution. Section 3.4 presents the statistical procedures used to test and validate the model: the Anderson–Goodman test of Markov dependence, the chi-square analysis of switching reasons, the bootstrap estimation of sampling uncertainty, and the sensitivity analysis of retention probabilities.

3.1 Study Area and Research Design

A quantitative, cross-sectional survey design was employed in the study. In Adamawa State's Girei Local Government Area, information was gathered at the Girei Modern Market. The market, about 15 km north of Yola, the state capital, serves traders, students, government employees, and rural households. This mix of

consumers makes it a suitable site for observing brand preference and switching in the instant noodle category in north-eastern Nigeria.

3.2 Data Collection, Sampling, and Timeframe

Data were collected with a structured, self-administered questionnaire that recorded the brand bought at the respondent's most recent purchase, the brand bought at the purchase before that, the reasons for switching, and basic socio-demographic information. The three brands most prominent in the market at the time of data collection, Indomie (S_1), Supreme (S_2), and Minimie (S_3), make up the state space of the model.

The discrete time step is defined by purchase occasions rather than by calendar time. Time t_0 is the respondent's previous purchase of instant noodles and t_1 is the most recent purchase, so each respondent contributes one observed transition, from the brand bought at t_0 to the brand bought at t_1. The questionnaire did not fix a calendar interval between the two purchases, so the elapsed time varies across respondents; for a frequently purchased product it is expected to be short. One model period should therefore be read as one purchase cycle, and projections for t = 2 and t = 3 refer to the second and third purchase cycles after t_1, not to fixed calendar months.

Respondents were recruited by convenience sampling at the market, and 100 usable responses were obtained. To place this sample size in context, Cochran's (1977) formula for estimating a proportion was applied as given in Eq. (2).

$$n_0 = \frac{z^2\, p(1-p)}{e^2} \tag{2}$$

where $z = 1.96$ for 95% confidence, $p = 0.5$ is the most conservative assumed proportion, and e is the margin of error. A margin of error of ± 5 percentage points would require $n_0 \approx 384$ respondents, whereas ± 10 percentage points requires $n_0 \approx 97$. The achieved sample of 100 therefore estimates an overall proportion to within about ± 9.8 percentage points at 95% confidence. Transition probabilities are estimated from row subsamples of 31 to 35 respondents and are less precise still; Section 4.7 quantifies this uncertainty. Given the single site, convenience recruitment, and modest sample size, the dataset is treated as an exploratory baseline cohort for Girei Modern Market, not as a representative sample of Adamawa State (see Section 4.9).

3.3 Formulation of Markov Chain Models

This subsection sets out the Markov chain model used in the study. Section 3.3.1 defines the state space and the estimation of the one-step transition probabilities, Section 3.3.2 describes how market shares are projected forward over successive purchase cycles, and Section 3.3.3 derives the long-run (steady-state) distribution toward which the shares converge.

3.3.1 Transition probabilities and state space

Let $S = \{S_1, S_2, S_3\}$, where $S_1 = Indomie, S_2 = Supreme, and\ S_3 = Minimie$. The likelihood that a customer who previously purchased brand i will purchase brand j on their subsequent purchase is known as the one-step transition probability, or P_{ij}, as shown in Eq. (3). Maximum likelihood is used to estimate the probability from the survey counts (Anderson & Goodman, 1957)

$$P_{ij} = \frac{n_{ij}}{\sum_j n_{ij}} \tag{3}$$

where n_{ij} is the number of respondents who shifted from brand i to brand j, and $\Sigma_j\, n_{ij}$ is the corresponding row total. By construction, the resulting 3×3 matrix $P = [P_{ij}]$ is row-stochastic, meaning that every row adds up to 1.

3.3.2 Market share projection

Given an initial market-share vector $\pi_0 = (\pi_1{}^0, \pi_2{}^0, \pi_3{}^0)$, the share vector t periods ahead is given in Eq. (4)

$$\pi_t = \pi_0 P^t \tag{4}$$

where P^t is the t-th power of P. Projections are computed for $t = 1, 2,$ and 3. Here π_0 is the proportion of respondents who bought each brand at their previous purchase, that is, the row totals of the count matrix divided by $n = 100$. It follows that $\pi_1 = \pi_0 P$ equals the proportion buying each brand at their most recent purchase (the column totals divided by n), which gives a check on the calculations. All projections were computed in double-precision floating-point arithmetic from the unrounded transition probabilities; values are rounded only for presentation.

3.3.3 Steady-state distribution

The long-run market-share vector $\pi^* = (\pi_1^*, \pi_2^*, \pi_3^*)$ solves the balance condition given in Eq. (5)

$$\left.\begin{array}{c} \pi^* P = \pi^* \\ Subject \quad to: \\ \pi_1^* + \pi_2^* + \pi_3^* = 1 \end{array}\right\} \tag{5}$$

If the chain is ergodic (irreducible and aperiodic), this steady state is unique and is reached from any starting distribution (Norris, 1997). The three balance equations are linearly dependent, so one of them is dropped and the other two are solved together with the normalization constraint, which gives a unique π*.

3.4 Statistical Tests and Model Validation

This subsection describes the procedures used to test the assumptions of the model and to assess the reliability of its estimates. Section 3.4.1 presents the Anderson–Goodman test of Markov dependence, and Section 3.4.2 explains why the order and time homogeneity of the chain cannot be tested with the present data. Section 3.4.3 describes the test of association between switching reasons and brands. Sections 3.4.4 and 3.4.5 set out the bootstrap estimation of sampling uncertainty and the sensitivity analysis of the retention probabilities.

3.4.1 Test of Markov dependence

Anderson and Goodman (1957) gave likelihood-ratio and chi-square tests of the order of a Markov chain. With one observed transition per respondent, the test that can be carried out is of zero order (independence) against first order. The null hypothesis H_0: $p_{ij} = p_j$ for all i states that the brand bought at t_1 does not depend on the brand bought at t_0. The Pearson statistic is given in Eq. (6)

$$\chi^2 = \sum_i \sum_j \frac{n_i (\hat{p}_{ij} - \hat{p}_j)^2}{\hat{p}_j} \tag{6}$$

where n_i is the number of respondents in row i and $\hat{p}_j = n_{+j} / n$ is the pooled proportion buying brand j at t_1. Under H_0 the statistic is asymptotically χ^2 with $(m-1)^2 = 4$ degrees of freedom for $m = 3$ states. The likelihood-ratio statistic $G^2 = 2 \Sigma_i \Sigma_j n_{ij} ln (\hat{p}_{ij} / \hat{p}_j)$ is also reported. Rejecting H_0 indicates that the previous brand carries information about the next choice, which is the dependence a Markov chain is designed to capture.

3.4.2 Order and time homogeneity

Testing first order against second order, and testing whether P is constant over time (stationarity), requires each consumer's purchases to be observed on at least three successive occasions, or transitions to be observed over two or more intervals (Anderson & Goodman, 1957; Bickenbach & Bode, 2003). The present cross-sectional

design records a single transition per respondent, so these two assumptions cannot be tested with the current data. They are retained as working assumptions, their consequences are examined through the sensitivity analysis in Section 3.4.5, and a panel design that would allow them to be tested is proposed in Section 4.9.

3.4.3 Association between switching reasons and brands

A Pearson chi-square test of independence was applied to the factor-by-brand table of switching reasons (Table 2), with Cramér's V as the effect size and adjusted standardized residuals used to locate the cells that drive any association (Agresti, 2013). Because respondents could cite more than one reason, the 311 citations are not independent observations, and the nominal p-value overstates the strength of evidence. The test is therefore interpreted descriptively, as an indication of how strongly the pattern of reasons differs across brands.

3.4.4 Sampling uncertainty

Each estimated transition probability is a proportion from a row subsample, with approximate standard error given in Eq. (7).

$$SE(\hat{p}_{ij}) = \sqrt{\frac{\hat{p}_{ij}(1-\hat{p}_{ij})}{n_i}} \tag{7}$$

Because π^* is a nonlinear function of all nine probabilities, its uncertainty was estimated with a parametric bootstrap (Efron & Tibshirani, 1993). In each of 10,000 replicates, new counts were drawn for each row from a multinomial distribution with the observed row total n_i and the estimated row probabilities, a new transition matrix was formed, and its steady state was computed. The 2.5th and 97.5th percentiles of the replicates give 95% percentile confidence intervals.

3.4.5 Sensitivity analysis

To assess how the long-run shares respond to the retention probabilities, each diagonal element p_{ii} was changed by $\delta = \pm 0.05$ and ± 0.10 (5 and 10 percentage points), one brand at a time. The off-diagonal elements of the same row were rescaled proportionally so that the row still sums to 1. This can be seen in Eq. (8)

$$\tilde{p}_{ii} = p_{ii} + \delta, \qquad \tilde{p}_{ij} = \frac{p_{ij}(1-p_{ii}-\delta)}{1-p_{ii}}, \quad j \neq i \tag{8}$$

This preserves the relative pattern of defections from brand i while changing its retention. The steady state of each perturbed matrix was recomputed from equation (3).

4. Results and Discussion

This section presents and interprets the results. It begins with the profile of respondents (Section 4.1) and the reasons they gave for switching brands (Section 4.2). The estimated transition probability matrix is then reported (Section 4.3), and the Markov dependence assumption is tested (Section 4.4). Sections 4.5 and 4.6 present the projected market shares over three purchase cycles and the long-run steady-state distribution. Section 4.7 assesses how far these results depend on sampling error and on the estimated retention probabilities. Section 4.8 discusses the findings in relation to earlier studies, and Section 4.9 sets out the limitations of the study and directions for future research.

4.1 Respondent Characteristics

Table 1 summarizes the 100 respondents by age, gender, and occupation.

Table 1: Socio-demographic Profile of Respondents (n = 100)

Variable	Category	Frequency (%)
Age Group	Under 18	27
	18–25	35
	26–35	23
	36–45	15
Gender	Male	58
	Female	42
Occupation	Student	34
	Unemployed	26
	Employed	21
	Self-Employed	19

The sample is youthful, with students making up the largest occupational category (34%) and 62% of respondents being 25 years of age or younger. Of the sample, 58% were men. A youthful, mostly student sample is reasonable for this market because instant noodles are inexpensive and easy to prepare, making them a frequent family dish in developing nations (MetaTech Insights, n.d.). When analyzing the data, the age profile is also important. Ehichoya and Omoregbe (2024), whose sample was likewise primarily young, discovered that Nigerian FMCG customers' intentions to switch were predicted by their level of confidence in social media influencers. As a result, a younger sample might be more willing to change than the general consumer base.

4.2 Switching Factors

Table 2 lists the reasons respondents gave for switching to each brand. Respondents could cite more than one reason, so the table counts citations (311 in total) rather than respondents, and the categories are not mutually exclusive.

Table 2: Consumer-Reported Reasons for Brand Switching by Destination Brand (Citations, Multiple Responses Allowed; n = 100 Respondents)

Factor	Indomie	Supreme	Minimie	Total
Price	12 (16.7; 15.6)	49 (36.3; 63.6)	16 (15.4; 20.8)	77 (24.8)
Taste/Flavor	9 (12.5; 19.6)	16 (11.9; 34.8)	21 (20.2; 45.7)	46 (14.8)
Product Availability	21 (29.2; 21.6)	31 (23.0; 32.0)	45 (43.3; 46.4)	97 (31.2)
Recommendations	7 (9.7; 20.0)	18 (13.3; 51.4)	10 (9.6; 28.6)	35 (11.3)
Promotions/Discounts	6 (8.3; 30.0)	13 (9.6; 65.0)	1 (1.0; 5.0)	20 (6.4)
Advertising	17 (23.6; 47.2)	8 (5.9; 22.2)	11 (10.6; 30.6)	36 (11.6)
Total	**72** (23.2)	**135** (43.4)	**104** (33.4)	**311** (100.0)

Note: Cells show the number of citations, followed in parentheses by the column percentage (share of that brand's citations) and the row percentage (share of that factor's citations). The Total column and Total row give shares of all 311 citations. Respondents could cite more than one reason, so citations are not independent observations. $\chi^2\,(10) = 44.97, p < 0.001$; Cramér's $V = 0.27$ (interpreted descriptively; see Section 3.4.3).

Overall, product availability received the most citations (97; 31.2%), followed by price (77; 24.8%). The pattern of reasons differs clearly across brands ($\chi^2\,(10) = 44.97, p < 0.001$; Cramér's $V = 0.27$; one of 18 cells had an expected count below 5, at 4.63). Given the multiple-response structure, this result is read as evidence of a moderate association rather than as an exact test. The adjusted standardized residuals show where the association lies. Price was cited far more often than expected for Supreme (49 citations; 36.3% of Supreme's

citations; residual +4.1), consistent with Supreme competing on price. Availability was over-represented for Minimie (45 citations; 43.3%; residual +3.3), suggesting that many of Minimie's new buyers chose it when it was on the shelf, possibly when their preferred brand was not. Advertising was over-represented for Indomie (17 citations; 23.6%; residual +3.6) and under-represented for Supreme (residual −2.7), and promotions were rarely cited for Minimie (1 citation; residual −2.8). These findings are consistent with research showing that availability shapes brand choice when preferred brands are hard to obtain (Sowunmi *et al.*, 2022) and that price drives switching in Nigeria's inflationary FMCG market (Oladipo, 2025).

4.3 Transition Probability Matrix

The switching counts give the transition count matrix N in Table 3.

Table 3: Raw Transition Count Matrix (N): Previous Purchase (t_0) by Most Recent Purchase $(t_1), n = 100$

From \ To	Indomie (S_1)	Supreme (S_2)	Minimie (S_3)	Row Total
Indomie (S_1)	16	10	5	31
Supreme (S_2)	5	22	8	35
Minimie (S_3)	9	13	12	34

Note: Rows give the brand bought at the previous purchase (t_0) and columns the brand bought at the most recent purchase (t_1). Column totals are 30 (Indomie), 45 (Supreme), and 25 (Minimie); all counts sum to $n = 100$.

Dividing each row of N by its total gives the estimated transition probability matrix P in Table 4.

Table 4: Estimated Transition Probability Matrix (P) with Standard Errors

From \ To	Indomie (S_1)	Supreme (S_2)	Minimie (S_3)
Indomie (S_1)	0.516 (0.090)	0.323 (0.084)	0.161 (0.066)
Supreme (S_2)	0.143 (0.059)	0.629 (0.082)	0.229 (0.071)
Minimie (S_3)	0.265 (0.076)	0.382 (0.083)	0.353 (0.082)

Note: Entries are $\hat{p}_{ij} = n_{ij} / \Sigma_j n_{ij}$ from Table 3 (row Totals 31, 35, and 34), rounded to three decimal places, with approximate standard errors from equation (5) in parentheses. Each row is a probability distribution: the unrounded probabilities in every row sum exactly to 1.

With 62.9% of its buyers staying with the brand at the next purchase, Supreme has the highest retention rate. Indomie retained 51.6% of its buyers and lost 32.3% to Supreme. Minimie had the lowest retention rate (35.3%) and lost 38.2% of its buyers to Supreme, the largest flow between any two brands in the matrix. In raw counts, Supreme gained 10 buyers from Indomie and 13 from Minimie while losing 5 and 8 to them, consistent with the price and availability advantages indicated in Table 2. The row subsamples are small, however, and the approximate 95% confidence intervals for the retention probabilities are 0.340–0.692 for Indomie, 0.468–0.789 for Supreme, and 0.192–0.514 for Minimie, so differences between brands should be read with this uncertainty in mind.

4.4 Tests of Markov Assumptions

The Anderson–Goodman test rejects the hypothesis that the brand bought at t_1 is independent of the brand bought at t_0 (Pearson $\chi^2\,(4) = 14.27, p = 0.006$; $G^2(4) = 13.96, p = 0.007$). All expected counts under independence exceed 5 (minimum 7.75), so the chi-square approximation is adequate, and the association is moderate (Cramér's V = 0.27). The previous purchase therefore carries real information about the next one. A zero-order model, in which every consumer draws the next brand from the same market-wide distribution regardless of history, is rejected in favor of the Markov specification. As explained in Section 3.4.2, the data cannot distinguish a first-order from a higher-order chain or test stationarity; these remain assumptions, and their consequences are examined in Section 4.7.

4.5 Market Share Projections

Starting from $\pi_0 = (0.31, 0.35, 0.34)$, Table 5 shows the projected shares for three periods and the steady state.

Table 5: Projected Market Shares (%) Over Three Periods and in the Steady State ($n = 100$)

Period	Indomie (%)	Supreme (%)	Minimie (%)
Initial (t=0)	31.00	35.00	34.00
Period 1	30.00	45.00	25.00
Period 2	28.53	47.52	23.95
Period 3	27.85	48.23	23.92
Steady State	27.46	48.55	23.99

Note: Shares are computed as $\pi_t = \pi_0 P^t$ in double-precision arithmetic from the unrounded transition probabilities and rounded to two decimal places for display; each row sums to 100% before rounding. Period 1 equals the observed shares at the most recent purchase (30, 45, and 25 of the 100 respondents) exactly, as implied by the choice of π_0.

After one purchase cycle, Supreme's share increased from 35.0% to 45.0%, and by Period 3, it was 48.2%, within 0.4 percentage points of its steady-state share of 48.5%. As anticipated from the selection of π_0, the Period 1 shares (30%, 45%, and 25%) correspond to the percentages of respondents purchasing each brand at their most recent purchase. Indomie's share decreases in each period, reaching 27.9% by Period 3 and 27.5% over time, a loss of 3.54 percentage points from its initial share. A net loss of 10.01 percentage points results from Minimie's steep decline in the first period, its lowest value (23.92%) in Period 3, and a minor recovery to its steady-state share of 23.99%. Because the second-largest eigenvalue of P is 0.334, convergence is quick, and the difference between the projected and steady-state shares decreases by almost two-thirds per period. Each share is within 0.4 percentage points of its long-run value by Period 3.

4.6 Steady-State Analysis

Solving $\pi^* P = \pi^*$ together with $\pi_1^* + \pi_2^* + \pi_3^* = 1$ gives the balance Eqs. (9) - (12):

$$0.484\,\pi_1^* = 0.143\,\pi_2^* + 0.265\,\pi_3^* \quad (9)$$

$$0.371\,\pi_2^* = 0.323\,\pi_1^* + 0.382\,\pi_3^* \quad (10)$$

$$0.647\,\pi_3^* = 0.161\,\pi_1^* + 0.229\,\pi_2^* \quad (11)$$

$$\sum_{i=1}^{3} \pi_i^* = 1 \quad (12)$$

Because Eq. (9) to (11) are linearly dependent, Eq. (12) is dropped, and Eqs. (9), (10), and (11) are solved together. Using the unrounded transition probabilities, the exact solution is $\pi^* = (5642, 9975, 4930)/20547$, that is: $\pi^* = (0.2746,\ 0.4855,\ 0.2399) \Rightarrow$ Indomie: 27.5%, Supreme: 48.5%, Minimie: 24.0%

Since every entry in P is strictly positive, the chain is irreducible and aperiodic. The distribution that the market approaches from any initial point is the steady state (Norris, 1997). Regardless of the initial split, Supreme would settle at roughly 48.5% of the market, Indomie at roughly 27.5%, and Minimie at roughly 24.0% if the current switching pattern continues.

4.7 Sampling Uncertainty and Sensitivity Analysis

The steady-state shares in Section 4.6 are point estimates from a sample of 100 respondents, and each row of the transition matrix rests on only 31 to 35 respondents. This subsection examines how far these results can be relied upon in two ways: through bootstrap confidence intervals that reflect sampling error (Table 6), and through a sensitivity analysis that shows how the long-run shares respond when

each brand's retention probability is changed (Table 7). Table 6 reports bootstrap 95% confidence intervals for the steady-state shares.

Table 6: Bootstrap 95% Confidence Intervals for Steady-State Market Shares (10,000 $Replicates, n = 100$)

Brand	Point estimate (%)	Bootstrap mean (%)	Bootstrap SD (pp)	95% CI (%)
Indomie	27.46	27.50	6.58	15.1–41.1
Supreme	48.55	48.79	7.24	35.1–63.6
Minimie	23.99	23.71	5.17	13.7–34.0

Note: Parametric bootstrap: the counts in each row of Table 3 were resampled from a multinomial distribution with the observed row total and estimated row probabilities, and the steady state of each resampled matrix was computed. Intervals are the 2.5th and 97.5th percentiles; pp = percentage points.

The intervals are wide, spanning 20 to 29 percentage points, which is the direct consequence of estimating each row of P from 31 to 35 respondents. The exact long-run shares are therefore imprecise. The direction of change is more stable: Supreme had the largest steady-state share in 94.8% of replicates, and its steady-state share exceeded its initial 35.0% in 97.6% of replicates. The Indomie and Minimie intervals overlap substantially, and Indomie ranked above Minimie in only 65.3% of replicates, so their relative order is not established. Table 7 shows how the steady state responds when each brand's retention probability is changed by ±5 and ±10 percentage points.

Table 7: Sensitivity of Steady-State Market Shares (%) to Changes in Brand Retention Probabilities

Retention changed	δ	Indomie	Supreme	Minimie
Baseline	—	27.46	48.55	23.99
Indomie ($p_{11} = 0.516$)	−0.10	23.88 (−3.58)	50.94 (+2.40)	25.18 (+1.18)
	−0.05	25.54 (−1.91)	49.83 (+1.28)	24.63 (+0.63)
	+0.05	29.68 (+2.23)	47.06 (−1.49)	23.26 (−0.74)
	+0.10	32.30 (+4.84)	45.31 (−3.24)	22.39 (−1.60)
Supreme ($p_{22} = 0.629$)	−0.10	30.61 (+3.15)	42.64 (−5.91)	26.75 (+2.75)
	−0.05	29.14 (+1.68)	45.40 (−3.14)	25.46 (+1.47)
	+0.05	25.53 (−1.93)	52.16 (+3.61)	22.31 (−1.68)
	+0.10	23.29 (−4.17)	56.35 (+7.81)	20.35 (−3.64)
Minimie ($p_{33} = 0.353$)	−0.10	28.37 (+0.91)	50.16 (+1.61)	21.47 (−2.52)
	−0.05	27.94 (+0.48)	49.40 (+0.85)	22.66 (−1.33)
	+0.05	26.92 (−0.54)	47.59 (−0.96)	25.49 (+1.50)
	+0.10	26.31 (−1.15)	46.51 (−2.04)	27.19 (+3.19)

Note: One retention probability is changed at a time; the off-diagonal entries of the same row are rescaled with equation (6) so that each row still sums to 1. Values are steady-state shares (%), with the change from the baseline in percentage points in parentheses.

Three results stand out. First, the long-run shares respond most to Supreme's retention probability: a 10-point fall in p_{22} lowers Supreme's steady-state share by 5.9 points, and a 10-point rise increases it by 7.8 points. The market-wide outcome therefore depends most on how well the growing brand holds its buyers. Second, each brand's own share moves in the same direction as its retention, by about 3.6 to 4.8 points per 10-point change for Indomie and 2.5 to 3.2 points for Minimie, with the gains coming mainly at Supreme's expense. Third, Supreme remains the largest brand in every scenario, with a minimum share of 42.6% against a maximum of 32.3% for either rival. The main qualitative conclusion is therefore robust to plausible errors in the retention estimates, while the precise equilibrium values should be treated as indicative.

4.8 Discussion

Supreme's growth has two sources. It has the highest retention rate in the market (62.9%) and attracts the largest shares of both competitors' buyers (32.3% of Indomie's and 38.2% of Minimie's). A brand that keeps its own

buyers while drawing in those of its rivals strengthens its position on both fronts. The result is consistent with wider evidence that Nigerian consumers have been switching brands in response to price (Oladipo, 2025). The projected shares converge quickly: each is within 0.4 percentage points of its long-run value by Period 3. The speed of convergence is governed by the second-largest eigenvalue modulus of P, here 0.334, so the gap to equilibrium shrinks by about two-thirds each purchase cycle and halves in less than one cycle. This follows from the high rate of switching in the category. The average retention probability is only about 0.50, so a large part of each brand's buyer base is exchanged every cycle; in categories with strong repeat buying, where retention probabilities approach 0.9, the second eigenvalue is close to 1 and adjustment takes many periods. Earlier applied studies show slower or qualitatively different dynamics. Kassa *et al.* (2017) found restaurant shares still shifting over successive monthly steps, and because one of their states lost no customers, their chain was absorbing, with that state eventually capturing the whole market. Here every transition probability is positive, so the chain is ergodic and converges to an interior equilibrium in which all three brands survive. Two cautions apply. First, a period is a purchase cycle, so rapid convergence in periods may still correspond to several weeks of calendar time. Second, repeat-buying research finds that shares in established FMCG categories are usually close to stationary (Ehrenberg *et al.*, 2004). The large predicted gain for Supreme, about 13.5 percentage points, therefore suggests either that the market was out of equilibrium at the time of the survey, plausibly because of recent price shocks, or that part of the shift reflects sampling error, as the wide intervals in Table 6 allow. Repeated measurement is needed to tell these explanations apart. Indomie's position is harder to explain. It received more advertising citations (17) than either competitor, yet it retained only 51.6% of its buyers and lost almost one-third to Supreme. Advertising citations measure what consumers' recall, not what firms spend, so this study cannot link spending to outcomes directly. Several mechanisms may nonetheless explain why awareness is not translating into retention. In low-involvement, frequently bought categories, advertising works mainly by keeping a brand familiar and salient; it rarely overrides a price difference or an empty shelf at the moment of purchase (Ehrenberg *et al.*, 2004). Indomie is widely regarded as the best-known brand in the Nigerian noodle category, so further advertising adds little new awareness, while inflation has increased the importance of price gaps between brands. Advertising also cannot convert a buyer where the product is unavailable, and availability was the most frequently cited driver of switching. Finally, advertising by a well-known brand may raise interest in the category as a whole, and some of the resulting purchases may go to cheaper substitutes. Together these points suggest a mismatch between Indomie's communication emphasis and the price- and availability-driven choices that dominate this market.

Of the three brands, Minimie received the most taste and flavor citations (21), but its market position does not yet reflect this. The most frequent reason for switching to Minimie was availability (45 citations), indicating that many consumers choose it when they see it on the shelf. Its low retention rate (35.3%) indicates that many of these buyers leave again, possibly because the brand's availability is inconsistent. Sowunmi *et al.* (2022) reported similar behavior, with some consumers switching because their preferred brand was scarce or a cheaper one was available.

4.9 Limitations and Directions for Future Research

The results should be read as an exploratory baseline for one market, for four reasons. First, sample scale limits precision. With n = 100, an overall proportion is estimated to within about ±9.8 percentage points, and each transition probability rests on only 31 to 35 respondents, giving standard errors of 0.06 to 0.09 (Table 4). Because the steady state compounds the errors in all nine probabilities, the 95% intervals for the long-run shares span 20 to 29 percentage points (Table 6). Precision improves only with the square root of the row counts: estimating each retention probability to within ±10 percentage points would require about 96 respondents per origin brand, or roughly 300 in total. The ranking of Supreme first is robust, but the precise equilibrium values and the ordering of Indomie and Minimie are not. Second, respondents were recruited by convenience at a single

market. Shoppers who agree to complete a questionnaire on a market day may differ from other consumers, and the sample is young (62% aged 25 or under) and largely made up of students, a group that may switch more readily than the wider population (Ehichoya & Omoregbe, 2024). The transition probabilities describe conditions at Girei Modern Market and should not be generalized to Adamawa State. Third, the design records one transition per respondent. The Anderson–Goodman test confirms that current choice depends on the previous one, but the first-order property and the stationarity of P could not be tested, and the projections assume both. If consumers carry loyalty across several purchases, a first-order chain will tend to overstate the speed of adjustment; if P shifts as prices change, the steady state describes where the market would settle only under current conditions. The sensitivity analysis shows that the main conclusion is robust to moderate changes in retention, but it is not a substitute for a formal test. Previous purchases were also self-reported and may be recalled inaccurately, and the reasons in Table 2 are multiple responses, which limits formal inference on that table. Fourth, future research should address these limits directly. A multi-center probability sample, for example a stratified or cluster sample across markets such as Yola Main Market and Jimeta Modern Market and across urban, peri-urban, and rural areas, would support inference at state level. A panel or purchase-diary design recording at least three successive purchases per consumer would permit Anderson–Goodman tests of first against second order and of time homogeneity across intervals. Larger samples would also allow transition matrices to be estimated by consumer segment, or hidden Markov models with covariates to be fitted (Kumaraswamy & Bhatracharyulu, 2023a), and would provide the inputs needed for decision models that evaluate pricing and distribution strategies directly.

5. Conclusion and Recommendations

This section draws together the main findings of the study and considers their practical implications. Section 5.1 summarizes the results in relation to the study's four objectives: identifying the causes of switching, estimating the transition matrix, projecting market shares, and deriving the long-run distribution. It also restates the conditions under which the results should be read. Section 5.2 translates the brand-level findings into recommendations for the managers of Indomie, Supreme, and Minimie.

5.1 Conclusion

This study fitted a discrete-time Markov chain to brand-switching data from 100 instant noodle consumers at Girei Modern Market, Adamawa State. Using a three-brand state space (Indomie, Supreme, and Minimie), the estimated 3 × 3 transition matrix was used to project market shares three periods ahead and to derive the long-run steady state. The Anderson–Goodman test confirmed that current brand choice depends on the previous purchase, supporting the Markov specification. Supreme leads at equilibrium with a projected share of 48.5%, reflecting its price position and its ability both to retain and to attract buyers, while Indomie and Minimie settle at 27.5% and 24.0%, respectively. All projected shares are within 0.4 percentage points of their long-run values by the third purchase cycle. Bootstrap intervals show that these equilibrium values are imprecise at the present sample size, but Supreme's leading position holds in about 95% of bootstrap replicates and in every sensitivity scenario. As an exploratory baseline from a single market, the study shows that Markov chain analysis is a practical, low-cost way to monitor market dynamics in Nigeria's packaged food industry, in line with applications in other developing economies (Halim & Sitompul, 2024; Kumaraswamy & Bhatracharyulu, 2023a; Sowunmi *et al.*, 2022). Confirming the findings will require larger, multi-center samples observed over several purchase occasions.

5.2 Recommendations

The results suggest distinct priorities for each brand. Given the exploratory nature of the data, they are best treated as directions for managers to test rather than as definitive prescriptions:

(vi) **Indomie**

i. Since price and availability, rather than brand recognition, are driving switching in this market, a portion of the marketing budget should be shifted from general advertising to targeted price discounts and increased point-of-sale exposure.

ii. Commission consumer research on factors that contribute to low retention, such as taste or formulation, and utilize the findings to inform the creation of new products or limited-edition flavors.

(vii) **Supreme**

i. While the brand is still strong, expand distribution into Adamawa State's peri-urban and rural areas. To preserve its high retention rate, think about implementing a formal loyalty program.
ii. Make an investment in flavor development, as Minimie now excels in taste.

(viii) **Minimie**

i. Prioritize broader and more dependable distribution. Customers switched to Minimie primarily for availability (45 citations, compared to 21 for flavor), but the brand only retains roughly one-third of its customers, so consistent supply is probably more important for growth than product modifications.

ii. Make use of the taste advantage while marketing to students and other young consumers, who comprise the majority of this market's clientele.

Author Contributions

Conceptualization, B.I.D. and B.U.D.; methodology, B.I.D.; software, B.I.D.; validation, B.U.D. and Y.H.B.; formal analysis, B.I.D.; investigation, B.I.D. and Y.H.B.; resources, U.A.; data curation, B.U.D.; writing—original draft preparation, B.I.D.; writing—review and editing, B.I.D., B.U.D., Y.H.B., and U.A.; visualization, B.I.D.; supervision, B.U.D.; project administration, B.I.D. All authors have read and agreed to the published version of the manuscript

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The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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