Household Consumption Characteristics of Cookies: The Case of Uganda

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Abstract

The cookie consumption and purchase characteristics of households were investigated in six cities in Uganda using household survey data. Cookies can be fortified with vitamins to improve child nutrition. The application of a Logit model permitted the identification of factors significantly affecting household decision to eat cookies. They are household food buyer/preparer's age, employment status, education level, household monthly income, household location, number of children from 4 to 18 years-old and its squared value. The purchase decision was modeled as a two-stage or double-hurdle process. The household purchase decision is shaped by its main food buyer/preparer's employment status and education level, household location, household monthly income, and the number of children age 4 to 18 years old as well as its squared value. Higher values of these variables, but the squared number of children encourage the purchase decision. However, the decision of purchase counts of cookie boxes is shaped by another set of variables, including the frequency of eating cookies, household location, household monthly income, the number of children age 4 to 18, the type of cookie box purchased (cookie purchase is made as per piece purchase and per packet purchase), and its price. The findings provide important insights for the local cookie producers and marketers, as the identified characteristics and the directional effects are of direct use in the formulation of the marketing and merchandising decisions. The findings are also valuable for policymakers, who concerned about improving nutrition for school children.

Keywords: Survey data, nutrition, peanuts, protein, purchase frequency

Introduction

Uganda maintained an average real GDP growth of 7.48 percent from 2003 through 2011 (World Bank, *Indicators Database*), despite global economic downturn that begun in 2008. Food demand is expected to grow rapidly due to the increasing national income and expanding population. However, with the youngest and fastest growing population on the African continent (AfricanEconomicOutlook.org, *African Economic Outlook 2012*), Uganda continues to face its long existing challenges of poverty and child malnutrition. The diet in Uganda remains poor in micronutrient-rich foods and undernourishment affects 15 percent of the population (FAO, *Nutrition Country Profiles*).

Biscuits are distributed by international relief agencies (e.g., United Nations World Food Program) to alleviate the most urgent needs. Fortified biscuits and cookies are used in school feeding program to improve school children's micronutrient status (e.g., iron-fortified cookies by Chilean School Lunch Program, Walter et al. 1993). Cookies are associated with rather affluent households, but they can also represent a potentially nutritious snack, especially if the ingredients are thoughtfully selected. Such cookies are convenient to serve as breakfast food or snacks, yet assure child consumers an adequate amount of calories and nutrients to properly function. In Uganda, a possible, locally available, ingredient that can be used in cookie production is the addition of peanut meal. Peanuts are high in protein and fat, and, therefore, in combination with carbohydrate ingredients can make cookies a nutritionally balanced food.

The understanding of household decision to consume and purchase cookies and factors affecting the consumption volume have economic value and important marketing implications for local producers and marketers, given Uganda's growing GDP and, thus, the growing consumer purchasing power. The identified consumer and household characteristics and their directional effects are of immediate use in the formulation of marketing and merchandising decisions. This paper also examines the effect of the presence of children on household cookie consumption decisions, the finding from which provides insights for policymakers who are concerned about improving nutrition for school children.

An extension of the study of household cookie consumption is the possibility of utilizing cookies as a source of protein for children and population at large by adding groundnut meal as an ingredient. The results are useful for policymakers because the improvement of school children nutrition is possible using domestically supplied ingredients. This paper adds to empirical literature by providing household-level analysis of food consumption and purchase decisions in Uganda, specifically, identifying the affecting household characteristics, and the process of decision-making. The study uses a unique data set collected from urban households in towns including Kampala, the capital city.

Specifically, the paper examines the relationship between the household demographic features, including the presence of children of various ages, and the decision to eat and, reportedly to purchase cookies and the number of cookies purchased. Although it is reasonable to expect that the presence of children is likely the driving force behind the decision to consume cookies and influences the volume consumed, the socio-economic household characteristics are also considered, recognizing that the preferences for cookies and the ability to purchase are shaped, among others, by household budgets.

Conceptual Framework

This paper studies households' sequential decisions of whether to eat and buy cookies and if so, how many to purchase. For this study purpose, two models were formulated for the decisions to eat and purchase cookies, respectively.

The Decision to Eat Cookies: A Logit Regression Model

A qualitative choice model based on a random utility maximization developed by McFadden (1980) provides the theoretical foundation for model specification. Specifically, a logit model derived from the random utility maximization process is developed to identify and quantify the effects of factors that affect household decisions to consume cookies. In particular, the probability of eating cookies at least once a week is estimated using households' demographic features as explanatory variables.

Consider a household facing two alternatives, eating cookies at least once a week or less often. The household makes the choice between the two that provides the greater utility. A household's decision is affected by both observable factors and unobservable characteristics of the chooser's underlying preferences. Let U_1 be the utility of eating cookies at least once a week and U_2 be that of eating cookies less often. The linear random utility models are formulated as

$$U_1 = \boldsymbol{w}'\boldsymbol{\beta_1} + \boldsymbol{z_1}'\boldsymbol{\gamma_1} + \varepsilon_1 \text{ , and} \tag{1}$$

$$U_2 = \boldsymbol{w}'\boldsymbol{\beta_2} + \boldsymbol{z_2}'\boldsymbol{\gamma_2} + \varepsilon_2, \tag{2}$$

where the observable vector of characteristics of the individual household is denoted by $\mathbf{w}$, and the attributes of the two choices are denoted by the vectors $\boldsymbol{z_1}$ and $\boldsymbol{z_2}$, respectively. The random terms of ε_1 and ε_2 represent the stochastic elements that are specific and known only by an individual, but not observable from the survey data.

Using a latent variable y^* as the difference between utilities from the two choices, we get:

$$y^* = U_1 - U_2 = [\boldsymbol{w}'(\boldsymbol{\beta_1} - \boldsymbol{\beta_2}) + \boldsymbol{z_1}'\boldsymbol{\gamma_1} - \boldsymbol{z_2}'\boldsymbol{\gamma_2} + \varepsilon_1 - \varepsilon_2 = \boldsymbol{x}'\boldsymbol{\beta} + \varepsilon \quad (3)$$

where $\boldsymbol{x}'\boldsymbol{\beta}$ includes all the observable elements of the difference of the two utility functions and ε denotes the difference between the two random elements.

While the actual utility different y^* is unobservable, the choice observed is of greater utility. Thus, our choice observation of the frequency of eating cookies y_1 is 1 if y^* is positive; y_1 is zero if $\mathrm{y}^*$is non-positive.

The outcome is ultimately driven by the random elements in the utility function as the probability of y_1 equals to 1 is

$$P(y_1 = 1 | w, z_{1,} z_2) = P(U_1 > U_2 | w, z_{1,} z_2) = P(y^* > 0 | \boldsymbol{x}_1) = P[\boldsymbol{x}'\boldsymbol{\beta} + \varepsilon > 0 | \boldsymbol{x}] =$$

$$P(\varepsilon > -\boldsymbol{x}'\boldsymbol{\beta} | \boldsymbol{x}) = P(\varepsilon < \boldsymbol{x}'\boldsymbol{\beta} \,|\boldsymbol{x}) \quad (4)$$

where $\boldsymbol{x}'\boldsymbol{\beta}$ collects all of the observable elements of the difference of the two utility functions and ε denotes the difference between the two random elements, which has a standardized logistic distribution with variance $\pi^2/3$.

Thus, we model the probability of household eating cookies at least once a week as

$$P(y_1 = 1 | \boldsymbol{x}) = P(\varepsilon < \boldsymbol{x}'\boldsymbol{\beta} \,|\boldsymbol{x}) = \Lambda(\boldsymbol{x}'\boldsymbol{\beta}) \quad (5)$$

where $\Lambda(t) = \frac{\exp(t)}{1+\exp(t)}$. In particular, the variables in the vector $\boldsymbol{x}$ include respondent's age, employment status, education level, log of total household income in the month preceding the survey, household location, the number of children from four to 18 years old and its squared value. The logarithm function for the logistic probability model is

$$LL_1(\beta) = \sum_{i=1}^{n} \{y_{1i}\, Ln[\Lambda(x_i\beta)] + (1 - y_{1i}) Ln[1 - \Lambda(x_i\beta)]\}. \quad (6)$$

Consistent parameter estimates of the vector of $\boldsymbol{\beta}$ that maximize the loglikelihood function $LL_1(\beta)$ can be obtained by the logistic regression procedure in SAS.

The Decision to Purchase Cookies: A Double-Hurdle Model

Researchers have long hypothesized a two-stage choice process in which consumers first decide whether to buy a commodity and then, choose a specific product with desired attributes to purchase and the amount of purchase (e.g. Bettman 1979; Gensch 1987; Shocker et al. 1991; Wright and Barbour 1977). These studies have also proposed that consumers use different decision rules in each of the two stages. Following the above well accepted hypothesis, we assume that households follow a two-stage decision-making process in that they first decide whether to purchase cookies and, then, the amount of purchase. The hurdle model captures the two-stage nature of the decision-making process and, therefore, has an appealing interpretation. One feature of the survey data is that the survey collected households' cookie purchase quantity in the number of packages at their last purchase, and 37.5 percent of the sample observations are zeros in the counts. Therefore, a hurdle regression for count data model, originally proposed by Mullahy (1986), was applied to the decision to purchase cookies. In the current study, the first decision of whether to make a purchase can be modeled using the logit approach. The second decision, to purchase cookies, can be analyzed by a zero-truncated Negative Binomial regression model due to the truncated and discrete counting nature of the data. These two decisions are not necessarily shaped by the same factors (Cragg 1971). Instead, different explanatory variables are allowed to have different impacts at each stage of the decision process.

Similarly to the modeled decision to eat cookies in the previous section, the purchase decision purchase is modeled as a latent variable:

$$q = \boldsymbol{X}'\boldsymbol{\alpha} + \epsilon, \tag{7}$$

where $\boldsymbol{X}$ is a vector of household characteristics affecting purchase decisions, $\boldsymbol{\alpha}$ is a vector of coefficients, and ϵ is independently distributed following the standardized logistic distribution with variance $\pi^2/3$. The latent variable q, represents the unobservable utility difference between making or not making a purchase. The observed variable, purchase counts, y_2 is zero if q is non-positive. However, different than in the first, here y_2 equals q if q is positive.

The first part of the hurdle model is given by

$$P(y_2 = 0|X_1) = P(q < 0|X_1) = P(\epsilon < -\boldsymbol{X_1}'\boldsymbol{\alpha}|X_1) = \Lambda(-\boldsymbol{X}_1'\boldsymbol{\alpha}) = \theta. \tag{8}$$

The probability that an observed value of y_2 count falls under the Negative Binomial distribution with the dispersion parameter k and mean μ is given by:

$$f_{k,\mu}\,(y_2|X_2) = \frac{\Gamma(y_2+k^{-1})}{\Gamma(k^{-1})y_2!}\left(\frac{1}{1+k\mu}\right)^{k^{-1}}\left(\frac{k\mu}{1+k\mu}\right)^{y_2}, y_2 = 0,1,2,\ldots, \text{ where } \mu = \exp(\boldsymbol{X_2}'\boldsymbol{\gamma}) \tag{9}$$

The probability of y_2 being zero under the untruncated Negative Binomial distribution is $\left(\frac{1}{1+k\mu}\right)^{k^{-1}}$.

Truncated at zero, then the equation (9) would become:

$$f_{k,\mu}\,(y_2|y_2 > 0) = \frac{f_{k,\mu}\,(y_2)}{P_{k,\mu}\{y_2>0\}} = \frac{f_{k,\mu}\,(y_2)}{1-P_{k,\mu}\{y_2=0\}}$$

$$= \frac{\Gamma(y_2+k^{-1})}{\Gamma(k^{-1})y_2!}\left(\frac{1}{1+k\mu}\right)^{k^{-1}}\left(\frac{k\mu}{1+k\mu}\right)^{y_2}\frac{1}{1-\left(\frac{1}{1+k\mu}\right)^{k^{-1}}}\,,\ y_2 = 1,2,\ldots \tag{10}$$

and the probability density function for positive y_2 is given by:

$$f(y_2|X_1,X_2) = (1-\theta)\frac{\Gamma(y_2+k^{-1})}{\Gamma(k^{-1})y_2!}\left(\frac{1}{1+k\mu}\right)^{k^{-1}}\left(\frac{k\mu}{1+k\mu}\right)^{y_2}\frac{1}{1-\left(\frac{1}{1+k\mu}\right)^{k^{-1}}}$$

$$y_2 = 1,2,\ldots, \tag{11}$$

Equations (8) and (11) form the two parts of the double-hurdle model. The log-likelihood function for the hurdle regression model is

$$LL_2(\alpha,\gamma,k) = \sum_{i=1}^{n}\left\{\begin{matrix} I(y_2=0)\log(\theta)+ \\ I(y_2>0)\left(\begin{matrix} log(1-\theta)+log\,\Gamma\left(y_2+\frac{1}{k}\right)-\log(y_2!)-\log\Gamma\left(\frac{1}{k}\right) \\ -\left(y_2+\frac{1}{k}\right)\log(1+k\mu)+y_2\log(k\mu)-\log\left(1-(1+k\mu)^{-\frac{1}{k}}\right)\end{matrix}\right)\end{matrix}\right\} \quad (12)$$

Estimates of the dispersion parameter k and consistent parameter estimates of the vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$ that maximize the log-likelihood function $LL_2(\alpha,\gamma,k)$ can be obtained by the PROC NLMIXED procedure in SAS (Liu and Cela, 2008).

Moreover, equation (10) approximates zero-truncated Poisson distribution with the mean parameter μ as one that approaches the limit as k →0 holding μ fixed. Therefore, a test of the Poisson distribution is often carried out by testing the hypothesis k=0 using the Wald or likelihood ratio test (Greene, 2012).

The Survey Data

The data are from a household survey conducted from February to June in 2011. A total of 1,646 households were randomly selected from six towns in Uganda, including Kampala, the capital, Gulu, Lira, Mable, Soroti, and Serere. Respondents shared information about households' demographic and socio-economic features. They also provided details about their consumption of cookies. The latter includes the frequency of eating cookies, the typical quantity of cookie packages purchased and the unit price paid for their most recent cookie box at the purchase.

The definitions of variables and descriptive summary statistics of the survey data are shown in Table 1. Out of the whole sample, 71.0 percent of the household heads are male.

However, females represent 27.9 percent of the survey respondents. The average age of the 1,621 respondents who answered the question is 35.3 years old; and 69.4 percent of the respondents are married. About 21.4 percent of the respondents are permanent or contract employees. The percent of respondents that have an education level of no less than secondary lower level is 35.4 percent. About 51.3 percent of the surveyed households are from the capital city, Kampala. The average household size is about six persons. In a household, the average number of children from 4 to 18 years of age is 2.3. The household total income in the month preceding the survey averages 674,134.82 Uganda Shillings (UGX). With regard to cookie consumption, 31.0 percent of the households reported to eat cookies at least once a week in the four weeks preceding the interview. About 53 percent of respondents would like to eat cookies more often. Not surprisingly, 56 percent respondents buy cookies, and the number of packages at a single purchase occasion ranges from 1 to 30 packages, with an average of 3.2 packages. Among the 922 respondents who reported the volume of their purchase, about 84 percent buy cookies in a unit described as a packet, while the remaining respondents buy cookies by piece. Among the 906 respondents who reported their unit price, the unit price (regardless whether it is a packet or a piece) ranges from 50 UGX per piece to 50,000 UGX (for a very large packet), and averages 2,616.72 UGX. Those who usually purchase a packet (where Unit=1in Table 1), on average, buy about 2.8 packets at one time. The per-packet price the respondents paid at their purchase is 2917.52 UGX, but the range is wide, from 100 UGX to 50,000 UGX. In contrast, respondents who usually purchase by piece, on average, buy 5.2 pieces at one purchase and pay an average per piece price of 984.75 UGX.

Heterogeneity arises because the units of purchased cookies vary in terms of their net weight or the number of pieces in a single package. Therefore, the unit price of cookies has a heterogeneous nature, as larger packets of cookies are associated with higher per packet price. The survey data provide inadequate information to address this issue, but the price variable is still included in the model estimation, with the purpose to partly account for the variation in the purchase counts. Due to heterogeneity, the price variable however does not bear a negative effect on the purchase amount.

Along with the information whether a purchase is made by per piece or piece packet, the cookie purchase counts generally provide a good measure for a household's cookie consumption. From author's observations in Uganda, a larger cookie is usually sold as an individual item and a packet of cookies typically includes five cookies, each of which is about 1.5 inch in diameter. The price of cookie packet, 5 in a small package, is between 2,000 UGX and 3,000 UGX, while one large individual cookie is typically priced at 1, 000 UGX. Such tendency is confirmed by the survey data (Table 1) – the average price for cookies sold per piece is 984.75 UGX, and the average price for cookie packet is 2,917.52 UGX.

Logit Model Results for the Decision to Eat Cookies

Table 2 presents parameter estimates and relevant statistics from the estimation of the decision to eat cookies. All the explanatory variables included in the model have statistically significant effect on the decision to eat cookies, and these effects are of the expected signs. The decision to eat cookies was positively influenced by the increase in income, and respondent's education level. The stability of employment encouraged the decision to eat cookies. The decision, however, was negatively influenced by the respondent's age and the location of a household, that is, households in Kampala, the capital city of Uganda, were found to have a lower probability of eating cookies at least once a week. In addition to the conventionally demographic features affecting the decision to eat a specific food listed above, the presence of children from 4 years old to 18 years old was found to positively influence a household's decision to eat cookies more often. A very large number of children, however, discouraged a household to eat cookies more often, as indicated by the negative sign of the squared number of children used in this specification.

The estimated coefficients (Table 2) lack meaningful economic interpretation *per se*. A more meaningful approach from the standpoint of making policy recommendations is to estimate the marginal effects, which measure the change in probability of eating cookies at least once a week corresponding to a change in each explanatory variable. The marginal effects reported in Table 2 are the averages of individual marginal effects. A one-year increase in respondent's age on average decreased the household's probability of eating cookies at least one a week by 0.23 percent. On average, households where respondents were a permanent or contract employee had an 8.24 percent higher probability of eating cookies at least once a week than households whose respondents had a less stable employment status, *ceteris paribus*. A respondent had at least a secondary lower education level were on average associated with a 7.46 percent higher probability of eating cookies more often than those with less education. A one percent increase in monthly household total income on average positively influenced the probability of eating cookies more often by slightly more than 7 percent. An interesting finding is that households living in Kampala, the capital of Uganda, on average, had a 5.8 percent lower probability of eating cookies at least once a week. A possible reason is that households in the capital city have more food choices and cookies are one of many available foods. For example, respondents from Kampala ate more often bread and buns than respondents from other towns (Florkowski et al., 2012) and cookies might have been a less attractive food item. An important finding is that the presence of children encouraged the household decision to eat cookies more often. The result suggests household choices similar to those in developed economies where cookies are a common food item for children age 4 to 18 years. More interestingly, according to the results (Table 2), as the number of children increases, the probability of the decision to eat cookies decreases, as could be expected, but the decrease is negligible. Overall, the presence of children in Ugandan urban households strongly influences the decision to eat cookies. As the number of children increases, the probability of eating cookies at least once a week also increases. However, the negative effect of the squared number of children implies a large number of children discourage consumption decision.

Table 2 also reports several goodness-of-fit measures for the Logit model of decision to eat cookies. One measure is the log likelihood ratio test, the second measure is the pseudo R-square, and the third is Hosemer and Lemeshow goodness-of-fit test, which examines whether there is a significant difference between the observed and predicted values of the response variable. The last measure indicates how well the model classified the household correctly based on the estimated probabilities. The model generally performed well. The log likelihood ratio test for the specified model was highly significant leading to the acceptance of the null hypothesis against the model that only includes a constant term. The overall goodness-of-fit measure of the pseudo R-Square is about 6.4 percent, which is quite low, but expected for qualitative response models based on cross-sectional data. The Hosemer and Lemeshow goodness-of-fit test does not reject the null hypothesis that there is no difference between the observed and predicted response variable, indicating the model fits the data well. The ability of the model to produce correct classification of households' cookie consuming behavior was 64.7 percent. Overall, the computed statistical measures indicate that the model provides satisfactory explanatory power and reasonably fits the data.

Hurdle Model Results for the Decision to Purchase Cookies

As shown in Table 3, in the first-stage equation for the purchase decision, the respondent's employment status, education level, household location, the household income in the month preceding the survey, the number of children age 4 to 18 years old and the value of this number squared significantly influenced the household's probability of purchasing cookies. If a respondent was a permanent or contract employee– *ceteris paribus* – then his or her household's probability of purchasing cookies was 10.9 percent higher than those who have a less stable employment status. A higher education level was related with a 9.1 percent higher probability of purchasing cookies. If a respondent resided in the capital city, the probability of purchasing cookies was 12.1 percent higher than that among respondents from other cities. A one percent increase in monthly household income results in a 5.4 percent higher probability of purchasing cookies. Again, the presence of children from 4 to 18 years old increased the probability of buying cookies, but a very large number of children discourages the purchase decision.

The reported measurements of goodness-of-fit in Table 3 for the decision to buy cookies suggest the model performs well. The Pseudo R-square is 0.070, the likelihood ratio test rejects a model only with a constant, the Hosemer and Lemeshow Goodness-of-Fit test fails to reject the null hypothesis of good fit, and the correctly predicted outcomes are 65.2%.

In Hurdle Two of purchase counts, the affecting factors differed from those in the first-stage equation. Here, the affecting variables are the frequency of eating cookies, household location, monthly income (in logarithm), number of children of 4 to 18 years old, unit price of cookie box, and the unit (packet or piece) of such cookie package. In general, more stable employment status, higher education level, residing in cities other than the capital, higher monthly household income, and the presence of children, respectively – *ceteris paribus* – is associated with more purchase counts.

Because of the discrete nature of purchase counts and the Negative Binomial Distribution, the marginal effect of each explanatory variable is relatively harder to present, as one cannot take derivatives to obtain the marginal effects. Instead, Table 4 gives the difference of predicted purchase counts for each level of the dummy variables, and Table 5 presents the predicted purchase counts with respective to the number of children and monthly household income, respectively evaluated at their different levels, the other variables are evaluated at their means. While we cannot estimate the conventional marginal effects, Table 4 and Table 5 line out the representative household purchase counts at the specific variable levels.

Conclusions

The decision to eat and buy cookies, respectively, by urban households in Uganda is modeled using a Logit choice model and a double-hurdle model. The decision to eat cookies were positively affected by increase in monthly household income, food buyer/preparer's education level, and the stability of employment, but negatively influenced by the location in the Capital city (relative to the other five areas), the respondent's age. While the presence of children age 4 to 18 years old drives up a household's probability of eating cookies at least once a week, a large number of children discourage consumption, though this effect is minor.

The decision to purchase cookies is essential a two-stage process – first the household decides whether to buy or not, then it decides the 'intensity' of purchase, i.e., how many to purchase. While the respondents' age, employment status and education level, household location, household total monthly income, number of children and its squared value shape the decision whether to buy cookies or not, the decision of the counts of cookie box to purchase is shaped by variables including the frequency of eating cookies, household monthly income, household location, unit price of cookies, and the size of the cookie unit, as well as the number of children of 4 to 18 years old.

The results from above two models reveal a strong link between the decision of cookie consumption and the employment status, the income and education levels of a household's food buyer/preparers. The results also demonstrate regional differences in the households' consumption decisions. The findings provide important insights for the local cookie producers and marketers, as the identified characteristics and the directional effects are of direct use in the formulation of the marketing and merchandising decisions. The results also indicate the presence and the number of children plays an important role in households' consumption decisions. Therefore, the results are also valuable for policy makers who are concerned about improving nutrition for school children.

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Table 1. The summary of descriptive statistics of sample variables

Variable	Description/Units	N	Min	Max	Mean	Median	Std. dev.
	Socio-economic and Demographic Factors						
Malehead		1646			0.710		0.454
Male	1 if the respondent is male, 0 otherwise	1643			0.279		0.449
Age	Respondent's age, in years	1621	17	89	35.331	32	12.354
Married	Marital status, 1 if married, 0 otherwise	1643			0.694		0.461
Employ	Respondent's employ status, 1 if permanent employee or contract employee, 0 otherwise	1642			0.214		0.411
Education	Respondent's education level, 1 if at least secondary lower (A level), 0 otherwise	1616			0.354		0.478
Income	Total household income in the previous month of survey, in Uganda Shilling (UGX)	1495	1,000	67,000,000	674,134.82	400,000	2,081,765.35
Location	Household location, 1 if Kampala, the capital of Uganda, 0 otherwise	1646			0.513		0.500
NumFam	Total number of household members	1646	1	26	6.324	6	2.675
NumAdult	Number of adults in a household	1646	1	16	3.267	3	1.425
NKids4_18	Number of children from 4 to 18 years old in a household	1646	0	14	2.300	2	1.938
	Cookies Consumption, Purchase and Preference						
EatFreq	Respondent's frequency of eating cookie, 1 if at least once a week, 0 otherwise	1465	0	1	0.310	0	0.463
More	1 if the respondent would like to eat cookies more often, 0 otherwise	1646	0	1	0.529	1	0.500
Purchase	1 if the respondent buy cookies, 0 otherwise	1646	0	1	0.560	1	0.497
NumPack	Number (nonzero) of packages of cookies bought at the respondent's last purchase	921	1	30	3.175	2	2.870
Unit	1 if the price is per packet of cookies, 0 if the price is per cookie	922	0	1	0.844	1	0.363
NumPack (Unit=0)		144	1	30	5.243	5	4.120
NumPack (Unit=1)		778	0	23	2.788	2	2.388
Price	Per package price paid for cookies at the respondent's last purchase, in UGX	906	50	50,000	2,616.72	2,000	3,807.87
Price(Unit=0)		141	50	12,000	984.75	500	1,571.36
Price(Unit=1)		765	100	50,000	2,917.52	2,000	4,017.63

Table 2. The Logit Estimation Results for the Decision to Eat Cookies at Least Once a Week

Variable name	Estimated coefficient	Standard error	Pr>ChiSq	Marginal effect
Constant	-5.194	0.908	<.0001	
Income[a]	0.351	0.072	<.0001	0.0706
Education	0.371	0.142	0.0092	0.07f46
Age	-0.012	0.006	0.0417	-0.0023
Employ	0.411	0.154	0.0076	0.0824
NKids4_18	0.1980	0.092	0.0318	0.0398
NKids4_18 squared	-0.035	0.014	0.0137	-0.0071
Location	-0.289	0.138	0.0359	-0.0580

[a] Expressed in logs.

Goodness-of-fit measures

Log Likelihood value	- 769.2445	Pr>Chisq
Likelihood Ratio	85.8662	<0.0001
Pseudo R-square	0.0642	
Hosemer and Lemeshow Test	8.9890	0.3432
Percent correctly predicted	64.7 percent	

Note: The total number of observations is 1,294.

Table 3. Estimation Results of Hurdle One for Purchase Decision

Variable name	Coeff. Est.	Std. Err.	Pr>ChiSq	Marginal Effect
Constant	-3.357	0.752	<0.0001	
Employ	0.476	0.147	0.0012	0.109
Education	0.3962	0.129	0.0021	0.091
Location	0.527	0.119	<0.0001	0.121
Log of Income	0.234	0.061	0.0001	0.054
NKids4_18	0.149	0.072	0.0386	0.034
NKids4_18 squared	-0.028	0.111	0.0068	-0.006

Goodness-of-fit Measures

Log Likelihood Value	-953.978	Pr>Chisq
Likelihood Ratio	106.644	<0.0001
Pseudo R-square	0.070	
Hosemer and Lemeshow test	3.867	0.8689
Percent correctly predicted	65.2percent	

Note: The total number of observations is 1,469.

Table 4. Estimation Results of Hurdle Two for Purchase Quantity

Hurdle Two: zero-Truncated Negative Binomial Regression						
	Parameter Estimate			Marginal Effect		
Variable	Coeff. Est.	Std. Err.	Pr>|t|	Estimate	Std. Err.	Pr>|t|
Constant	-1.0043	0.4664	0.0316			
EatFreq	0.2764	0.0687	<0.0001	0.6931	0.1717	<0.0001
Location	-0.1875	0.0779	0.0163	-0.4440	0.1855	0.0169
Log of Income	0.1160	0.0352	0.0010	See Table 5		
Nkids4_18	0.0362	0.0187	0.0529	See Table 5		
Unit	-0.9867	0.0955	<0.0001	-2.9573	0.4776	<0.0001
Log of Price	0.1536	0.0365	<0.0001			
k	0.3901	0.0562	<0.0001			
Measures of Goodness-of-Fit						
Number of Observation	816					
Log Likelihood Value	3124.0					
Likelihood Ratio (v.s. constant term only)	2470.65	<0.0001				

Table 5. Marginal Effect of non Dummy Variables

Variable	Variable Value	Predicted Purchase Counts*	Std. Err.	Pr<|t|
Nkids4_18	0	2.1450	0.1324	<.0001
Nkids4_18	1	2.7009	0.1508	<.0001
Nkids4_18	2	2.8024	0.1432	<.0001
Nkids4_18	3	2.9077	0.1539	<.0001
Nkids4_18	4	3.0170	0.1834	<.0001
Nkids4_18	5	3.1303	0.2276	<.0001
Nkids4_18	6	3.2479	0.2828	<.0001
Nkids4_18	7	3.3700	0.3466	<.0001
Nkids4_18	8	3.4966	0.4177	<.0001
Nkids4_18	9	3.6280	0.4957	<.0001
Nkids4_18	10	3.7643	0.5803	<.0001
Nkids4_18	12	4.0525	0.7696	<.0001
Nkids4_18	14	4.3627	0.9868	<.0001
Variable	Variable Value	Predicted Purchase Counts*	Std. Err.	Pr<|t|
Income #	Min (1000)	1.1828	0.2608	<.0001
Income	25th Percentile (200,000)	2.1696	0.1123	<.0001
Income	50th Percentile (400,000)	2.3489	0.1009	<.0001
Income	Mean (674,134.82)	2.3348	0.1009	<.0001
Income	75th Percentile (750,000)	2.5242	0.1164	<.0001
Income	Max (67,000,000)	4.2221	0.7646	<.0001

*While other variables at their mean values; # enters the model in the form of logarithm.