A BIVARIATE COUNT MODELLING APPROACH IN ANALYZING CONVENIENCE AND NON-CONVENIENCE CONSUMPTION OF FOOD PREFERENCE IN WINDHOEK, NAMIBIA

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Abstract

Globalization coupled with urbanization has placed a significant effect on the food systems of developing countries in the world, leading to a myriad lifestyle change that has become one of the most important influences in dietary patterns. The nutritional transition has affected the dietary pattern and nutrient intake greatly and has led to a rise in the purchases and consumption of processed and convenience foods, which are prepared foods designed for simplicity of consumption but are associated with rising rates of diet-related non-communicable diseases in Low- and middle-income countries (LMICs). This chapter jointly analyzed paired consumption of both convenience and non-convenience food that are exhibiting correlations, using a household food security survey, conducted in Windhoek. This is illustrated by applying both the untruncated and the right-truncated bivariate Poisson models to examine factors that influence convenience and non-convenience food consumption patterns both on a weekly and monthly basis. The results found that overall, the untruncated (conditional/marginal) model fitted the data better. Whereas the consumption of food on a monthly basis was more on the non-convenience foods, the purchases of convenience was frequent on a weekly basis and from multiple food sources. The choice of food purchase both at weekly and monthly preference was influenced by sex, marital status, education level and work status.

Key words: Convenience and Non-Convenience foods, Bivariate Poisson Regression, (Un)Truncated, urbanization.

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1.1. Introduction

Globalization has had a significant effect on the food systems of developing countries around the world. As a complex and multifaceted phenomenon, globalization is considered by some as a form of capitalist expansion which entails the integration of local and national economies into a global, unregulated market economy (Shalmali, 2007). Forces manifested by globalization, such as market and trade liberalization, capital flow, and urbanization have changed the nature of food systems by increasing the diversity and affordability of food, but also by changing its quality and nutritional value (Black, 2016).

In developing countries undergoing rapid urbanization combined with globalization, the process includes changes in the sociocultural environment such as mass media marketing and the widespread availability of less traditional foods, which play an important role in influencing tastes and preferences. Consumer's food choices or preferences have been attributed to factors such as growing foreign direct investments that contributes to the rise of fast-food restaurants and western-style supermarkets by offering greater variety, quality, convenience and competitive prices in high-value added foods. In urban areas, men and women are driven into the workforce in order to maintain their lifestyles. Working hours and commuting times are often long and, with growing numbers of family members entering the workforce, there is less time available to prepare food and hence there is a greater desire and necessity to consume meals outside the home.

Traditional meals and mealtimes are replaced by spontaneous often unplanned food purchases on street corners or in small kiosks that provide family members with at least one and often several meals per day. Street foods are becoming increasingly important as both a cheap and quick meal option and as an income-generating strategy. Secondary factors such as marketing, advertising, the appeal of new products, new retail outlets including supermarkets and multinational fast-food chains contribute to dietary adaptation and convergence. Aside from the driving force of time constraints, part of the rapid adoption of new foods in the diet stems from successful advertising (Lang, 2003).

Convenience foods are prepared food designed for simplicity of consumption. These foods products are prepared food products that can be sold as ready-to-eat dishes; as room-temperature, precooked and frozen products and hot products. Convenience food can include products such as candy, soft drinks, fast food; nuts, fruits, processed meats and cheeses and canned products such as soups and pasta dishes (Jackson et al., 2018). Consumption is often associated with rising rates of diet-related non-communicable diseases in Low- and Middle-Income Countries (LMICs) (Khan, 2013).

Studies of Dietary patterns have become popular in nutritional epidemiology (Smith, Emmett, Newby, & Northstone, 2011). Traditional analysis examined diseases in relation to a single or a few nutrients or foods. However, people do not eat isolated nutrients. Instead, they eat meals consisting of a variety of foods with complex combinations of nutrients. A typical household would consume either convenience or consume non-convenience or consume both types of food. The high degree of inter-correlation among nutrients as well as among foods makes it difficult to attribute effects to single dietary components. For these reasons, a more prudent analysis that simultaneously estimates factors that are associated with the preference of non-convenience and convenience food groups is required.

Event counts such as the number of convenience and non-convenience foods consumed are likely to be jointly dependent (Karlis & Ntzoufras , 2005). To understand fully the drivers of preference of food choices (Convenience vs. Non-convenience), we will employ multidimensional measures that jointly estimate the risk factors and are able to accommodate heterogeneity attributes. Different count data may possess different characteristics and therefore cannot be used with particular count data models. Poisson regression model provides a basis for the analysis of count data. Due to the over-dispersion and/or excess number of zeros that are frequently present in empirical count data sets, the Poisson regression model is frequently only of limited use. In order to analyze bivariate count data, the plain Poisson regression model needs to be extended.

Bivariate Poisson models are appropriate for modeling paired count data exhibiting correlation and require joint estimation (Karlis & Ntzoufras, 2005). The application of bivariate count models often assumes a bivariate Poisson distribution which assumes the conditional mean of each count variable equals the conditional variance. One more shortcoming of commonly used bivariate count models is that they can only accommodate non-negative correlation between the paired counts.

The bivariate Poisson is the most widely used model for bivariate counts. It was proposed by (Holgate, 1964) and presented by (Johnson & Kotz, 1969). Leiter & Hamdan (1973) proposed bivariate probability models applicable to traffic accidents and fatalities. Several approaches have been discussed by various authors with the development of bivariate Poisson distribution with various assumptions. Amongst others, the most comprehensive one has been proposed by (Kocherladota & Kocherlakota , 1992). The bivariate Poisson form is further shown using a trivariate reduction method (Jung, 1993) allowing for correlation between the variables. Karlis & Ntzoufras (2005) implemented the maximum likelihood estimation for bivariate Poisson models and their diagonal inflated variations. Furthermore, (Islam & Chowdhurry, 2015), (Chowdrhurry & Islam, 2016), (Islam & Chowdhurry, 2017) and (Chowdhury & Islam, 2019) developed untruncated, zero-truncated and right truncated bivariate Poisson model for covariates dependence based on the extended generalized linear model. Despite vast application of bivariate poisson regression models in count data, there is no literature on application of bivariate poisson in the area of food consumption. This study thus extends bivariate count modelling approach to analyze convenience and non-convenience consumption of food preference.

1.2. Materials and Methods

1.2.1. The AFSUN-HCP Data

This study used the AFSUN-HCP Household Food Security Baseline Survey (2016) which collected a wide range of demographic, economic and food consumption, and sourcing data at the household level. Households surveyed in the ten constituencies of Windhoek were identified using a two-stage sampling design. Primary sampling units (PSUs) were first randomly selected from a master frame developed and demarcated for the 2011 Population and Housing Census. Within the 10 constituencies, a total of 35 PSUs were selected covering the whole of Windhoek, and 25 households were systematically selected in each PSU. The sampled PSUs and households were located on maps, which were used to select households for in-person interviews. Household heads (or their spouses/ partners) were recruited to complete the survey.

1.2.2. Outcome Variables

We consider two possibly dependent and correlated response variables namely Y_1, which is the total number of households consuming convenience food (CONVENIENCE) and Y_2, which is the total number of times each household consumes non-convenience foods (NON-CONVENIENCE).

1.2.3. Explanatory Variables

The regressor variables in this study are: Age of head of household (1- <19, 2- 20-29, 3- 30-39, 4- 40-49, 5- >50), Sex of head of household (1-Male, 2-Female), Marital Status Sex of head of household (1- Unmarried, 2- Married, 3- Living together/cohabitating, 4- Widowed), Educational level Sex of head of household (1- None, 2- Primary education, 3- Secondary education, 4- Tertiary education) and Work Status Sex of head of household (1- Self-employed, 2- Formal employed, 3- Unemployed).

Convenience and non-convenience foods have been categorized based on the source purchased and further measured on the number of times a household made use of a source, weekly or monthly basis and estimates were made separately for each. Convenience food sources include fast foods/take-away, restaurants, spaza/tuckshop, Street seller/trader/hawker and begging from the streets while non-convenience food sources comprise supermarkets, small-shops, Open markets, and food grown by households in rural areas.

1.2.4. Review of Bivariate Count Models Data

1.2.4.1. Bivariate Poisson Regression

The Bivariate Poisson model is the most used model among the bivariate count models. A well-established approach, according to (Chou & Steenh, 2011), is to generate the bivariate Poisson distribution by convolutions of Poisson random variables (Kocherladota & Kocherlakota , 1992). Let Y_1 represent the convenience food and Y_2 be non-convenience food consumed by household members over a week and month time period:

$$y_{1i} = y_{1i}^{*} + \mu_i \qquad (1)$$

$$y_{2i} = y_{2i}^{*} + \mu_i \qquad (2)$$

Where y_{1i}^{*} ~Poisson (λ_{1i}) and y_{2i}^{*} ~Poisson (λ_{2i}) are independently distributed. The joint probability density function of the bivariate Poisson can be defined as follows:

$$f(y_{1i}, y_{2i}|x_i) = \left[\prod_{j=1}^{2} \frac{exp(-\lambda_{ji})\lambda_{j_i}^{y_{ji}}}{y_{ji}!}\right] exp(-\lambda_3) \sum_{s=0}^{m} \binom{y_{1i}}{s} \binom{y_{2i}}{s} s! \left(\frac{\lambda_3}{\lambda_{1i}\lambda_{2i}}\right)^{s} \qquad (3$$

Where $m = min(y_{1i}, y_{2i})$ and $\lambda_{ji} = exp(x_{ji}\beta)$. The Poisson distribution is known to be restrictive due to its equi-dispersion property, viz., with the mean and variance both equal to μ_j.

$$E(Y_{it}) = Var(Y_{it}) = \mu_{it}, \quad t = 1,2 \qquad (4)$$

The model allows only for non-negative correlation between the counts and restricts the mean to be equal to the variance for each of the respective marginal distributions (Chou & Steenh, 2011). The marginal distributions of the model are still Poisson, and the correlation between the two count variables (conditioned on the covariates) is individual specific, being a function of the λ_{ji} and λ_3.

$$corr(y_1, y_2) = \lambda_3/\sqrt{(\lambda_1)(\lambda_2)} \qquad (5)$$

The maximum likelihood estimator of the correlation between y_1 y_2 shown by (Leiter & Hamdan, 1973) is:

$$cor\hat{r}(y_1, y_2) = \left(\frac{\bar{y}_2}{(\bar{y}_1+\bar{y}_2)}\right)^{\frac{1}{2}} \qquad (6)$$

1.2.4.2. Bivariate Truncated Poisson Model

The bivariate truncated models are mostly used if the observations (y_{1i}, x_{1i}) or (y_{2i}, x_{2i}) or both in some ranges are totally lost and the joint distribution of observed counts is restricted. When the count data are only observed over a portion of the response variable's range, this is referred to as truncation (Cameron & Trivedi , 1999). A series may be truncated from below (left truncated) or truncated from above (right truncated) or un-truncated (Gurmu & Elder, 2008). The truncated models can be grouped as follows:

1.2.4.3. Un- Truncated Bivariate Poisson

The untruncated model in this study is defined as, the number of occurrences of convenience food Y_1 over a week or month follows Poisson distribution with parameter λ_1 and the occurrence of non-convenience food, Y_2, is also Poisson with parameter, $\lambda_1 y_1$. The joint pdf of Y_1 and Y_2 is:

$$g(y_1, y_2) = \frac{e^{-\lambda_1}\lambda_1{}^{y_1}e^{-\lambda y_1}(\lambda_2 y_1)^{y_2}}{y_1!y_2!},\ y_1 = 0,1, \ldots .: \lambda_1, \lambda_2 > 0 \qquad (7)$$

1.2.4.4. Zero- Truncated Bivariate Poisson

The joint distribution of the Zero Truncated Bivariate Poisson model can be obtained from the marginal and conditional distributions (Chowdhury & Islam, 2019):

$$g(y_1, y_2) = \ g_2(y_2|y_1).\,g_1(y_1) = \frac{(\lambda_2 y_1)^{y_2}}{y_2!(e^{\lambda_2 y_1}-1)} * \ \frac{\lambda_1{}^{y_1}}{y_1!(e^{\lambda_1}-1)} = \ \frac{(\lambda_2 y_1)^{y_2}\lambda_1{}^{y_1}}{y_1!\,y_2!(e^{\lambda_1}-1)(e^{\lambda_2 y_1}-1)} \qquad (8)$$

where the link functions are:

$$ln\,\lambda_1 = X'\beta_1\,and\ \ ln\,\lambda_2 = X'\beta_2 \qquad (9)$$

The log-likelihood function is:

$$ln\,L = \sum_{i=1}^{n}\left[\ y_{1i}(x_i'\beta_1) - ln(y_{1i}!) - ln\left(e^{e^{x_i\beta_1}} - 1\right) + y_{2i}(x_i{}'\beta_2) + y_{2i}\,ln(y_{1i}) - \right.$$

$$\left. ln(y_{2i}!) - \ ln\left(e^{y1_i e^{x_i{}'\beta_2}} - 1\right)\right]$$

(10)

1.2.4.5. Right – Truncated bivariate Poisson.

Right truncation results from loss of observations greater than some specified values (Cameron & Trivedi , 1999). The joint distribution of the right truncated bivariate Poisson distribution for number of occurrences of convenience food, Y_1, in a week or month interval and number of occurrences of non-convenience food, $Y_{2,}$ can be represented by:

$$g(y_1, y_2) = g(y_2|y_1).g(y_1) = c_1c_2e^{-\lambda_1}{\lambda_1}^{y_1}e^{-\lambda_2 y_1}(\lambda_2 y_1)^{y_2}/(y_1!\,y_2!) \quad (11)$$

the bivariate exponential form for the joint distribution of Y_1 and Y_2 can be shown as:

$$g(y_1, y_2) = e^{\{y_1 \ln \lambda_1 + y_2 \ln \lambda_2 - \lambda_1 - \lambda_2 y_1 + y_2 \ln y_1 - \ln y_1! - \ln y_2! + \ln c_1 + \ln c_2\}} \quad (12)$$

The loglikelihood function is:

$$\ln L = \sum_{i=1}^{n}\{y_{1i} \ln \lambda_1 + y_{2i} \ln \lambda_2 - \lambda_1 - \lambda_2 y_{1i} + y_{2i} \ln y_{1i}! - \ln y_{21}! + \ln c_1 + \ln c_{2y_1}\} \quad (13)$$

$$= \sum_{i=1}^{n}\{y_{1i}\grave{x}_{1\iota}\beta_1 + y_{2i}\grave{x}_{2\iota}\beta_2 - e^{\grave{x}_{1\iota}\beta_1} - e^{\grave{x}_{1\iota}\beta_2}y_{1i} + y_{2i} \ln y_{1i} - \ln y_{1i}! - \ln y_{2i}! + \ln c_1 + \ln c_{2y_1}\} \quad (14)$$

1.2.5. Other Bivariate Regression Models

1.2.5.1. Bivariate Negative Binomial Regression Model

Lakshminarayana et al., (1999) defined a bivariate Poisson distribution as a product of Poisson marginals with a multiplicative factor and correlation coefficient can be positive, zero, or negative depending on the value of λ, the multiplicative factor parameter. Famoye (2010) adopted adopted a similar approach as Lakshminarayana et al., (1999) and defined the bivariate negative binomial distribution as a product of negative binomial marginals. The probability function of the bivariate negative binomial distribution is given by:

$$P(y_1, y_2) = \binom{m_1^{-1}+y_1-1}{y_1}\theta_1^{y_1}(1-\theta_1)^{m_1^{-1}}\binom{m_2^{-1}+y_2-1}{y_2}\theta_2^{y_2}(1-\theta_2)^{m_2^{-1}} \times [1+\lambda(e^{-y_1} - c_1)(e^{-y_2} - c_2)], \quad (15)$$

Where $c_t = E(e^{-Y_t}) = [\frac{1-\theta_t}{1-\theta_t e^{-1}}]$ $(t = 1, 2)$ and $y_1, y_2 = 0,1,2$ .... Furthermore, the marginal distributions of $Y_t(t = 1, 2)$ is defined as a negative binomial with the following mean and variance:

$$\mu_t = \frac{m_t^{-1}\theta_t}{1-\theta_t} \quad (16)$$

$$\sigma_t^2 = m_t^{-1}\theta_t/(1-\theta_t)^2 \quad (17)$$

Additionally, the correlation coefficient can either be positive, zero, or negative depending on the value of the multiplicative factor parameter λ, is defined by:

$$\rho = \lambda c_1 c_2 A_1 A_2/(\sigma_1\sigma_2) \quad (18)$$

1.2.5.2. Bivariate Generalized Poisson Regression Model (BGPR)

Famoye (2010) defined a BGPR as a product of univariate generalized Poisson marginals which allows negative, zero, or positive correlation.

The probability distribution of the BGPR is given by (Famoye, 2010b):

$$P(y_1, y_2) = \prod_{t=1}^{2}\left[\frac{\theta_t^{y_t}(1+\alpha_t y_t)^{y_t-1}}{y_t!}exp[-\theta_t(1+\alpha_t y_t)]\right][1+\lambda(e^{-y_1} - c_1)(e^{-y_2} - c_2)] \quad (19)$$

Whereby $c_t = E(e^{-Y_t}) = \exp[\theta_t(s_t - 1)$. Additionally, the marginal distributions of $Y_t(t = 1, 2)$ is defined as a negative binomial with the following mean and variance:

$$\mu_t = \theta_t/(1 - \alpha_t\theta_t) \quad (20)$$

$$\sigma_t^2 = \theta_t/(1 - \alpha_t\theta_t)^3 \quad (21)$$

The correlation coefficient can be written as $\rho = \sigma_{12}/(\sigma_1\sigma_2) = \lambda(c_{11} - c_1\mu_1)(c_{22} - c_2\mu_2)/(\sigma_1\sigma_2)$. The correlation coefficient can either be positive, zero or negative depending on the value of the multiplicative factor, λ (Famoye, 2010b).

1.2.5.3. Bivariate Poisson Inverse Gaussian (BPIG)

Suppose Y_1, Convenience foods, and Y_2, non-Convenience foods, are two random variables that are Poisson distributed and independent from each other and has mean $\nu\mu_1$ and $\nu\mu_2$ with variance $Var(Y_1) = \mu_1 + \mu_1^2\tau$ and $Var(Y_2) = \mu_2 + \mu_2^2\tau$. Variable V is defined as a random variable that has an Inverse Gaussian distribution with the following probability density function (Mardalena et al., 2021):

$$g(\nu) = (2\pi\tau\nu^3)^{-0.5}e^{-(\nu-1)^2/2\tau\nu}, \quad \nu > 0 \quad (22)$$

Furthermore, the BPIG distribution based on the inverse Gaussian mixture distribution is defined by the following joint distribution:

$$f(y_1, y_2;\ \mu_1, \mu_2, \tau) = \left(\frac{2z}{\pi}\right)^{\frac{1}{2}} \frac{\mu_1^{y_1}\mu_2^{y_2}e^{\frac{1}{\tau}}K_{s(z)}}{(z\tau)^{y_1+y_2}\ y_1!y_2!} \quad (23)$$

With $= y_1 + y_2 - \frac{1}{2}$, $z = \sqrt{\frac{1}{\tau^2} + \frac{2(\mu_1+\mu_2)}{\tau}}$, and $K_{y_1+y_2-\frac{1}{2}}\left(\frac{1}{\tau}\sqrt{1 + 2\tau(\mu_1 + \mu_2)}\right)$.

The Bivariate Poisson Inverse Gaussian Regression is defined as a regression model with two correlate variables (Mardalena et al., 2021). Suppose y_{ij} is the jth response variable for the ith observation and given a random sample $(Y_{i1}, Y_{i2}) \sim BPIG\ (\mu_{ij}, \tau)$ where $i = 1,2, \dots, n$ and $j = 1,2$, then the BPIGR model can be defined as follows:

$$ln\left[\frac{E(Y_{ij})}{q_i}\right] = X_i^T \beta_j \qquad (24)$$

Whereby $E(Y_{ij}) = \mu_j = q_i e^{X_i^T \beta_j}, q_i$ is the exposure variable, $X_i^T = [1\ \ x_{1i}\ \ x_{2i}\ \ \dots\ x_{pi}]_{1\times(p+1)}$ is the kth predictor variable vector $(k = 1,2, \dots, p)$ for the ith observation $(i = 1,2, \dots . n)$ and the jth response variable $j = 1,2,$ $\beta_j = [\beta_{jo}\ \ \beta_{j1}\ \ \beta_{j2} \dots \dots \dots \beta_{jp}]$ is a regression coefficient vector with $(k + 1) \times 1$ dimension for the jth response variable.

1.2.5.4. Bivariate Poisson-Laguerre Polynomial Model

If $g(v_{1i}, v_{2i})$ is approximated by Laguerre polynomial of order one, we obtain the bivariate Poisson- Laguerre polynomial density given by:

$$f(y_{1i}, y_{2i}|x_i) = \left[\prod_{j=1}^{2} \frac{(\theta_{ji})^{y_{ji}}}{y_{ji}!}\right] M^{(y_1,y_2)}(-\theta_{1i}, -\theta_{2i}) \qquad (25)$$

$$Where\ M^{(y_i,y_2)}(-\theta_{1i}, -\theta_{2i}) = \left[\prod_{j=1}^{2} \frac{\Gamma(y_{ji}+\alpha_j)}{\Gamma(\alpha_j)} \lambda_j^{\alpha j} (\lambda_j + \theta_{ji})^{-(\alpha_j + y_{ji})}\right] \Psi_i \qquad (26)$$

$$With\ \lambda_j = \frac{1}{1+\rho_{11}^2}[\alpha_j + \rho_{11}^2(\alpha_j + 2)] \qquad (27)$$

$$And\ \Psi_i = \frac{1}{1+\rho_{11}^2}[1 + 2\rho_{11}^2\sqrt{\alpha_1\alpha_2}(1 - n_{1i})(1 - n_{2i}) + \rho_{11}^2\alpha_1\alpha_2(1 - 2n_{1i} + n_{1i}\xi_{1i})(1 - 2n_{2i} + n_{2i}\xi_{2i})] \qquad (28)$$

$$n_{ji} = \frac{y_{ji}+\alpha_j}{\alpha_j}\left(1+\frac{\theta_{ji}}{\lambda_j}\right)^{-1} \; and \; \xi_{ji} = \frac{y_{ji}+1+\alpha_j}{\alpha_j}\left(1+\frac{\theta_{ji}}{\lambda_j}\right)^{-1}$$

(29)

Unlike the bivariate Poisson-lognormal distribution, the Poisson-Laguerre polynomial model has a closed form and can be easily implemented within the likelihood framework (Chou & Steenh, 2011).

1.2.5.5. Bivariate Hurdle and Zero-Inflated Model

When the observed data shows a high frequency of the zero-zero condition $(Y_1 = 0, Y_2 = 0)$, zero-modified count models are applied. There are two approaches to treating this issue. First, the bivariate hurdle model, which consists of two parts: a binary outcome model (logit or probit) in the first part and a bivariate truncated count model in the second (Mullahy,1986). The interpretation that positive observations result from passing the zero-zero hurdle or threshold is made possible by this partition. The bivariate hurdle model is appealing because it reflects a two-part decision-making process (Chou & Steenh, 2011). The probability density function of the bivariate hurdle model is given by:

$$h(y_{1i}, y_{2i}|x_i) = \begin{cases} \pi_I & y_{1i} = 0, y_{2i} = 0 \\ (1-\pi_i)\frac{\pi_i}{\frac{f(y_{1v}y_{2i}|x_i)}{1-f(y_{1i}=0,y_{2i}=0)}} & y_{1i} > 0, \;\; y_{2i} > 0 \end{cases}$$

(30)

where $\pi_i = \Pr(y_{1i} = 0, y_{2i} = 0)$ is defined as the cumulative density function (CDF) of the logit or probit regression selection model and $\frac{f(y_{1v}y_{2i}|x_i)}{1-f(y_{1i}=0,y_{2i}=0)}$ is the probability density function of a bivariate truncated count regression model.

Secondly, another approach to model excess zeros in the count data is the bivariate zero-inflated count models. Bivariate zero-inflated model assumes that the zero counts come from two sources not one source as in the bivariate hurdle model (Chou & Steenh, 2011). The zero-inflated model is used when a count data set shows a large proportion of zeros. A bivariate zero-inflated model can be constructed by increasing the probability of the event $(Y_1 = 0, Y_2 = 0)$ and decreasing the other joint probabilities.

A logit or probit model is used to determine the probability of counts being the zero-zero state. The bivariate zero-inflated probability density function is given by:

$$h(y_{1i}, y_{2i}|x_i) = \begin{cases} \pi_i + (1-\pi_i) f(y_{1i} = 0, y_{2i} = 0) & y_{1i} = 0, y_{2i} = 0 \\ (1-\pi_i) f(y_{1i}, y_{2i}|x_i) & y_{1i} > 0,\ \ y_{2i} > 0 \end{cases}$$

(31)

where $\pi_i = \Pr(y_{1i} = 0, y_{2i} = 0)$ is the cumulative density function (CDF) of the logit or probit regression, and $f(y_{1i}, y_{2i}|x_i)$ is the density function.

1.2.5.6. Bivariate Censored Model

A sequence is said to be censored from below (left censored) or censored from above (right censored). When high counts are not observed, censored samples may result, or they may be required by the survey's design. Thus, right censoring is the most common form in the analysis of bivariate count models (Chou & Steenh, 2011). Given the bivariate counts are right censored at $r = (r_1, r_2)$ so that $y_{ji} = 1, 2, \ldots, r_j \ for \ j = 1,2$.. Letting $f(y_{1i}, y_{2i};\ \varphi)$ denote the complete bivariate density (Gurmu and Elder, 2000), the log-likelihood function for the right-censored bivariate count model is:

$$LL(y_1 y_2|\varphi) = \sum_{i=1}^{n} d_i [ln\, f(y_{1i}, y_{2i};\ \varphi)] + [1 - d_i]\, ln[\ 1 - \sum_{l=0}^{r_1-1} \sum_{m=0}^{r_2-1} f(y_{1i} = l, y_{2i} = m;\ \varphi)$$

(32)

where $d_i = 1$, if y falls in the uncensored region, and $d_i = 0$ otherwise.

1.2.5.7. **Diagonal Inflated Bivariate Poisson Model**

One drawback of the bivariate Poisson model is that since its marginal distributions are Poisson distributions, which demand that the mean and variance be equal, they cannot handle overly or inadequately scattered data (Yunteng, Yao-Jan, Jonathan, & Yinhai, 2011). Karlis & Ntzoufras (2005) proposed the diagonal inflated bivariate Poisson model to fix this problem. This model uses a more general form developed on the basis of zero-inflated models and the probabilities of the diagonal elements are inflated in the probability table. The diagonal inflated bivariate Poisson model can be defined based on the bivariate regression model as follows (Yunteng et al., 2011).

$$f_{IBP}(x,y) = \begin{cases} (1-p_m)f_{BP}(x,y|\lambda_1,\lambda_2,\lambda_3) & x \neq y \\ (1-p_m)f_{BP}(x,y|\lambda_1,\lambda_2,\lambda_3) + p_m f_D(x|\theta,J), & x = y \end{cases}$$

(33)

where $p_m$is the mixing proportion, $p_m f_D(x|\theta,J)$ is the probability mass function of a discrete distribution $D(x;|\theta)$. $D(x;|\theta)$ can be a Poisson, geometric, or a simple discrete distribution. The marginal distributions of a diagonal inflated bivariate Poisson regression model are mixtures of distributions with one Poisson component.

1.2.6. Comparison of the Models of Goodness-of-Fit

The goodness of fit of a statistical model describes how well it fits into a set of observations. The two commonly used goodness-of-fit statistics for model selection are Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) calculated as:

$$AIC = -2L + 2q$$

(34)

$BIC + \; -2L + q ln(N)$

(35)

When comparing models as to fit, lower values of either the AIC or BIC indicate a better fit. The AIC were mainly used to conclude because they have an advantage that they can be used to descriptively compare all models regardless of whether one is nested or not within another.

1.2.7. Statistical Analysis

Descriptive statistics were generated to summarize the levels of convenience and non-convenience food consumption by household members. In this study, we fitted a bivariate Poisson regression model using both the joint and conditional arguments. The Bivariate Poisson model is recommended for modelling paired count data exhibiting correlation. Estimations and tests for over and under-dispersion for both the right truncated and the Untruncated Bivariate Poisson regression to relate convenience and non-convenience food consumption with bio-demographic and socio-economic variables were performed. R package for bivariate Poisson GLM with covariates "bpglm" was used to fit the models (Chowdhury & Islam, 2019).

1.3. Results

1.3.1. Frequency Distribution of Consumption of Convenience and Non-convenience Food

Table 15 shows frequencies of household's consumption of convenience and non-convenience foods. Households purchased convenience foods on a weekly basis were more from street sellers/traders/hawkers (46.1%) and Spaza/Tuck-shops (33.7%), while 13.3 percent were obtained food from fast foods/Takeaways and 6.2 percent from restaurants. However, monthly purchases were fewer and increased for non-convenient food purchases with 80.1 percent of the food purchased on a monthly basis at Supermarkets.

Table 1: Convenience and Non-Convenience Food Sources

Source	**Frequency**	
	Weekly	**Monthly**
Convenience Food Sources		
Fast foods/Take away	60 (13.3%)	64 (56.6%)
Restaurants	28 (6.2%)	18 (15.9%)
Spaza/Tuckshop	152 (33.7%)	12 (10.6%)
Street seller/trader/hawker	208 (46.1%)	17 (15.0%)
Begging	3 (0.7%)	2 (1.8%)
Non-Convenience Food Sources		
Supermarket	174 (30.9%)	544 (80.1%)
Small Shops	115 (20.4%)	36 (5.3%)
Open Markets	272 (48.3%)	83 (12.2%)
Food grown by households in rural areas	2 (0.4%)	16 (2.4%)

Table 16 shows the cumulative total number of purchases from each source constituting convenience and non-convenience food. At least 90.7% of individuals did not shop from any source in a week and 7.5 % utilized only one source within the convenience food sources. Non-Convenience food sources mostly provide food to be cooked at home.

Table 2: Convenience food sources

Convenience Food Sources	**Weekly**		**Monthly**	
	Count	***Frequency (%)***	***Count***	***Frequency (%)***
	0 = fast food/take away	3557 (90.7%)	0	3507 (89.4%)
	1 = Restaurants	295 (7.5%)	1	297 (7.6%)
	2 = Spaza/Tuck-shops	58 (1.5%)	2	94 (2.4%)
	3 = Street seller/trader/hawker	8 (0.2%)	3	17 (0.4%)
	4 = Begging	4 (0.1%)	4	7 (0.2%)
	Mean	0.115	**Mean**	0.395
	Std. dev	0.312	**Std. dev**	0.714

Furthermore, Table 17 shows that at least 7.3 percent visited at least one food source and 3.2 percent visited at least 2 sources on a weekly basis. Additionally, Table 17 shows that 8.9

percent visited at least one source monthly and 7.5 percent 2 sources. Overall, on the non-convenience food sources, households preferred to shop monthly than weekly.

Table 3: Non-convenience food sources

Non-convenience Food Sources	**Weekly**		**Monthly**	
	Count	***Frequency (%)***	***Count***	***Frequency (%)***
	0 = Supermarket	3500 (89.2%)	0	3182 (81.1%)
	1 = Small shops	288 (7.3%)	1	350 (8.9%)
	2 = Open markets	127 (3.2%)	2	296 (7.5%)
	3 = Food grown by households in rural areas	7 (0.2%)	3	94 (4.4%)
	Mean	0.14	**Mean**	0.31
	Std. dev	0.445	**Std. dev**	0.714

1.3.2. Bivariate Distribution of Outcome Variables

Table 18 shows the relationship between Convenience food consumed weekly and non-convenience food consumed weekly as well as monthly consumption in a contingency format. The p-values indicate significant associations. About half of the households purchase non-convenience food at least from one (1) or two (2) non-convenience shops on a weekly basis. The same pattern is noted with the monthly purchasing whereby above half of the purchases were made from one (1) non-convenience source. There is also an observable upward trend on purchasing, food from Convenience food sources. Households tend to purchase convenience food from multiple sources (more than 2) on a weekly and monthly basis (Table 18).

Table 4: Crosstabulation of Convenience and Non-convenience Food Sources

Convenience ~Weekly	**Non-Convenience ~ Weekly**					***P-Value***
	0=Super-market	***1=Small shops***	***2= Open markets***	***3= Food grown by households in rural areas***	***Total***	
0 = Fast foods/Take away	3386	146	27	0	3559	<0.001
1 = Restaurants	90	119	84	1	294	
2 = Spaza/Tuck-shops	21	22	12	2	57	
3= Street seller/trader/hawker	3	1	2	2	8	
4 = Begging	0	1	2	1	4	
Total	3500	289	127	6	3922	

Convenience~ Monthly	Non-Convenience ~ Monthly					*P-Value*
	0=Super-market	*1=Small shops*	*2= Open markets*	*3= Food grown by households in rural areas*	*Total*	
0 = Fast foods/Take away	3175	217	112	7	3511	<0.001
1 = Restaurants	6	100	123	65	294	
2 = Spaza/ Tuck-shops	1	30	52	10	93	
3= Street seller/trader/hawker	0	3	6	8	17	
4= Begging	0	0	3	4	7	
Total	3182	350	296	94	3922	

1.3.3. Application of Bivariate Poisson Models on the Convenience and Non-Convenience Food Sources

1.3.3.1. Comparative Fit of Bivariate Poisson Models

Various Bivariate Poisson regression models were jointly fitted on Convenience and Non-Convenience data. AIC and BIC values are presented in Table 19 were used to select the best model. Firstly, the Bivariate Poisson model was fit with constant only for both the untruncated and the right truncated models. Secondly, the Bivariate Poisson model was fit with covariates for both models. The AIC of 3646.976 Untruncated Bivariate Poisson (Full model) on a weekly basis was the least among all the fitted models and thus the full model fits the data better.

Table 5: Summary of the Fitted Bivariate Poisson Regression Models

Frequency	Model	2x Log Likelihood	Akaike Information Criterion (AIC)	Bayesian Information Criterion (BIC)
Weekly	Untruncated Bivariate Poisson (Constant only)	-1960.897	3925.795	3938.343
	Untruncated Bivariate Poisson (Full model)	-1787.488	3646.976	3870.246
Monthly	Untruncated Bivariate Poisson (Constant only)	-2222.053	4448.106	4460.655
	Untruncated Bivariate Poisson (Full model)	-2011.454	4094.909	4318.178

1.3.3.2. Weekly utilization of food sources: Untruncated Bivariate Poisson Regression

Firstly, the Bivariate Poisson model was fit with constant only as depicted in Table 20. The output shows the detail model statistics (AIC, BIC, etc.,) and parameter estimates (coefficients, t-value, p-value, adjusted S.E, and adjusted p-values). The AIC of 3925.8 in the reduced model is greater than the AIC of 3908. 5 in the Full model, thus the full model fits the data better.

Table 6: Fit for Bivariate Poisson Model (marginal/conditional): Constant only (reduced model)

Variable name	Coeff.	S.E	t.value	p.value	Adj.S.E	Adj. p.value
Y1: Constant	-2.170	0.047	-45.921	<0.001	0.054	<0.001
Y2: Constant	0.225	0.042	5.328	<0.001	0.0494	<0.001

Note. Loglik. = −1960.897, AIC = 3925.795, AICC = 3925.8, BIC = 3938.343, Deviance = 3087.749, P-1=1.35, P-2=1.37

The results of the fit of bivariate Poisson model are shown in Table 21 and 22 for both unadjusted and adjusted for over- or under-dispersion. It further provided the detail models statistics (e.g., AIC, BIC, etc) and parameter estimates showing the coefficients, standard error, t-value, p-value adjusted standard error and adjusted p-values. Here we model two possibly correlated dependent variables: (1) Convenience foods (2) non-Convenience foods. The Bivariate Poisson regression models shows that the variables education (secondary), age (all categories) and Income (20,000-49,999) are important determinants of both convenience and non-convenience food groups. The positive coefficients of education (none, primary), work (self-employed), sex (male), marital status (living together) shows a higher association on the convenience food sources.

Table 7: Fit of Bivariate Poisson Model (marginal/conditional) for both unadjusted and adjusted, for over- or under-dispersion (Full model)

Variable Names	Coefficients (Coeff)	Standard Error (s.e)	t.value	p.value	Adj.s.e	Adj.p.value
Convenience: Constant	-2.218	0.617	-3.596	0.000	0.719	0.002
Education: None	0.064	0.239	0.269	0.788	0.278	0.818

Education: Primary	0.014	0.219	0.066	0.948	0.255	0.955
Education: Secondary	-0.355	0.207	-1.714	0.087	0.241	0.141
Education: Tertiary (reference)						
Work: Self-employed	0.113	0.220	0.514	0.607	0.257	0.659
Work: Formal employed	-0.071	0.148	-0.478	0.633	0.172	0.682
Work: Unemployed (reference)						
Sex: Male	0.108	0.100	1.078	0.281	0.117	0.355
Sex: female (reference)						
Marital: Unmarried	-0.102	0.604	-0.169	0.866	0.703	0.885
Marital: Married	-0.134	0.609	-0.219	0.826	0.710	0.851
Marital: Living together	0.674	0.605	1.114	0.265	0.705	0.339
Marital: Widowed (reference)						
Age: <19	0.134	0.223	0.601	0.548	0.260	0.606
Age: 20-29	0.336	0.221	1.522	0.128	0.258	0.192
Age: 30-39	0.067	0.232	0.290	0.772	0.270	0.804
Age: 40-49	-0.042	0.238	-0.176	0.860	0.278	0.880
>50 (reference)						
Income: 2500-4999	-0.007	0.272	-0.025	0.980	0.317	0.983
Income: 5000-9999	-0.421	0.395	-1.066	0.286	0.461	0.360
Income: 10000-19999	-0.250	0.525	-0.477	0.634	0.611	0.683
Income: 20000-49999	-0.771	1.016	-0.759	0.448	1.184	0.515
Income: 0-2499 (reference)						

Table 8: Fit for Bivariate Poisson Model (marginal/conditional) for both unadjusted and adjusted, for over- or under-dispersion (Full model)…… Cont.

Variable Names	Coeff.	s.e	t.value	p.value	Adj.s.e	Adj.p.value
Non-convenience: Constant	-1.387	1.022	-1.358	0.175	1.205	0.250
Education: None	0.276	0.235	1.173	0.241	0.277	0.320
Education_ Primary	0.215	0.219	0.981	0.327	0.258	0.406
Education_ Secondary	0.422	0.211	2.002	0.045	0.249	0.090
Education_ Tertiary (reference)						
Work: Self-employed	0.227	0.195	1.165	0.244	0.230	0.324
Work: Formal employed	-0.087	0.137	-0.636	0.525	0.161	0.590
Work: Unemployed (reference)						
Sex: Male	0.162	0.096	1.691	0.091	0.113	0.152
Sex: female (reference)						
Marital: Unmarried	0.408	1.037	0.393	0.694	1.224	0.739
Marital: Married	0.843	1.027	0.821	0.412	1.212	0.487
Marital: Living together	0.343	1.037	0.330	0.741	1.223	0.779
Marital: Widowed (reference)						
Age: <19	0.854	0.280	3.051	0.002	0.330	0.010
Age: 20-29	0.781	0.272	2.869	0.004	0.321	0.015
Age: 30-39	0.926	0.263	3.523	0.000	0.310	0.003
Age: 40-49	0.662	0.258	2.561	0.010	0.305	0.030
>50 (reference)						

Income: 2500-4999	0.005	0.239	0.019	0.985	0.282	0.987
Income: 5000-9999	0.214	0.330	0.647	0.517	0.389	0.583
Income: 10000-19999	0.637	0.372	1.709	0.087	0.439	0.147
Income: 20000-49999	1.568	0.658	2.383	0.017	0.776	0.043
Income: 0-2499 (reference)						

Note. Loglik. = −1787.488, AIC = 3646.976, AICC = 3648.446, BIC = 3870.246, Deviance = 2805.341, P-1=1.36, P-2=1.39

1.4. Discussion

Several models exist for different Count data types. It is critical to know the properties and assumptions of different models. Bivariate Poisson model are appropriate for modelling paired count data exhibiting correlation (Karlis & Ntzoufras, 2005) . In this study, we used the dataset of Windhoek AFSUN 2016 Household dataset to relate the Convenience and Non-Convenience Food Consumption both on a weekly and monthly base.

Convenience food often implies a lack of effort or concern, whether by choice or necessity. Highly processed food production and consumption are steadily increasing in both high-income and lower-income countries (Pan American Health Organization (PAHO), 2015). Parallel to this, the prevalence of obesity and other diet-related chronic non-communicable diseases (NCDs), such as type II diabetes, hypertension, and some common cancers, is increasing worldwide (Lim, et al., 2012). This study found that the households consume convenient food more often on a weekly basis and tend to utilize multiple convenient sources. On the other hand, the study revealed that households did not visit non-convenient food sources as often on a weekly basis and rather purchased their convenient foods monthly. According to Martinez Steel, Popkin, Swinburn, & Monteiro, (2017), the poor nutritional quality of ultra-processed foods coupled with their high availability, low cost, and aggressive marketing, which result in excessive consumption, can lead to obesity and other chronic diet related NCDs.

This chapter employed both the Untruncated and the Right-Truncated Bivariate models. The Bivariate Poisson models were further expanded to allow for covariates, for both the Univariate Poisson Regression with constants only and the Untruncated Poisson Regression full model. The parameter estimates confirmed that the variables age, marital status and educational level had an effect on the convenience food consumption. Hwang & Choe (2016) explained that households headed by younger, more educated, and time constrained managers were more likely to buy prepared meals. Employment creates time constraints from both the time spent working and the time spent commuting. These time constraints shift consumer demand from grocery store foods to restaurant meals. The shift to full-service restaurants is most notable when all adults in the household are employed (Rahkovsky, Jo, & Carlson, 2018). The model statistics, particularly the AICs were used to compare and select the best fitted model. The Untruncated models specifically the full model proved to fit the data best compared to the right truncated model.

1.5. Conclusions

There has been tremendous growth and demand of the convenience food industry recently. Traditional meals and meals prepared at home are replaced by, often, unplanned food purchases from street corners, take-aways or restaurants. Convenience foods are described to be cheap and easy to prepare but the health benefits are questionable. The aim of this study was to apply bivariate count modelling approaches in analysing convenience and non-convenience consumption of food preference in Windhoek households. This study used the frequency of purchasing food from Convenience food Sources and Non-Convenience food sources variables from the AFSUN Windhoek dataset, 2016. In order to model frequency of occurrence/ count data that are correlated and needs to be jointly estimated, this study employed bivariate Poisson regression models, both un-truncated and right truncated. Although the consumption of food on a monthly basis was more on the non-convenience foods, the purchases of Convenience was frequent on a weekly basis and in multiple food sources. Convenience foods are mostly highly processed and of poor nutritional quality and can lead to a higher prevalence of NCDs. The untruncated models fit the data best. In conclusion, the model proved that the variables age, marital status, educational level of head of household and work status influenced the choices of food a household makes.

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