Niche Market Meats in Bulgaria

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Meat and meat-product consumption of households experiencing income compression is modeled using the frequencies reported in a survey to account for their production of livestock or poultry. A zero-inflated count-data model was deemed appropriate because some households did not report any consumption within a month of the ten meat and meat-product categories considered in this study. Some products—e.g., goat meat and ham—were consumed very infrequently, yet they represent two very different items. Age of individuals had a negative effect on consumption. Although household income increased the consumption frequency of some items, education negatively influenced the consumption of goat meat. Males ate ham and sausage more often than did females. Effects of religious beliefs were consistent with expectations, with some groups reporting less-frequent consumption of pork and pork products than the omitted group. Policy makers and meat marketers should recognize the differences in socio-demographic profiles of consumers regarding the consumption of the ten meats and meat-products considered in this study because some are consumed by distinct population segments.

The immediate cause of collapse of the centrally planned system in Bulgaria was the unsustainable government budget deficit. In the process of restoring fiscal balance the country adopted a market mechanism to discover equilibrium prices. Despite implementation of the market mechanism, almost all companies and farms continued for a while to be owned by the state. Market reforms were inconsistently implemented, causing the GDP to contract over an extended period. Restoration of a balanced budget resulted in a decrease in real value of government transfers, while the restructuring of the economy led to a real decrease in wages. Households experienced a compression of incomes and were forced to adjust their consumption. Among food categories affected by the change in real incomes was meat and meat products. Livestock production dramatically declined, while meat prices increased to reflect the market equilibrium, encouraging some households to increase their production of livestock. Household livestock production often included goats, sheep, and poultry, which have low feed requirements and relatively fast growth and are of manageable size. With an increase in home meat supply, purchase data did not accurately reflected the actual consumption of meat products.

Consumption-behavior studies encounter a problem if formulating practical recommendations to consumers who do not report using a product or a service. Some studies have noted the difficulty in distinguishing among the non-consumers with regard to reasons for not buying a product in formulating recommendations for action (Park and Florkowski 2000). Some people may choose not to consume a product because of a complete lack of preference for it, while others do not consume it during the observed period for other reasons but will consume it once the underlying cause is no longer present. Advancements in modeling address the observed non-consumption by differentiating abstention from lack of consumption. Available techniques are applicable to data describing the consumption frequency by integer values such as the monthly consumption of a specific product. We model the factors affecting monthly meat and meat-product consumption frequency in Bulgaria using the zero-inflated count-data model.

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Modeling Meat-Consumption Frequency

Zero-inflated count-data models examine situations where the underlying data-generating process may be divided into two distinct phases: the first in which the count moves from zero to some binary discrete distribution with probability (π), and the second which generates the event counts with probability

$(1-\pi)$. Thus zero values that are part of count data can be viewed as observations of corner solutions and zero values from the binary probability mass can be interpreted as exact zeros resulting from an abstention or some other non-economic decision. The probability function for the zero-inflated Poisson (ZIP) is

$$(1)\quad \Pr(y_i) = \pi + (1-\pi_i)e^{-\lambda_i} \text{ and}$$

$$\Pr(y_i = j) = (1-\pi_i)\frac{e^{-\lambda_i}\lambda_i^j}{j!},\ j = 1,2,...$$

where y_i is a meat or meat-product consumption frequency; π_i is the probability of an observation coming from the "automatic zero" state; $1-\pi_i$ is the probability of an observation coming from the Poisson count state; and λ_i is the compound count mean assumed as $\lambda_i = \exp(x_i\beta)$, where x_i is (k x 1) vector of independent variables and β is a vector of parameters.

The ZIP is a mixture of Poisson event count distribution and a discrete probability mass at zero. The mean and variance of the distribution are

$$(2)\quad E(y_i) = (1-\pi_i)\lambda_i \text{ and}$$
$$Var(y_i) = (1-\pi_i)\lambda_i(1+\pi_i\lambda_i).$$

The alternative that we consider is that y_i has a zero-inflated negative binomial (ZINB) distribution as

$$(3)\quad \Pr(y_i = j) = \begin{cases} \pi + (1-\pi_i)\left(\dfrac{1}{1+\alpha\lambda_i}\right)^{1/\alpha}, & j = 0 \\ (1-\pi_i)\dfrac{\Gamma(y_i + {}^1/_\alpha)}{y_i!\Gamma({}^1/_\alpha)}\left(\dfrac{1}{1+\alpha\lambda_i}\right)^{1/\alpha}\left(\dfrac{\alpha\lambda_i}{1+\alpha\lambda_i}\right)^{y_i}, & j = 1,2,... \end{cases}$$

where λ_i and α are the mean and variance parameters of the conditional negative binomial model. The expected mean and variance for ZINB is

$$(4)\quad E(y_i) = (1-\pi_i)\lambda_i \text{ and}$$
$$Var(y_i) = (1-\pi_i)\lambda_i(1+\pi_i\lambda_i+\alpha\lambda_i).$$

As the parameter α in the ZINB approaches zero, the conditional negative-binomial model with added zeros reduces to a ZIP distribution. On the other hand, as α increases the conditional model becomes more skewed with a heavier tail and thus a higher probability of a zero observation and larger counts are expected. The parameter π has a potential impact for testing between models. When π is one, the underlying distribution is a simple probability mass at zero and when π is zero, the ZIP and ZINB probability distributions are reduced to compound count models. In addition, both models induce over-dispersion. Tests for over-dispersion are complicated by the fact that when π is zero, the ZIP and ZINB reduce to their respective standard count models and when α is zero, the ZINB reduces to the ZIP model. In this study both models were estimated and we use the Likelihood Ratio (LR) test and the penalized Consistent Akaike Information Criteria (CAIC) for model evaluation (Gurmu and Trivedi 1996).

For use of regression model we assume the specific forms

$$(5)\quad \log(\lambda_i) = x_i'\beta \text{ and } \log\left(\frac{\pi_i}{1-\pi_i}\right) = \tau x_i'\beta\ ,$$

where τ is a scalar parameter and implies that $\pi_i = (1+\lambda_i^{-\tau})^{-1}$ (Lambert 1992). The basic assumption implied for the zero-inflated model is that the two sets of covariates in both Poisson and binary logit models may or may not coincide. However, when the same set of exogenous variables is used in both models, more parsimonious models can be developed by assuming that the linear predictors from both models are related in some way. The simplest models are the zero-inflated Poisson-tau, ZIP (τ), and the zero-inflated negative binomial-tau, ZINB (τ). The τ is a multiplicative function of covariates explaining standard count models.

The likelihood and its corresponding log-likelihood functions for the zero-inflated models can easily be constructed as

$$L(\tau,\beta;x) = \prod_{y_i=0}\Pr(y_i=0)\prod_{y_i>0}\Pr(y_i=j)$$

$$(6)\quad L(\tau,\beta;x) = \sum_{y_i=0}1_{j=0}\log(\Pr(y_i=0)) + \sum_{y_i>0}1_{j>0}\log(\Pr(y_i=j)) \qquad j = 0,1,2,...$$

Data

The data come from a survey of households drafted by a multidisciplinary team of researchers from the United States and Bulgaria and collected in 1997. Following a pretest on a group of Bulgarian consumers, the Bulgarian National Statistical Services distributed the questionnaires to 2,500 households residing in all statistical districts and collected by enumerators 4 weeks later, yielding 2,133 completed questionnaires, an 85-percent response rate. Questions asked about daily, weekly, and monthly consumption frequencies of 102 food items, including 10 meats and meat products, and about socio-economic characteristics of respondents. Table 1 shows the descriptive statistics.

Results

A substantial number of households did not report any consumption of some meats or meat products, even after accounting for dietary preferences that could have been related to religious beliefs of a respondent. Table 2 shows estimation results for consumption frequencies of ten meats and meat products using the ZINB model. The ZINB model outperformed the ZIP model in terms of both predictive accuracy and the CAIC (Table 3). Because of the limited length of this report, a direct comparison of estimation results is not provided.

Beef was consumed infrequently. In the ZINB model, income, full-time employment, and education above the elementary level positively affected the consumption frequency. Being a Christian and residing in northern or coastal Bulgaria lowered the consumption frequency.

Married respondents and those from large households or residing in the Coastal region were more likely to eat lamb than were respondents who were not married, from small households, or residents of the other regions. Some families who raise sheep and individuals who are married or from large households appear to have enough resources to engage in sheep production, likely causing a consumption increase. Respondents defining themselves as Christians ate lamb less often than did those of other religious beliefs or the non-religious.

Goat consumption has the highest observed zero counts among meat consumption. The ZINB model had only two significant coefficients, suggesting a positive affect of marital status and a negative effect of education on goat-consumption frequency. Goats are very undemanding in terms of feed, but the preference for goat meat is low.

Age and gender did not affect chicken-consumption frequency, while being a resident of the northern region lowered chicken consumption in comparison to residents of the Metropolitan and Southern regions. The frequency of poultry consumption was not influenced by age, marital status, or gender; respondents residing in the Northern region of Bulgaria or who considered themselves as Muslim did not differ in poultry consumption frequency from those of religious groups or regions omitted from the specification.

Ham was eaten by a small percentage of surveyed households, but sausage consumption was more common. Still, the model estimation indicated that high income, more education, full-time employment, and being male increased consumption frequency. The negative effect on ham consumption was exerted by increasing age, being a Muslim, and residing in the Northern region.

Kremvirshi, a type of Bulgarian sausage often made with beef, is one of the most often consumed meat products. According to the results, all variables were significantly influencing the consumption frequency in case of the ZINB model except for marital status, gender, being a Muslim, or residing in the Coastal region. Among variables with a significant influence, age and being a resident of the Northern region lowered consumption frequency compared to younger respondents or residing in the Southern and Metropolitan regions.

Finally, in case of liver-consumption frequency, results showed that being fully employed, declaring religious preference as Christian, or being a resident of the Coastal region increased consumption, but being a resident of the Northern region lowered consumption.

Conclusions

Overall, differences in estimation results between the ZIP and ZINB models were substantial and consistent. Among variables that most often lost statistical significance were the respondent's age, marital status, and being a Muslim. Gender and the household size were in the second group of variables most often becoming insignificant once the model changed from the ZIP to ZINB. From the standpoint of developing and implementing a marketing strategy, all the variables likely to loose their significance mattered. However, differences in consumption frequency occurred most often in equations representing meats or meat products of

Table 1. Variable Definition and Descriptive Statistics.

Variable	Definition	Percent of zeros	Mean	Standard deviation
Dependent variable				
Pork	Monthly frequency consumption	25.79	2.9756	4.69
Beef	Monthly frequency consumption	79.20	0.4349	1.71
Lamb	Monthly frequency consumption	44.29	1.3930	3.32
Goat	Monthly frequency consumption	93.62	0.1262	0.88
Chicken	Monthly frequency consumption	24.19	2.2180	4.19
Poultry	Monthly frequency consumption	61.90	1.2080	3.59
Ham	Monthly frequency consumption	81.45	0.4574	1.96
Sausage	Monthly frequency consumption	19.25	4.6594	8.48
Liver	Monthly frequency consumption	45.49	1.0683	1.90
Kremvirshi	Monthly frequency consumption	21.85	3.4259	5.76
Individual characteristics				
Income x 10^{-3}	Monthly household income, in Leva		1.6818	1.02
Age	Age in years		52.3706	16.87
Household size	Actual numbers		2.8429	1.47
Marital status	1 = Married		0.6259	0.48
Gender	1 = if person is male		0.3292	0.47
Employment	1 = if the person is employed		0.4080	0.49
Education	1 = High school and above		0.6349	0.48
Religion				
Christian	1= if the person is Christian		0.9137	0.28
Muslim	1 = if the person is Muslim		0.0608	0.24
Other	1 = if the person is other than Christian or Muslim		0.0254	0.16
Region				
Metropolitan or South			0.5681	0.50
Coastal			0.1322	0.34
North			0.2993	0.46

Note: N = 2005.

Table 2. Parameter Estimates for Meat and Meat Products Consumption Frequencies from Zero-Inflated Count Data Models.

	Zero-inflated negbin									
Variable	Pork	Beef	Lamb	Goat	Chicken	Poultry	Ham	Sausage	Liver	Kremvirshi
Constant	.2812[a] (2.10)	.0350 (.32)	.2515[b] (1.95)	-1.7074 (-1.11)	-.2602 (-1.24)	-.4725[a] (-3.52)	-.0631 (-.21)	.6876[a] (2.77)	.0146 (.19)	.4625[a] (2.15)
Income	.0990[a] (5.73)	.0369[a] (2.19)	-.0000 (-.02)	.0489 (.44)	.1039[a] (5.34)	.0570[a] (2.13)	.2336[a] (5.21)	.1087[a] (4.10)	.0206 (1.32)	.0928[a] (3.78)
Age	-.0059[a] (-4.36)	-.0008 (-.72)	-.0000 (-.02)	-.0125 (-.95)	.0005 (.34)	.0019 (1.26)	-.0210[a] (-5.46)	-.0079[a] (-4.05)	-.0010 (-1.26)	-.0055[a] (-2.77)
Household size	.1182[a] (9.66)	.0143 (1.20)	.0755[a] (5.62)	-.0954 (-1.04)	.0815[a] (7.36)	.0537[a] (3.52)	-.0072 (-.16)	.1086[a] (4.75)	.0036 (.44)	.0756[a] (4.41)
Marital status	.1803[a] (3.61)	-.0295 (-.93)	.2469[a] (4.06)	.8980[a] (2.69)	.1230[a] (2.83)	-.0065 (-.16)	-.0740 (-.58)	-.0222 (-.38)	.0109 (.53)	.0041 (.08)
Gender	.0723 (1.56)	.0446 (1.57)	.0003 (.02)	-.0708 (-.25)	.0377 (.77)	.0613 (1.32)	.1742[b] (1.81)	.1223[a] (2.25)	.0449 (1.64)	.0083 (.18)
Employment	.1967[a] (3.59)	.0850[a] (2.21)	.0026 (.04)	.5202 (1.56)	.1156[a] (2.53)	.1652[a] (2.77)	.4214[a] (3.55)	.3722[a] (7.43)	.1186[a] (2.61)	.2956[a] (5.02)
Education	.0447 (.84)	.1079[a] (2.52)	-.0106 (-.19)	-1.1825[a] (-2.68)	.1510[a] (2.73)	.1196[a] (2.18)	.6173[a] (4.02)	.3514[a] (5.02)	-.0189 (-.93)	.3659[a] (5.28)
Religion										
Muslim	-1.0800[a] (-8.45)	-.0208 (-.22)	-.2244 (-1.27)	1.0433 (.83)	.3401[b] (1.80)	.1433 (1.44)	-.9018[a] (-2.52)	.0563 (.29)	.1050 (1.63)	.2067 (1.36)
Christian	.4512[a] (4.17)	-.1610[a] (-2.08)	-.3157 (-2.61)[a]	1.0119 (.84)	.3478 (1.95)[b]	.2627[a] (3.17)	-.0418 (-.23)	.3829[a] (2.12)	.1070 (1.86)[b]	.3407[a] (2.37)
Region										
Coastal	.0256 (.39)	-.1429[a] (-2.50)	.2756[a] (3.20)	.2784 (.71)	.5648[a] (10.45)	.2507[a] (2.58)	-.0059 (-.05)	-.1440[b] (-1.94)	.2283[a] (2.40)	.1039 (1.28)
Northern	-.1591[a] (-3.36)	-.1868[a] (-2.91)	.0006 (.02)	.0527 (.19)	-.3015 (-5.23)[a]	.0146 (.26)	-.7885[a] (-4.96)	-.4087[a] (-6.71)	-.0474[b] (-1.82)	-.4402[a] (-8.77)
Alpha	1.0151[a] (24.32)	1.9299[a] (16.13)	1.6656[a] (23.74)	5.9496[a] (3.12)	.8648[a] (20.55)	3.0708[a] (15.00)	1.5632[a] (9.92)	1.1484[a] (20.72)	.9037[a] (14.86)	.9609[a] (24.72)
Tau	-5.1910[a] (-5.26)	-6.6766[a] (-2.88)	-3552.0439 (-.02)	-.1181 (-.29)	-30378.1893 (-.00)	-8.7801[a] (-2.37)	-.8604[a] (-3.54)	-15796.1188 (-.00)	-22.3788[b] (-1.75)	-15.9087 (-1.34)

[a] 5% significance level.
[b] 10% significance level.

Table 3. Actual and Fitted Frequency and Models Performances.

	Pork			Beef		
	Actual	ZIP	ZINB	Actual	ZIP	ZINB
# of zero counts predicted	517	1051	531	1588	1082	1622
# of positive counts predicted	1488	954	1474	417	923	383
Log-likelihood		−5849.4286	−4299.5614		−1735.5478	−1532.1629
CAIC		11810.7014	8719.5704		3582.9398	3184.7734
LR_1		97.3488	3.772		752.520	−26.3118
LR_2	3099.7344			406.7698		
	Lamb			**Goat**		
	Actual	ZIP	ZINB	Actual	ZIP	ZINB
# of zero counts predicted	888	1128	969	1877	1829	1887
# of positive counts predicted	1117	877	1036	128	176	118
Log-likelihood		−3854.8061	−3295.3578		−739.6301	−626.7674
CAIC		7821.4564	6511.1632		1591.1044	1373.9824
LR_1		1531.8758	−3.8266		326.5896	−2.5748
LR_2	1318.8966			255.7254		
	Chicken			**Poultry**		
	Actual	ZIP	ZINB	Actual	ZIP	ZINB
# of zero counts predicted	485	1101	606	1241	1098	1218
# of positive counts predicted	1520	904	1399	764	907	787
Log-likelihood		−4955.5964	−3884.6335		−3408.0907	−2749.8993
CAIC		10023.0370	7889.7146		6928.0256	5620.2462
LR_1		347.0678	7.4164		2581.1224	−17.1930
LR_2	2141.9258			1316.3828		

Note: CAIC = −2 * Log-likelihood + # of parameters used * (Log(N) + 1); LR_1 = −2 * (Standard Count Model Log-likelihood − Zero-inflated Count Model Log-likelihood); and LR_2 = −2 * (ZIP Log-likelihood − ZINB Log-likelihood). LR is distributed as χ^2 with df 1. Minus sign greater than 3.84 critical level in absolute value favors the null hypothesis.

Table 3. Actual and Fitted Frequency and Models Performances (Continued).

	Ham			Sausage		
	Actual	ZIP	ZINB	Actual	ZIP	ZINB
# of zero counts predicted	1633	1648	1746	386	1012	439
# of positive counts predicted	372	357	259	1619	993	1566
Log-likelihood		−1608.8120	−1379.5427		−7838.4638	−5030.8056
CAIC		3329.4682	2879.5330		15788.7718	10182.0588
LR_1		706.6156	−40.4566		2048.2556	1.2586
LR_2	458.5386			5615.3164		
	Liver			**Kremvirshi**		
	Actual	ZIP	ZINB	Actual	ZIP	ZINB
# of zero counts predicted	912	1229	908	438	1033	479
# of positive counts predicted	1093	776	1097	1567	972	1526
Log-likelihood		−3215.7142	−2839.3051		−6253.2283	−4535.3372
CAIC		6543.2726	5799.0578		12618.3008	9191.1220
LR_1		9.0976	−45.0343		386.1434	−75.2464
LR_2	752.8182			3435.7822		

Note: CAIC = −2 * Log-likelihood + # of parameters used * (Log(N) + 1); LR_1 = −2 * (Standard Count Model Log-likelihood − Zero-inflated Count Model Log-likelihood); and LR_2 = −2 * (ZIP Log-likelihood − ZINB Log-likelihood). LR is distributed as χ^2 with df 1. Minus sign greater than 3.84 critical level in absolute value favors the null hypothesis.

relatively smaller importance in the meat industry—some likely produced at home—with the exception of beef. Examples of such products include lamb, kremvirshi, poultry (other than chicken), and liver. Least frequent differences were found in results for chicken, sausage, and pork—i.e., meats or meat products most often eaten in Bulgarian households. Two items, beef and ham, were eaten infrequently, but the reasons for this low consumption frequency seem to vary. Although raising incomes will increase the consumption of both products, beef consumption seems to be guided by a more complex set of reasons than is ham consumption.

From the practical standpoint, this report suggests a particular caution in selection of the specific model, especially if the food item under consideration is eaten less often. Some meats or meat products may attract a segment of the population. Recognizing characteristics that differentiate this segment from other groups is essential for the formulation of accurate and detailed recommendations. Access to a large and detailed database is essential for improving future empirical studies of food-consumption frequency.

When data are severely skewed with the short right tail (i.e., 90 percent of the consumption frequency collapsed on first five counts, i.e., between zero and five in our sample) and outliers are present, it causes a likelihood to deteriorate and does not improve prediction of the sample. To account for these problems with count-data models, further research should focus on the application of the Inverse Gaussian-Poisson (IG-P) model.

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