Habits in Frequency of Purchase Models: The Case of Fish in France

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ABSTRACT

The quantity purchased in a period is the result of two decisions: the frequency of purchase and the average purchase on each occasion. We introduce habit formation into demand systems modelling each of these decisions. An econometric model is estimated by Bayesian methods. The data generating processes of the frequency and quantity decisions are assumed to follow, respectively, a multivariate Poisson log-normal distribution and a multivariate gamma log-normal distribution. We estimate the systems using French scanner data for purchases of fish. The results suggest that habits in purchase frequencies are important, while habits in average purchased quantities are less important. Furthermore, we find that price changes are important for explaining average quantities purchased but have only minor effects on purchase frequencies.

Keywords: Demand system, fish, France, frequency of purchase, habit formation.

JEL: C34, D12

1. INTRODUCTION

Goods may be habit forming such that current preferences for a good depend on past consumption of the good. The importance of habits in purchase decisions for ordinary consumer goods is well documented in the economic literature (e.g., Havranek, Rusnak, & Sokolova, 2017). Habits have frequently been found to be important in demand system analysis for food (e.g., Gracia, Gil, & Angulo, 1998; Rickertsen, 1998) and fish (e.g., Asche, 1996; Asche, Salvanes, & Steen, 1997). For a review of this literature we refer the reader to Daunfeldt, Nordstöm, & Thunström (2012).

The strength of habits may be measured by a habit formation parameter taking a value between zero and one. A value of zero corresponds to no habit formation and as the value approaches one it implies that consumption becomes more and more determined by habits. In a meta-analysis, Havranek, Rusnak, & Sokolova, (2017) find that the average value of the habit formation parameter is 0.4. However, estimates vary significantly between micro and macro data with an average of 0.6 in studies using macro data and 0.1 in studies using micro data. The authors suggest that a likely reason for this difference is that estimates based on macro data likely show significantly higher habit formation due to higher aggregation level, longer time horizons, and lower data frequency, since consumption goods are more likely to display durability in higher data frequencies and thus counteracting the observed habit formation.

Durability was defined by Spinnewyn (1981) as the physical depreciation rate of a durable good. The durability parameter takes a value between zero and one. A value of zero implies no depreciation, and a value of one implies complete depreciation in the period. In Spinnewyn's (1981) formulation, the net effect of habits and durability determines the effect of previous period's consumption on current period's consumption. However, since Spinnewyn (1981) defined the durability parameter as the physical depreciation of durable goods, previous studies of non-durable goods typically do not include this parameter. One exception is Zhen et al. (2011) who estimate the demand for different non-alcoholic beverages with varying degrees of storability. Their estimated durability parameter for whole milk and low-fat milk was not zero, and they suggest that the durability parameter reflects more than the physical depreciation such as consumers' preferences for shopping frequencies. Based on this interpretation, we do not restrict the durability parameter to zero in our study of the demand for fresh fish. To make the distinction between physical depreciation, as reflected by the durability parameter, and personal preference, we will refer to our parameter as a duration parameter.

Research applying micro data to study the effects of habits and consumer purchasing behavior has focused on product choice and expenditure shares (Adamowicz & Swait, 2012; Alessie & Kapteyn, 1991; Arnade & Gopinath, 2006; Browning & Collado, 2007; Dynan, 2000; Fuhrer, 2000; Heaton, 1995; Holt & Goodwin, 1997; Rickertsen et al., 1995; Rickertsen, 1998; Zhen et al., 2011). The relationships between purchase frequency, habits, and duration have, as far as we know, not been investigated. Previous research by Robin (1993) and Buason & Agnarsson (2020) demonstrate that purchase frequencies are important for explaining consumer purchasing behavior. Thus, it is worth investigating whether habit formation and duration are more important for purchase frequency than for expenditure shares in micro data. To study the relationships between purchase frequency, habits, and duration, we divide the household's decision of how much to buy in one period into two decisions: (i) the frequency of shopping and (ii) the average purchase on each shopping trip.

An understanding of how habits and duration influence these two decisions can be used to formulate marketing strategies such as a loss-leader pricing strategy. This strategy involves reducing the price of some products below their marginal cost and simultaneously increase the price of other products (e.g., Chen & Rey, 2012; In & Wright, 2014; Buason, Kristofersson, & Rickertsen, 2020). In many situations, consumers buy multiple categories of grocery and find it convenient to buy them from a single store. These consumers are known as one-stop shoppers and have different shopping preferences relative to multi-stop shoppers, for example, due to tighter time constraints or a lower preference for shopping (Thomassen et al., 2017). Good candidates for price reductions are products that have a relatively high own-price elasticity and moderate habits in the frequency of shopping. Good candidates for price increases are products with a relatively low own-price elasticity but a high degree of habits in average purchases. Our methodology can potentially be used to investigate whether a product is a good loss-leader candidate. However, our empirical analysis includes only fresh fish, and we would need to include other products to develop a plausible example of an effective loss-leader strategy.

We follow Spinnewyn (1981), Pashardes (1986), Muellbauer & Pashardes (1992), and Zhen et al. (2011) and introduce durability and habits. As discussed above, our duration parameter reflects consumer preferences more than physical depreciation, and it reduces the speed at which goods need to be acquired to maintain an optimal level of the service stock. Habits have the opposite effect of duration on purchases, and more habitual consumers need greater flows of goods to reach their desired level of the service stock.

Purchase frequencies have rarely been incorporated into consumer demand analysis. However, some studies have used infrequency of purchase models (e.g., Meghir and Robin, 1992; Robin, 1993; and Buason & Agnarsson, 2020). These studies use purchase frequencies instead of a binary choice of whether to purchase or not. Robin (1993) showed that when a demand system is adjusted by the predictions from such a count data model, it explains more of the variation in the data than a conventional double-hurdle model.[1]

To estimate a multivariate count data model with unrestricted covariance structures for more than two goods is challenging. For example, Meghir & Robin (1992) and Robin (1993) estimated their count data demand equations without allowing for any covariance structure between the equations in their systems. A few studies have estimated count data demand systems with unrestricted covariance structure. Examples include Buason, Kristofersson, & Rickertsen (2020); Chib & Winkelmann (2001); and Egan & Herriges (2006). These studies either use Bayesian methods or standard maximum likelihood. The simulation-based methods, such as the random walk Metropolis algorithm that is used in Bayesian estimation, do not require numerical integration to get an explicit solution to the likelihood function but only sampling from the posterior. The simulation-based methods do therefore not suffer as much from the curse of dimensionality as the Gaussian quadrature.

This article adds to the literature in three ways. First, we extend the models developed in Spinnewyn (1981) and Muellbauer & Pashardes (1992), by allowing the choice of service stocks to be derived from two decisions: (i) how often to purchase each good and (ii) the average purchase on each occasion. We incorporate the dynamic structure of habit formation and duration into a semi-logarithmic demand specification, which is the standard specification of the expected value of count data models.

Second, we extend the model presented in Buason, Kristofersson, & Rickertsen (2020) by introducing habit formation. As in their model, our model allows for the joint estimation of

[1] Even though count data models have not been used frequently in demand analysis of consumer goods they have frequently been used in health economics, environmental economics, and marketing. The dependent variable in these studies are typically the number of visits to doctors, the number of trips to a recreational site or frequency of shopping (Deb & Trivedi, 2002; Egan & Herriges, 2006; Uncles & Lee, 2006).

purchase frequencies and average purchased quantities on each shopping occasion. For the purchase frequencies, a multivariate Poisson log-normal mixture (MPLN) distribution is used,[2] and for the average quantities a multivariate gamma log-normal (MGLN) distribution is used. Our empirical model allows for an unrestricted covariance structure between the equations in each subsystem and also between the two subsystems of the model. However, for ease of computation, we assume that the two subsystems are stochastically unrelated but let the covariance structure between equations in each system be unrestricted.[3]

Third, the model is applied to French scanner data for fresh fish purchases over the period 2005-2008. Our empirical system consists of wild, farmed, and other fish, which the consumers do not know whether is wild or farmed. We refer to the last category as other fish.[4]

2. THEORETICAL MODEL

Following Spinnewyn (1981), and Muellbauer & Pashardes (1992), let Z_{it} be the utility generating services in period *t* provided by the flow of good x_i purchased in period *t* or before, i.e., the model differentiates between the period of purchase and the periods when utility is gained from the purchased good. Let Z_{it} be defined as the weighted sum of the logarithm of current and past purchases as follows:

$$Z_{it} = \sum_{\tau=0}^{\infty} d_i^{\tau} \ln x_{it-\tau} = \ln x_{it} + d_i Z_{it-1}. \quad (1)$$

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[2] This model was introduced by Aitchison & Ho (1981).

[3] This simplifying assumption could lead to an incorrect specification of the variance if the two systems are stochastically correlated, but it does not lead to inconsistent or biased estimates of the parameters.

[4] Discussion on wild versus farmed fish can be found in, for example, Herrmann et al. (1993), Asche et al. (2005), Asche & Guttormsen (2014), Rickertsen et al. (2017).

The degree of durability of good x_i is determined by a simple duration parameter d_i, where $0 \leq d_i < 1$. As discussed above, the parameter d_i does not just reflect the biological durability of the good, but also personal preference of time between purchases (Zhen et al., 2011). For example, fresh fish is not a durable good, however, this lack of durability does not imply that a purchase of fresh fish today has no impact on purchases of fresh fish in the next period.[5]

We modify Equation (1) by assuming that the decision of purchased quantity x_{it} of good *i* in a time period *t* is determined by two decisions: (i) how often to purchase good *i* in period *t* and (ii) the average quantity purchased on each shopping occasion in the period. These decisions are expressed by the identity $x_{it} \equiv n_{it} q_{it}$, where n_{it} is purchase frequency and q_{it} is average quantity.

We follow Muellbauer & Pashardes (1992) and assume that habits are developed over time, where the desired level of the utility generating service stock Z_{it}^* is defined as follows:

$$Z_{it}^* = \exp(Z_{it} - \phi_i Z_{it-1}), \tag{2}$$

where habits are introduced by the parameter ϕ_i for each good and $0 \leq \phi_i < 1$, i.e., habits are treated as the opposite of duration. The grater the habit formation parameter is the larger service stock Z_{it} needs to be maintained to reach the desired level of the utility generating stock Z_{it}^*. Substituting Equation (1) into Equation (2) gives:

$$\begin{aligned} Z_{it}^* &= \exp(\ln x_{it} + d_i Z_{it-1} - \phi_i Z_{it-1}) \qquad (3) \\ &= x_{it} \exp\big((d_i - \phi_i) Z_{it-1}\big). \end{aligned}$$

If duration d_i dominates habits ϕ_i, then the total effect is positive and the utility generating stock is greater than the quantity of good *i* purchased in period *t*. The opposite is true when habits dominate duration. We are interested in the specific effects of duration and habits. To separately

[5] The durability of good x_{it} could also be modelled by a decay function. However, for simplicity we use one duration parameter.

identify these effects, we need to know either the value of the duration or habit parameter. We estimate the duration parameter from Equation (1) by using the initial condition of the service stock and solve for the estimated habit formation parameter.[6]

Following Zhen et al. (2011), a consumer's lifetime utility is assumed to be weakly separable over time such that:

$$U = v[v_t(Z_{0t}^*, \dots, Z_{mt}^*), v_{t+1}(Z_{0t+1}^*, \dots, Z_{mt+1}^*), \dots, v_T(Z_{0T}^*, \dots, Z_{mT}^*)], \tag{4}$$

and the present value of the lifetime budget constraint is:

$$W_t = \sum_{\tau=t}^{T} \sum_{i=0}^{m} \hat{p}_{i\tau} Z_{i\tau}^*, \tag{5}$$

where $\hat{p}_{i\tau}$ is the user's cost in period τ of service stock $Z_{i\tau}^*$. This user's cost can be thought of as rational or myopic. Neither assumption has proven to be consistently more accurate (Zhen et al., 2011), and we use the myopic assumption.[7]

Due to the weakly separable utility function (4), the consumer can allocate the period to period budget $y_t = \sum_i \hat{p}_{it} Z_{it}^*$ and maximizes the utility $v_t(Z_{0t}^*, \dots, Z_{mt}^*)$ in each period separately. This gives an *m* dimensional system of Marshallian demand functions of the form, $Z_{it}^* = g(\hat{p}_{it}, y_t)$ in each period. Substituting Equation (3) into one of these demand functions gives the following expressions:

$$x_{it} \exp\big((d_i - \phi_i) Z_{it-1}\big) = g(\hat{p}_{it}, y_t) \tag{6}$$

$$x_{it} = g(\hat{p}_{it}, y_t) \exp\big((\phi_i - d_i) Z_{it-1}\big).$$

[6] We describe how we estimate the duration parameter from Equation (1) using the initial conditions of the service stock in Section 4.1.

[7] Under the myopic assumption, the consumer does not account for the user cost of stocks.

Equation (6) gives the demand for good x_{it} including the effects of habits and duration. Given $x_{it} \equiv n_{it}q_{it}$, it follows that $g(\hat{p}_{it}, y_t) \equiv n(\hat{p}_{it}, y_t)q(\hat{p}_{it}, y_t)$, and substituting this expression into Equation (6) gives:

$$n_{it}q_{it} = n(\hat{p}_{it}, y_t)q(\hat{p}_{it}, y_t)\exp\big((\phi_i - d_i)Z_{it-1}\big). \tag{7}$$

The multiplicative form of Equation (7) allows us to analyze two systems of demand equations in each period, $n_{it}(\cdot)$ and $q_{it}(\cdot)$. We assume that the habit and duration parameters can be additively separated, $\phi_i = \psi_i + \omega_i$ and $d_i = \varphi_i + \zeta_i$, where ψ_i and φ_i are the habit and duration parameters of the frequency part, and ω_i and ζ_i are the habit and duration parameters of the average quantity part of the model. Equation (7) can be rewritten as:

$$n_{it}q_{it} = n(\hat{p}_{it}, y_t)\exp\big((\psi_i - \varphi_i)Z_{it-1}\big)q(\hat{p}_{it}, y_t)\exp\big((\omega_i - \zeta_i)Z_{it-1}\big). \tag{8}$$

3. STATISTICAL MODEL

The frequency of shopping $n_i = (n_{i11}, n_{i12}, \dots, n_{iKT})$ is assumed to follow a discrete distribution $f_{Ni}(n_i|\beta_i, C)$, for $n_{ikt} = 0,1,2, \dots$, where β_i is a vector of parameters, $k = 1,2, \dots, K$ denotes households, $t = 1,2, \dots, T$ denotes time periods, n_{ikt} is an observed value of the random variable N, and C is a matrix of explanatory variables. The average purchases $q_i = (q_{i11}, q_{i12}, \dots, q_{iKT})$ are only observed when a trip to the shop takes place. Thus, the variable $q_i|n_i > 0$ is assumed to follow a continuous distribution $f_{Qi|n_i>0}(q_i|\alpha_i, C, n_i > 0)$, defined only over positive values, where α_i is a vector of parameters, and q_{ikt} is an observed value of the random variable Q.[8] The data generating process for average quantity purchased is therefore given by the two-part model:

$$f_Q(q_i|\alpha_i,C) = \begin{pmatrix} \Pr(N=0|\beta_i,C) & \text{if } q_i = 0 \\ \Pr(N>0|\beta_i,C) f_{Qi|n>0}(q_i|\alpha_i,C,n_i>0) & \text{if } q_i > 0 \end{pmatrix}. \tag{9}$$

The decisions to purchase a good and how much to purchase of the good in each trip are likely to be related decisions, and it is desirable to model them as stochastically correlated. Furthermore, the demand for one good is directly related to the demand to the other, and we would therefore like to allow for correlation between the equations within each of the two systems. To model these correlations, we introduce random effects to the densities $f_{Ni}(n_i|\beta_i,C,b_{Ni})$ and $f_{Qi|n>0}(q_i|\alpha_i,C,n_i>0,b_{Qi})$, where b_{Ni} and b_{Qi} are the random effects for frequencies and average quantities, respectively. They are assumed to follow a multivariate normal distribution:

$$\begin{bmatrix} b_N \\ b_Q \end{bmatrix} \Bigg| D \sim MVN\left(\begin{bmatrix} 0^m \\ 0^m \end{bmatrix}, \begin{bmatrix} D_N & D_{NQ} \\ D_{NQ} & D_Q \end{bmatrix}\right), \tag{10}$$

where $b_N = (b_{N1}, \dots, b_{Nm})$, $b_Q = (b_{Q1}, \dots, b_{Qm})$, and D is the unrestricted block covariance matrix. The joint probability density function for n_i and q_i is:

$$p(n_i, q_i|\beta_i, \alpha_i, D, C) =$$

$$\int \prod_{t=1}^{T} f_{Ni}(n_{ikt}|\beta_i, C, b_{Nikt})\, f_{Qi|n>0}(q_i|\alpha_i, C, n_i > 0)\phi(b_{ik}|0, D)db_{ik}. \tag{11}$$

The product operator is inside the integral since b_N and b_Q each have one draw for the T random variables $n_{ik1}, n_{ik2}, \dots, n_{ikT}$ and $q_{ik1}, q_{ik2}, \dots, q_{ikT}$, respectively. Thus, there is a new

[8] The conditional mean of n_i and q_i are given as follows: $\mathrm{E}(n_i|\beta_i, C, b_{Ni})$, $\mathrm{E}(q_i|\alpha_i, C, b_{Qi}) = \Pr(N>0|\beta_i, C)\mathrm{E}(q_i|\alpha_i, C, n_i>0, b_{Qi})$. The marginal effects of $\mathrm{E}(q_i|\alpha_i, C, b_{Qi})$ are given by: $\frac{\partial \mathrm{E}(q_i|\alpha_i, C, b_{Qi})}{\partial c_i} = \frac{\partial \mathrm{E}(q_i|\alpha_i, C, n_i>0, b_{Qi})}{\partial c_i}\Pr(N>0|\beta_i, C)$.

draw for each cluster, but not for each time period within a cluster. The likelihood is then given by:

$$L = \prod_{k=1}^{K} \prod_{i=1}^{M} p(n_i, q_i | \beta_i, \alpha_i, D, C). \tag{12}$$

Since the joint density $p(n_i, q_i | \beta_i, \alpha_i, D, C)$ does not have a closed form solution, the likelihood L is difficult to optimize with conventional Newton methods, so we use simulation based methods.[9]

3.1. Distribution Assumptions

To be able to estimate the parameters of our model, the conditional distribution assumptions of $n_i | \beta_i, C$ and $q_i | \alpha_i, C, n_i > 0$ need to be determined. The number of shopping trips is assumed to follow a Poisson distribution, $n_i | \beta_i, C, \sim \text{Poisson}(\mu_i)$ and the average quantity purchased in each trip is assumed to follow a gamma distribution $q_i | \alpha_i, C, n_i > 0 \sim \text{Gamma}(\kappa_i, \eta_i)$. The parameter of the Poisson distribution is specified as $\lambda_i = \exp(C_i \beta_i)$. The mean of the gamma distribution is specified as $\kappa_i \eta_i = \exp(C_i \alpha_i)$. Now let $v_{io} = \exp(b_{io})$, where $v_{io} = \left(v_{i1o}, v_{i2o}, \dots, v_{iJo}\right)$, and $v_{io} \sim LN(\mu_o, \Sigma_o)$, where $\mu_o = \exp\left(0.5 \text{diag}(D_o)\right)$, and $o = N, Q$. The variance covariance matrix is then $\Sigma_o = \left(\text{diag}(\mu_o)\right)[\exp(D_o) - 11'] \left(\text{diag}(\mu_o)\right)$. Multiplying both means with this random effect gives, $\lambda_i v_{Ni} = \exp(C_i \beta_i + b_{Ni})$ and $\kappa_i \eta_i v_{Qi} = \exp\left(C_i \alpha_i + b_{Qi}\right)$. To simplify the analysis, the covariance between n_i and q_i is assumed to be zero.[10] However, a non-restricted covariance matrix is assumed between clusters within both parts of the model. Equation (10) is then reduced to:

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[9] For less complex problems, the Gaussian-quadrature could be used.
[10] This assumption could lead to incorrect variance specification but will not result in inconsistent parameter estimates.

$$\begin{bmatrix} b_N \\ b_Q \end{bmatrix} \Bigg| D \sim MVN\left(\begin{bmatrix} 0^m \\ 0^m \end{bmatrix}, \begin{bmatrix} D_N & 0_{NQ} \\ 0_{NQ} & D_Q \end{bmatrix}\right). \tag{13}$$

The Poisson part of this model is the log-normal Poisson model in Atchinson and Ho (1989), and it is possible to derive the mean and variance of the marginal distribution of n_i without integration. Let $\tilde{\lambda}_i = \lambda_i \mu$, where $\tilde{\lambda}_i = (\tilde{\lambda}_{i11}, \tilde{\lambda}_{i12}, \ldots, \tilde{\lambda}_{iKT})$ and $\tilde{\Lambda}_i = \mathrm{diag}(\tilde{\lambda}_i)$. Applying the law of iterated expectations, one obtains $E(n_i|\beta_i, C, D_N) = \tilde{\lambda}_i$ and $\mathrm{var}(n_i|\beta_i, C, D_N) = \tilde{\Lambda}_i + \tilde{\Lambda}_i[\exp(D_N) - 11']\tilde{\Lambda}_i$. Then, the covariance between n_{ikt} and n_{ift} is calculated as: $\mathrm{cov}(n_{ikt}, n_{ift})$ $= \tilde{\lambda}_{ikt} \;\; (\exp(d_{Nikt,ift}) - 1) \;\; \tilde{\lambda}_{ift} \;\; = \;\; \lambda_{ikt} \;\; \exp\left(0.5(d_{Nikt,ikt})\right) \;\; (\exp(d_{Nikt,ikf}) - 1) \;\; \lambda_{jkt}$ $\exp\left(0.5(d_{Nift,ift})\right)$. For a more detailed derivation of this result see Atchinson and Ho (1989).

The mean and variance of the marginal distribution of q_i can also be derived without integration.[11] We start by defining $\delta_{ikt} \equiv \kappa_{ikt}\eta_{ikt}$, and the mean of the marginal distribution of q_i is:

$$\begin{aligned} \mathrm{E}[q_{ikt}|\beta_i, C, D_Q] &= \mathrm{E}_{v|\delta}\left[\mathrm{E}_{q|\delta,v}[q_{ikt}|\delta_{ikt}, v_{ikt}, D_Q]\right] \\ &= \mathrm{E}_{v|\delta}[\delta_{ikt}v_{ikt}] = \delta_{ikt}\mathrm{E}_{v|\delta}[v_{ikt}] = \delta_{ikt}\mu \equiv \tilde{\delta}_{ikt}. \end{aligned} \tag{14}$$

The variance of the marginal distribution of q_i is:

$$\begin{aligned} &\mathrm{var}[q_{ikt}|\beta_i, C, D_Q] \\ &= \mathrm{E}_{v|\delta}\left[\mathrm{var}_{q|\delta,v}[q_{ikt}|\delta_{ikt}, v_{ikt}, D_Q]\right] + \mathrm{var}_{v|\delta}\left[\mathrm{E}_{q|\delta,v}[q_{ikt}|\delta_{ikt}, v_{ikt}, D_Q]\right] \\ &= \mathrm{E}_{v|\delta}[v_{ikt}\kappa_{ikt}\eta_{ikt}^2] + \mathrm{var}_{v|\delta}[v_{ikt}\delta_{ikt}] \\ &= \kappa_{ikt}\eta_{ikt}^2\mathrm{E}_{v|\delta}[v_{ikt}] + \delta_{ikt}^2\mathrm{var}_{v|\delta}[v_{ikt}] \\ &= \kappa_{ikt}\eta_{ikt}^2\mu + \delta_{ikt}^2\mu^2(\exp(d_{Qkk}) - 1) \end{aligned} \tag{15}$$

[11] The mean and variance of the marginal distribution of q_i have, as far as we know, not been derived in the literature.

$$\eta_{ikt}\tilde{\delta}_{ikt} + \tilde{\delta}_{ikt}^2\left(\exp\left(d_{Qkk}\right) - 1\right).$$

Let $\tilde{\delta}_i = \left(\tilde{\delta}_{i11}, \tilde{\delta}_{i12}, \dots, \tilde{\delta}_{iKT}\right)$, $\eta_i = (\eta_{i11}, \eta_{i12}, \dots, \eta_{iKT})$, $\widetilde{\Delta}_i = \text{diag}\left(\tilde{\delta}_i\right)$, and $\mathrm{H}_i = \text{diag}(\eta_i)$. Equation (15) is rewritten in matrix form as:

$$\text{var}\left[q_i|\beta_i, C, D_Q\right] = \mathrm{H}_i\widetilde{\Delta}_i + \widetilde{\Delta}_i\left(\exp\left(D_Q\right) - 11'\right)\widetilde{\Delta}_i. \tag{16}$$

The covariance between q_{ikt} and q_{ift} becomes:

$$\text{cov}\left(q_{ikt}, q_{ift}\right) = \tilde{\delta}_{ikt}\left(\exp\left(d_{Qikt,ift}\right) - 1\right)\tilde{\delta}_{ift} \tag{17}$$

$$= \delta_{ikt}\exp\left(0.5\left(d_{Qikt,ikt}\right)\right)\left(\exp\left(d_{Qikt,ift}\right) - 1\right)\exp\left(0.5\left(d_{Qift,ift}\right)\right)\delta_{ift},$$

$$k \neq f.$$

3.2. Priors and Markov Chain Monte Carlo Sampling

To estimate our model using Bayesian methods, we use uninformative priors, see for example Chib and Winkelmann (2001) for a discussion. Let $\beta \sim \mathrm{N}(\beta_0, B_0^{-1})$, $\alpha \sim \mathrm{N}(\alpha_0, A_0^{-1})$, $\kappa \sim \text{Gamma}(k_0, s_0)$, $D_N^{-1} \sim \text{Wishart}(v_{N0}, R_{N0})$, and $D_Q^{-1} \sim \text{Wishart}\left(v_{Q0}, R_{Q0}\right)$, where $\beta_0, B_0, \alpha_0, A_0, k_0, s_0, v_{N0}, R_{N0},\ v_{Q0},$ and R_{Q0} are known hyperparameters and $\text{Wishart}(\cdot,\cdot)$ is the Wishart distribution with v_{o0} degrees of freedom and scale matrix R_{o0}, where $o = N, Q$. By Bayes theorem, the posterior density of the two parts of the model are proportional to the following expressions:

$$\phi(\beta|\beta_0, B_0^{-1})f_W(D_N^{-1}|v_{N0}, R_{N0})\prod_{k=1}^{K}\prod_{i=1}^{M}f_N(n_{ik}|\beta, b_{Nik})\,\phi(b_{Nik}|0, D_N), \tag{18}$$

$$\phi(\alpha|\alpha_0, A_0^{-1})f_W\left(D_Q^{-1}\middle|v_{Q0}, R_{Q0}\right)\prod_{k=1}^{K}\prod_{i=1}^{M}f_{Q|n>0}\left(q_{ik}\middle|\alpha, b_{Qik}, n_{ik} > 0\right)\phi\left(b_{Qik}\middle|0, D_Q\right), \tag{19}$$

where f_W is the Wishart distribution. We construct Markov chains using the blocks of parameters b_N, b_Q, β, α, D_N and D_Q, and their full conditional distributions:

$$[b_N|n, \beta, D_N]; \quad [\beta|n, b_N]; \quad [D_N|b_N], \tag{20}$$

$$[b_Q|q, \alpha, D_Q]; \quad [\alpha|q, b_Q]; \quad [D_Q|b_Q]. \tag{21}$$

The simulation output is generated by recursively simulating these distributions, using the most recent values of the conditioning variables in each step. The sampling of b_N and b_Q starts with specifying the target densities:

$$\pi(b_N|n, \beta, D_N) = \prod_{k=1}^{K} \prod_{i=1}^{M} \pi(b_{Nik}|n_{ik}, \beta, D_N), \tag{22}$$

$$\pi(b_Q|q, \alpha, D_Q) = \prod_{k=1}^{K} \prod_{i=1}^{M} \pi(b_{Qik}|q_{ik}, \alpha, D_Q). \tag{23}$$

To sample the density of the kth household of the ith cluster of the target densities, we specify:

$$\begin{aligned} \pi(b_{Nik}|n_{ik}, \beta, D_N) = c_{ik}\phi(b_{Nik}|0, D_N) \prod_{t=1}^{T} \exp[-\exp(C_{ikt}\beta_t + b_{Nikt})] \\ \times [-\exp(C_{ikt}\beta_t + b_{Nikt})]^{n_{ikt}} \\ \equiv c_{ik}\pi^{+}(b_{Nik}|n_{ik}, \beta, D_N), \end{aligned} \tag{24}$$

$$\begin{aligned} \pi(b_{Qik}|q_{ik}, \alpha, \kappa, D_Q) = i_{ik}\phi(b_{Qik}|0, D_Q) \prod_{t=1}^{T} \frac{q_{ikt}^{C_{ikt}\alpha_t + b_{Nikt}}}{\Gamma(C_{ikt}\alpha_t + b_{Nikt})\kappa^{C_{ikt}\alpha_t + b_{Qikt}}} \\ \times \exp[-q_{ikt}/\kappa] \\ \equiv i\pi^{+}(b_{Qik}|q_{ik}, \alpha, \kappa, D_Q). \end{aligned} \tag{25}$$

The target distributions are a Poisson log-normal mixture distribution and a Gamma log-normal mixture distribution. We utilize a random walk Metropolis algorithm.[12] The proposal density is found by approximating the target density around the modal value by a multivariate *t*-distribution. Let $\hat{b}_{Nik} = \operatorname{argmax} \ln \pi^{+}(b_{Nik}|n_{ik}, \beta, D_N)$ and $V_{b_{Nik}} = \left(H_{b_{Nik}}\right)^{-1}$ be the inverse of the Hessian of $\ln \pi^{+}(b_{Nik}|n_{ik}, \beta, D_N)$ at the mode $\hat{b}_{Nik}$. To find these estimates, we use the Newton-Raphson algorithm. Then, our proposal density is $b_{Nik}^{(s)} \left| b_{Nik}^{(s-1)} \sim t\left(b_{Nik}^{(s-1)}, V_{b_{Nik}}, v\right)\right.$, where *v* is the degrees of freedom and *s* indicates the draw number. We then make a random draw e_{ik} from $t\left(0, V_{b_{Nik}}, v\right)$, where $b_{Nik}^{(s)} = b_{Nik}^{(s-1)} + e_{ik}$ and we moved from $b_{Nik}^{(s-1)}$ to $b_{Nik}^{(s)}$ with probability

$$r = \min \left\{ \frac{\pi^{+}\left(b_{Nik}^{(s)} \middle| n_{ik}, \beta, D_N\right)}{\pi^{+}\left(b_{Nik}^{(s-1)} \middle| n_{ik}, \beta, D_N\right)}, 1 \right\}. \tag{26}$$

Next, we sample u from a uniform distribution $\mathrm{U}(0,1)$ and if $u < r$ then $b_{Nik}^{(s)} = b_{Nik}^{*}$ otherwise $b_{Nik}^{(s-1)} = b_{Nik}^{*}$. We use the same steps for the sampling of b_Q.

The sampling of β and α follows the same approach, and the respective target distributions are given as follows:

$$\pi(\beta|n, b_N, D_N) = \phi(\beta|\beta_0, B_0^{-1}) \prod_{k=1}^{K} \prod_{i=1}^{M} \prod_{t=1}^{T} \exp[-\exp(C_{ikt}\beta_t + b_{Nikt})] \tag{27}$$

$$\times [-\exp(C_{ikt}\beta_t + b_{Nikt})]^{n_{ikt}}$$

$$\pi\left(\alpha \middle| q, b_Q, \kappa, D_Q\right) = \phi(\alpha|\alpha_0, A_0^{-1}) \prod_{k=1}^{K} \prod_{i=1}^{M} \prod_{t=1}^{T} \frac{q_{ikt}^{C_{ikt}\alpha_t + b_{Nikt}}}{\Gamma(C_{ikt}\alpha_t + b_{Nikt})\kappa^{C_{ikt}\alpha_t + b_{Qikt}}} \tag{28}$$

$$\times \exp[-q_{ikt}/\kappa].$$

[12] For a discussion of the random walk Metropolis algorithm, see for example Roberts et al. (1997).

Sampling D_N^{-1} and D_Q^{-1} is a simpler process than the other two blocks of parameters, since we specify a hyperprior, which result in a Wishart distribution. We sampled D_o^{-1}, $o = N, Q$, from a distribution proportional to:

$$f_W(\, D_o^{-1} | v_{o0}, R_{o0}^{-1}) \prod_{k=1}^{K} \prod_{i=1}^{M} \phi(b_{oik} | 0, D_o). \tag{29}$$

The distribution of $D_o^{-1} | b_0$ then results in a Wishart distribution:

$$D_o^{-1} | b_0 \sim \text{Wishart}\left(M + v_{o0}, \left[R_{o0}^{-1} + \sum_{k=1}^{K} \sum_{i=1}^{M} (b'_{oik} b_{oik}) \right]^{-1} \right), \tag{30}$$

with $M + v_{o0}$ degrees of freedom and a scale matrix $[R_{o0}^{-1} + \sum_{k=1}^{K} \sum_{i=1}^{M} (b'_{oik} b_{oik})]^{-1}$.

4. DATA AND VARIABLE SPECIFICATION

We use a scanner data set, which was collected by TNS Worldpanel and include weekly purchases of fresh fish for about 6,000 French households over the period 2005-2008. The data set includes a detailed description of social, geographical and other characteristics of the participating households. For simplicity, we do not include household characteristics in our analysis. A large proportion of zero observations is a standard problem when working with micro data, and we reduced the number of zero observations by aggregating the data over months.[13]

4.1. Specification of Variables

[13] The problem of zero observations is also reduced when the data generating process is discrete as in the Poisson distribution with a positive probability of observing a zero.

To estimate Equation (8), the total service stock of each type of fish Z_{ikt} needs to be predicted. The first three months of the first year in the sample (2005) were used to predict Z_{ikt}. From Equation (1), the relationship between the first two periods for one household *k* can be written as:

$$Z_{ik1} = \ln x_{ik1} + \left(\frac{d_i}{1-d_i}\right)\ln x_{ik0}. \tag{31}$$

The functional form for $n(p_{it}, y_t)$ and $q(p_{it}, y_t)$ given by Equations (6) and (7) is assumed to be semi-logarithmic. Thus, $g(p_{it}, y_t) \equiv n(p_{it}, y_t)q(p_{it}, y_t)$ is also semi-logarithmic. Equation (6) can then be written as:

$$x_{ik2} = \exp(C_{ikt}\gamma_i + (\phi_i - d_i)Z_{ik1}) \tag{32}$$

$$\ln x_{ik2} = C_{ikt}\gamma_i + (\phi_i - d_i)\ln x_{ik1} + (\phi_i - d_i)\left(\frac{d_i}{1-d_i}\right)\ln x_{ik0}$$

Equation (32) is estimated to obtain an estimate of d_i, where d_i is used to predict Z_{ikt}, and Equation (8) is estimated by the following two systems of equations:

$$E(n_{ik}|C_i) = \exp\left(\beta_{ik} + \sum_{s=1}^{S}\beta_{is}\left(\frac{p_{sk}}{CPI}\right) + \theta_i\left(\frac{y_k}{CPI}\right) + (\psi_i - \varphi_i)\hat{Z}_{ikt-1} + b_{Nik}\right) \tag{33}$$

$$E(q_{ik}|C_i) = \exp\left(\alpha_{ik} + \sum_{s=1}^{S}\alpha_{is}\left(\frac{p_{sk}}{CPI}\right) + \varpi_i\left(\frac{y_k}{CPI}\right) + (\omega_i - \zeta_i)\hat{Z}_{ikt-1} + b_{Qik}\right), \tag{34}$$

where the price of fish category *i* for household *k* is p_{ik}, the total fish expenditure of household *k* is y_k, and *CPI* is the French consumer price index.[14]

4.2. Descriptive Statistics

[14] The semi-logarithmic demand equations in Equations (32) and (33) are integrable when the restrictions $\beta_{is} = 0 \; \forall \; i \neq s$ and $\theta_i = \theta \; \forall \; i$ are imposed (LaFrance & Hanemann, 1989).

The descriptive statistics of our variables are given in Table 1. The dependent variables in the count data system are the frequency of purchase of wild fish, farmed fish, and other fish. Wild fish mainly consists of cod and other white fish and farmed fish mainly consists of salmon. The average frequency of purchase of wild fish is around 1.5 per month. This relatively low frequency is still higher than for the other two fish types. Even though fresh fish is an infrequently purchased product among many consumers, the main reason for these low average values is the large number of zero observations. The dependent variables in the continuous part of the model are the truncated average quantities purchased of the three types of fish. These quantities are around 660 to 700 grams. However, there are large variations within each type of fish. For example, the minimum quantity of wild fish is 15 grams while the maximum quantity is more than 15 kilograms.

The data set does not contain any information regarding prices. The prices are therefore calculated as unit values by dividing expenditures by quantities for each type of fish on each purchase occasion. When zero purchases are recorded there is no unit value available and the average unit value is used. This approach has been frequently used in demand studies (e.g., Allais et al., 2010; Bertail & Caillavet, 2008; Buason & Agnarsson, 2020).[15]

We estimate the duration parameters d_i in Equation (32) for wild, farmed, and other fish. The duration parameters are 0.599, 0.442, and 0.441, respectively. We use these parameter estimates to predict the lagged service stock for each of the three fish types, as described in Section 4.1. The predicted values of the service stocks are about 1,658, 504, and 924 grams for wild, farmed, and other fish as shown by the stock variables in Table 1. The other explanatory variables are the price variables (unit values divided by the *CPI*) and the expenditure variable (households'

[15] This method is not without problems since prices will be influenced by choices of quality of fish or store, which potentially introduce endogeneity problems.

total expenditures on fresh fish divided by the *CPI*), the annual time dummy variables, and a monthly time trend.

(Table 1 about here)

5.1. Empirical Results

Tables 2 – 4 present the results from the estimation of the MPLN and MGLN systems for each of the three fish types. The tables show the parameter estimates, associated *t*-values, and Geweke *Z*-scores.[16] Table 2 presents the results for wild fish. Except for the constant term and the price in the average quantity part, all Markov Chains are stationary and the associated parameters can be interpreted reliably. The stock parameter is positive in both equations, which implies that habits dominate duration in both equations. Using the estimates of the net effects of habits and duration in the two systems and the predicted total duration, we can calculate the habit parameter. For wild fish the habit parameter is about 0.60, where most of the habit formation is due to purchase frequency as can be seen from the estimates of the stock parameters.[17]

Table 3 presents the results for farmed fish. The Geweke *Z*-scores indicate that all the Markov Chains are stationary. The stock parameter is positive in both equations, which implies that habits dominate duration in both equations, i.e., habits result in more frequent and higher purchases of farmed fish. Using calculations corresponding to the calculations in footnote 17, we find that the habit parameter for farmed fish is 0.44. The habit effect is somewhat lower than for wild fish, and most of the habit formation is due to purchase frequency.

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[16] The Geweke convergence test is a test of stationarity of the Markov chains. For a discussion of this test, see Nylander et al. (2008).

[17] To find the habit parameter for wild fish, we add the estimated stock parameters from both the frequency and average quantity part given in Table 2, which is 0.00045. Next, we add this parameter (0.00045) to the predicted duration parameter presented in the previous subsection, which is 0.599 and the resulting parameter is 0.59945 or about 0.60.

Table 4 presents the results for other fish. The Geweke *Z*-scores indicate that all the Markov chains are stationary. The results are similar to those of wild and farmed fish, which is as expected given that other fish consists of a mixture of wild and farmed fish. The habit parameter is 0.44 and again most of the habit formation is due to purchase frequency.

(Table 2 about here)

(Table 3 about here)

(Table 4 about here)

Table 5 shows the parameter estimates and associated *t*-values for the cross-equation covariance matrix for the frequency and average quantity parts of the model. The demand for wild fish is defined as the first equation, farmed fish as the second equation and other fish as the third equation. Sigma11, Sigma22, and Sigma33 refer to the variance of the random effects of the three demand equations. Sigma12 and Sigma21 show the covariance between the random effects of the equations for wild and farmed fish, and Sigma13 and Sigma31 show the covariance between the equations for wild and other fish. Finally, Sigma23 and Sigma32 are the covariances between the equations for farmed and other fish. The covariance is positive between wild and farmed fish indicating a positive correlation between the purchases of wild and farmed fish. This positive covariance suggests that those who consume wild fish also consume farmed fish. However, there are negative correlations between wild and other fish and between farmed and other fish, which suggest that the buyers of wild and farmed fish are somewhat different than those who buy other fish.

(Table 5 about here)

5.2. Elasticities

Table 6 presents the elasticities and associated *t*-values for frequencies of purchase, average purchased quantities, and total purchased quantities as calculated from Equations (33) and (34). The effects of net habits in these equations are constructed from the habit components of frequencies and average quantities. All the elasticities are statistically significant at the 1% level.

When the stock of wild fish increases by 10%, the purchase frequency increases by 0.66%, the average quantity increases by 0.05%, and total purchases by 0.71%. The results for farmed and other fish are similar. These results demonstrate that habits play an important role in fish purchases, and the effects of net habits mainly works through increased purchase frequencies.

The own-price elasticities indicate that price changes have greater effect on average quantities than on frequencies. When the price of wild fish is reduced by 10%, the purchase frequency is increases by 1.2%, the average quantity increases by 3.2%, and total purchases increases by 4.3%. The results for farmed and other fish are similar.

As discussed in Section 2, the expenditure elasticities for frequency of purchase have to be the identical for the three fish types to fulfill the symmetry condition in a semi-logarithmic demand system. However, the total expenditure elasticities for average purchases can differ between the fish types. For wild fish, the total expenditure elasticity for purchase frequency is 0.15, for average purchases 0.19, and for total purchases 0.34.

(Table 6 about here)

The differences in absolute value between net habit, own-price and total expenditure elasticities for the purchase frequencies, average purchases and total purchases for the three types of fish are presented in Table 7. The *t*-values for tests of no difference in the elasticities are also shown.

There is no statistically significant difference between any of the stock elasticities. Thus, net habits for purchasing the three types of fish are very similar. However, there are several significant differences between the own-price elasticities for frequencies, average quantities and total quantities. The purchase frequency of wild fish is significantly more price sensitive than the purchase frequency of farmed or other fish, and the total quantity of wild fish is significantly more price sensitive than the total quantities of farmed or other fish. The expenditure elasticities for total purchases are statistically different at the 1% level for wild and farmed fish and farmed and other fish. Farmed fish is less expenditure elastic than wild fish but more expenditure elastic than other fish.

(Table 7 about here)

6. CONCLUSIONS

The model of Spinnewyn (1981) and Muellbauer & Pashardes (1992) has been extended in two ways. First, we specify the dynamic structure of habit formation and duration to fit into a semi-logarithmic demand specification. Second, we allow for product specific net habits in the frequency of purchase decision and the average quantity purchased decision rather than having one total effect on the resulting total purchased quantity.

Net habits are introduced into a Bayesian framework for the joint estimation of demand systems of purchase frequencies and average purchased quantities. This framework allows for an unrestricted covariance structure within each demand system.

Our econometric model is applied to French scanner data for fresh fish purchases. We include wild fish, farmed fish, and other fish in our demand systems. We find that net habits on total quantities purchased are mainly due to habits in purchase frequencies, while habits in average quantities purchased are of minor importance. We find no significant differences of net habits among the three types of fish. On the other hand, price effects on total quantities are mainly due to changes in average quantities purchased rather than frequencies. Fresh wild fish is more price elastic than the other two fish types both in terms of purchase frequency and total quantity purchased. However, the own-price elasticities of the average quantities do not differ much across the fish types. Similar own-price elasticities of farmed fish and other fish suggest that consumers do not distinguish between farmed fish and fish that does not display any information about whether it is wild or farmed.

Havranek, Rusnak, & Sokolova, (2017) found an average habit formation effect of 0.6 in studies using macro data and 0.1 in studies using micro data, while our estimated habit formation without duration is between 0.4 - 0.6. Havranek, Rusnak, & Sokolova, (2017) suggest that the reason why one observes higher degree of habit formation in micro data is because consumption goods are more likely to display durability in higher data frequencies. This explanation is consistent with our results. We find significant duration effects, i.e., personal preferences for long time intervals between shopping trips. Our results therefore suggest that neglecting habits and duration could result in too low estimates of demand changes over time in response to changes in prices.

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Table 1: Descriptive Statistics, 2005-2008 (Monthly)

Variable	Description	Mean	Std. Dev	Min	Max
Frequency wild	Number of trips to buy wild fish	1.51	1.65	0.00	27.00
Frequency farmed	Number of trips to buy farmed fish	0.94	0.88	0.00	14.00
Frequency other	Number of trips to buy other fish	1.31	1.20	0.00	16.00
Quantity wild	Truncated average purchased quantities of wild fish (grams)	669.75	631.80	14.66	15172.20
Quantity farmed	Truncated average purchased quantities of farmed fish (grams)	701.00	642.89	20.00	11175.00
Quantity other	Truncated average purchased quantities of other fish (grams)	658.87	549.70	11.80	10475.40
Stock wild	The lagged service stock of wild fish (grams)	1657.54	2204.19	0.00	34650.19
Stock farmed	The lagged service stock of farmed fish (grams)	504.33	837.95	0.00	19012.51
Stock other	The lagged service stock of other fish (grams)	924.20	1208.82	0.00	21364.52
Expenditure	Household’s total expenditures on fresh fish divided by CPI	0.14	0.14	<0.01	2.52
Price wild	Unit value of wild fish (per kilo) divided by CPI	0.10	0.03	<0.01	0.59
Price farmed	Unit value of farmed fish (per kilo) divided by CPI	0.09	0.02	<0.01	0.58
Price other	Unit value of other fish (per kilo) divided by CPI	0.10	0.03	<0.01	0.58

Table 2: Posterior Summary for Wild Fish Based on the MPLN and MGLN Distributions

	Frequency			Average Quantity		
Variable	Mean	t-value	Geweke Z	Mean	t-value	Geweke Z
Constant	0.06	3.45	-0.72	6.47	501.39	2.28
(Stock wild) ·1,000	0.40	22.40	0.00	0.05	3.08	0.00
Price wild	-1.12	-10.56	0.15	-4.82	-68.81	-3.61
Expenditure	1.06	75.99	-0.06	2.20	140.40	0.18
Dummy06	-0.08	-9.20	-0.57	0.07	8.42	-0.53
Dummy07	-0.11	-12.21	-1.50	0.09	10.14	-0.37
Dummy08	-0.15	-15.31	0.56	0.10	11.58	0.11
Month	-0.01	-11.76	0.31	0.03	3.70	-0.74

Notes: MPLN = multivariate Poisson log-normal and MGLN = multivariate gamma log-normal. Geweke *Z* provides the *Z*-value for a test of stationarity of the Markov chains. The Stock wild variable is multiplied by 1,000 for scaling purposes.

Table 3: Posterior Summary for Farmed Fish Based on the MPLN and MGLN Distributions

	Frequency			Average Quantity		
Variable	Mean	t-value	Geweke Z	Mean	t-value	Geweke Z
Constant	-0.48	-18.22	1.84	6.57	373.48	1.22
(Stock farmed) ·1,000	0.13	28.20	0.00	0.02	4.74	0.00
Price farmed	-0.64	-3.35	-0.85	-5.94	-53.27	-0.64
Expenditure	1.06	75.99	-0.06	2.20	140.40	0.18
Dummy06	-0.09	-7.37	-0.19	0.05	4.60	-1.05
Dummy07	-0.03	-2.46	-1.21	0.06	4.81	-1.62
Dummy08	-0.05	-4.06	-1.48	0.09	7.56	-1.06
Month	-0.00	-2.72	-0.15	0.05	4.46	-0.27

Notes: MPLN = multivariate Poisson log-normal and MGLN = multivariate gamma log-normal. Geweke *Z* provides the *Z*-value for a test of stationarity of the Markov chains. The Stock farmed variable is multiplied by 1,000 for scaling purposes.

Table 4: Posterior Summary for Other Fish Based on the MPLN and MGLN Distributions

	Frequency			Average Quantity		
Variable	Mean	t-value	Geweke Z	Mean	t-value	Geweke Z
Constant	0.03	1.55	0.68	6.45	500.29	0.74
(Stock other) ·1,000	0.08	24.75	0.00	0.01	4.57	0.00
Price	-0.71	-6.19	0.13	-4.76	-63.77	0.19
Expenditure	1.06	75.99	-0.06	2.20	140.40	0.18
Dummy06	-0.09	-9.56	-0.06	0.08	9.65	-0.80
Dummy07	-0.12	-11.76	-1.36	0.09	10.34	-1.32
Dummy08	-0.14	-13.44	-0.43	0.10	12.66	-1.42
Month	-0.01	-7.02	-1.08	0.05	5.66	-0.07

Notes: MPLN = multivariate Poisson log-normal and MGLN = multivariate gamma log-normal. Geweke *Z* provides the *Z*-value for a test of stationarity of the Markov chains. The Stock other variable is multiplied by 1,000 for scaling purposes.

Table 5: Posterior Summary Cross-Equation Covariance Matrix based on MPLN and MGLN Distributions

	Frequency			Average Quantity		
Variable	Mean	t-value	Geweke Z	Mean	t-value	Geweke Z
Sigma11	0.55	36.15	0.45	0.13	36.17	-0.03
Sigma12	0.08	8.52	0.32	0.10	32.21	1.27
Sigma13	-0.15	-20.81	-0.10	0.10	34.16	0.11
Sigma21	0.08	8.52	0.32	0.10	32.21	1.27
Sigma22	0.60	33.55	-1.29	0.13	30.63	0.30
Sigma23 ·10	-0.05	-0.64	-0.93	0.92	32.31	1.28
Sigma31	-0.15	-20.81	-0.10	0.10	34.16	0.11
Sigma32 ·10	-0.05	-0.64	-0.93	0.92	32.31	1.28
Sigma33	0.39	36.06	-0.80	0.11	34.16	-0.44

Notes: MPLN = multivariate Poisson log-normal and MGLN = multivariate gamma log-normal. Geweke *Z* provides the *Z*-value for a test of stationarity of the Markov chains. The multiplications following Sigma23 and Sigma32 indicate scaling.

Table 6: Elasticities for Purchase Frequencies, Average Quantities, and Total Quantities

Purchase Frequency	Wild Fish		Farmed Fish		Other Fish	
	Estimate	t-value	Estimate	t-value	Estimate	t-value
Stock·10 [a]	0.66	22.40	0.65	28.20	0.70	24.75
Own price	-0.12	-10.56	-0.06	-3.35	-0.07	-6.19
Total expenditure	0.15	75.99	0.15	75.99	0.15	75.99
Average Quantity	**Wild Fish**		**Farmed Fish**		**Other Fish**	
	Estimate	t-value	Estimate	t-value	Estimate	t-value
Stock·10 [a]	0.05	3.08	0.05	4.74	0.07	4.57
Own price	-0.32	-68.81	-0.27	-53.27	-0.31	-63.77
Total expenditure	0.19	140.40	0.15	140.40	0.20	140.40
Total Quantity	**Wild Fish**		**Farmed Fish**		**Other Fish**	
	Estimate	t-value	Estimate	t-value	Estimate	t-value
Stock·10 [a]	0.71	21.20	0.70	27.77	0.77	24.16
Own price	-0.43	-36.17	-0.33	-17.78	-0.38	-30.33
Total expenditure	0.34	143.05	0.30	134.27	0.35	143.73

Note: [a] The elasticities of each stock variable is multiplied by 10 for ease of presentation.

Table 7: Absolute Values of Elasticity Differences for Purchase Frequencies, Average Quantities, and Total Quantities

	Frequency		Average Quantity		Total Quantity	
	Difference	t-value	Difference	t-value	Difference	t-value
Stock (wild - farmed)·100 [a]	0.12	0.33	0.02	0.10	0.14	0.34
Stock (wild - other)·100 [a]	0.39	-0.96	0.16	-0.77	0.56	-1.21
Stock (farmed - other)·100 [a]	0.52	-1.42	0.18	-1.05	4.66	-1.73
Price (wild - farmed)	0.06	-2.66	0.04	-6.25	0.10	-4.46
Price (wild - other)	0.04	-2.81	0.01	-1.05	0.05	-3.00
Price (farmed - other)	0.01	0.53	0.04	5.11	0.05	2.10
Expenditure (wild - farmed)	-	-	0.04	24.40	0.04	13.05
Expenditure (wild - other)	-	-	<0.01	-2.06	<0.01	-1.19
Expenditure (farmed - other)	-	-	0.05	-26.37	0.05	-14.23

Note: [a] The elasticities differences for each stock variable is multiplied by 100 for ease of presentation.