DEPARTMENT OF FOOD AND RESOURCE ECONOMICS
UNIVERSITY OF COPENHAGEN

IFRO Working Paper

Rational inattention or rational overreaction? Consumer reactions to health news

Martin Browning
Lars Gårn Hansen
Sinne Smed

2013 / 14

IFRO Working Paper 2013 / 14

Rational inattention or rational overreaction? Consumer reactions to health news

Authors: Martin Browning, Lars Gårn Hansen, Sinne Smed

www.ifro.ku.dk/english/publications/foi_series/working_papers/

Department of Food and Resource Economics (IFRO)

University of Copenhagen

Rolighedsvej 25

DK 1958 Frederiksberg DENMARK

www.ifro.ku.dk

Rational inattention or rational overreaction? Consumer reactions to health news*

Martin Browning
Dept. of Economics, University of Oxford
Martin.Browning@economics.ox.ac.uk

Lars Gårn Hansen
Dept. of Food and Resource Economics, University of Copenhagen

Sinne Smed
Dept. of Food and Resource Economics, University of Copenhagen

September 2013

Abstract

We investigate differences in how consumers of fish react to media information about long term health effects of eating fish. We specify a dynamic empirical model that allows for heterogeneity in all basic parameters of consumer behavior as well as in how consumers react to information. We estimate the model using a unique houshold panel tracking consumption, prices, news stories and media habits over 24 quarters. Prior studies find/suggest that the consumers most likely to be 'rationally ignorant' of long term health effects are inattentive to health news. In contrast we find that these consumers react more dramatically to health news than the consumers who most likely are well informed.

JEL: D1,C5

Key words: health information, consumer behaviour, pervasive heterogeneity

*We thank Carol Propper and participants at seminars and workshops for comments. We also thank GfK ConsumerTracking Scandinavia for use of their data. This research was supported by the Danish Council for Independent Research - Social Sciences and the OPUS project. OPUS (Optimal well-being, development and health for Danish children through a healthy New Nordic Diet) is supported by a grant from the Nordea Foundation.

1. Introduction

Most people rank news media as a primary source of information about diet-related long term health benefits and risks (Brown and Walsh-Childers (2002); Verbeke (2005); Greiner et al (2010)) yet the strength of demand reactions to such information seems to vary substantially across different consumers[1]. This may reflect variation in preferences but it may also be the result of distorted reactions to news on the part of some consumers. The latter is suggested by the widely accepted, so called "rational ignorance" theory. The theory of the "rationally ignorant" consumer (Swinnen et al (2005); McCluskey and Swinnen (2004)) posits that consumers weigh the cost of acquiring and processing information against the expected gains from optimizing their food consumption in accordance with this information. Thus consumers who for example eat little of a given food may not find it worth while to investigate about its health effects nor to attend to health news, which implies that their reactions to news are sub-optimal. However, though inattention to news has been the main focus of most prior literature, "rational ignorance" could also lead consumers to 'over-react' to news about long term health effects. The contribution of our paper is that we use a unique panel data set to estimate the impact of health news (on the consumption of different types of fish) using a model that quite generally allows the effect of news and other key behavioral parameters to be heterogeneous across individual households. Prior studies find that consumption of fish and knowledge of long term health effects of eating them are correlated (e.g. Verbecke et al 2007, Pieniak et al 2008) and our results indicate this correlation in our sample as well. Like prior studies our results are consistent with many consumers being rationally ignorant. However, in contrast to prior literature we find that the consumers most likely to be 'rationally ignorant' in our data sample appear to 'over-react' to news rather than being inattentive to it.

We consider how the allocation of consumption between two types of fish (fatty and lean fish)[2] is affected by two types of news concerning fish. The first type of news is presented as generic to all types of fish. Examples include a newspaper reporting that 'fish mongers are selling old fish' or a television report on a government study

[1] A number of studies on public information campaigns, published scientific articles and mass media stories have found that information about long term health effects have significant but relatively small effects on food demand (Kim and Chern (1999); Brown and Schrader (1990); Chang and Kinnucan (1991); Rickertsen et al (2003); Adhikari (2006); Tonsor et al (2010); Smed (2012)). The few studies invastigating this find that such reactions are heterogenous (Shimshack et al, 2007; Smed and Jensen, 2005; Smed, 2012, Smed and Andersen, 2012).

[2] The only other empirical study that focuses specifically on how information affects fish consumption is Shimshack et al, 2007. In addition, there are a number of experimental studies on how information affects consumers' valuation of fish (for example, Roosen et al, 2009; Verbeke, 2008).

stating that 'it is healthier to eat more fish and less meat'. The second type of news item concerns the relative healthiness of fatty fish versus lean fish. Here there are two main components; positive information stating that fatty fish contains omega-3 fatty acids[3] and the negative information stating that fatty fish contain dioxins. The data we use are drawn from a Danish consumer panel that follows a sample of households for 24 quarters from 1997(1) to 2002(4). This time period is characterized by a steady load of health news with varying intensity but nothing resembling a food scare.

In order to investigate differences in how consumers use information we specify and estimate a dynamic parametric demand model that allows for heterogeneity in all of the parameters of consumer behavior ('*pervasive heterogeneity*'). We also allow that the individual parameters are *codependent.*; this allows us to investigate whether, for example, heavy purchasers of one type of fish react more to information than light users. We employ a nonlinear parametric factor model to characterize the joint distribution of the individual random parameters. The parameters of this joint distribution are estimated using indirect inference; Gouriéroux, Phillips and Yu (2010) provide the theoretical basis for indirect inference as a bias reduction method for dynamic panel models. As always, modelling the initial values is critical for a dynamic process; here we follow Chamberlain (1980) and Wooldridge (2005) and model the initial value parametrically and then condition all subsequent heterogeneity on the initial value.

Additionally, we show how, within our model, the impact of news can be directly related to an equivalent price change that would have the same impact. This allows us to interpret and compare reactions to information for different consumers in a clear and consistent way.

A number of empirical studies find substantial heterogeneity in consumers' behavior in self-reported use of health information labels (e.g. Grünert and Wills, 2007; Gutherie et al, 1995 and Nayga and Rodolfo, 1996) and in self reported reactions to information (e.g. Variyam et al, 1996; Ippolito and Mathios, 1990; Chern and Zuo, 1995; Kornelis et al, 2007) as well as in observed reactions to information (Shimscack et al, 2007; Smed and Jensen, 2004; Smed, 2012, Smed and Andersen, 2012). However, only a handful of studies have tried to investigate this heterogeneity using panel data estimation on household food consumption. Verbeke and Ward, (2001) and Smed (2012), use micro panel data but these studies only allow for heterogeneous 'fixed effects' in expenditure patterns (levels differ), while the impact

[3] There is an almost linear relationship between the amount of omega 3 fatty acids and the total amount of fat in fish.

of information is assumed to be homogeneous. Schimscack (2007) and Smed and Andersen (2012) use micro panel data to investigate heterogeneity in the reactions to information between different groups of consumers while assuming that within group behavior is homogenous. To our knowledge the present study is the first to estimate a model that allows both the impact of health information and other core behavioral parameters to be heterogeneous across individual consumers. In addition to basic preference parameters, we allow both short and long run information impacts to vary across individual households. Estimation of this rich model of health information use is made possible by our long consumer panel with a unique combination of detailed registration of purchase behavior and comprehensive data on information flows to households.

We find that the consumers who most likely are 'rationally ignorant' react more dramatically to news than the consumers who most likely are well informed and our results suggest that this is an over-reaction. Thus in our sample it appears that 'rational ignorance' leads to overreaction to news rather than to inattention. This finding may be of interest to policy makers since it suggests that there may be a significant segment of ignorant consumers who tend to overreact to information about long term health effects. This could, for example, be important to consider when issuing public health warnings about food or when designing food marketing regulations such as the EU regulations currently being implemented which will allow food producers to make health claims on their products.

In the next section we discuss the theory of information that underpins our model and allows us to interpret the results. In the following sections we develop our model of demand and information, our estimation method and present our data. We then present our results and conclude the paper.

2. Theory about how consumers react to health news

The common starting point for theories about how consumers use information is that processing information and making decisions is costly. The core of 'rational ignorance' theory (Swinnen et al (2005); McCluskey and Swinnen (2004)) is that consumers may remain uninformed because the costs of processing information and making decisions are larger then the expected gains. The heuristic-systematic model of information processing (Chaiken, 1980) and the Elaboration Likelihood Model of Persuasion (Petty and Cacioppo,1986), originating from psychology and behavioral science, perceive consumers as having two different information processing strategies at their disposal: a careful/precise processing strategy, requiring more effort, and a fast/imprecise strategy, requiring less effort. Though both theories have a greater focus on decision errors, automatic behavioral reactions and persistent 'irrationality' they can also be interpreted as the result of a cost/benefit based choice regarding how much effort to put into information processing.

These theories suggest that everyday purchase decisions, such as choosing between fatty and lean fish, use simplified heuristic information processing because the costs of systematic processing are relatively large compared to what is at stake in the given purchasing situation. Furthermore, the heuristic processing of similar news items is likely to be linked over time and will likely also depend critically on what implications the received news has for her. Thus consumers may differ qualitatively in how a specific type of news influences their purchasing behavior; they may differ in how they weigh current news relative to past news items of the same type and they may differ in the strength of their reaction. For example, a health conscious consumer who eats a lot of fatty fish and periodically receives media information that 'fatty fish contains dioxin' is likely to find it worthwhile to investigate about what implications dioxin in fatty fish has for her and her family. News items received by consumers with a good understanding of the health implications are interpreted in this light and they may trigger a 'heuristic' decision process consistent with this background knowledge. Such a consumer may also make the effort to remember past news items and use them efficiently (in a fashion resembling Bayesian updating) when making her consumption choice. Even though this consumer does not undertake a systematic information search and processing each time she gets new information, her day-to-day behavior may give a similar result since the 'rule of thumb' guiding her is based on a sound background understanding of what these news items imply.

In contrast, other consumers may not have found it worthwhile to invest effort in understanding what implications such news has or to invest effort in remembering news items about fatty fish received in the past. Such consumers may therefore use different rules of thumb for interpreting news than consumers who have invested in background knowledge. Which rule of thumb they use may depend critically on why they have not found it worthwhile to invest in background knowledge or in remembering past news items.

For consumers who are uninterested in health, it is rational not to invest in background knowledge. It also seems logical that their lack of concern will lead to 'rational inattention' to health news and hence the 'rule of thumb' for such consumers would be to not react. This reaction pattern (rational inattention) has been the focus for much of the literature cited above which tries to understand why many consumers appear not to react to nutrition and health information provided by the authorities.

Other consumers might be concerned about health, but do not find it worthwhile to investigate fatty fish because they rarely eat this type of fish. Here it is not obvious that rational ignorance will lead to 'rational inattention'. If such a consumer receives news that 'fatty fish contain dioxins' she will be alarmed if she is considering to buy fatty fish because she is concerned about health. In fact she may be unduly alarmed if she does not recall past (positive) news items about fatty fish. Further, realizing that she has little solid knowledge about the health implications of dioxin in fatty fish, she may base the 'rule of thumb' guiding her reaction to such news on this uncertainty. If she is risk averse, she will attach a higher utility weight to negative outcomes and a 'rational' rule of thumb reaction might be to base the demand reaction on a pessimistic ('worst case') evaluation of the implications of the received news item. In this case 'rational' ignorance could lead to 'rational overreaction' to current news. An example of this is reported by Verbeke et al. (2002) and Verbeke and Ward (2006). Here a widely publicized incident of dioxin poisoning of beef sold in Belgium caused a substantial decline in demand by consumers. The authors document that many consumers were uncertain about the health risk caused by the incident and presumably many consumers perceived a cost of remaining 'ignorant'. Yet only a few consumers were reported to engage in an active information search as a result. Instead many consumers chose to remain 'ignorant' and to reduce their beef consumption based on their objectively pessimistic prior evaluations of the implied health risk even though they realized this evaluation was uncertain.

In our case we consider the substitution reactions of consumers, who receive news that is easily identified as concerning fatty fish and news that presents itself as concerning fish generally[4]. We cannot identify an 'objectively correct' reaction to general news. This is because general news applies to both types of fish whereby its relative importance for each will depend on the consumers prior perception of their relative healthiness. If, for example, a consumer is mainly concerned about her own weight and for this reason perceives lean fish as healthier than fatty fish she may correctly interpret general information about the healthiness of fish as a reminder that eating especially lean fish is a good idea. On the other hand a consumer mainly concerned about getting enough Omega3 fatty acids may correctly interpret the same general information as a reminder that eating especially fatty fish is a good idea.

In contrast some consumer reactions to fatty fish news can clearly be charac-

[4]There is virtually no news in our data that clearly presents itself as being only about lean fish.

terized as ‘objectively incorrect’. Consumers who interpret news in the objectively correct way will know that fatty fish news concerns fatty fish and if they react they will react to positive news by substituting toward fatty fish. A substitution reaction in the opposite direction is therefor a clear indication that the consumer is interpreting the news incorrectly and so must to some extent be ignorant of the health effects of eating fatty fish. However, ignorant consumers may also exhibit reactions to this type of news that are not clearly identifiable as ‘objectively incorrect’. Ignorant consumers may, for example, be inattentive or they may react in the ‘objectively correct’ direction but overreact to the information they receive.

We are interested in comparing how well informed consumers react to news with how ignorant consumers react. We expect that the more fatty fish a consumer eats the more likely she is to have invested effort in becoming knowledgeable about the health effects of eating fatty fish because the incentive to investigate about fatty fish is greater for consumers who eat a lot of fatty fish. Prior studies surveying fish consumers on their knowledge about health effects of eating fish find this correlation (e.g. Verbecke et al 2007, Pieniak et al 2008) and our results suggest that this is also the case in our sample. We further expect the reaction to news of knowledgeable consumers to be more objectively correct then the reactions of ignorant consumers. On the other hand, we have no clear prior expectation about how ignorant (less knowledgeable) consumers will react to news. Many earlier studies seem to find (or assume) that ignorant consumers will be inattentive to news and exhibit no reaction. However, as discussed above overreactions to news are also consistent with the underlying theory if consumers are ignorant for other reasons than being unconcerned about health. We find evidence of such over-reactions in our study.

The rich landscape of possible reactions to news makes our empirical investigation a challenge. For example, some consumers may exhibit little reaction to current news because they are not concerned about health and therefor inattentive while others react in the same way because they are concerned and knowledgeable consumers using Bayesian updating and therefore give relatively little weight to current news compared to past news (‘strong priors’) when they react. Our ambition is to differentiate knowledgeable from ignorant consumers and to understand how their reactions to health information differ. To do this the model we estimate must allow consumers who prefer fatty fish and consumers who prefer lean fish to react differently to current as well as past news. We therefore specify and estimate an empirical model that, in addition to heterogeneity in basic consumer preferences, allows for heterogeneity across consumers in all three dimensions of the effect of news discussed above (its direction, its scale and the relative importance of current and past news).

3. The demand model for one individual

3.1. Baseline budget shares

We consider the demand for two goods: fatty fish and lean fish. We assume that preferences over the two types of fish are separable from all other goods. Denoting the quantities of the two goods by q_f and q_l, respectively, we assume that the sub-utility function for fish takes the Cobb-Douglas form:

$$v(q_f, q_l) = (q_f)^{\alpha} (q_l)^{1-\alpha} \tag{3.1}$$

where the parameter α controls the taste for fatty fish relative to lean fish. Denote absolute prices by p_f and p_l, respectively, and total expenditure on fish by x. The budget constraint is:

$$p_f q_f + p_l q_l = x \tag{3.2}$$

The budget share for fatty fish is given by:

$$\omega = \frac{p_f q_f}{x} = \alpha \tag{3.3}$$

This implies that budget shares are independent of the level of total expenditure (homotheticity) and relative prices; in the empirical section we provide tests for these strong assumptions. We allow α to vary from period to period due to taste shocks, seasonality and health news; denote the value in period t by α_t. This gives a censored model in which the budget share for fatty fish in period t is given by:

$$\omega_t = \min(1, \max(\alpha_t, 0)) \tag{3.4}$$

3.2. The news indices

We construct two indices for news concerning the healthiness of fish. The first is an index that reflects general information on fish that is not clearly identified as being about either fatty or lean fish. For example, a news item that states that "fishmongers are selling old fish" would be negative general news whereas an item states that "it is healthy to eat more fish and less meat" would be positive general news. The general net index in period t is denoted $\tilde{g}_t$; it is calculated as the number of good news items minus the number of bad news items; fuller details are given in the data section below. The second set of news items are clearly identified as being about fatty fish. Here negative news is generally about poisonous dioxins which accumulate in the fatty tissue in fatty fish. Positive news usually concerns the presence of omega-3 fatty acids in fatty fish. We denote the net count variable by $\tilde{d}_t$. In the empirical analysis, the indices are household specific (details are given below) so that identification of the impact of news depends partly on the cross-section (between) variation and partly on the time series variation within each household.

The values of the two raw net indices vary between -15 and $+10$. For the empirical analysis, we take a transformation of the two count net measures to give a decreasing marginal impact of news. Specifically, we take:

$$\begin{aligned} g_t &= \tanh\left(\tilde{g}_t/5\right) \\ d_t &= \tanh\left(\tilde{d}_t/5\right) \end{aligned} \tag{3.5}$$

This symmetric transformation bounds the g_t and d_t variables to between -1 and $+1$, with a value of zero if the net number of news items is equal to zero. With this transformation, a change in $\tilde{g}_t$ from zero to one gives a change in g_t of approximately 0.2 which is the same change in $\tilde{g}_t$ if we go from 5 to 10 items of raw net news.

3.3. Incorporating news

The general form we take for the evolution of α over time is a first order autoregressive model:

$$\alpha_t = (\mu + \beta m_t + \lambda (t-1))(1-\rho) + \rho\alpha_{t-1} + \delta d_t + \gamma g_t + \sigma\varepsilon_t \text{ with } \rho \in [-1, 1] \tag{3.6}$$

where m_t is a dummy for the first quarter (the other quarters were not significantly different from each other) and λ captures a linear trend. The random variable ε_t is a serially uncorrelated taste shifter which is assumed standard Normally distributed. The parameters (δ, γ) give the consumer's perception of the impact of the two types of news on preferences.[5] If δ is positive, then more positive news about fatty fish will increase the contemporaneous demand for fatty fish. Finally, ρ captures how important the consumer perceives past news to be for current preferences.

We have three cases to consider (where we set $m_t = \varepsilon_t = \lambda = 0$ for a cleaner exposition). If $\rho = 0$, then we have a *static* model:

$$\alpha_t = \mu + \delta d_t + \gamma g_t \tag{3.7}$$

[5] In the empirical analysis we develop a Lagrange multiplier (LM) test that indicates that more complicated dynamics in the impact of news are not needed.

in which news has a contemporaneous impact but is 'forgotten' in the next period in which tastes revert to μ. The extreme converse is the *unit root* case in which $\rho = 1$. This gives:

$$\alpha_t = \alpha_{t-1} + \delta d_t + \gamma g_t \tag{3.8}$$

In this case, no news again leaves tastes unchanged. However, positive news would cumulate and would lead to a permanently higher level of the taste for fatty fish (a 'unit root'). This specification has some of the flavor of Bayesian updating since current news leads to an adjustment of beliefs about the healthiness of fish (as encapsulated in the value of α_t), with no adjustment if there is no (net) news.

If $\rho \in]-1, 1[$ we have the *stationary* case in which tastes revert to the mean with some adjustment (if $\rho \neq 0$). In the stationary case, the impact of news dies away and with no news, tastes revert to the 'mean' given by μ, with the speed of reversion ("forgetting") governed by ρ. Given a short run impact of δ, the long impact is given by:

$$\delta^{LR} = \frac{\delta}{1-\rho} \tag{3.9}$$

This implies that the effect of a permanent change in the news loading[6] is greater than the instantaneous effect if and only if ρ is positive. Thus a positive value for ρ implies a 'moderated' immediate reaction to news which builds up to a larger long run effect as the permanent shift in the news loading materializes. A negative value on the other hand implies an 'exaggerated' immediate reaction which is moderated over time even though the loading increase persists.

3.4. A price interpretation for news

Incorporating news as in (3.6) allows a clear interpretation of the news coefficients. For simplicity, consider the static model (3.7) with no general news. Assume an interior solution so that the budget share, ω, is equal to α and drop the time subscripts. Taking logs of both sides (3.3) of and substituting by (3.7) we have:

$$\ln q_f = \ln(\mu + \delta d + \gamma g) + \ln x - \ln p_f \tag{3.10}$$

Considering a change in the news index and the log price and evaluating at $d = g = 0$, we have:

$$\Delta \ln q_f = \frac{\delta}{\mu}\Delta d + \frac{\gamma}{\mu}\Delta g - \Delta \ln p_f \tag{3.11}$$

[6] An increase in the news loading of the current and all future periods.

A change in the raw fatty news level, $\tilde{d}$, from zero to one item, gives $\Delta d = 0.2$. Setting the (interior) budget share $\omega = \mu$, this in turn leads to an increase in the demand for the good of $100 * \left(0.2\frac{\delta}{\omega}\right)\%$. The same increase in demand would have been given by a $100 * \left(0.2\frac{\delta}{\omega}\right)\%$ *decrease* in the price of fatty fish. Thus we can interpret the effect of news as though it was a price change. To illustrate, values of $\delta = 0.1$ and $\omega = 0.3$ give that going from zero to one raw news item would have the same effect as a 6.6% price fall.

4. Heterogeneity

4.1. Allowing for pervasive heterogeneity

We now address how to introduce heterogeneity into the models above. The structure we develop allows for the possibility that high users of fatty fish (relative to lean fish) may be more responsive to news concerning fatty fish. On the other hand, such users might be well informed (having 'tight priors') and be less responsive to news. This is also possible in our model.

We allow that all of the parameters in (3.6) may be idiosyncratic, except for the trend.[7] The specification for household h is given by:

$$\alpha_{ht} = (\mu_h + \beta_h m_t + \lambda (t-1))(1-\rho_h) + \rho_h \alpha_{h,t-1} + \delta_h d_{ht} + \gamma_h g_{ht} + \sigma_h \varepsilon_{ht} \tag{4.1}$$

for $t = 2, ..T$. This specification has six structural parameters per household, that are allowed to be heterogenous:

$$(\mu_h, \rho_h, \gamma_h, \delta_h, \beta_h, \sigma_h) \tag{4.2}$$

and one common parameter for the trend, λ. We refer to the parameters as model parameters since they govern the evolution of budget shares for a given household. Our primary focus of interest is the joint distribution of the news parameters (γ, δ) but we must also allow that these may be statistically dependent with the other parameters. If we had a very long panel ($T \simeq 100$, for example), we could estimate the parameters for each household and then take the empirical distribution as the joint distribution. Since we only have 24 observations per household, we resort to a random coefficients model.

[7] Tests for heterogeneous trends did not indicate that this was required.

4.2. The random coefficients structure

In a dynamic model such as (4.1) we have to specify the first observation, α_{h1}. To do this we follow Chamberlain (1980) and Wooldridge (2005) and first model the initial observation and then condition further heterogeneity on these values. We model the initial observation as:

$$\alpha_{h1} = \tau_0 + \tau_1' \mathbf{z}_h + \exp(\tau_2) \sinh(c_3 + \exp(c_4)\varepsilon_{h1}) \tag{4.3}$$

where $\mathbf{z}_h$ is a vector of demographics observed in the first period. The four demographics we include are the age and education of the main shopper and two family structure variables: a dummy for only one adult in the household and the number of dependent children present at the beginning of the sample period. The variable ε_{h1} is a standard Normal, assumed independent of everything else and the $\exp(\tau_2)$ is to ensure that the standard deviation is positive. The sinh transformation for the residual is a convenient generalization of the normal; see Hansen, McDonald and Theodossiou (2007). The parameters c_3 and c_4 control the skewness and kurtosis respectively; if $c_3 = 0$ and $\exp(c_4)$ is small, then this transformation gives a close approximation to a normal distribution.

To allow for heterogeneity in the parameters in the dynamic process, (4.1), we employ a two factor structure.[8] Let η_{h1} and η_{h2} be independent standard Normals. We parameterize using the following semi-triangular structure:

$$\begin{aligned}
\mu_h &= \phi_{10} + \phi_{11}\alpha_{h1} + \exp(\psi_{11}) \sinh(c_3 + \exp(c_4)\eta_{h1}) \\
\rho_h &= 2 * \ell(\phi_{20} + \phi_{21}\alpha_{h1} + \psi_{21}\eta_{h1} + \exp(\psi_{22})\eta_{h2}) - 1 \\
\sigma_h &= \exp(\phi_{30} + \phi_{31}\alpha_{h1} + \psi_{31}\eta_{h1} + \psi_{32}\eta_{h2}) \\
\delta_h &= \phi_{40} + \phi_{41}\alpha_{h1} + \psi_{41}\eta_{h1} + \psi_{42}\eta_{h2} \\
\gamma_h &= \phi_{50} + \phi_{51}\alpha_{h1} + \psi_{51}\eta_{h1} + \psi_{52}\eta_{h2} \\
\beta_h &= \phi_{60} + \phi_{61}\alpha_{h1} + \psi_{61}\eta_{h1} + \psi_{62}\eta_{h2}
\end{aligned} \tag{4.4}$$

where $\ell(y) = e^y / (1 + e^y)$ is the inverse logistic function so that $\rho \in (-1, 1)$.[9] This structure imposes that (δ, γ, β) are Normally distributed and that the standard deviations, σ_h, are log-Normally distributed. Note that we use the same common parameters c_3 and c_4 for the non-normality of the mean as for the starting values.[10]

The equations (4.3) and (4.4) give a nonlinear random coefficients model. We

[8] Preliminary investigations showed that two factors were enough.

[9] This explicitly rules out that anyone has a unit root. The empirical results below decisively reject the hypothesis that anyone has a unit root.

[10] Tests for this restriction did not reject.

refer to the parameters $(\tau_0, \tau_1', \tau_2, c_3, c_4, \phi_{10}, ..\psi_{62})$ as *distribution parameters* since they characterize the joint distribution of the model parameters. The terms ϕ_{i1} allow that the ith model parameter may be correlated with the initial value. The 'cross terms' ψ_{ij} for $j \neq i$ allow for dependence between the model parameters.

4.3. Simulating the evolution of budget shares

To estimate we use a simulation based estimator. This requires us to simulate series of T budget shares for H synthetic households[11] for a given set of values for $(\tau_0, \tau_1', \tau_2)$, $(\phi_{10}, ..\psi_{62})$ and the common parameters (λ, c_3, c_4). We do this by using the following steps for household h:

1. Draw values for independent $N(0,1)$ random variables ε_{ht} for $t = 1, 2, ..T$ and $h = 1, ...H$. Then draw $2H$ values independent $N(0,1)$ random variables for $\{\eta_{h1}, \eta_{h2}\}$.

2. Use the ε_{h1}'s, the values of $\mathbf{z}_h$, the values of $(\tau_0, \tau_1', \tau_2)$ and (c_3, c_4) and equation (4.3) to generate initial values $\{\alpha_{11}, ..\alpha_{H1}\}$.

3. Use the α_{h1}'s; the η_{h1}'s and the values of $(\phi_{10}, ..\psi_{63})$ to generate $6H$ values for the $(\mu_h, \beta_h, \rho_h, \gamma_h, \delta_h, \sigma_h)$ model parameters.

4. Use $(\mu_h, \beta_h, \rho_h, \gamma_h, \delta_h, \sigma_h)$ and λ to generate series for $\{\alpha_{h2}, ..\alpha_{hT}\}$, using (4.1).

5. Given the series $\{\alpha_{h1}, ..\alpha_{hT}\}$, generate budget shares series $\{\omega_{h1}, \omega_{h2}, ..\omega_{hT}\}$ using (3.4).

5. Estimation method

5.1. Indirect inference

We estimate the distribution parameters using indirect inference. Gouriéroux, Phillips and Yu (2010) derive the properties of the indirect inference estimator in the context of a fully parametric dynamic panel model. Indirect inference requires us to specify *auxiliary parameters* (ap's) that will be matched between the actual data and the simulated data. There are two principal criteria for the choice of auxiliary parameters. First, they should be quick to calculate since they are embedded in an optimization routine. For example, in the individual regressions specified below we

[11] In practice, we replicate the data R times so that we have $R*H$ simulated households. Setting $R = 1$ here is for expositional clarity.

use OLS for censored regressions rather than iterative maximum likelihood procedures. Second, the auxiliary parameters should be related to the distribution factors. This does not require any particular auxiliary parameter to be a H-consistent estimator of a given distribution parameter but only that the Jacobian of the function from the distribution parameters to the auxiliary parameters (the 'binding function') is of full rank. A necessary condition for this is that we have at least as many auxiliary parameters as distribution parameters.

The first set of ap's we calculate is to provide ap's for the parameters of the initial conditions in (4.3). To do this we regress the mean of the first period budget shares on the four demographic variables:

$$\omega_{h1} = b_0 + b_1 z_{1h} + ...b_4 z_{4h} + \zeta_h \tag{5.1}$$

We also calculate the standard deviation of the estimated OLS residuals, $\hat{\zeta}_h$, which we denote $\hat{b}_5$. We record the parameters $\left(\hat{b}_0, \hat{b}_1, ..\hat{b}_4\right)$ and also the vector of predicted residuals:

$$\hat{\zeta}_h = \omega_{h1} - \left(\hat{b}_0 + \hat{b}_1 z_{1h} + ...\hat{b}_4 z_{4h}\right) \tag{5.2}$$

This captures the initial distribution net of observable variation.

To capture the dynamics we run an $AR(1)$ regression for each household and then use statistics based on the set of individual parameters. Specifically, we first run the analogue of (4.1) without the common trend (the latter is dealt with below):

$$\omega_{ht} = a_{h1} + a_{h2} d_t + a_{h3} m_t + a_{h4} g_t + a_{h5} \omega_{h,t-1} + u_{ht} \tag{5.3}$$

for each individual household, $h = 1, ..H$ and for $t = 2, ..T$. The estimates are denoted $(\hat{a}_{h1}, \hat{a}_{h2}, \hat{a}_{h3}, \hat{a}_{h4}, \hat{a}_{h5})$. These are, of course, biased estimates of the parameters in (4.1). There are two primary sources of bias. The first is the familiar small-T bias for time series AR models. The second source of bias is that these regressions take no account of the censoring at zero and unity. The virtue of indirect inference is that the bias is the same for the simulated data as for the actual data. In this sense, indirect inference provides a bias reduction technique for dynamic panel data models (see Gouriéroux, Phillips and Yu (2010)).

For each household, we record the five regression coefficients and the standard deviation of the OLS error term:

$$\hat{u}_{ht} = \omega_{ht} - (\hat{a}_{h1} + \hat{a}_{h2} d_t + \hat{a}_{h3} m_t + \hat{a}_{h4} g_t + \hat{a}_{h5} \omega_{h,t-1}) \tag{5.4}$$

which we denote $\hat{a}_{h6}$. Together with the residual from the initial value regression, this gives seven 'primary' values for each household:

$$\left\{\hat{a}_{h1}, \hat{a}_{h2}, \hat{a}_{h3}, \hat{a}_{h4}, \hat{a}_{h5}, \hat{a}_{h6}, \hat{\zeta}_h\right\} \tag{5.5}$$

These provide the principal source for estimating the distribution parameters.

A further set of individual statistics are then calculated to provide (LM style) diagnostic tests for our specification. Specifically, we record the within household correlation between $\hat{u}_{ht}$ and a linear trend, log relative prices, log total expenditure and the lagged values of the two news series:

$$\text{correlation between } \hat{u}_{ht} \text{ and } \left\{t-1, \ln\left(\frac{p_{at}}{p_{lt}}\right), \ln\left(x_{ht}\right), \hat{u}_{ht-1}, d_{t-1}, g_{t-1}\right\} \tag{5.6}$$

The trend is to allow us to estimate the common trend (λ)in the model. The next two statistics will pick up any price or income effects on budget shares; this is to check the validity of the Cobb-Douglas assumption. The fourth correlation is the first order auto-correlation of the estimated residuals which allows for the possibility that we may have an incorrect dynamic specification. Finally, the two lagged news variables will pick up if there are any effects of past news that are not accounted for by the dynamics in (4.1). This gives an additional six values for each household; denote these $\{\hat{c}_{h1}, ...\hat{c}_{h6}\}$ respectively.

To construct auxiliary parameters we take the mean and standard deviation of each of $\{\hat{a}_{h1}, \hat{a}_{h2}, \hat{a}_{h3}, \hat{a}_{h4}, \hat{a}_{h5}, \hat{a}_{h6}\}$[12] and the means of $\{\hat{c}_{h1}, ...\hat{c}_{h6}\}$. This gives 18 auxiliary parameters, denoted $\{\theta_1, ..\theta_{18}\}$. To pick up any codependency between the model parameters and between these and the initial value, we also record the correlations between $\left\{\hat{a}_{h1}, \hat{a}_{h2}, \hat{a}_{h3}, \hat{a}_{h4}, \hat{a}_{h5}, \hat{a}_{h6}, \hat{\zeta}_h\right\}$; this gives an additional 21 auxiliary parameters; denoted $\{\theta_{19}, ..\theta_{39}\}$.

Finally, we also calculate two ap's that are designed to check that our estimation of the extent of censoring fits the aggregate number of censored values over the whole sample. These ap's are 'smoothed' means of the dummies for being zero or unity. Specifically, we take:

$$\begin{aligned} \theta_{40} &= \frac{1}{HT}\sum_h \sum_t \left[2 * \left(1 - \Phi\left(20 * w_{ht}\right)\right)\right] \\ \theta_{41} &= \frac{1}{HT}\sum_h \sum_t \left[2 * \left(1 - \Phi\left(20 * \left(1 - w_{ht}\right)\right)\right)\right] \end{aligned} \tag{5.7}$$

where $\Phi(.)$ denotes the cdf of the standard Normal. The cdf $\Phi(20 * w_{ht})$ is equal to

[12] The mean of the initial regression residuals is zero and the standard deviation is already given by $\hat{b}_5$ above.

0.5 if $w_{ht} = 0$; between 0.5 and 1 for values very close to zero and effectively unity if w_{ht} is above a small positive value. Thus θ_{40} (respectively, θ_{41}) is strictly increasing in the number of values close to zero (respectively, unity).

To these auxiliary parameters we append the six initial value parameters $\left\{\hat{b}_0, \hat{b}_1, ..\hat{b}_5\right\}$, denoted $\{\theta_{42}, ..\theta_{47}\}$.

These 47 statistics give a rich description of the across time and across household variation in the data. To fit the parameters of the model we use the 42 ap's associated with the primary set of values:

$$\{\theta_1, ..\theta_7, \theta_{13}, ..\theta_{47}\} \tag{5.8}$$

This always gives an over-identified (OI) model for the parameters in (4.3) and (4.4). We use the remaining 5 ap's:

$$\{\theta_8, ...\theta_{12}\} \tag{5.9}$$

as conventional goodness of fit (GF) measures ('moment tests'). We thus have two tests of the specification: the OI test statistic and the GF test statistic.

5.2. Allowing for sampling effects

The scheme just described needs modification to take account of two aspects of the sampling and simulation. First, we do not observe fish purchases in every period for all households. Consequently we cannot construct budget shares for every household/period. To deal with this we replace missing values for budget shares with the mean of the non-missing values for that household. This induces an obvious bias in estimation toward finding a more stationary process than actually holds. When we simulate, we replicate each household in the sample R times. For each simulated household we put the budget share to 'missing value' in the same periods as for the actual household being replicated. Thus the simulated data has the same bias as the actual data when we fill in missing values with the mean budget share. Thus the use of indirect inference allows us to deal with this sampling issue in an effective (albeit, inefficient) way.

The second sampling issue is that in the data we have 16 households who never buy fatty fish and in the simulated data we may have households that never buy or only buy fatty fish. Clearly the presence of such households does not allow us to run individual regressions for every household as in the previous sub-section. One option would be to drop the households that always have a zero budget share but this introduces a sample selection bias into the estimation procedure; that some households are never moved to buy fatty fish even if there is positive news about it is a potentially important element of the analysis. To account for this, we retain these households and modify the construction of the ap's. Specifically, for households that always have zero budget share we effectively replace the value in the 12th period by 0.01 when calculating the OLS parameters in (5.3). In practice, we use a smoothed version of this in which replacement is made smoothly conditional on the mean budget share. There is effectively no replacement if the mean is above 0.01 and there is full replacement if the mean is zero. For small values of the mean budget share, the replacement is a convex combination of the mean and zero. Once again this modification introduces a bias but, as before, the bias is the same for the actual data as for the simulated data.

6. Data

The data we use in our analysis are provided by GfK Consumerscan Scandinavia Denmark[13], which maintains, among other activities, a consumer panel. Households in the panel report purchases of foods and other staples in terms of quantity, price and other product characteristics. Each purchase diary is filled in by the diary keeper and is sent to GfK on a weekly basis. About 20 per cent of the households leave the panel each year with exiting households being replaced by a similar type of household. For each shopping trip the diary keeper reports: the day of the week and time of the day, the name of the store, who participated in the trip and the total expenditure on the trip. For almost all goods in all periods the value and volume of the product is recorded. For weeks in which the particular household does not hand in a purchase diary we input the average weekly consumption for this particular household within the same quarter. We aggregate the data to quarterly observations and the data covers the period from first quarter 1997 to the fourth quarter 2002, in total 24 quarters.

Additionally to the purchase data, the households complete an annual questionnaire on their background, including social and demographic characteristics (family size, age, number of children, level of education, region, income etc.); media habits (for example, their preferred newspapers and magazines and the frequency of reading these) together with several attitude questions concerning food consumption.

By combining the households media habits with indices on media coverage of the health consequences of fish consumption, household exposure to new information can be dated. The indices are based on an extensive search in a database Infomedia, covering all types of articles in Danish newspapers and broadcasts on the two major

[13] GfK Consumerscan Scandinavia, see http://www.gfk.dk

Danish TV channels. Firstly four indices are constructed; a positive and a negative index about fish consumption in general as well as a positive and a negative index specific for the consumption of fatty fish. The positive index for general fish consumption is based on all articles that in some way mention that fish is healthy whereas the negative index is based on all article that in some way mention the adverse health consequences of fish consumption in general. An example of the former would be an article that mentions that fish contains less fat than meat or that fish contains healthy vitamins and minerals. An example of a negative article would be an article that stated that fish mongers are selling old fish or that fish might contain coloring or other pollutants. The positive and negative fatty fish index are based on articles where the health effects are clearly attributed to fatty fish in the news item[14]. The negative index for fatty fish is mainly about dioxin contamination of fatty fish, whereas the positive index is mainly about healthy omega3 saturated fats in fatty fish.

When we aggregate the information data to quarterly observations, we take account for if the article is in the newspapers in the beginning, the middle or in the end of each quarter by constructing a floating index. Specifically we give full weight to a report in the first month of a quarter and decreased weight to the two months before and after the first month. For example, for quarter II (months $4-6$) the floating index is constructed as:

$$f_{II} = \frac{1}{3}f_2 + \frac{2}{3}f_3 + f_4 + \frac{2}{3}f_5 + \frac{1}{3}f_6 \tag{6.1}$$

where f_t denotes the news reports in month t.

We also have information about each household's media habits and construct a household specific index based on how many editions out of 7 weekly editions of a particular newspaper the household reads. Information indices are constructed for each particular newspaper and are matched with indices of household media use. Finally the media use indices are multiplied with the newspaper specific information indices and summed over newspapers to construct household specific information indices regarding fish generally and fatty fish specifically.

We select on households being observed for all 24 quarters and having all the media information we employ; this gives a sample size of 600 households. We then select on households purchasing fish for at least 12 quarters out of the 24 which leaves a sample size of 505 households. This selection leaves us with a non-representative sample which, obviously, buys more fish than the average household. Single males

[14] As already noted above there is virtually no news in our data that clearly presents it self as being about lean fish.

are dramatically under-represented and single females are rather over-represented. Additionally our sample is older and slightly less educated than the nationally representative household.

7. Results

7.1. The fit of the preferred model

We began with estimates of the general unrestricted model as given in (4.3) and (4.4). This model has 32 parameters to be estimated. Since we have 42 auxiliary parameters for fitting, the over–identifying (OI) test statistic has 10 degrees of freedom. The value of the OI test statistic is 38.8 which is a formal rejection of the general model. However, the fit looks worse since many of the ap's are so tightly estimated so that even small deviations appear to be statistically significant.[15] As well as the portmanteau OI test, we also keep 5 auxiliary parameters back to test for deviations from the general model. The goodness of fit test for these is 4.9 which indicates that the restrictions arising from the the Cobb-Douglas form are not rejected. This also implies that there are no more dynamics in the news variables and no serial correlation that is not accounted for.

Given the estimates of the unrestricted model, we then conducted a general to specific specification search in which we sequentially removed the coefficient with the lowest t-value. This lead us to drop 10 parameters from the general model. The preferred model has 22 parameters and an OI test statistic of 44.7 implying a quasi-likelihood ratio $\chi^2(10)$ statistic of 5.9. The most important restriction from this specification search is that we excluded three heterogeneity coefficients in the effect of the fatty fish news; that is, $\phi_{41} = \psi_{41} = \psi_{42} = 0$ in (4.4). Including the most significant of these, ϕ_{41}, in the preferred specification gave a decrease of 0.8in the criterion. All of the other parameters are heterogeneous. The only significant demographic in the initial value equation (4.3) is age, with older households having a higher budget share for fatty fish.

7.2. Parameter estimates

In Table 7.1 we present the parameter estimates for the distribution parameters in (4.4). The implications of these estimates are presented in the next subsection. An important feature of the parameter estimates is that the estimate for the homo-

[15]For example, the ap for the proportion of zeros in the pooled data (θ_{40}) has values of 0.330 and 0.355 for the data sample and the simulated sample respectively. The standard error is 0.010 so the difference has a t-value of 2.3.

Parameter	Estimate	se
ϕ_{10}	0.11	0.05
ϕ_{20}	0.12	0.04
ϕ_{30}	-0.88	0.02
ϕ_{40}	0.10	0.03
ϕ_{50}	-0.07	0.02
ϕ_{60}	-0.13	0.02
ϕ_{11}	0.29	0.04
ϕ_{21}	0.17	0.07
ϕ_{31}	0.14	0.04
ψ_{11}	-1.57	0.27
ψ_{21}	0.15	0.06
ψ_{31}	0.08	0.04
ψ_{51}	-0.10	0.02
ψ_{61}	-0.04	0.02
ψ_{22}	-0.74	0.09
ψ_{62}	-0.06	0.02
λ ($\times 100$)	0.74	0.10
c_3	-0.04	0.14
c_4	-0.01	0.14
τ_0	-0.44	0.14
τ_{11}	0.10	0.02
τ_2	-0.85	0.22

Table 7.1: Distribution parameter estimates

geneous fatty fish news coefficient (ϕ_{40}) is positive (0.1) and highly significant (a t-value of 4.0)[16]. We find no evidence of heterogeneity in the response of budget shares to fatty fish news. This does not seem to be due to lack of power since the mean effect is quite precisely estimated. Another important feature of our estimates is that the estimated mean of the general news effect (ϕ_{50}) is negative (-0.07) and also highly significant. There is clear evidence of heterogeneity in this effect since the corresponding heterogeneity coefficient is highly significant.

Table 7.2 presents the marginal distributions of the model parameters that display some heterogeneity (except for the unimportant first quarter dummy). As can be seen, the general news coefficient (γ) has a negative median but with 25% of the sample having a positive effect and a substantial part of the sample having an effect close to zero. Another important feature of the results is that the auto-regressive parameter (ρ) is not widely dispersed about zero.

Table 7.3 presents the correlations of the heterogeneous model parameters. As we would expect in a two factor model, there is a good deal of co-dependence between

[16] If we include the (insignificant) heterogeneity term ϕ_{41}, 98%of the distribution for δ is positive.

Parameter	10%	25%	50%	75%	90%
μ	-0.29	-0.07	0.13	0.33	0.54
σ	0.36	0.39	0.42	0.46	0.49
ρ	-0.26	-0.11	0.07	0.24	0.38
γ	-0.20	-0.14	-0.07	-0.00	0.05

Table 7.2: Marginal distributions of model parameters

	μ	σ	ρ	γ
μ	1	–	–	–
σ	0.86	1	–	–
ρ	0.38	0.38	1	–
γ	-0.79	-0.59	-0.33	1

Table 7.3: Correlations for model parameters

the parameters. In particular, those with a high budget share (μ large) cut back more on the proportion spent on fatty fish when they hear good general news.

7.3. Economic implications

In the following we compare the reactions of consumers with a high budget share of fatty fish to the reactions of low budget share consumers when they receive news about the health effects of eating fish. We do this because we expect that consumers who buy a lot of fatty fish will be better informed about the health effects of eating fatty fish then consumers who seldom buy them. This is likely to be the case if taste preferences explain why some consumers eat little fatty fish, because these consumers would then have little incentive to investigate about fatty fish. Prior studies about how knowledgeable fish consumers are about health effects of eating fish find such a positive correlation between knowledge and consumption (e.g. Verbecke et al 2007, Pieniak et al 2008). However, we cannot a priori rule out that a negative (or zero) correlation could apply in our sample. A negative correlation could result if consumers who care about health and therefor investigate about fatty fish find them to be less healthy than lean fish and for this reason decide not to eat them. We do not have any measures of consumers knowledge in our data, however, the consumer reactions to general health news we see in our study are consistent with a positive correlation and inconsistent with a negative correlation.

To interpret consumer reactions to news we use the equivalent price effect. This effect is given by equation (3.11) as the change in the fatty fish price that would be needed to cause a short run demand reaction equal to the estimated demand reaction to one news item. Figure 7.1 presents the estimated short run equivalent

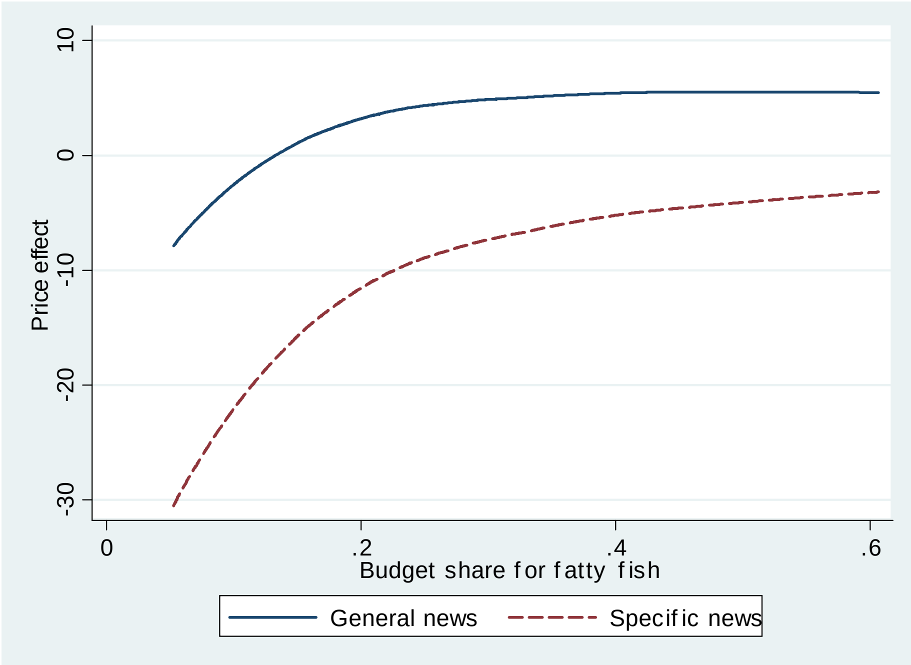

Figure 7.1: The price equivalents for general and specific news

price effects of fatty fish news and general news against the budget share for fatty fish.[17]

We see that general health news (the solid curve in figure 7.1) affects the fatty fish budget share over most of the budget share span with positive news affecting consumption like a reduction in the fatty fish price for low budget share consumers and like a price increase for fatty fish for those who eat relatively more fatty fish. Thus low budget share consumers perceive general health news as mostly relevant for fatty fish while the reverse is true for high budget share consumers. This suggests that consumers who eat little fatty fish perceive these fish to be relatively more healthy (compared to lean fish) then do consumers who eat a lot of fatty fish. The implication of this is that the reason these consumers eat relatively little fatty fish cannot be that they perceive these fish to be less healthy. This would seem to rules out a negative correlation between knowledge about and consumption of fatty fish in our data set. The reason these consumers eat less fatty fish must instead be their taste preferences. This makes it likely that our sample is characterized by the same positive correlation between knowledge and consumption as found in other studies of fish consumers.

Turning to the effect of specific fatty fish news (the broken curve in figure 7.1),

[17]The budget share values have been trimmed below at 0.05 and above at 0.6 for presentational convenience.

Percentile of budget share	10%	25%	50%	75%	90%
Budget share for fatty fish	0.05	0.15	0.28	0.44	0.61
Dynamic parameter ρ	-0.26	-0.11	-0.07	0.24	0.38

Table 7.4: How consumers dynamic reactions depend on their fatty fish budget share

we see that the price effect is always negative (the qualitatively 'correct' reaction). However, the magnitude of equivalent price effect is over six times greater for consumers with a low fatty fish budget share (of 0.1) than for consumers with a high budget share (of 0.61). This implies that consumers with a low budget share of fatty fish consider news about this type of fish to be substantially more important than consumers who eat a lot of this type of fish. Thus, rather than ignoring fatty fish news, it appears that low budget share consumers react more than high budget share consumers. This suggests that the low budget share consumers who most likely are less well informed then high budget share consumers would seem to be overreacting to the fatty fish health information they receive.

Looking at consumers dynamic reactions the first important result (already noted above) is that the heterogenous dynamic adjustment parameter, ρ, is distributed around zero. Thus long run effects are fairly close to the immediate effects of information implying that most consumers focus on current news items and attach relatively little weight to past news items. This specifically implies that virtually no consumers acts like a Bayesian updater.

However, there is a noticeable difference in how consumers adjust their immediate reaction to news over time depending on their fatty fish budget share. Recall that the interpretation of ρ values greater than and less than zero as consumers with moderated and exaggerated immediate reactions to news respectively. This is shown in table 7.4 where mean values of the dynamic adjustment parameter ρ for consumers with different fatty fish budget shares are presented. We see that consumers with high fatty fish budget shares have a tendency in the Bayesian direction. They exhibit 'moderated' immediate reactions to news ($\rho > 0$) that increase in the long run (by $20-30\%$) if the news loading increase persists. Consumers with low fatty fish budget share on the other hand exhibit 'exaggerated' immediate reactions ($\rho < 0$) that are reduced in the long run (by $10-20\%$) even if the news loading increase persists. Although the magnitude of these dynamic effects is small the difference in sign is significant. This reinforces the impression that consumers who eat little fatty fish are less knowledgeable about fatty fish health effects then consumers who eat a lot of fatty fish and that the consumers most likely to be ignorant of fatty fish health effects tend to overreact to fatty fish health news.

8. Conclusions

Using a unique consumer panel we estimate a model of how food consumers use health information concerning the consumption of fish. The model allows for heterogeneity across households in basic preference parameters and in both short run and long run impacts of health information.

Our results suggest that some consumers react to health information on a knowledgeable background while others are less knowledgeable (or 'rationally ignorant'). This is in line with the conclusions and speculations in many prior studies of consumer reactions to information about long term health effects. However, our results contrast the dominant prior finding (or in many cases the presumption/interpretation) that rationally ignorant consumers are inattentive to such information and therefore do not react to it. We find that the consumers most likely to be rationally ignorant in our sample react more dramatically to news than the consumers who most likely are well informed. This resembles the over-reaction we see in some food scares, though it is much less dramatic. It seems that in our sample many ignorant consumers are concerned about health and appear to overreact to health information.

This suggests that there may generally be an important segment of uninformed food buyers who both misinterpret and overreact to 'run of the mill' health information. Taking account of this type of consumer reaction when designing public information strategies and regulations about health information may be important in many cases. This could, for example, be important to consider when issuing public health warnings or other public information about the health effects of food consumption. This could also be important to consider when designing food marketing regulations such as the EU regulations currently being implemented which will allow food producers to make health claims on their products. If ignorant consumers do not react to such health information then it will not harm them. Further if such claims help knowledgeable consumers in their choice then the directive may improved consumer welfare. However, if there is a significant segment of ignorant consumers who tend to overreact to health information then allowing profit focussed firms and talented marketing specialists to send health messages to these consumers may be problematic.

References

[1] Adhikari, M., L. Paudel, J.F. Houston, K.P. Paudel and J. Bukenya. (2006), "Impacts of Cholesterol Information on Meat Demand: An Application of Updated Cholesterol Index," *Journal of food distribution research*, 37, 61-68

[2] Becker, G.S. (1965), "A Theory of the Allocation of Time", *Economic Journal*, 75, 493-517.

[3] Brown, J.D. and K. Walsh-Childers. (2002), "Effects of media on personal and public health". In Media Effects: Advances in Theory and Research, J. Bryant and D. Zillmann, (eds), 453–488 ,NJ, Lawrence Erlbaum Associates.

[4] Brown, D.J. and L.F. Schrader. (1990), "Cholesterol information and shell egg consumption", *American Journal of Agricultural Economics*, 72, 548-55.

[5] Chang, H. and H.W. Kinnucan.(1991), "Advertising, information and product quality: the case of butter," *American Journal of Agricultural Economics*, 73, 1195-1203.

[6] Chaiken, S. (1980), "Heuristic versus systematic information processing and the use of source versus message cues in persuasion", *Journal of Personality and Social Psychology*, 39, 752–766.

[7] Chamberlain, G. (1980), "Analysis of Covariance with Qualitative Data", *Review of Economic Studies*, 47, 225.238.

[8] Chern, W.S. and Zuo, J. (1995), "Alternative measures of changing consumer information on fat and cholesterol", paper presented at the annual meeting of the American Agricultural Economics Association, Indianapolis, IN, 6-9 August.

[9] Coffey, B.K., T.C. Schroeder and T.L. Marsh. (2011), "Disaggregated household meat demand with censored data" *Applied Economics*, 43(18), 2343 - 2363

[10] Dahlgran R.A. and D.G. Fairchild. (2002); "The Demand Impacts of Chicken Contamination Publicity - A Case Study", *Agribusiness*, 18(4), 459-474

[11] Fox, J. A., D.J. Hayes and J.F. Shogren. (2002)" Consumer preferences for food irradiation: how favorable and unfavorable descriptions affect preferences for irradiated pork in experimental auctions", *Journal of Risk and Uncertainty*, 24, 75–95

[12] Gouriéroux, C.; P. C. B. Phillips and J. Yu. (2010), "Indirect Inference for Dynamic Panel Models", *Journal of Econometrics*, 157(1), pp. 68-77.

[13] Greiner, A., K.C. Smith and E. Guallar. (2010), "Something fishy? News media presentation of complex health issues related to fish consumption guidelines", *Public Health Nutrition*, 13, 1786–1794.

[14] Grossman M. (1972), “On the concept of health capital and the demand for health”, *Journal of Political Economy*, 80, 223-255.

[15] Grunert, K.G. and J.M. Wills. (2007), “A review of European research on consumer response to nutrition information on food labels”, *Journal of Public Health*, 14, 385–399.

[16] Guthrie J.F.; C.J. Geiger, L.E. Cleveland and S. Welsh. (1995), “ Who uses nutrition labelling and what effect does label use have on diet quality?” *Journal of Nutritional Education*, 27, 163-172.

[17] Hansen C., McDonald J. and P. Theodossiou. (2007), “Some flexible parametric models for partially adaptive estimators of econometric models”, *Economics*, 1:2007-7. http://dx.doi.org/10.5018/economics-ejournal.ja.2007-7

[18] Ippolito P.M. and A.D. Mathios. (1990), ”Information and advertising: The case of fat consumption in the United States”, *American Economic Review*, 85(2), 91-95

[19] Ishida T., N. Ishikawaet and M. Fukushige. (2010), “Impact of BSE on bird flu on consumers’ meat demand in Japan”, *Applied Economics*, 42, 49-56.

[20] Kim, W. and W.S. Chern.(1999), “Alternative measures of health information and demands for fats and oils in Japan”, *Journal of Consumer Affairs*, 33, 92-109.

[21] Kinnucan, H.W., Ø. Myrland, and L. Paudel. (2003), “ Relative impacts of health information and advertising on commodity markets: US meats”, in Chern, W.S. and K. Rickertsen, (Eds), Health Nutrition and Food Demand, CABI Publishing, Cambridge, MA.

[22] Kornelis, M., J. de Jonge, L.J. Frewer and H Dagevos. (2007), “Consumer Selection of Food-Safety Information Sources”, *Risk Analysis*, 27(2), 327 - 335.

[23] Marsh T.L., T.C. Schrodeder and J. Mintert. (2004), “Impact of meat products recalls on consumer demand in the USA”, *Applied Economics*, 36, 897–909.

[24] McCluskey, J. J. and J.F.M. Swinnen. (2004). “Political economy of the media and consumer perceptions of biotechnology”, *American Journal of Agricultural Economics*, 86, 1230–1237.

[25] Mizerski, R. (1982), “An attribution explanation of the disproportionate influence of unfavorable information”, *Journal of Consumer Research*, 9, 301–310.

[26] Mo L. (2013), “Impact of food safety on US poultry demand”, *Applied Economics*, 45(9), 1121-1131.

[27] Nayga R.M. and M. Rodolfo. (1996), ”Determinants of consumers’ use of nutritional information on food packages, Journal of Agricultural and Applied Economics, 28, 303-312.

[28] Petty R.E and J.T. Cacioppo(1986). "Communication and persuasion: Central and Peripheral routes to Attitude change. New York: Springer

[29] Piggott, N. and T. Marsh. (2004), “Does Food Safety Information Impact U.S. Meat Demand?” American Journal of Agricultural Economics, 86, 154-174.

[30] Pieniak Z., W.Verbeke, I.Vermeir, K.Bruns, S.O.Olsen“Consumer Interest in Fish Information and Labelling”,Journal of International Food & Agribusiness Marketing, 19:2-3, 117-141.

[31] Rickertsen K., D. Kristofersson and S. Lothe. (2003), “Effects of health information on Nordic meat and fish demand,” Empirical Economics, 28(2), 249–273.

[32] Roosen J., S. Marette, S. Blanchemanche and P. Verger. (2009), “Does Health Information Matter for Modifying Consumption? A Field Experiment Measuring the Impact of Risk Information on Fish Consumption,” Applied Economic Perspectives and Policy, 31(1), 2-20.

[33] Shimshack, J.P., M.B. Ward, and T.K.M. Beatty. (2007). “Mercury Advisories: Information, Education, and Fish Consumption,” Journal of Environmental Economics and Management, 53, 158-79.

[34] Smed S. and L. M. Andersen. (2012), “Information or Prices, Which Is Most Powerful in Increasing Consumer Demand for Organic Vegetables,” International Business Research, 5(12), 175-195.

[35] Smed S. (2012), “Information and consumer perception of the organic attribute – the case of fresh fruit and vegetables,” Agricultural Economics, 43(S1), 33-48.

[36] Smed, S. and J.D. Jensen. (2005), ”Food Safety Information and Food Demand,” British Food Journal, 107(3), 173-186.

[37] Smith, M., E.O. van Ravenswaay and S.R. Thompson. (1988). “Sales Loss Determination in Food Contamination Incidents: An Application to Milk Bans in Hawaii,” American Journal of Agricultural Economics, 70, 513-20.

[38] Swinnen, J. F. M., McCluskey, J. J. and Francken, N. (2005), "Food safety, the media, and the information market". In D. Colman and N. Vinck (eds), Reshaping Agriculture's Contribution to Society. Oxford: Blackwell, 175–188.

[39] Tonsor, G.T., J.R. Mintert, and T.C. Schroeder. (2010). "U.S. Meat Demand: Household Dynamics and Media Information Impacts," Journal of Agricultural and Resource Economics, 35(1), 1-17.

[40] Tselepidakis E. (2012), " Food safety and the demand for meat products," Selected paper for the AAEA, annual meeting, Seattle Washington, August 12-14

[41] Variyam J.N. and J. Blaylock. (1996), "A probit latent variable model of nutrition information and dietary fibre intake", American Journal of Agricultural Economics, 78(3), 628-639

[42] Verbeke, W. (2005), "Agriculture and the food industry in the information age", European Review of Agricultural Economics, 32(3), 347-368

[43] Verbeke, W.; R. Ward and J. Viaene. (2000), "Probit analysis of fresh meat consumption in Belgium: exploring BSE and television communication impact, Agribusiness, 16, 215–234.

[44] Verbeke W. (2008): "Plenary Lecture- Impact of communication on consumers' food choices," proceedings of the Nutrition Society, 67, 281-288.

[45] Verbeke W., I.Vermeir, K.Brunsø (2007) "Consumer evaluation of fish quality

as basis for fish market segmentation", Food Quality and Preference 18, 651–661.

[46] Verbeke, W. and R. Ward. (2001), "A fresh meat almost ideal demand system incorporating negative TV press and advertising impact", Agricultural Economics, 25, 359–374.

[47] Wooldridge, J. (2005), "Simple Solutions to the Initial Conditions Problem for Dynamic, Nonlinear Panel Data Models with Unobserved Heterogeneity", *Journal of Applied Econometrics*, 20, 39-54