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WHAT AFFECTS PARENTS' CHOICE OF MILK? AN APPLICATION OF BAYESIAN MODEL AVERAGING

BY

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THESIS

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DEDICATION

献给我的爸爸妈妈，谢谢你们对我无条件的支持，鼓励和爱。

To my best friend Veronica, who goes through this journey with me.

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WHAT AFFECTS PARENTS' CHOICE OF MILK? AN APPLICATION OF BAYESIAN MODEL AVERAGING

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ABSTRACT

This study identifies the factors that influence parents' choice of milk for their children, using data from a unique survey administered in 2013 in Hunan province, China. In this survey, we identified two brands of milk, which differ in their prices and safety claims by the producer. Data were collected on parents' choice of milk between the two brands, demographics, attitude towards food safety and behaviors related to food. Stepwise model selection and Bayesian model averaging (BMA) are used to search for influential factors. The two approaches consistently select the same factors suggested by an economic theoretical model, including price and food expenditure per person. They also select other factors, such as the trust level of the safety claim and the number of averting behaviors. BMA finds strong evidence of model uncertainty, which suggests one single "true" model does not exist. Over 150 models are identified with a maximum 5% probability as the "true" model. Therefore, compared to stepwise model selection that does not account for model uncertainty, BMA is a more appropriate approach to identify the factors that influence parents' choice of milk.

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CHAPTER 1 INTRODUCTION

1.1 STATISTICS BACKGROUND AND LITERATURE REVIEW

Data analysis is used to study many empirical issues in Economics. Economic data tend to be observed data such as GDP, inflation, household income and expenditure. It is common practice to perform regression analysis using those data. Finding an appropriate regression model is an important step of the analysis. Since regression analysis does not imply a causal relationship, economists select explanatory variables for the regression model based on economic theory.

However, economic theory may not be explicit enough to identify exact explanatory variables that should be included in the regression model in some cases (Sala-i-Martin et al., 2004). There may be many explanatory variables that can potentially influence the response variable, but which explanatory variables should be included in the model is an important question that considers issues of model uncertainty.

Several models are usually explored and presented for research, but only one model is considered the “true” or best model. Explanatory variables for the best model can be selected based on certain selection criteria such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC) (Burnham and Anderson, 2004; Young, 2009).

However, the variation of estimates can be large across different models and differ completely with small but sensible changes in the model. This raises concerns about the robustness of the estimates (Young, 2009). It also indicates that a single “true” or best model may not exist. Many models have some probability of being the “true” model. Therefore, there is uncertainty about the “true” model.

A statistical method known as Bayesian model averaging (BMA) provides a solution to the issue of model uncertainty. BMA is a method that can be used to explore the most influential factors that impact a response variable (Amini and Parmeter, 2011). Instead of searching for one model, BMA accounts for model uncertainty by averaging possible models and makes inferences about parameters from multiple models (Penny et al. 2006). Finally, BMA also provides better predictive ability than adopting a single model (Raftery et al. 1997).

BMA has been applied in many economic areas (Moral-Benito, 2015). Some studies use BMA to find a group of robust determinants of economic growth or the influence of certain explanatory variables on economic growth such as amenities and religion (Fernández et al., 2001; Deller and Lledo, 2007; Young, 2009). BMA has also been used to investigate determinants of many other variables such as labor income inequality, economic return to schooling, currency crises, and forecast such as inflation and exchange rate (Garratt et al. 2003; Wright, 2003; Tobias and Li, 2004; Cuaresma and Slacik, 2009; Koske and Wanner 2013).

1.2 MILK MARKET IN CHINA

In this study, we examine the determinants of parents’ choice of milk for their children in China. As mentioned in Cheng and Thacher (2016), China is one of the largest producers of cow’s milk in the world with a production over 30,000 thousand metric tons per year since 2011 (USDA 2015). But the yearly per person consumption of fluid milk in China is less than onequarter of that of US consumers (Canadian Dairy Information Centre, 2015). Even though China has low consumption of fluid milk, milk is a common part of children's diet, especially in urban areas. The China Health and Nutrition Survey in 2006 found 38% of urban children and 5% of rural children between 7 and 17 years old drank milk and yogurt within 3 days of the survey with younger children more likely to drink milk (Du et al., 2010).

Between 2005 and 2013, more than 20 food safety incidents and issues were reported to involve milk and milk products in China. For instance, chemicals such as melamine and leather-hydrolyzed protein were added to milk or milk products to enhance nitrogen and fake protein levels of milk in tests. A national brand of milk contained 140% higher level of aflatoxin than the required level. Prolonged exposure to these toxins may make consumers more likely to develop liver damage, heavy metal poisoning, and cancer (Life Times, 2011; Arthur Yau, 2012). In the most serious reported incident in 2008, melamine found in baby formula affected 300,000 infants and caused six deaths. Therefore, it is important to improve milk safety in the market.

1.3 RESEARCH QUESTION

Since there is more than one brand of milk on the market, Chinese consumers' choice of milk can influence demand. A better understanding of the factors that influence consumers' choice can provide information for both policy makers and producers. Policy makers can utilize consumer preferences to implement more efficient food safety policies to improve milk safety, while producers of safe milk can use it to find strategies to compete with producers of unsafe milk. We intend to use Bayesian model averaging (BMA) to identify factors that influence consumers' choice of milk.

As previously mentioned, BMA can identify potential factors that are not directly identified by economic theory. BMA accounts for model uncertainty by considering multiple models simultaneously and therefore provides more robust results. Moreover, the theoretical model in Cheng and Thacher (2016) finds that milk price and household income should influence the choice of milk. If BMA concludes that these two variables do influence the choice of milk, then the data support the theoretical model. This provides some evidence that BMA can play a key role in identifying potentially important factors.

1.4 SUMMARY OF RESULTS

In this study, we have found strong evidence of model uncertainty in that all selected models have no more than 5% probability of being the "true" model. Therefore, it is appropriate and recommended to use BMA to find influential factors on the choice of milk based on a group of possible models. We find that milk price and household food expenditure per person, which is used to approximate household income, can be very likely to influence the choice of milk. This is consistent with economic theory. There are also some other factors that influence the choice of milk.

CHAPTER 2 METHODOLOGY

2.1 SURVEY QUESTIONS AND VARIABLES

In 2013, we conducted an IRB approved anonymous survey on parents' attitudes towards food safety among urban parents of first and second year elementary students in two cities, Changsha and Huaihua, in Hunan province, China. Four schools were randomly selected from each city for the survey. We handed out a total of 1385 surveys to children at school to take home to their parents. We received 1205 responses, or a response rate of 87%.

We focus on urban parents instead of general consumers because it is common for urban children to drink milk. They are vulnerable to food safety risks but more likely to be exposed to those risks. Therefore, urban parents represent consumers with a greater demand for milk safety and would receive greater benefit from that improvement. Moreover, elementary schools have 100% enrollment rate that is higher than daycare or preschools. This allows us to receive more representative responses.

Parents from the same city had very diverse demographics for both cities. Therefore, we are not concerned about the city difference. However, school location can reflect prices of goods consumed by a household. And prices can potentially influence parents' choice of milk through their food budget.

There are four versions of the survey with only one question that varied between surveys. Each school received a relatively equal number of surveys for each version. Twenty questions from the survey are relevant to this study (see Appendix A for relevant questions from the first version of the survey). One question gives the respondent a choice between two brands of milk and is used to obtain the response variable and the price of milk. The other 19 questions pertain to demographics, attitude towards food safety, and behaviors related to food, which may influence the choice of milk (see Appendix A Table A.1 for variables definitions). Fifty-four potential explanatory variables are created based on the questions in the survey.

Question 11 gives the respondent a choice between two brands of milk, A and B, and provides corresponding prices and food safety claims. Brand A is 3 yuan (about 50 cents) per 250ml without any special food safety claim. This was the most common price of milk at the time the survey was conducted. Brand B has a higher price and varies across different versions of the survey at 6, 9, 12 and 15 yuan per 250ml, respectively. Brand B has a claim by the producer that the food is guaranteed to be safe. Question 11 is used to create an indicator variable *y* to indicate whether a parent chose milk brand B. Variables *price.6* to *price.15* are indicator variables that indicate the version of survey a parent received. We chose 15 yuan as the top price because it was the highest price of milk we can find in the market at the time. We vary the price of brand B in different versions to investigate whether the change of this price influences the choice of milk (Cheng and Thacher, 2016).

Question 12 is a follow-up question and examines the parents' level of trust about the safety claim of brand B. While there is no guarantee that the safety claim is reliable, parents' perception of the safety claim can influence their choice of milk.

If a parent indicated in question 10 that his/her child never drank milk, the parent was asked to skip questions 11 and 12. This generates missing values for questions 11 and 12.

Question 2 asks the respondent about three food safety incidents reported in the news just before the survey was conducted. The first and third incidents were related to food sold or produced in Hunan province. The second incident was related to food sold or produced in another province. *Localnews* counts the number of food safety incidents between the first and third incidents a parent heard about or saw on the news.

Question 4 asks parents whether they heard of, saw or even knew the meaning of three food safety management systems (HACCP, ISO9000, ISO22000) and five food safety labels (pollution-free agricultural product, green food, quality safety, organic food and a fake label). These systems and labels were created to help improve food safety and knowledge of food brands. We create an index, *knowledge*, to indicate how much attention parents paid to these systems and labels. For each system or label, if a respondent heard of, saw or even knew the meaning, they get 1 point. We assign 0, otherwise. All points are summed with the exception of the fake label. The maximum score for this question is 7. But if a parent claimed that he/she heard or knew the meaning of the fake label, 50% is deducted from his/her points.

Question 6 is used to create an indicator variable that represents whether a parent considered price as one of the most important characteristics in identifying safe food. This was not necessarily true in the Chinese food market at the time. But if a parent considered price as one of the most important characteristics, he/she would be more likely to choose the more expensive brand.

Since household income is a sensitive question, respondents may hesitate to provide this information, which would generate more missing values in the data. To avoid this issue, we ask for food expenditure in question 7 to approximate income. A household with high food expenditure may indicate that they care more about food and are willing to pay more for it. Therefore, their choice of milk may be similar to high-income households.

Question 7 asks for household food expenditure range since it may be difficult to provide an exact number. We use the midpoint of the first six ranges and the lower bound of the highest range to create a continuous variable for household food expenditure. This helps reduce the number of explanatory variables in the model and simplify the interpretation. We divide total household food expenditure by 100 times household size (question 17) to create monthly food expenditure per person in 100 yuan to better reflect household wealth. This variable should also influence on the choice of milk (Cheng and Thacher, 2016).

Similarly, question 8 asks for a range of the highest affordable increase in food expenditure. We use the upper bound of the first 12 ranges and 2000 yuan for the highest range to create a continuous variable. We then divide it by 100 times household size to create the affordable increase in food expenditure per person in 100 yuan.

Question 14 asks parents to identify specific averting behaviors they used to avoid food safety issues, such as making their own processed food, growing vegetables or raising poultry, etc. For this study, it is important to determine how many actions respondents took since more actions may indicate their demand for safer food. Therefore, we count the number of averting behaviors parents identified to create the variable *averting*.

Question 20 asks for education level. To reduce the number of explanatory variables in the model, we create a continuous variable *education* by summing the numbers in Table 2.1 up to the highest level of education for each respondent to reflect years of education.

Table 2.1 Years of education by education level

Education level	Elementary school	Junior high school	Senior high school	Junior college	Bachelor's degree	Master's degree	Doctorate degree
Years of education	6	3	3	3	4	2	4

2.2 DATA

Out of 1205 survey responses, 20 respondents indicated their children never drank milk. Their responses are excluded. There are 37 observations with missing values, which comprise only 3% of total observations. This should not have a significant impact on the results. Therefore, we drop observations with missing values. These exclusions result in a sample size of 1148 observations.

Descriptive statistics are listed in Table A.2, Appendix A. Approximately 93% of children drank milk and 66% drank milk almost every day. This confirms that milk is common in children's diet in urban China. For the response variable, 80% of parents preferred brand B (with a higher price and safety claim) to brand A. This is not surprising given the majority of parents had heard of the food safety incidents mentioned in the survey. And 99% of parents responded were more or less concerned about the current food safety situation in Hunan province. Even though the safety claim of brand B was not completely reliable, 46% of parents chose to trust it, while 29% of parents were neutral about it. Only 1% of parents considered price to be one of the most important characteristics in identifying safe food.

Parents also took some action to improve the safety of food they consumed. Approximately 92% of parents used mass media to check food safety information. Respondents used an average of three averting behaviors to avoid unsafe food. Also, 75% of parents took action to deal with a food quality or safety problem. But the average *knowledge* index of 3.58 out of 7 indicates that many parents were not very familiar with food safety management systems and labels, which were created to help identify safe food.

Approximately 60% of respondents were female. Respondents could be parents or grandparents with an average age of 37 and 13 years of education. On average they spent 449 yuan per person on food monthly. They could also afford a maximum food expenditure increase of 167 yuan per person per month. This is more likely to cut into expenditure on leisure than saving or other expenditures. Respondents were more likely to purchase food at a supermarket. The majority of stores or markets where they shopped did not publish food safety inspection results. Finally, 38% of parents had friends or relatives with a food related job.

Since this survey targets a specific group of consumers, population information is not available. It is difficult to show the representativeness of our sample. Table 2.2 presents a comparison between all residents of Changsha and Huaihua and those in our sample. In both cities, the respondents in our sample had a higher education level than residents of the general population. One reason may be that our respondents were younger and had mostly finished their education. The sample respondent in Changsha had lower food expenditure per person than the general population, while the opposite case is true for the sample respondent in Huaihua. Therefore, we use caution in interpreting the results since they may not be extrapolated to the general population.

Table 2.2 Comparison between population and sample

	Sample		Population	
	Changsha	Huaihua	Changsha	Huaihua
Annually food expenditure per person	5646	5147	7366	4446
Years of eduaction	13.1	13.5	12.5	8.5

Note: 1. Population data source: Statistical Bureau of Hunan Province
2. Since Hunan Statistical Yearbook 2014 does not include food expenditure data from 2013, we use food expenditure data from 2012 with adjustment of inflation.
3. Population years of education in Huaihua is 2010 data.

2.3 BINARY LOGISTIC REGRESSION MODEL

Our data have a binary response variable for which brand of milk respondents preferred (y). We are interested in whether and how the 54 potential explanatory variables (see Appendix A Table A.1 for a list of variables) impact the probability of choosing brand B. We model this using a logistic regression framework. Assume that y_i is the choice of brand by person i, $i = 1, \dots, 1148$, where

$$y_i = \begin{cases} 1\ if\ brand\ B\ is\ chosen \\ 0\ if\ brand\ A\ is\ chosen \end{cases}$$

The probabilities of choosing brands A and B given X_i, a vector of explanatory variable for person i, are $Pr(\, y_i = 0|X_i) = 1 - p_i(X_i; \beta)$ and $Pr(\, y_i = 1|\, X_i) = p_i(X_i; \beta)$ respectively, where β is a parameter vector with k elements, which includes parameters of all explanatory variables and an intercept.

In this case, it is not appropriate to assume $p_i(X_i; \beta)$ is a linear function of X_i since a linear function cannot guarantee the probability is between 0 and 1 (Dobson and Barnett, 2008). There are three other reasonable alternatives for the functional form $p_i(X_i; \beta)$. The first is a probit function. It assumes $p_i(X_i;\beta)$ is the cumulative probability function (CDF) of the normal distribution. $\Phi()$ denotes the CDF.

$$p_i(X_i;\beta) = \Phi\left(X_i'\beta\right)$$

. Therefore,

$$\Phi^{-1}(p_i) = X_i'\beta$$

The second is a logit link function. It assumes $p_i(X_i;\beta)$ is the CDF of the logistic distribution:

$$p_i(X_i;\beta) = \frac{\exp\left(X_i'\beta\right)}{1+\exp\left(X_i'\beta\right)}$$

Therefore,

$$\log\left(\frac{p_i}{1-p_i}\right) = X_i'\beta$$

The left-hand side can be interpreted as the log odd of success over the probability of failure.

The third is a complementary log-log link function. It assumes $p_i(X_i;\beta)$ is the CDF of an extreme value distribution:

$$p_i(X_i;\beta) = 1-\exp\left[-\exp(X_i'\beta)\right]$$

Therefore,

$$\log[-\log(1-p_i)] = X_i'\beta$$

Model selection procedures can determine which variables among the 54 potential explanatory variables should be included as elements of X_i for the final model(s).

2.4 MODEL SELECTION METHODS

2.4.1 STEPWISE MODEL SELECTION

Although there are many variables in our data that potentially influence parents' choice of milk, a minimal number of explanatory variables should be included in X_i without losing useful information. The Akaike Information Criterion (AIC) can be used for model comparison (Akaike, 1973).

$$AIC = -2 \ln L + 2k$$

where $\ln L$ is the maximum log-likelihood function and k is the number of parameters in the model. The term $\ln L$ captures a larger log-likelihood from a better model, while the term $2k$ includes a penalty for including more explanatory variables in the model. A lower AIC value indicates the model is a better fit and, therefore, is preferred.

In classical statistics, stepwise model selection is a technique used to find the best model with different combinations of explanatory variables by comparing the AIC values. There are two types of selection procedures. The first is forward stepwise selection. It begins with a null model and adds variables step by step and then determines which model is the best fit by comparing AIC values. The second is backward stepwise selection. It begins with a full model that includes all possible variables and eliminates variables step by step and then compares AIC values. We can also compare AIC values for all the best models under different link functions to determine which function is the most appropriate.

Bayesian Information Criterion (BIC) is another criterion that can be used for model selection:

$$BIC = -2\ln L + k\ln(n)$$

where n is the number of observations. The BIC is similar to the AIC in that a lower BIC value indicates a model is a better fit. An F-test can also be used to compare models.

To calculate AIC or BIC, a maximum likelihood estimation approach can be used to estimate β and to find the maximum log-likelihood function. For the logistic regression models in this study, the likelihood function with n observations can be rewritten as

$$L(\beta) = \prod_{i=1}^{n} p_i(X_i;\beta)^{y_i}[1 - p_i(X_i;\beta)]^{1-y_i}$$

This is based on the probability of observing the current data. The goal is to find the β that maximizes this probability. To achieve this goal, one can take the natural log of the likelihood function.

$$\ln L(\beta) = \sum_{i=1}^{n} \{y_i \ln p_i(X_i;\beta) + (1 - y_i)\ln[1 - p_i(X_i;\beta)]\}$$

To maximize $\ln L(\beta)$, we take the first partial derivative of $\ln L(\beta)$ with respect to all elements of β and set these derivatives equal to zero (Green, 1984),. The first partial derivative is

$$\frac{\partial \ln L(\beta)}{\partial \beta_k} = \frac{\partial \ln L(\beta)}{\partial p_i(X_i;\beta)} \frac{\partial p_i(X_i;\beta)}{\partial \beta_k} = \sum_{i=1}^{n} \left[\frac{y_i}{p_i(X_i;\beta)} \frac{\partial p_i(X_i;\beta)}{\partial \beta_k} - \frac{1-y_i}{1-p_i(X_i;\beta)} \frac{\partial p_i(X_i;\beta)}{\partial \beta_k} \right]$$

$$= \sum_{i=1}^{n} \left[\frac{y_i - p_i(X_i;\beta)}{p_i(X_i;\beta)\big(1-p_i(X_i;\beta)\big)} \right] \frac{\partial p_i(X_i;\beta)}{\partial \beta_k} = 0 \qquad (1)$$

where β_k is any element of the coefficient vector β, $k, l = 0,1, \ldots K$. The first partial derivative can also be written in matrix form as

$$\frac{\partial \ln L(\beta)}{\partial \beta} = A^T u \qquad (2)$$

where u is the n-vector of $\left\{\frac{\partial \ln L(\beta)}{\partial p_i}\right\}$ and A is the $n \times k$ matrix of $\left\{\frac{\partial p_i}{\partial \beta}\right\}$.

The Hessian matrix is

$$H = \nabla^2 L(\beta) = \begin{bmatrix} \frac{\partial^2 \ln L(\beta)}{\partial {\beta_1}^2} & \frac{\partial^2 \ln L(\beta)}{\partial \beta_1 \, \partial \beta_2} & \cdots & \frac{\partial^2 \ln L(\beta)}{\partial \beta_1 \, \partial \beta_K} \\ \frac{\partial^2 \ln L(\beta)}{\partial \beta_2 \, \partial \beta_1} & \frac{\partial^2 \ln L(\beta)}{\partial {\beta_2}^2} & \cdots & \frac{\partial^2 \ln L(\beta)}{\partial \beta_2 \, \partial \beta_K} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial^2 \ln L(\beta)}{\partial \beta_K \, \partial \beta_1} & \frac{\partial^2 \ln L(\beta)}{\partial \beta_K \, \partial \beta_2} & \cdots & \frac{\partial^2 \ln L(\beta)}{\partial {\beta_K}^2} \end{bmatrix} \qquad (3)$$

where the second partial derivative is

$$\frac{\partial^2 \ln L(\beta)}{\partial\beta_k\,\partial\beta_l} = \sum_{i=1}^{n}\left\{\left[-\frac{\frac{\partial p_i(X_i;\beta)}{\partial\beta_l}\frac{\partial p_i(X_i;\beta)}{\partial\beta_k}}{p_i(X_i;\beta)\big(1-p_i(X_i;\beta)\big)}\right]\right.$$

$$-\left[\frac{y_i - p_i(X_i;\beta)}{p_i{}^2(X_i;\beta)\big(1-p_i(X_i;\beta)\big)^2}\right][1-2p_i(X_i;\beta)]\frac{\partial p_i(X_i;\beta)}{\partial\beta_l}\frac{\partial p_i(X_i;\beta)}{\partial\beta_k}$$

$$\left.+\left[\frac{y_i - p_i(X_i;\beta)}{p_i(X_i;\beta)\big(1-p_i(X_i;\beta)\big)}\right]\frac{\partial^2 p_i(X_i;\beta)}{\partial\beta_k\,\partial\beta_l}\right\}$$

$$= -\sum_{i=1}^{n}\left\{\frac{1-[y_i - p_i(X_i;\beta)]}{p_i(X_i;\beta)\big(1-p_i(X_i;\beta)\big)}\right.$$

$$\left.+\frac{[y_i - p_i(X_i;\beta)][1-2p_i(X_i;\beta)]}{p_i{}^2(X_i;\beta)\big(1-p_i(X_i;\beta)\big)^2}\right\}\ \frac{\partial p_i(X_i;\beta)}{\partial\beta_l}\frac{\partial p_i(X_i;\beta)}{\partial\beta_k} \tag{4}$$

β_k and β_l are any element of the coefficient vector β, $k, l = 0,1, \ldots\ K$. Let

$$w_i = \frac{1-[y_i - p_i(X_i;\beta)]}{p_i(X_i;\beta)\big(1-p_i(X_i;\beta)\big)} + \frac{[y_i - p_i(X_i;\beta)][1-2p_i(X_i;\beta)]}{p_i{}^2(X_i;\beta)\big(1-p_i(X_i;\beta)\big)^2}$$

Then

$$\frac{\partial^2 \ln L(\beta)}{\partial\beta_k\,\partial\beta_l} = -\sum_{i=1}^{n} w_i\ \frac{\partial p_i(X_i;\beta)}{\partial\beta_l}\frac{\partial p_i(X_i;\beta)}{\partial\beta_k}$$

Thus, the Hessian matrix can be written in the following form

$$H = -A^T W A \tag{5}$$

where W is a diagonal matrix with w_i as diagonal elements. The Hessian matrix must be negative definite to ensure the existence of a maximum log-likelihood value.

Equation (1) represents a system of k nonlinear equations with k unknown coefficients. To solve for the coefficients numerically and, therefore, estimate the parameters in the logistic model, R uses an iteratively reweighted least squares (IRLS) algorithm that follows a Newton-Raphson method.

The Newton-Raphson method uses a Taylor series expansion to transform the system of k non-linear equations into general linear form that can be solved. The general form of a first degree Taylor series expansion of $f(\beta)$ at the point $\beta = \beta^0$ is

$$f(\beta) \approx f(\beta^0) + (\beta - \beta^0)f'(\beta^0)$$

Set $f(\beta) = 0$ to obtain

$$\beta = \beta^0 - \frac{f(\beta^0)}{f'(\beta^0)}$$

In our case, $f(\beta) = \frac{\partial \ln L(\beta)}{\partial \beta}$. Therefore,

$$\begin{aligned}\beta = \beta^0 - H^{-1}\frac{\partial \ln L(\beta)}{\partial \beta}|_{\beta=\beta^0} &= \beta^0 + (A^TWA)^{-1}A^Tu \\ &= (A^TWA)^{-1}A^TWA\beta^0 + (A^TWA)^{-1}A^TWW^{-1}u \\ &= (A^TWA)^{-1}A^TW(A\beta^0 + W^{-1}u)\end{aligned}$$

Here β has the same form as the general least squares regression with a weight matrix W and a variance-covariance matrix W^{-1}. This is equivalent to finding the β^* that minimizes

$$[W^{-1}u + A(\beta - \beta^*)]^T W [W^{-1}u + A(\beta - \beta^*)]$$

The IRLS algorithm assumes initial values for the weight matrix W. It uses the least squares method to estimate β and u. It then uses the estimated u to find a new weight matrix W and estimates β and u again. This process is repeated until β converges, which is the final estimate of β. At the same time, we can obtain the maximum value of log-likelihood function $\ln L(\beta)$, and calculate the AIC value for the stepwise model selection.

One drawback of the stepwise model selection is that it only searches for one best model with the lowest AIC value. As previously mentioned, model uncertainty, where more than one model is associated with some probability of being the "true" model, may exist. Therefore, we use another, Bayesian model averaging, to address this issue.

2.4.2 BAYESIAN MODEL AVERAGING

Bayesian model averaging (BMA) is another model selection method, which provides a solution for the potential issue of model uncertainty. A fundamental difference between classical (frequentist) and Bayesian methodology is that classical methodology assumes the data are random and the parameters are fixed, whereas Bayesian methodology assumes fixed data and random parameters. In Bayesian methodology, we are interested in the posterior probability of a parameter through Bayes' theorem. The posterior probability of a parameter β given data Y is

$$P(\beta|Y) = \frac{P(Y|\beta)P(\beta)}{P(Y)} \propto P(Y|\beta)P(\beta)$$

where $P(Y|\beta)$ is the likelihood function, and $P(\beta)$ is the prior probability. Bayesian methodology may require numerical techniques such as Markov Chain Monte Carlo (MCMC) methods for repeated sampling from the posterior distribution to provide inferences about parameters or predictions (Congdon, 2006).

BMA also uses Bayes' theorem to decompose the posterior probability of parameters, but it incorporates the probability of different models being the "true" model given the data to account for model uncertainty. The posterior probability of a parameter β given the data D is

$$P(\beta|D) = \sum_{i=1}^{2^K} P(\beta|M_i, D)P(M_i|D)$$

where K is the number of explanatory variables in the data and M_i is a model with any possible combination of those explanatory variables, including the null model with only a constant and no explanatory variable. $i = 1, 2, \dots, 2^K$. This is an average of the posterior probabilities from each model weighted by the posterior probability of models. This reflects the probability of the explanatory variables influencing the response variable across different models (Raftery et al., 1995; Hoeting et al., 1999; Eicher et al., 2011).

The posterior probability of model M_i is unknown. But we can write this posterior probability in the following form using Bayes theorem:

$$P(M_i|D) = \frac{P(D|M_i)P(M_i)}{\sum_{j=1}^{2^K} P(D|M_j)P(M_j)} \qquad (6)$$

where the marginal likelihood of model M_i is

$$P(D|M_i) = \int P(D|\beta_i, M_i)\, P(\beta_i|M_i)d\beta_i \qquad (7)$$

$P(M_i)$ is the prior probability of M_i being the true model. β_i is the vector of parameters of model M_i. $P(D|\beta_i, M_i)$ is the likelihood of model M_i. $P(\beta_i|M_i)$ is the prior probability of coefficients in model M_i. In general, the integral given in equation (7) can be difficult to compute.

Raftery (1995) and (1996) provide a method to estimate $P(D|M_i)$. It decomposes $P(D|M_i)$ into components that can be easily calculated by statistical software. Equation (7) can be rewritten in the following simplified form.

$$P(D) = \int P(D|\beta)P(\beta)\,d\beta$$

Let $f(\beta) = \ln[P(D|\beta)P(\beta)]$. The Taylor series expansion of $f(\beta)$ at $\beta = \beta^0$ is

$$f(\beta) \approx f(\beta^0) + (\beta - \beta^0)^T f'(\beta^0) + \frac{1}{2}(\beta - \beta^0)^T f''(\beta^0)(\beta - \beta^0)$$

where $f'(\beta^0)$ is the vector of first partial derivatives of $f(\beta)$ evaluated at β^0 and $f''(\beta^0)$ is the Hessian matrix of second partial derivatives of $f(\beta)$ evaluated at β^0. Since we want to maximize $f(\beta)$ at $\beta = \beta^0$, $f'(\beta^0) = 0$. Therefore,

$$f(\beta) \approx f(\beta^0) + \frac{1}{2}(\beta - \beta^0)^T f''(\beta^0)(\beta - \beta^0)$$

and

$$P(D) \approx \int \exp[f(\beta)]\,d\beta = \exp[f(\beta^0)] \int \exp\left[\frac{1}{2}(\beta - \beta^0)^T f''(\beta^0)(\beta - \beta^0)\right] d\beta$$

The Laplace method for integrals allows us to further approximate $P(D)$ as

$$P(D) \approx \exp[f(\beta^0)]\,(2\pi)^{k/2}|\Sigma|^{-1/2}$$

where k is the number of parameters and $\Sigma = -f''(\beta^0)$ is the $k \times k$ inverse Hessian matrix of $f(\beta)$ evaluated at β^0. Therefore, equation (7) can be rewrite as

$$P(D|M_i) \approx P(D|\beta_i^0, M_i)P(\beta_i^0|M_i)(2\pi)^{\frac{k_i}{2}}|\Sigma_i|^{-\frac{1}{2}}$$

$$\Rightarrow 2\ln P(D|M_i) \approx 2\ln P(D|\beta_i^0, M_i) + 2\ln P(\beta_i^0|M_i) + k_i \ln(2\pi) - \ln|\Sigma_i| \qquad (8)$$

The BMA package in R uses the following BIC approximation to approximate equation (8)

$$2\ln P(D|M_i) \approx 2\ln P\left(D|\hat{\beta}_i, M_i\right) - k_i \ln(n) = -BIC_i$$

where $\hat{\beta}_i$ is the maximum likelihood estimator, $P\left(D|\hat{\beta}_i, M_i\right)$ is the maximized value of the likelihood function, and k_i is the number of parameters in model M_i (Raftery et al., 2005). Therefore, the posterior probability of model M_i in equation (6) can be rewritten as

$$P(M_i|D) = \frac{\exp\left(-\frac{BIC_i}{2}\right) \times P(M_i)}{\sum_{j=1}^{2^K} \exp\left(-\frac{BIC_j}{2}\right) \times P(M_j)}$$

Since there is a group of possible "true" models, the influence of explanatory variables on the response variable should be decided based on the results of this group of possible "true" models. The posterior mean and standard deviation of β can be used to describe such influence with the following forms:

$$E(\beta|D) = \sum_{i=1}^{2^K} E(\beta|D, M_i)P(M_i|D) \qquad (9)$$

$$sd(\beta|D) = \sqrt{V(\beta|D)} = \sqrt{\sum_{i=1}^{2^K} [V(\beta|D, M_i) + E(\beta|D, M_i)^2]P(M_i|D) - E(\beta|D)^2} \qquad (10)$$

where $E(\beta|D, M_i)$ and $V(\beta|D, M_i)$ can be approximated by the corresponding maximum likelihood estimator $\hat{\beta}_i$ and the variance of $\hat{\beta}_i$.

CHAPTER 3 RESULTS

3.1 STEPWISE MODEL SELECTION

We use the "stepaic" command in the MASS package from R to perform a backward stepwise model selection. The model selected by assuming three different link functions (logit, probit, and cloglog) are almost identical except that logit does not choose *safeinfo.2*. For example, the final model for the probit link is

$$\begin{aligned}\Phi^{-1}[p(X;\beta)] = \beta_0 &+ \beta_1 \times school.5 + \beta_2 \times school.7 + \beta_3 \times concern.1 + \beta_4 \times concern.2 \\ &+ \beta_5 \times localnews + \beta_6 \times knowledge + \beta_7 \times safeinfo.2 + \beta_8 \times priceimp \\ &+ \beta_9 \times foodexppp + \beta_{10} \times fexpincppp + \beta_{11} \times mfreq.3 + \beta_{12} \times price.12 \\ &+ \beta_{13} \times price.15 + \beta_{14} \times trustclaim.1 + \beta_{15} \times trustclaim.2 + \beta_{16} \\ &\times trustclaim.4 + \beta_{17} \times trustclaim.5 + \beta_{18} \times averting + \beta_{19} \times dealres.1 \\ &+ \beta_{20} \times workfood + u\end{aligned}$$

Table 3.1 presents the results for the best fit model using the "glm" command in the MASS package from R for each link function. The AIC values for the three models are very close. Cloglog has the lowest AIC value, which indicates it is a slightly better fit than the other two models. However, the significance of some of the estimated coefficients is not consistent across different link functions (see grey area in Table 3.1). It is worth noting that food expenditure per person *foodexpp* is not significant in the cloglog model but significant in the other two models. Economic theory proposes food expenditure per person to be included in the regression model as an explanatory variable. This may suggest that probit or logit link functions are more appropriate in our case.

Table 3.1 Estimation result of the best fit model by link function

	Logit			Probit			Cloglog		
	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
(Intercept)	0.32	0.41		0.32	0.24		0.00	0.22	
school.5	0.40	0.26		0.23	0.15		0.22	0.13	**
school.7	0.93	0.31	**	0.53	0.17	**	0.45	0.15	*
concern.1	1.83	1.11	.	1.05	0.59	.	1.07	0.50	.
concern.2	-0.38	0.20	.	-0.21	0.11	.	-0.19	0.10	.
localnews	0.26	0.13	*	0.14	0.07	.	0.12	0.07	*
knowledge	-0.11	0.06	.	-0.07	0.04	.	-0.06	0.03	.
safeinfo.2	-	-		-0.17	0.11		-0.17	0.10	*
priceimp	2.26	1.13	*	1.26	0.62	*	1.27	0.55	*
foodexpp	0.12	0.06	*	0.07	0.03	*	0.07	0.03	
fexpincp	0.16	0.09	.	0.08	0.05	.	0.07	0.04	
mfreq.3	0.30	0.21		0.18	0.12		0.17	0.10	*
price.12	-0.51	0.21	*	-0.28	0.12	*	-0.23	0.11	***
price.15	-0.92	0.21	***	-0.52	0.12	***	-0.44	0.11	***
trustclaim.1	-2.17	0.39	***	-1.32	0.23	***	-1.48	0.29	***
trustclaim.2	-1.00	0.20	***	-0.60	0.12	***	-0.59	0.12	***
trustclaim.4	1.73	0.25	***	0.92	0.13	***	0.75	0.10	***
trustclaim.5	2.61	1.03	*	1.31	0.45	**	1.01	0.30	**
averting	0.19	0.06	**	0.11	0.04	**	0.10	0.03	.
dealres.1	-0.38	0.22	.	-0.22	0.12	.	-0.20	0.11	
workfood	-0.26	0.17		-0.16	0.10		-0.14	0.09	
No. of Obs.	1148			1148			1148		
AIC	915.11			913.23			913.06		
Null Deviance	1158.29			1158.29			1158.29		
Residual Deviance	875.11			871.23			871.06		

Note: the significance level are: '***'=0.001, '**'=0.01, '*'=0.05, '.'=0.1.

The goodness of fit of the three best models can be assessed using a likelihood ratio test. This test examines whether those three models (full model) are significantly better than the null model with no explanatory variables. The null hypothesis and alternative hypothesis are

$$H_0\text{: } null\ model\ is\ true \qquad H_A\text{: } full\ model\ is\ true$$

$$LRT = -2\left(\ln L_{null} - \ln L_{full}\right) = null\ deviance - residual\ deviance \sim \chi^2_{df\ null - df\ full}$$

A small $p - value = P(\chi^2_{df\ null-df\ full} \geq LRT)$ implies that we reject H_0.

Using the logit link as an example, $LRT = 1158.29 - 875.11 = 283.18$ and the degree of freedom of χ^2 is 19. The $p - value = 5.5 \times 10^{-49} < 0.001$. Therefore, the full model with the logit link function is significantly better than the null model. Similarly, the other two full models are also significantly better than the null model.

3.2 BAYESIAN MODEL AVERAGING

We use the “bic.glm” command in the BMA package from R to perform Bayesian model averaging. We assume a uniform distribution for the prior weight for each variable and model since we do not have much prior information.

Table 3.2 presents partial results for the posterior probability, posterior mean and posterior standard deviation for parameters using BMA with different link functions (see Appendix B Tables B.1, B.2 and B.3 for complete BMA result). The variables reported below either have a high probability of occurring in the group of selected models or provide an interesting implication. They are also selected by stepwise model selection, which indicates some consistency between stepwise model selection and BMA. But stepwise model selection includes variables in its best model that are not considered as important by BMA, such as *school.5* and *mfreq.3*.

Table 3.2 Selected posterior probability, mean and standard deviation from BMA

	Logit			Probit			Cloglog		
	p!=0	EV	SD	p!=0	EV	SD	p!=0	EV	SD
trustclaim.1	100	-1.96	0.36	100	-1.19	0.22	100	-1.30	0.27
trustclaim.2	100	-0.93	0.19	100	-0.56	0.11	100	-0.56	0.11
trustclaim.4	100	1.73	0.25	100	0.91	0.13	100	0.72	0.10
trustclaim.5	100	2.60	1.03	100	1.28	0.43	100	0.95	0.29
price.15	99.4	-0.71	0.21	99.1	-0.40	0.12	94.8	-0.32	0.13
price.12	25.7	-0.13	0.24	28	-0.08	0.14	24.6	-0.06	0.12
Averting	79.3	0.15	0.09	88.6	0.10	0.05	95.1	0.10	0.04
Foodexpp	73.8	0.13	0.09	75	0.07	0.05	83.5	0.07	0.04
Fexpincp	24	0.05	0.10	20.3	0.02	0.05	11.7	0.01	0.03
concern.2	48.2	-0.25	0.29	48.7	-0.14	0.17	43.8	-0.11	0.15
Priceimp	21.6	0.46	1.01	22.7	0.28	0.60	24.8	0.31	0.60
dealres.1	8	-0.03	0.13	10	-0.02	0.08	12	-0.03	0.08
Localnews	13	0.04	0.10	7.9	0.01	0.04	3.4	0.004	0.02
Number of model selected	150			182			161		
Posterior probability of selected model	≤0.049			≤0.041			≤0.047		
BIC	-7110			-7110			-7110		

More than 150 possible models are selected and averaged in determining which variables most likely influence our dependent variable. However, the highest posterior probability among the selected models is less than 0.05. This means that among the hundreds of selected models, each has less than a 5% probability of being the “true” model. This provides strong evidence of model uncertainty and supports the application of BMA to account for such uncertainty.

Since there is no single “true” model for this study, we cannot select a group of explanatory variables for one model and estimate their coefficients. However, BMA allows us to find the probability of each explanatory variable appearing in the group of selected models (see column labeled “p!=0” in Table 3.2). Explanatory variables that appear more often in selected models are more likely to influence the choice of milk. In this case, *trustclaim.*, *price.15*, *averting* and *foodexpp* are consistently selected as the most important explanatory variables with different link functions. The coefficients of these variables are also highly significant in the estimated result of stepwise model selection. BMA with different link functions consistently selects milk price and food expenditure variables, which is consistent with economic theory. This provides some evidence that BMA is reliable in identifying important explanatory variables.

BMA also allows us to recover the mean and standard deviation of the posterior distribution (see columns labeled “EV” and “SD”, respectively, in Table 3.2). These parameters reflect how each explanatory variable influences the choice of milk and the magnitude of the influence. The posterior mean for parameters across all three link functions have the same sign as the estimated coefficients from the stepwise model selection. Therefore, the results are robust across the link functions.

The “imageplot.bma” command in the BMA package from R provides a clear visual tool to view the probability of variables occurring in all models selected using different link functions (see Figures 3.1-3.3). A more continuous line (blue or red) indicates that the explanatory variable is more likely to appear in selected models, such as *trustclaim*. No line indicates the variable never appears in selected models, such as *school.2*. Blue and red lines denote negative and positive signs of the parameters, respectively.

Figures 3.1-3.3 show similar patterns across different link functions. Several explanatory variables are very likely to influence the choice of milk as indicated by a relatively continuous line. When milk price (*price.*) is high (15 yuan), it almost always (with 99.4% probability of appearing in selected models) decreased the probability of choosing brand B compared with a milk price of 6 yuan. This is reasonable because higher prices should decrease demand for brand B. The price of 12 yuan was less likely (with 25.7% probability of appearing in selected models) to have influence on the choice milk, while a milk price of 9 yuan had an imperceptible influence. This indicates that a small increase in price may not change parents' choice of milk. But if parents believed price was one of the most important characteristics to identify food safety (*priceimp*), they may be more likely to choose brand B.

Monthly food expenditure per person (*foodexpp*) and affordable increase in food expenditure per person (*fexpincp*) were also very likely to influence the choice of milk, especially *foodexpp*. Households with higher *foodexpp* and *fexpincp* tended to choose brand B. Since these households either had more disposable income or care more about food safety, it is reasonable to assume that they can afford and were willing to choose brand B. *Foodexpp* and *fexpincp* seem to be substitutes since there is a moderate correlation between them (the correlation coefficient is 0.47). Most models include only one of these variables but *foodexpp* is more likely of the two to occur in the selected models. The sum of their probability of appearance is over 95%.

Trust levels of the safety claim by the producer of brand B (*trustclaim.*) always had an influence on the choice of milk. But the sign of their coefficients tended to vary compared to parents who were neutral about the claim. Parents who more or less did not trust the claim were more likely to choose brand A and those who more or less trusted the claim were more likely to choose brand B. In general, the probability of choosing brand B increases with more trust.

The number of averting behaviors (*averting*) was also very likely to influence the choice of milk. Parents who took more action to avoid unsafe food tended to choose brand B. This is not surprising since the choice of brand B itself can be classified as an averting hebavior.

Concern levels (*concernl.*) also had an influence on the choice of milk. Compared to parents who were very concerned about the current food safety situation in Hunan province, those who were only somewhat concerned were more likely to choose brand A. If parents were not very concerned about food safety, they were not willing to pay more money for the safety claim.

There are two explanatory variables that were not very likely to influence the choice of milk, but had interesting implications. First, local food safety incidents were closely related to people's daily lives. Therefore, parents who heard more news reports about local food safety incidents tended to choose brand B, since news increased awareness of food safety issues.

Second, parents who spent a little time and energy dealing with a previous food quality or safety problem and were more satisfied with the results were more likely to choose brand A. These parents may have more confidence in procuring satisfactory results if they encountered any problems with brand A, while other parents may prefer to pay more money for brand B to avoid potential problems.

It is worth mentioning that the frequency of children drinking milk (*mfreq.*) was not very likely to influence the choice of milk. One possibility is that parents believed milk was an important source of nutrition for children and did not want to risk switching to a perceived unsafe brand of milk regardless of how frequently their children drank milk.

The “plot” command in the BMA package from R also provides posterior distributions of parameters graphically (see Appendix B Figures B.1, B.2 and B.3 for posterior distributions of all parameters). Figure 3.4 is an example of price parameters with a logit link function. The important explanatory variables, such as *price.15*, tend to have a higher peak than the other two price levels. The location of the peak relative to 0 also indicates the sign of the posterior mean, which is negative for *price.15*.

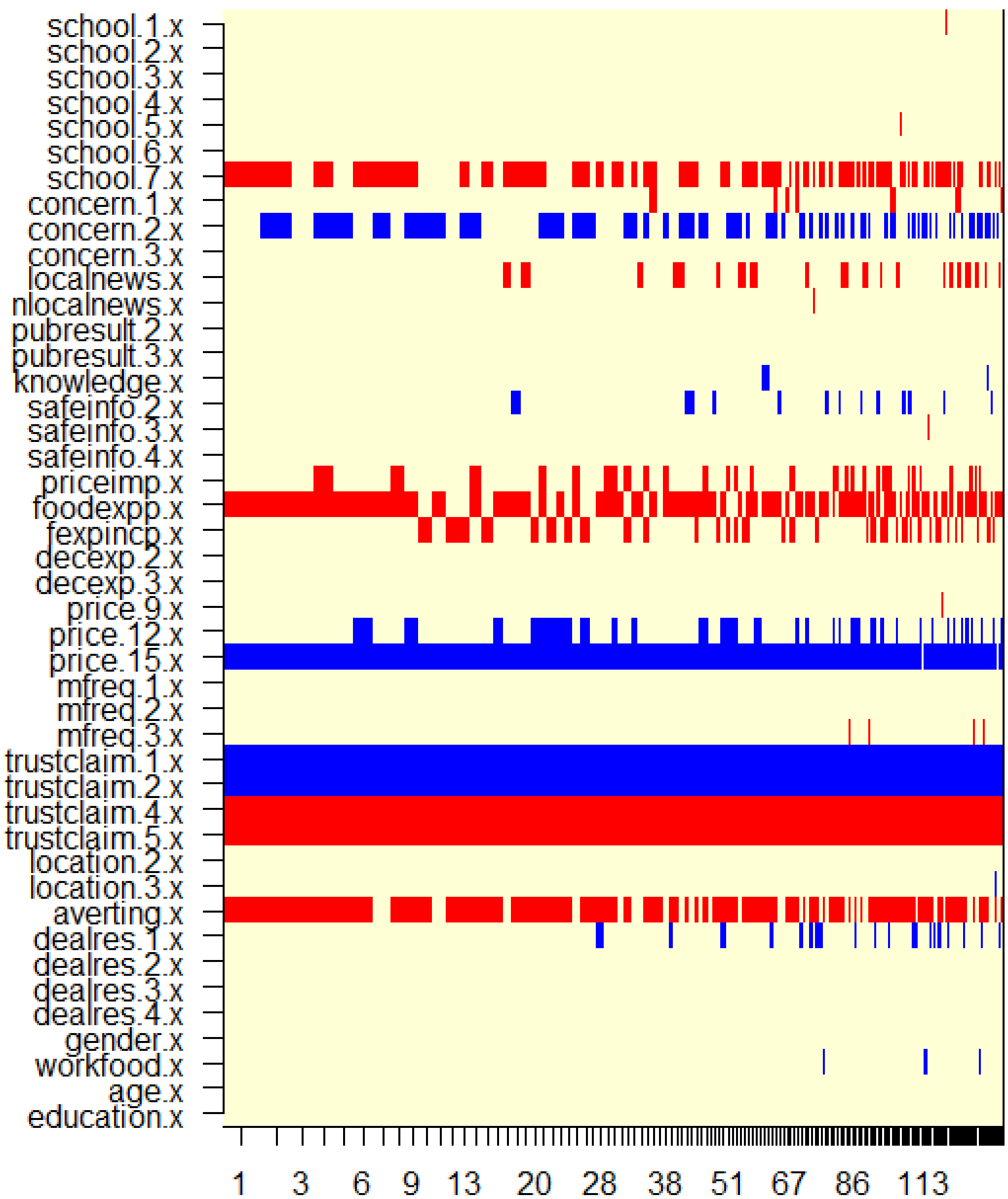

Figure 3.1 Models selected by BMA (logit)

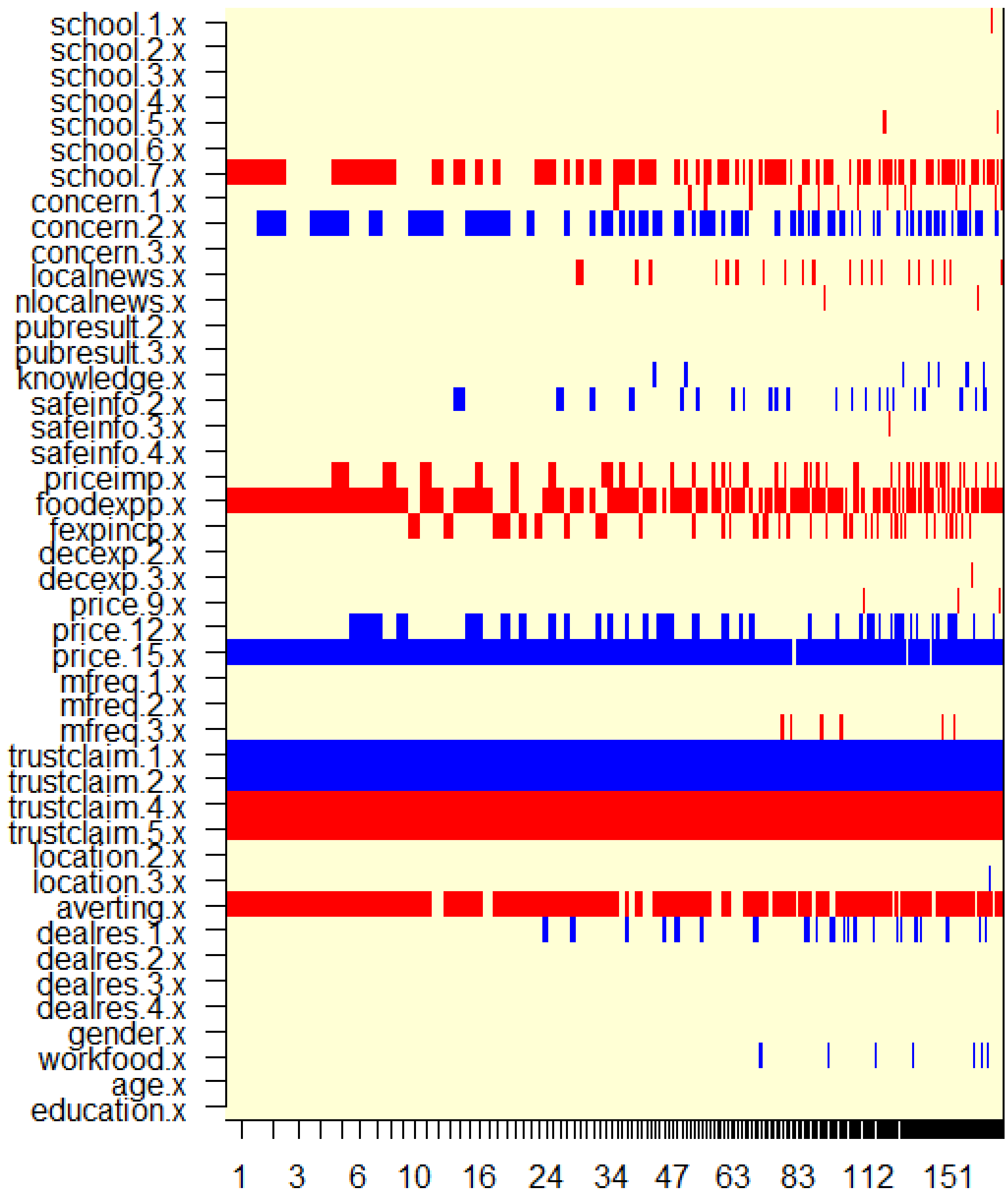

Figure 3.2 Models selected by BMA (probit)

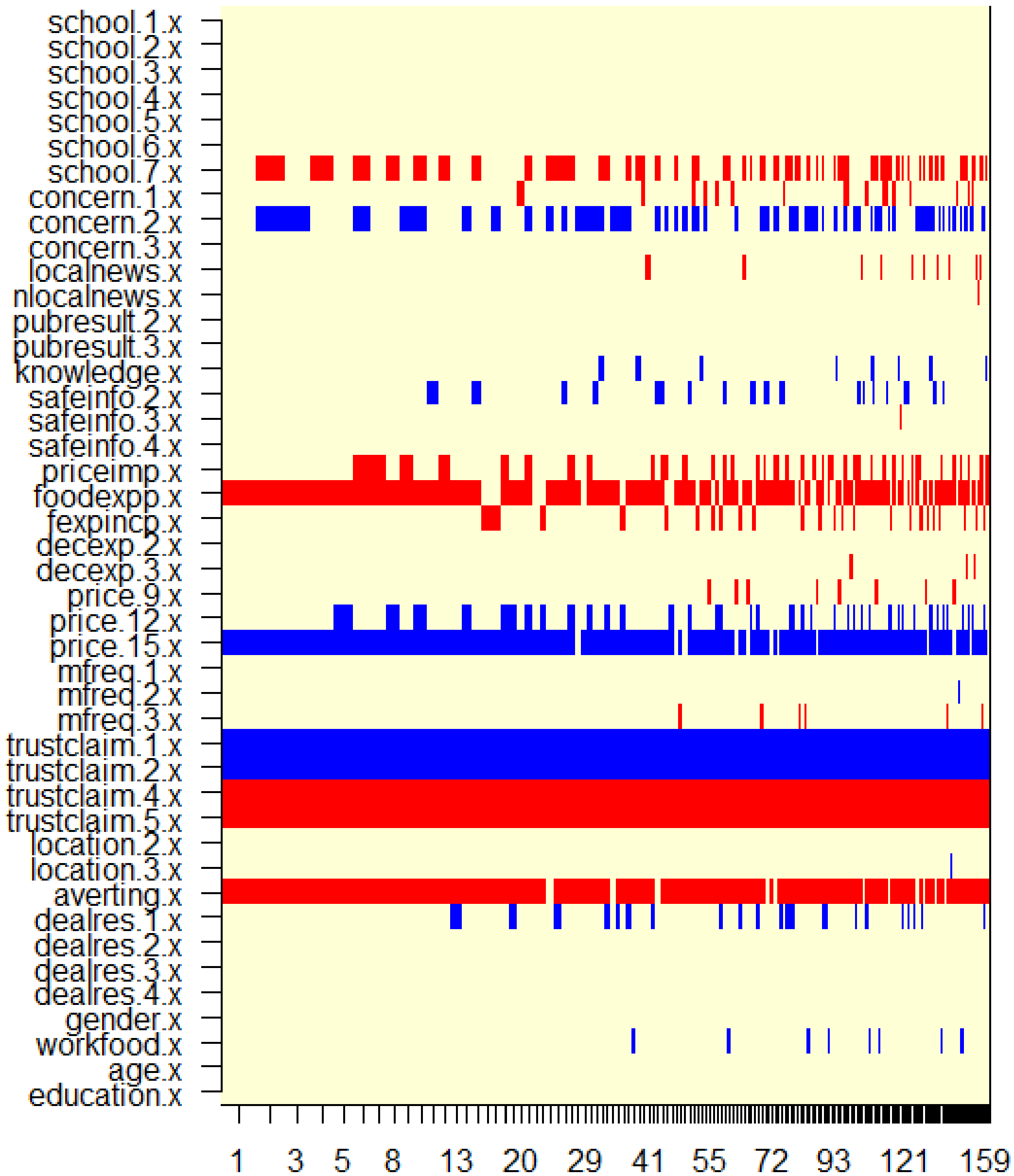

Figure 3.3 Models selected by BMA (cloglog)

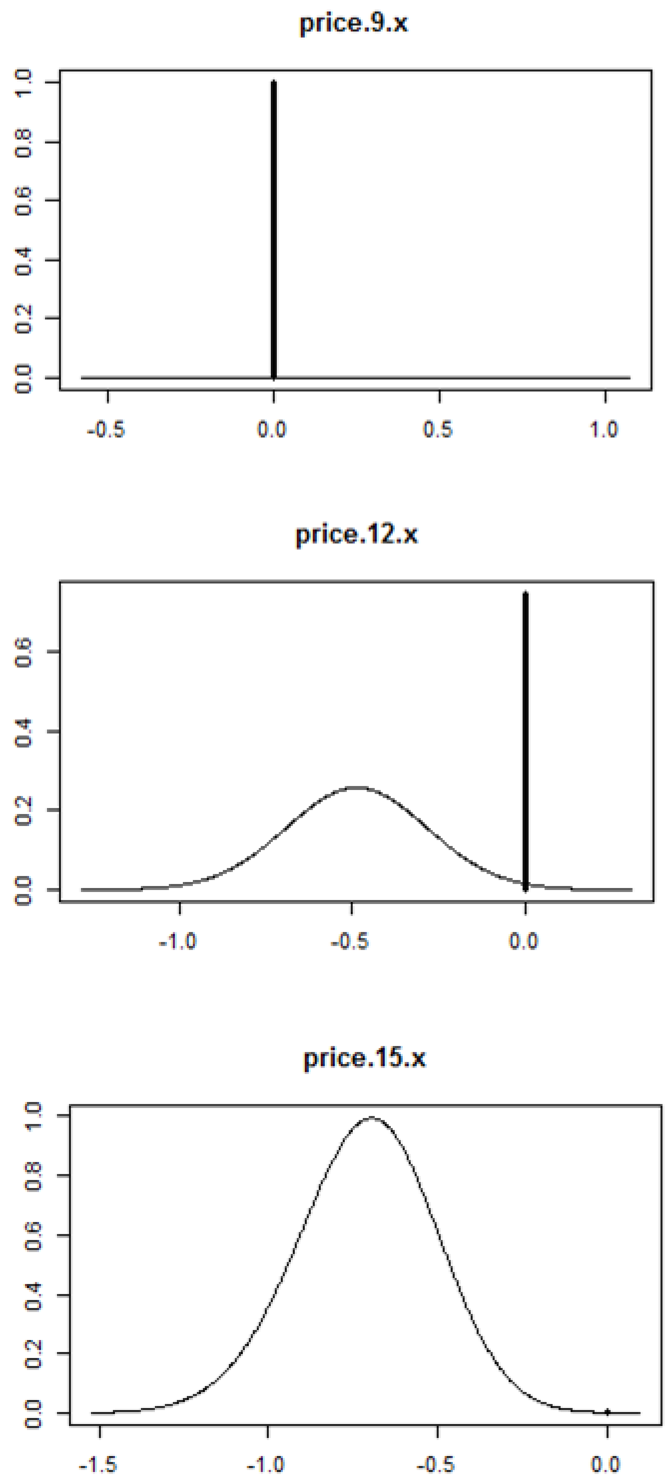

Figure 3.4 Posterior distributions of price parameters

CHAPTER 4 DISCUSSION

The model selection results presented here provide potential insight for food producers and policy makers. A large percentage of parents chose to trust food safety claims by the producer and were willing to pay more for the safety claim. This provides food producers an incentive to make false safety claims on unsafe foods and charge higher prices. Policy makers should implement policies to prevent these kinds of fraudulent claims.

Conversely, there are costs to producers to ensure food safety. But since a small increase in food price does not seem to influence consumer choice, food producers can increase price by a small amount to cover costs associated with food safety.

For some low-income households it may be difficult to afford more expensive brands to ensure the safety of the food they consume. But if policy makers provide consumers efficient and effective ways to solve any food safety issues, it can still minimize the impact of food safety risks for those households without bringing more living pressure.

CHAPTER 5 CONCLUSION

This study identifies the explanatory variables that impact parents' choice between two brands of milk using two model selection methods: stepwise model selection and Bayesian model averaging (BMA). While stepwise model selection finds one best model, BMA suggests strong model uncertainty. Therefore to consider only one model would not be appropriate.

However, there is consistency between the results from the two model selection methods. Both methods select similar variables such as milk price and food expenditure, which are consistent with economic theory. While model selection methods are purely based on the data, the consistency between the selected empirical model(s) and economic theory provides evidence that model selection methods can be a useful tool in economic research.

Model selection methods also select some interesting variables that may not be very common in previous studies, such as the result of consumer's previous experience in dealing with food quality and safety problems. This is the kind of variable that may be overlooked by economic theory but more or less supported by the data in determining the choice of milk. Thus, model selection methods can complement and provide valuable insights to current economic theory and methodology.

References:

Amini, Shahram M. and Christopher F. Parmeter. "Bayesian Model Averaging in R." *Journal of Economic and Social Measurement* 36, no. 4 (2011): 253–87.

Burnham, Kenneth P. and David R. Anderson "Multimodel Inference: Understanding AIC and BIC in Model Selection." *Sociological Methods & Research* 33, no. 2 (November 1, 2004): 261–304.

Canadian Dairy Information Centre. "Per Capita Global Consumption of Fluid Milk - Canadian Dairy Information Centre (CDIC)." December 8, 2015. Accessed June 25, 2016. http://www.dairyinfo.gc.ca/index_e.php?s1=dff-fcil&s2=cons&s3=consglo&s4=tm-lt.

Cheng, Yingzhe, Jennifer Thacher. "Price or Safety? The Milk Choice of Parents for Their Children in China" Working paper (2016).

Congdon, Peter. *Bayesian Statistical Modelling*. United Kingdom: Wiley, John & Sons, 2006.

Cuaresma, Jesús Crespo and Tomas Slacik. "On the Determinants of Currency Crises: The Role of Model Uncertainty." *Journal of Macroeconomics* 31, no. 4 (December 2009): 621–32.

Deller, Steven and Victor Lledo. "Amenities and Rural Appalachia Economic Growth." *Agricultural and Resource Economics Review* 36, no. 1 (April 2007): 107–32.

Dobson, Annette J. and Adrian G Barnett. *An Introduction to Generalized Linear Models, Third Edition*. 3rd ed. Boca Raton: Chapman & Hall/CRC, 2008.

Du, Wenwen, Huijun Wang, Zhihong Wang, Fengying Zhai, and Bing Zhang. "Trend of Milk Consumption Among Chinese Children and Adolescents Aged 7 to 17 Years Old in 9 Provinces from 1991 to 2006."*Chinese Journal of Epidemiology* 12 (2010): 1349–52.

Eicher, Theo S., Chris Papageorgiou, and Adrian E. Raferty. "Default Priors and Predictive Performance in Bayesian Model Averaging, with Application to Growth Determinants." *Journal of Applied Econometrics* 26, no. 1 (2011): 30-55.

Fernández, Carmen, Eduardo Ley, and Mark F. J. Steel. "Model Uncertainty in Cross-Country Growth Regressions." *Journal of Applied Econometrics* 16, no. 5 (September 2001): 563–76.

Garratt, Anthony, Kevin Lee, M. Hashem Pesaran, and Yongcheol Shin. "Forecast Uncertainties in Macroeconomic Modeling: An Application to the U.K. Economy." *Journal of the American Statistical Association* 98, no. 464 (December 2003): 829–38.

Green, P. J. . "Iteratively Reweighted Least Squares for Maximum Likelihood Estimation, and Some Robust and Resistant Alternatives." *Journal of the Royal Statistical Society* 46, no. 2 (1984): 149–92.

Koske, I. and I. Wanner. “The Drivers of Labour Income Inequality – an Analysis Based on Bayesian Model Averaging.” *Applied Economics Letters* 20, no. 2 (February 2013): 123–26.

Life Time. “Only unethical small companies produce ‘leather milk’.” 1997. Accessed June 25, 2016.
http://paper.people.com.cn/smsb/html/2011-02/22/content_751306.htm.

Moral-Benito, Enrique. “Model Averaging in Economics: An Overview.” *Journal of Economic Surveys* 29, no. 1 (2015): 46–75.

Penny, W., J. Mattout, and N. Trujillo-Barreto. “Bayesian model selection and averaging.” In *Statistical Parametric Mapping: The analysis of functional brain images,* edited by K. Friston, J. Ashburner, S. Kiebel, T. Nichols, and W. Penny, Elsevier, London, 2006

Raftery, Adrian E. “Bayesian Model Selection in Social Research.” *Sociological Methodology* 25 (1995): 111. doi:10.2307/271063.

Raftery, A. “Approximate Bayes Factors and Accounting for Model Uncertainty in Generalised Linear Models.” *Biometrika* 83, no. 2 (June 1, 1996): 251–66.

Raftery, Adrian E., Ian S. Painter, and Christopher T. Volinsky. “BMA: An R Package for Bayesian Model Averaging.” *R News* 5 (2005): 2–8.

Sala-i-Martin, Xavier, Gernot Doppelhofer, and Ronald I Miller. “Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach.”*American Economic Review* 94, no. 4 (September 2004): 813–35.

Tobias, Justin L. and Mingliang Li. “Returns to Schooling and Bayesian Model Averaging: A Union of Two Literatures.” *Journal of Economic Surveys* 18, no. 2 (April 2004): 153–80.

United States Department of Agriculture. “Dairy: World Markets and Trade.” December 2015. Accessed June 25, 2016. http://apps.fas.usda.gov/psdonline/circulars/dairy.pdf.

Wright, Jonathan H. “Bayesian Model Averaging and Exchange Rate Forecasts.” *Journal of Econometrics* 146, no. 2 (October 2008): 329–41.

Yau, Arthur. “Aflatoxins in Milk.” *Food Safety Focus* 67 (2012): 1–4. Accessed June 25, 2016. http://www.cfs.gov.hk/sc_chi/multimedia/multimedia_pub/files/FSF67_2012-02-15.pdf.

Young, Cristobal. “Model Uncertainty in Sociological Research: An Application to Religion and Economic Growth.” *American Sociological Review* 74, no. 3 (June 1, 2009): 380–97.

APPENDIX A

RELEVANT QUESTIONS FROM THE SURVEY (Version 1)

1. What is your current level of concern about food quality and safety in Hunan? *Circle one.*

Not at all concerned	Somewhat concerned	Fairly Concerned	Very concerned
(1)	(2)	(3)	(4)

2. Which of the following news did you hear or see recently? *Check all that apply.*

1	Ginger with Shennongdan
2	Fake lamb
3	Two people sold 40 tons of pork that die from sick
4	None of the above

3. Do any of the grocery stores or wet market at which you typically shop publish daily food inspection results for their agricultural products to consumers? *Check one.*

1	Yes
2	No
3	Not sure

4. In the following systems and food safety labels, have you previously heard of/seen any of them? Do you know their meaning? *Check all that apply*.

	I have heard of/seen it	I know it	I have never heard of/seen and do not know it
ISO 9000	1	2	3
ISO 22000	1	2	3
HACCP	1	2	3
质量安全	1	2	3
无公害农产品	1	2	3
绿色食品 GreenFood	1	2	3
健康食品	1	2	3
有机食品 CERTIFIED ORGANIC COFCC	1	2	3

5. Have frequently, if at all, do you use internet, TV, newspaper and other mass media to check whether a brand of food is safe? *Circle one.*

Never	Sometimes	Fairly often	Very often
(1)	(2)	(3)	(4)

6. Choose the 2 most important and the 2 least important characteristics that help you to identify whether a food is safe. *Check two for each.*

	Most important	Least important
Reputation of the brand	1	1
Appearance and taste of food	2	2
Price	3	3
Where the food is produced	4	4
Where the food is sold	5	5
Ingredients on the package	6	6
Manufacturing and expiration dates	7	7
Safety certification label on the package	8	8

7. What is your average monthly food expenditure? *Check one.*

1	Less than ￥499	5	￥2000 – 2499
2	￥500 - 999	6	￥2500 – 2999
3	￥1000 - 1499	7	More than ￥3000
4	￥1500 - 1999		

8. According to the financial situation of your household, what is the highest affordable increase in your monthly food expenditure?

1	Less than ￥25	8	Less than ￥700
2	Less than ￥100	9	Less than ￥800
3	Less than ￥200	10	Less than ￥1000
4	Less than ￥300	11	Less than ￥1200
5	Less than ￥400	12	Less than ￥1500
6	Less than ￥500	13	More than ￥1500
7	Less than ￥600		

9. Which category of spending would you have to decrease first in order to afford a higher food expenditure? *Check one.*

1	Savings
2	Leisure
3	Other (Please write it down)________________________________

10. On average, how frequently does your child drink milk? *Check one.*

1	Never **(⟶Go to question 13)**
2	Less than once a week
3	At least once a week
4	Almost every day

11. Currently there are two brands of milk (milk A and milk B) in domestic market. They look the same except the price and safety claim. Which brand would you choose for your children?

	Milk A	Milk B
Price:	￥3/250ml	￥6/250ml
Safety claim:	There is no special safety claim from the producer.	The producer claims that they guarantee the safety of this milk.
I choose ⟶	A	B

12. How much do you trust the safety claims of milk B in the above question? *Circle one.*

Do not trust at all	Somewhat not trust	Indifferent	Somewhat trust	Absolutely trust
(1)	(2)	(3)	(4)	(5)

13. Where do you usually buy groceries? *Check all that apply.*

1	Wet market
2	Supermarket
3	Other (Please write it down) ________________________________

14. Have you ever taken any of the following actions to avoid food safety issues? *Check all that apply.*

1	Avoid eating certain foods with a high food safety risk
2	Only choose the brands of food that you trust.
3	Use tricks you learnt from some sources to choose relatively safer food, such as observe appearance of food.
4	Make your own processed food, such as soy milk, sweet wine, etc.
5	Grow vegetables or raise poultry by yourself.
6	Get agricultural products from your farmer relatives.
7	Purchase imported foods instead of domestic foods in store and/or online.
8	Other (Please write it down)____________________________________
9	No. I have never done anything special to deal with food safety issues.

15. If you ever take any actions to deal with a food that has a quality or safety problem, what was the result in most cases? *Check one.*

1	I was satisfied with the final result, and I only spent a little time and energy.
2	I was satisfied with the final result, but I spent too much time and energy.
3	I was not satisfied with the final result, but I only spent a little time and energy.
4	I was not satisfied with the final result, and I spent too much time and energy.
5	I have never taken any actions.

16. What is your gender? *Check one.*

1	Male
2	Female

17. How many people live in this household including yourself? ________

18. Does anyone in your family work in food related industry, such as food processing, restaurant, grocery store, food inspection, etc? *Check one.*

1	Yes
2	No

19. What is your age? ____________________

20. What is the highest degree or level of school you have completed? *Check one.*

1	None	5	Junior college
2	Elementary school	6	Bachelor’s degree
3	Junior high school	7	Master’s degree
4	Senior high school	8	Doctorate degree

Table A.1 Variables definitions

Variable	Meaning	
y	The parent chose brand B of milk	
school.1	The first school in Changsha city	
school.2	The second school in Changsha city	
school.3	The third school in Changsha city	
school.4	The fourth school in Changsha city	
school.5	The first school in Huaihua city	
school.6	The second school in Huaihua city	
school.7	The third school in Huaihua city	
school.8	The fourth school in Huaihua city	
concernl.1	**Concern level of current food quality and safety in Hunan**	Not at all concerned
concernl.2		Somewhat concerned
concernl.3		Fairly concerned
concernl.4		Very concerned
localnews	The number of recent local news on food safety issues you have heard that are given in the survey	
nlocalnews	Whether you have heard a recent non-local news on food safety issues given in the survey	
pubresult.1	**Publication of food safety inspection results by store/market you went**	publish
pubresult.2		Not publish
pubresult.3		Not sure
knowledge	A knowledge index on food labels and food safety management systems. The survey provides three food safety management systems (HACCP, ISO9000, ISO22000) and five food labels (pollution-free agricultural product, green food, quality safety, organic food and a fake one). Those systems and labels are supposed to help improving food safety and guide people's choice of food brands. The survey asked parents if they had heard of/seen or even know the meaning of those labels and systems. For each system or label, if they had heard of/seen it or even know the meaning, they get 1 point. Otherwise they get 0 point. We sum the points except for the fake label. Therefore, parents can get at most 7 points. But if a parent claimed that he/she had heard of/seen or even knew the meaning of the fake label, we take 50% off from his/her points.	
safeinfo.1	**Frenquency of using mass media to check food safety information**	Never
safeinfo.2		Sometimes
safeinfo.3		Fairly often
safeinfo.4		Very often
priceimp	Price is one of the most important characteristics to identify safe food	
foodexpp	Monthly food expenditure per person in 100 yuan	

fexpincp	Affordable increase in food expenditure per person in 100 yuan	
decexp.1	**Additional food expenditure would decrease**	Saving
decexp.2		Leisure
decexp.3		Other
mfreq.1	**Frequency of children drinking milk**	Never
mfreq.2		Less than once a week
mfreq.3		At least once a week
mfreq.4		Almost every day
price.6	**Milk price of brand B in yuan per 250ml**	6
price.9		9
price.12		12
price.15		15
trustclaim.1	**Trust level of the special safety claim by the producer of brand B milk**	Not at all trust
trustclaim.2		Somewhat not trust
trustclaim.3		Neutral
trustclaim.4		Somewhat trust
trustclaim.5		Very trust
location.1	**Location of grocery shopping**	Wet market
location.2		Supermarket
location.3		Other
averting	The number of averting behaviors to avoid unsafe food. Those behaviors include avoid food with high safety risk, only choose brands you trust, use tricks to choose relatively safer food, make processed food at home, grow vegetables or raise poultry by yourself, get agricultural products from you farmer relatives, purchase imported foods, other	
dealres1	**Result from previous experience of dealing with food that has a quality or safety problem**	Satisfied & spent a little time and energy
dealres2		Satisfied & spent too much time and energy
dealres3		Not satisfied & spent a little time and energy
dealres4		Not satisfied & spent too much time and energy
dealres5		Not take action
gender	Male	
hhsize	Household size	
workfood	Have friends or relatives with food related job	
age	Age	
education	Years of education	

Note: All indicator variables take 1 if it is true, 0 otherwise.

Table A.2 Descriptive statistics of variables

Variable	Mean	Standard Deviation	Min	Max
y	0.80	0.40	0	1
school.1	0.08	0.27	0	1
school.2	0.11	0.31	0	1
school.3	0.18	0.39	0	1
school.4	0.11	0.31	0	1
school.5	0.14	0.35	0	1
school.6	0.14	0.35	0	1
school.7	0.12	0.32	0	1
school.8	0.13	0.34	0	1
concernl.1	0.01	0.11	0	1
concernl.2	0.23	0.42	0	1
concernl.3	0.39	0.49	0	1
concernl.4	0.36	0.48	0	1
localnews	1.46	0.69	0	2
nlocalnews	0.57	0.50	0	1
pubresult.1	0.14	0.34	0	1
pubresult.2	0.60	0.49	0	1
pubresult.3	0.27	0.44	0	1
knowledge	3.58	1.46	0	7
safeinfo.1	0.08	0.28	0	1
safeinfo.2	0.30	0.46	0	1
safeinfo.3	0.45	0.50	0	1
safeinfo.4	0.16	0.37	0	1
priceimp	0.01	0.12	0	1
foodexpp	4.49	1.77	0.42	10
fexpincp	1.67	1.20	0.042	7.5
decexp.1	0.32	0.47	0	1
decexp.2	0.59	0.49	0	1
decexp.3	0.09	0.28	0	1
mfreq.1	0.00	0.07	0	1
mfreq.2	0.09	0.29	0	1
mfreq.3	0.24	0.43	0	1
mfreq.4	0.66	0.47	0	1
price.6	0.24	0.43	0	1
price.9	0.26	0.44	0	1
price.12	0.25	0.43	0	1
price.15	0.26	0.44	0	1
trustclaim.1	0.04	0.19	0	1
trustclaim.2	0.21	0.41	0	1
trustclaim.3	0.29	0.46	0	1

trustclaim.4	0.42	0.49	0	1
trustclaim.5	0.04	0.19	0	1
location.1	0.17	0.38	0	1
location.2	0.82	0.38	0	1
location.3	0.00	0.07	0	1
averting	3.05	1.40	0	7
dealres1	0.25	0.44	0	1
dealres2	0.19	0.39	0	1
dealres3	0.18	0.38	0	1
dealres4	0.21	0.41	0	1
dealres5	0.17	0.38	0	1
gender	0.40	0.49	0	1
workfood	0.38	0.48	0	1
age	37.34	6.34	24	74
education	13.27	2.62	0	22
Numberof observations	1148			

APPENDIX B

Table B.1 BMA result (logit)

	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
Intercept	100.00	0.35	0.41	0.00	0.18	0.18	0.14	0.37
school.1	0.30	0.00	0.03	.	.	.	.	.
school.2	0.00	0.00	0.00	.	.	.	.	.
school.3	0.00	0.00	0.00	.	.	.	.	.
school.4	0.00	0.00	0.00	.	.	.	.	.
school.5	0.30	0.00	0.02	.	.	.	.	.
school.6	0.00	0.00	0.00	.	.	.	.	.
school.7	59.70	0.46	0.44	0.80	0.78	.	0.80	.
concern.1	3.60	0.06	0.39	.	.	.	.	.
concern.2	48.20	-0.25	0.29	.	-0.49	.	-0.54	-0.50
concern.3	0.00	0.00	0.00	.	.	.	.	.
localnews	13.00	0.04	0.10	.	.	.	.	.
nlocalnews	0.40	0.00	0.02	.	.	.	.	.
pubresult.2	0.00	0.00	0.00	.	.	.	.	.
pubresult.3	0.00	0.00	0.00	.	.	.	.	.
knowledge	1.30	0.00	0.01	.	.	.	.	.
safeinfo.2	6.50	-0.02	0.10	.	.	.	.	.
safeinfo.3	0.30	0.00	0.01	.	.	.	.	.
safeinfo.4	0.00	0.00	0.00	.	.	.	.	.
priceimp	21.60	0.46	1.01	.	.	.	2.26	.
foodexpp	73.80	0.13	0.09	0.18	0.17	0.15	0.18	0.15
fexpincp	24.00	0.05	0.10	.	.	.	.	.
decexp.2	0.00	0.00	0.00	.	.	.	.	.
decexp.3	0.00	0.00	0.00	.	.	.	.	.
price.9	0.30	0.00	0.02	.	.	.	.	.
price.12	25.70	-0.13	0.24	.	.	.	.	.
price.15	99.40	-0.71	0.21	-0.70	-0.68	-0.65	-0.67	-0.62
mfreq.1	0.00	0.00	0.00	.	.	.	.	.
mfreq.2	0.00	0.00	0.00	.	.	.	.	.
mfreq.3	1.30	0.00	0.04	.	.	.	.	.
trustclaim.1	100.00	-1.96	0.36	-1.95	-1.97	-1.94	-2.03	-1.95
trustclaim.2	100.00	-0.93	0.19	-0.94	-0.93	-0.93	-0.97	-0.92
trustclaim.4	100.00	1.73	0.25	1.73	1.75	1.70	1.74	1.72
trustclaim.5	100.00	2.60	1.03	2.62	2.59	2.64	2.59	2.61
location.2	0.00	0.00	0.00	.	.	.	.	.
location.3	0.30	0.00	0.08	.	.	.	.	.
averting	79.30	0.15	0.09	0.19	0.17	0.19	0.18	0.17

dealres.1	8.00	-0.03	0.13	.	.	.	.	.
dealres.2	0.00	0.00	0.00	.	.	.	.	.
dealres.3	0.00	0.00	0.00	.	.	.	.	.
dealres.4	0.00	0.00	0.00	.	.	.	.	.
gender	0.00	0.00	0.00	.	.	.	.	.
workfood	1.00	0.00	0.03	.	.	.	.	.
age	0.00	0.00	0.00	.	.	.	.	.
education	0.00	0.00	0.00	.	.	.	.	.
nVar				8	9	7	10	8
BIC				-7110	-7110	-7109	-7109	-7109
post prob				0.05	0.04	0.03	0.03	0.03

Notes: 1. p!=0 is the probability of each explanatory appears in selected models.
2. EV is the posterior mean of parameter.
3. SD is the posterior standard deviation of parameter.
4. post prob is the posterior probability of model.
5. Models 1-5 are the top five models with the highest posterior probability.

Table B.2 BMA result (probit)

	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
Intercept	100.00	0.25	0.23	0.04	0.15	0.13	0.24	0.12
school.1	0.20	0.00	0.01	.	.	.	.	.
school.2	0.00	0.00	0.00	.	.	.	.	.
school.3	0.00	0.00	0.00	.	.	.	.	.
school.4	0.00	0.00	0.00	.	.	.	.	.
school.5	0.50	0.00	0.02	.	.	.	.	.
school.6	0.00	0.00	0.00	.	.	.	.	.
school.7	56.10	0.24	0.25	0.44	0.44	.	.	0.45
concern.1	5.10	0.05	0.26	.	.	.	.	.
concern.2	48.70	-0.14	0.17	.	-0.29	.	-0.28	-0.31
concern.3	0.00	0.00	0.00	.	.	.	.	.
localnews	7.90	0.01	0.04	.	.	.	.	.
nlocalnews	0.50	0.00	0.01	.	.	.	.	.
pubresult.2	0.00	0.00	0.00	.	.	.	.	.
pubresult.3	0.00	0.00	0.00	.	.	.	.	.
knowledge	2.80	0.00	0.01	.	.	.	.	.
safeinfo.2	10.70	-0.02	0.07	.	.	.	.	.
safeinfo.3	0.50	0.00	0.01	.	.	.	.	.
safeinfo.4	0.00	0.00	0.00	.	.	.	.	.
priceimp	22.70	0.28	0.60	.	.	.	.	1.32
foodexpp	75.00	0.07	0.05	0.10	0.10	0.09	0.09	0.10
fexpincp	20.30	0.02	0.05	.	.	.	.	.
decexp.2	0.00	0.00	0.00	.	.	.	.	.
decexp.3	0.20	0.00	0.01	.	.	.	.	.
price.9	0.70	0.00	0.02	.	.	.	.	.
price.12	28.00	-0.08	0.14	.	.	.	.	.
price.15	99.10	-0.40	0.12	-0.40	-0.38	-0.37	-0.35	-0.37
mfreq.1	0.00	0.00	0.00	.	.	.	.	.
mfreq.2	0.00	0.00	0.00	.	.	.	.	.
mfreq.3	1.90	0.00	0.03	.	.	.	.	.
trustclaim.1	100.00	-1.19	0.22	-1.18	-1.19	-1.18	-1.18	-1.22
trustclaim.2	100.00	-0.56	0.11	-0.56	-0.56	-0.56	-0.56	-0.58
trustclaim.4	100.00	0.91	0.13	0.92	0.93	0.90	0.91	0.93
trustclaim.5	100.00	1.28	0.43	1.29	1.26	1.29	1.27	1.26
location.2	0.00	0.00	0.00	.	.	.	.	.
location.3	0.20	0.00	0.04	.	.	.	.	.
averting	88.60	0.10	0.05	0.11	0.10	0.11	0.10	0.11
dealres.1	10.00	-0.02	0.08	.	.	.	.	.
dealres.2	0.00	0.00	0.00	.	.	.	.	.
dealres.3	0.00	0.00	0.00	.	.	.	.	.

dealres.4	0.00	0.00	0.00	.	.	.	.	.
gender	0.00	0.00	0.00	.	.	.	.	.
workfood	1.90	0.00	0.02	.	.	.	.	.
age	0.00	0.00	0.00	.	.	.	.	.
education	0.00	0.00	0.00	.	.	.	.	.
nVar				8.00	9.00	7.00	8.00	10.00
BIC				-7110.00	-7110.00	-7110.00	-7109.00	-7109.00
post prob				0.04	0.04	0.03	0.03	0.02

Notes: 1. p!=0 is the probability of each explanatory appears in selected models.
2. EV is the posterior mean of parameter.
3. SD is the posterior standard deviation of parameter.
4. post prob is the posterior probability of model.
5. Models 1-5 are the top five models with the highest posterior probability.

Table B.3 BMA result (cloglog)

	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
Intercept	100.00	-0.09	0.20	-0.18	-0.16	-0.10	-0.25	-0.10
school.1	0.00	0.00	0.00	.	.	.	.	.
school.2	0.00	0.00	0.00	.	.	.	.	.
school.3	0.00	0.00	0.00	.	.	.	.	.
school.4	0.00	0.00	0.00	.	.	.	.	.
school.5	0.00	0.00	0.00	.	.	.	.	.
school.6	0.00	0.00	0.00	.	.	.	.	.
school.7	41.70	0.15	0.20	.	0.38	.	0.35	.
concern.1	7.10	0.07	0.30	.	.	.	.	.
concern.2	43.80	-0.11	0.15	.	-0.27	-0.25	.	.
concern.3	0.00	0.00	0.00	.	.	.	.	.
localnews	3.40	0.00	0.02	.	.	.	.	.
nlocalnews	0.20	0.00	0.01	.	.	.	.	.
pubresult.2	0.00	0.00	0.00	.	.	.	.	.
pubresult.3	0.00	0.00	0.00	.	.	.	.	.
knowledge	3.80	0.00	0.01	.	.	.	.	.
safeinfo.2	12.10	-0.02	0.07	.	.	.	.	.
safeinfo.3	0.30	0.00	0.01	.	.	.	.	.
safeinfo.4	0.00	0.00	0.00	.	.	.	.	.
priceimp	24.80	0.31	0.60	.	.	.	.	.
foodexpp	83.50	0.07	0.04	0.08	0.08	0.08	0.08	0.08
fexpincp	11.70	0.01	0.03	.	.	.	.	.
decexp.2	0.00	0.00	0.00	.	.	.	.	.
decexp.3	0.90	0.00	0.02	.	.	.	.	.
price.9	3.10	0.01	0.04	.	.	.	.	.
price.12	24.60	-0.06	0.12	.	.	.	.	-0.24
price.15	94.80	-0.32	0.13	-0.32	-0.31	-0.30	-0.34	-0.41
mfreq.1	0.00	0.00	0.00	.	.	.	.	.
mfreq.2	0.30	0.00	0.01	.	.	.	.	.
mfreq.3	2.60	0.00	0.03	.	.	.	.	.
trustclaim.1	100.00	-1.30	0.27	-1.28	-1.28	-1.28	-1.27	-1.29
trustclaim.2	100.00	-0.56	0.11	-0.55	-0.55	-0.55	-0.55	-0.55
trustclaim.4	100.00	0.72	0.10	0.71	0.74	0.72	0.73	0.72
trustclaim.5	100.00	0.95	0.29	0.95	0.92	0.92	0.95	0.96
location.2	0.00	0.00	0.00	.	.	.	.	.
location.3	0.30	0.00	0.05	.	.	.	.	.
averting	95.10	0.10	0.04	0.11	0.09	0.10	0.11	0.11
dealres.1	12.00	-0.03	0.08	.	.	.	.	.
dealres.2	0.00	0.00	0.00	.	.	.	.	.

dealres.3	0.00	0.00	0.00	.	.	.	.	.
dealres.4	0.00	0.00	0.00	.	.	.	.	.
gender	0.00	0.00	0.00	.	.	.	.	.
workfood	3.30	-0.01	0.03	.	.	.	.	.
age	0.00	0.00	0.00	.	.	.	.	.
education	0.00	0.00	0.00	.	.	.	.	.
nVar				7	9	8	8	8
BIC				-7110	-7109	-7109	-7109	-7108
post prob				0.05	0.04	0.03	0.03	0.03

Notes: 1. p!=0 is the probability of each explanatory appears in selected models.
2. EV is the posterior mean of parameter.
3. SD is the posterior standard deviation of parameter.
4. post prob is the posterior probability of model.
5. Models 1-5 are the top five models with the highest posterior probability.

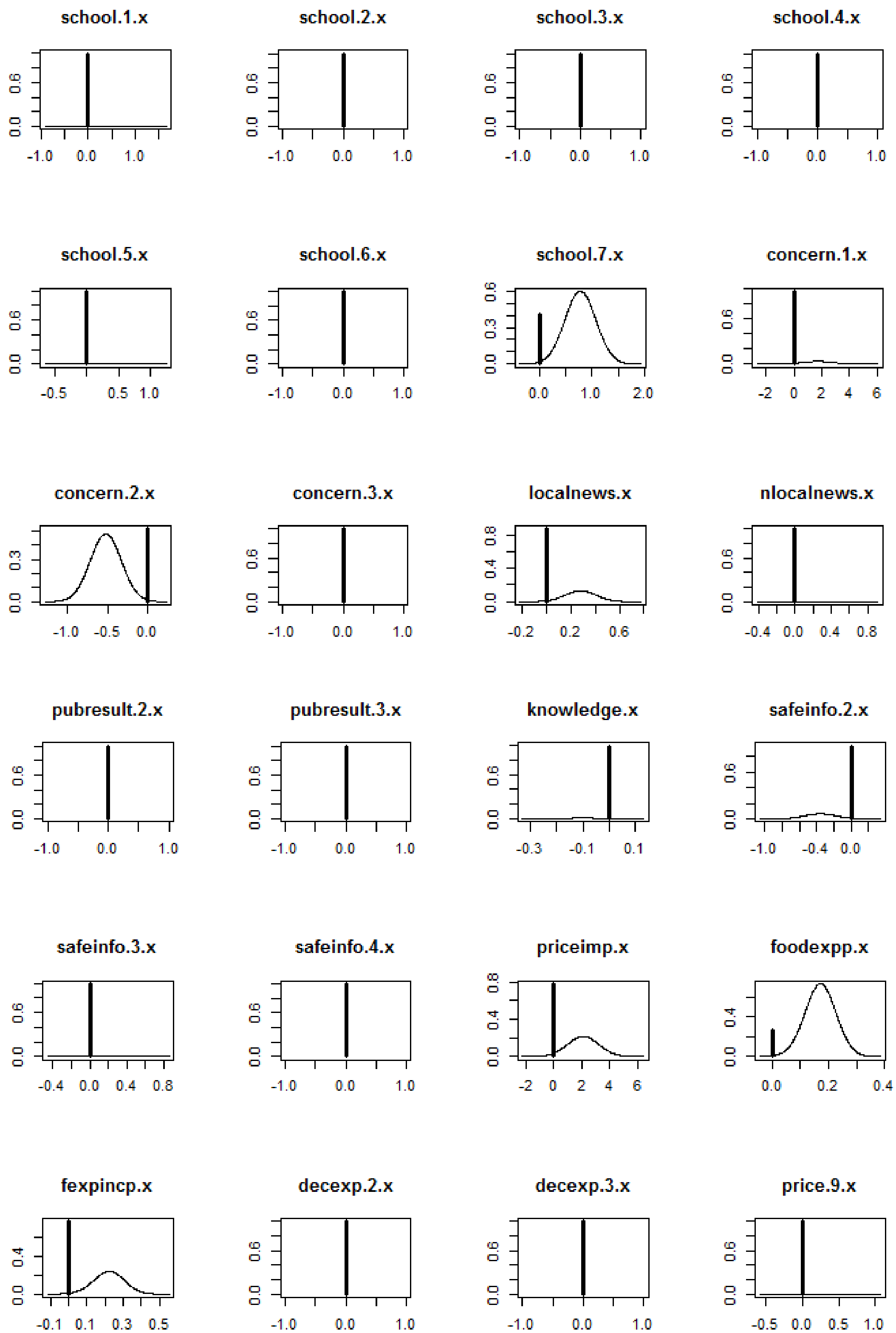

Figure B.1 Posterior distributions of parameters (logit)

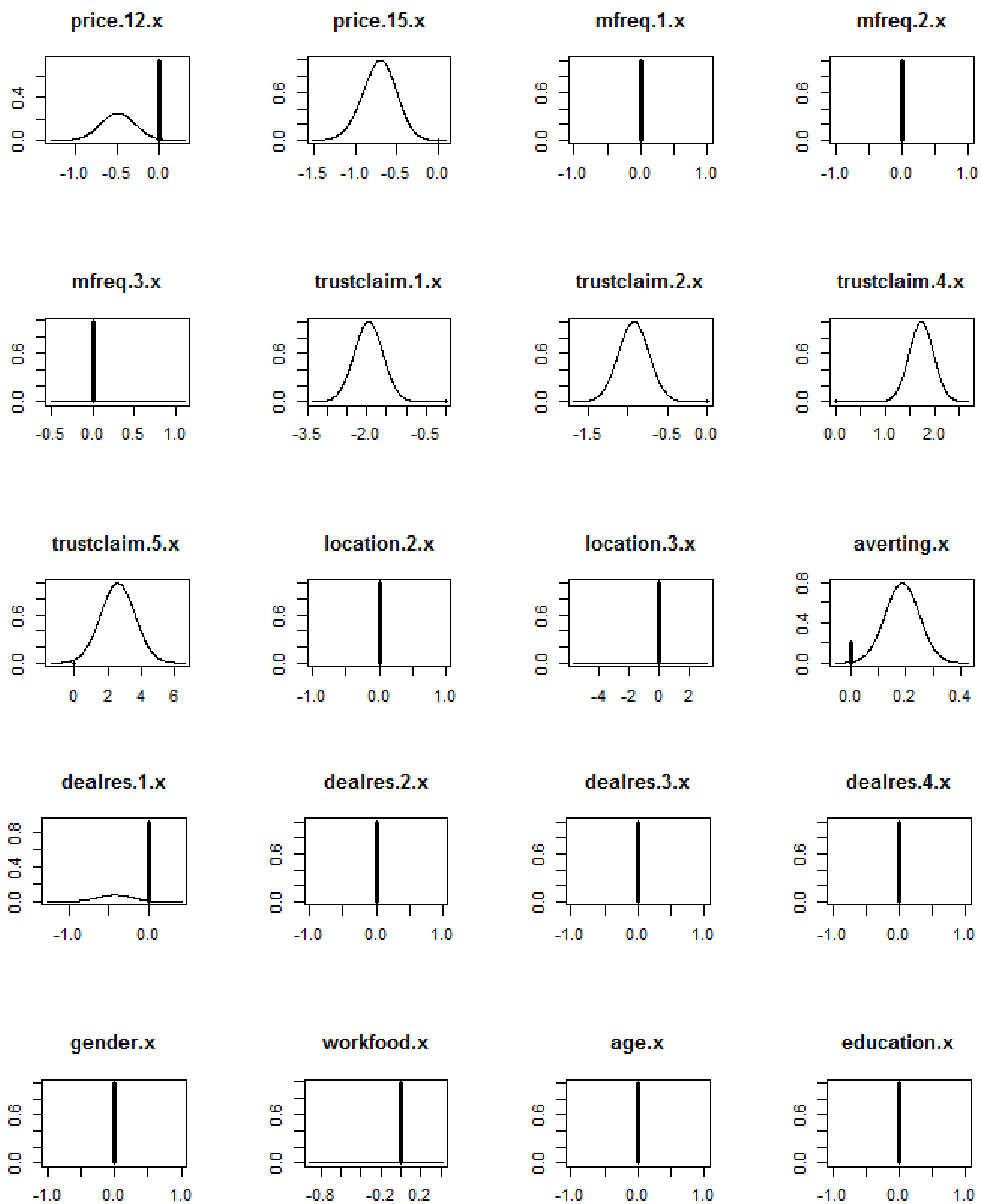

Figure B.1 Posterior distributions of parameters (logit)

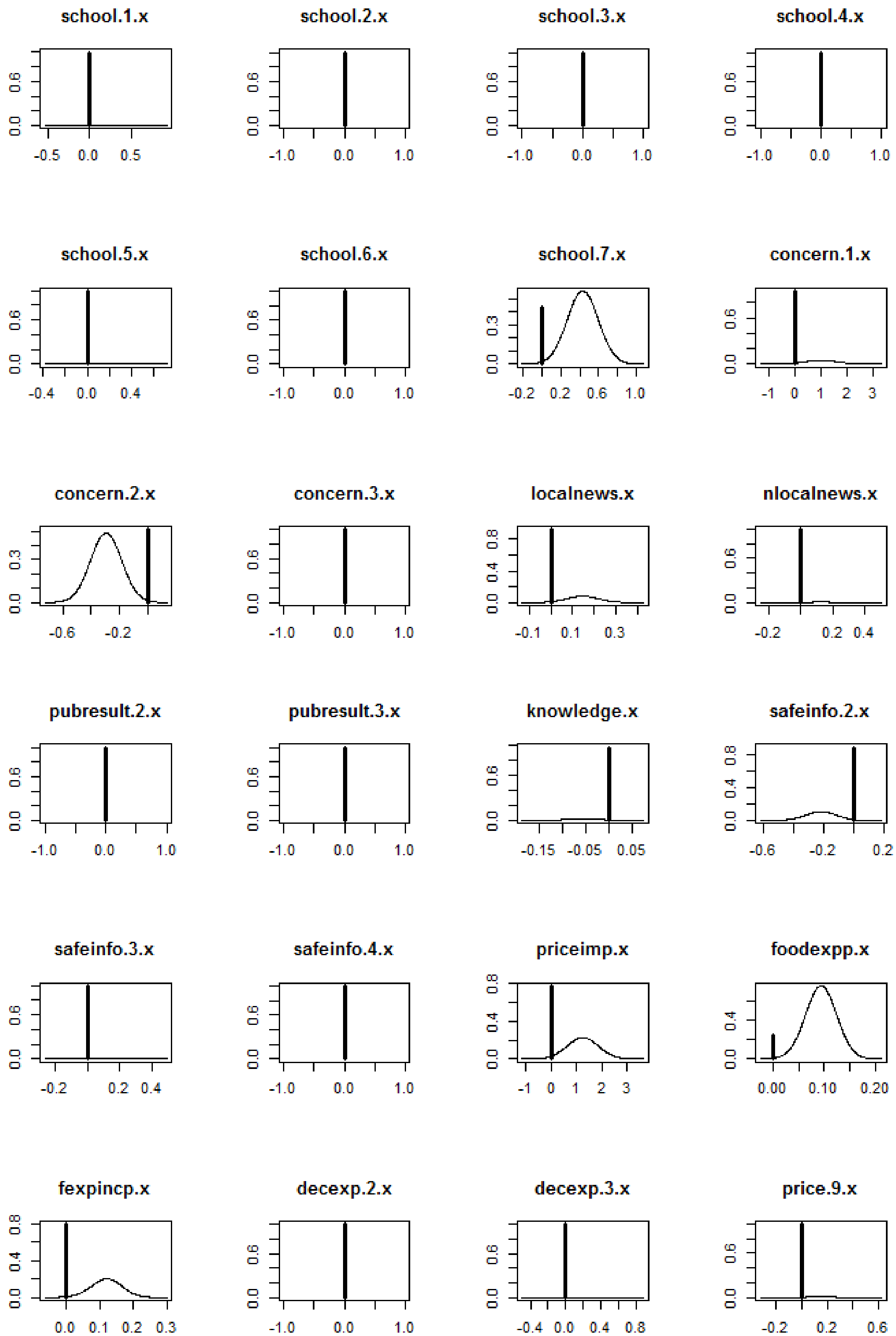

Figure B.2 Posterior distributions of parameters (probit)

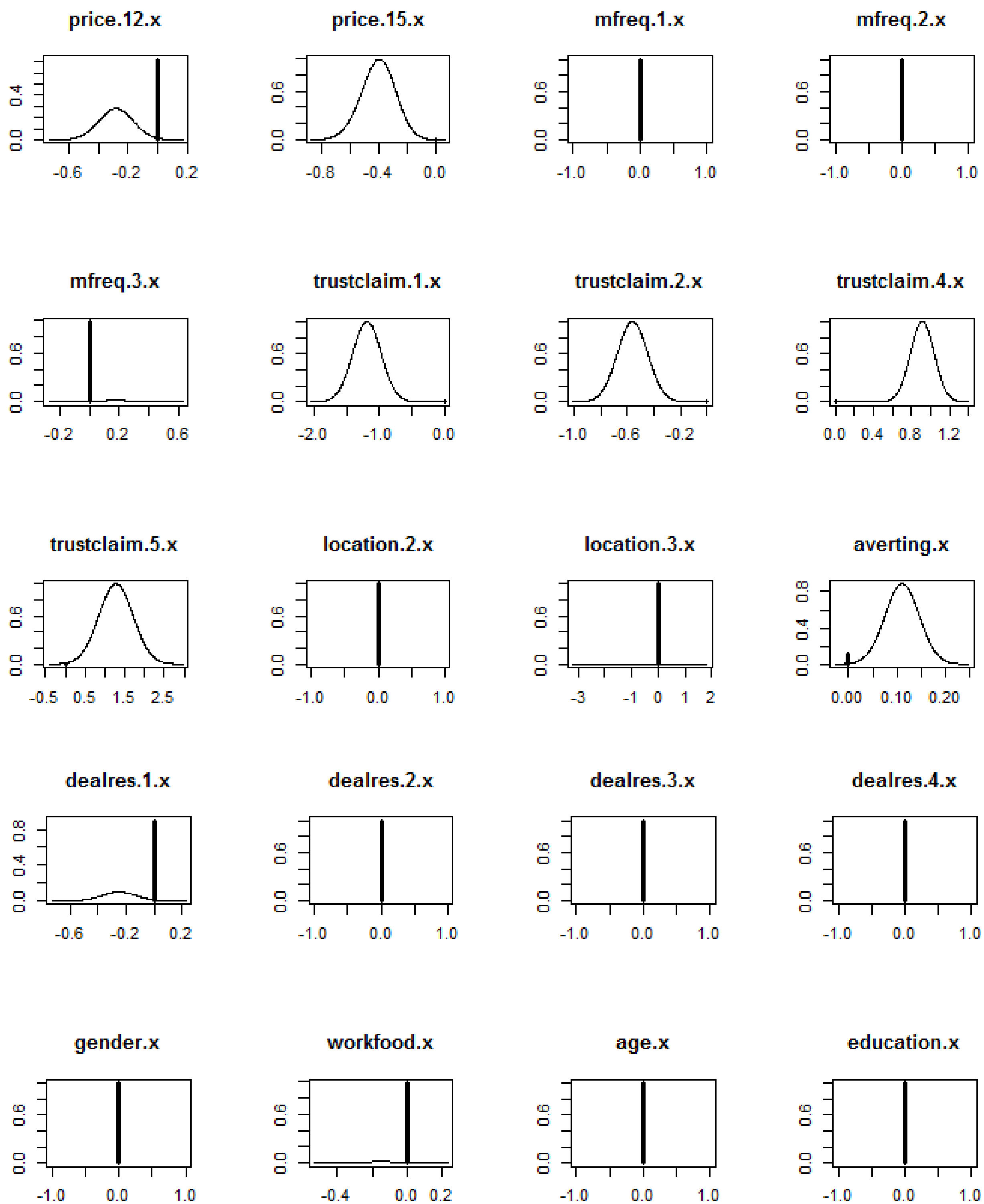

Figure B.2 Posterior distributions of parameters (probit)

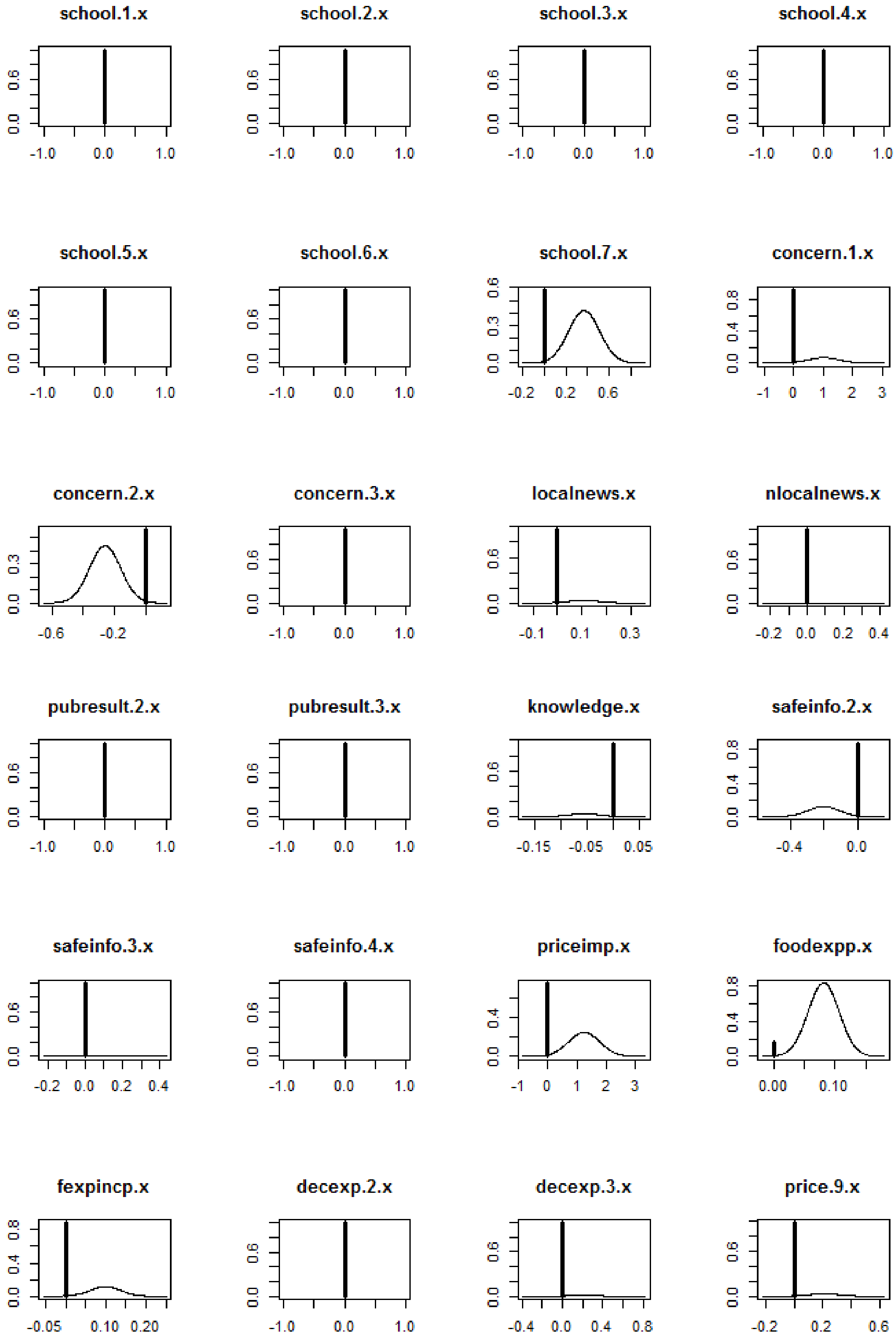

Figure B.3 Posterior distributions of parameters (cloglog)

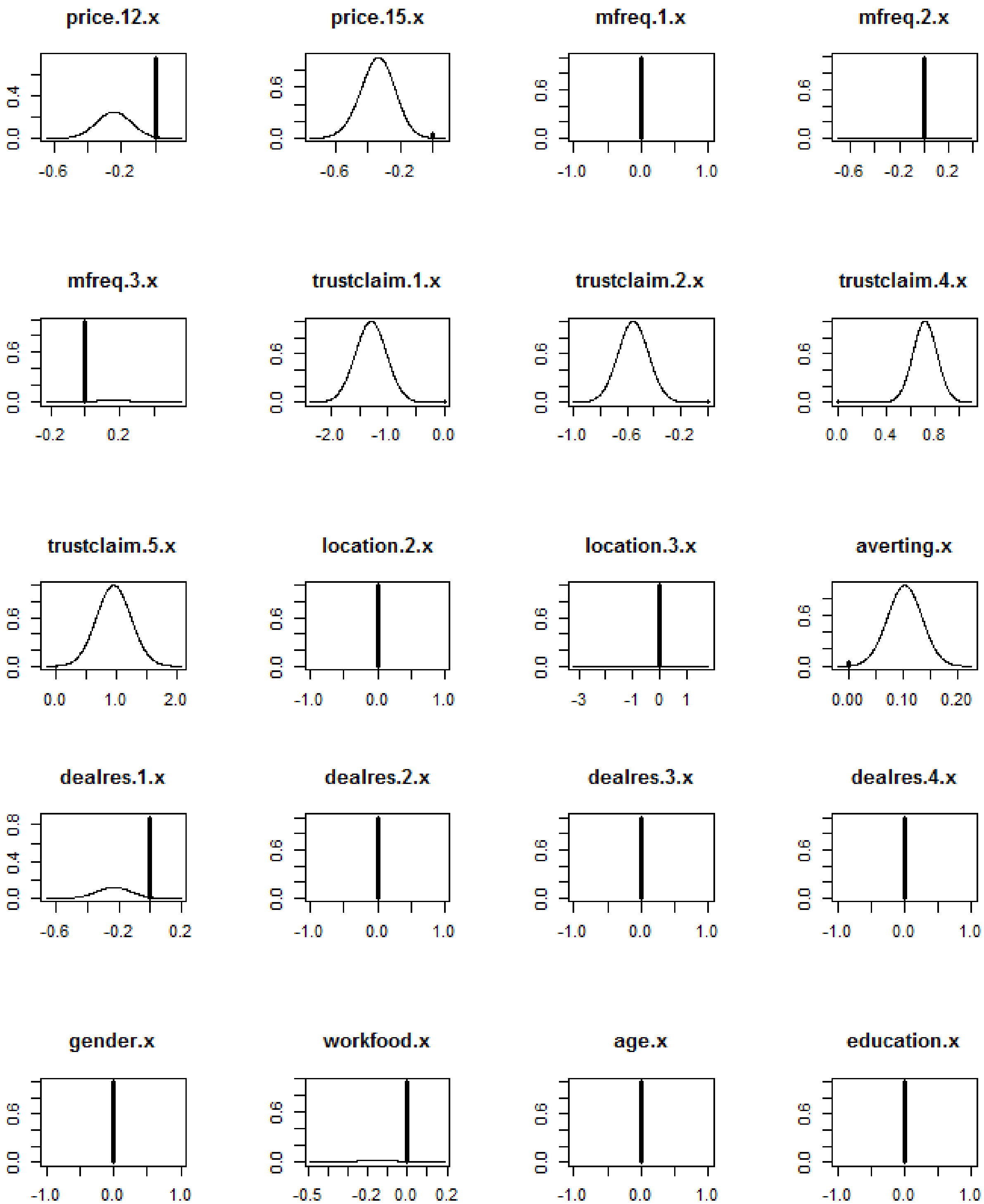

Figure B.3 Posterior distributions of parameters (cloglog)