中央研究院經濟所學術研討論文

IEAS Working Paper

Obesity and Risk Knowledge

Kamhon Kan and Wei-Der Tsai

IEAS Working Paper No. 04-A002

January, 2004

Institute of Economics
Academia Sinica
Taipei 115, TAIWAN
http://www.sinica.edu.tw/econ/

中央研究院　經濟研究所

INSTITUTE OF ECONOMICS, ACADEMIA SINICA

TAIWAN

Obesity and Risk Knowledge*

Kamhon KAN
Academia Sinica
Taipei, TAIWAN

Wei-Der TSAI
National Central University
Chungli, TAIWAN

Abstract

Obesity is an epidemic health problem in many developed countries, and it is an emerging public health concern in developing, transitional, and newly-developed countries. The purpose of this research is to investigate the relationship between individuals' knowledge concerning the health risks of obesity and their tendency to be obese (as measured by the "body mass index"). Instead of assuming that obesity is a pure physiological problem as in previous studies, we allow an individual's cost/benefit evaluation to play a role. Based on survey data from Taiwan, we investigate the relationship with the quantile regression technique. The results suggest that such a relationship does exist and it is different for males and females.

JEL Classification: I12, I18, C51
Keywords: Obesity, Overweight, Risk Knowledge, Quantile Regression

*We thank the editor, Professor Anthony Culyer, and two anonymous referees for constructive suggestions, which have led to substantial improvements on the paper. We also thank Professors Tsu-tan Fu, Wen-han Pan and Wen-jen Tsay for comments and suggestions on earlier versions of the paper.

Correspondence to: Kamhon Kan, Institute of Economics, Academia Sinica, Taipei, Taiwan 11529; (t) 886-2-27822791 (x505); (f) 886-2-27853946; (e) kk@sinica.edu.tw.

Obesity and Risk Knowledge

Abstract

Obesity is an epidemic health problem in many developed countries, and it is an emerging public health concern in developing, transitional, and newly-developed countries. The purpose of this research is to investigate the relationship between individuals' knowledge concerning the health risks of obesity and their tendency to be obese (as measured by the "body mass index"). Instead of assuming that obesity is a pure physiological problem as in previous studies, we allow an individual's cost/benefit evaluation to play a role. Based on survey data from Taiwan, we investigate the relationship with the quantile regression technique. The results suggest that such a relationship does exist and it is different for males and females.

1 Introduction

This paper investigates the relationship between obesity, as measured by the body mass index (BMI), and obesity health risk knowledge at the individual level. By obesity health risk knowledge, we refer to an individual's awareness of the harmful health consequences that obese people are liable to incur. Other things being equal, an individual who is aware of the connection between obesity and certain harmful health consequences will have higher perceived or expected costs associated with obesity than one who is not aware of such a connection. Accordingly, the possession of knowledge on obesity's health risks prevents an individual from being overweight. By adopting this approach, we implicitly assume that individuals are rational and that obesity, to some extent, has to do with decision making involving the cost/benefit analysis concerning obesity. This departs from previous research on obesity, which mostly addresses the issue from physiological and genetic perspectives. While recognizing the roles of physiological and genetic factors, this research allows individuals' perception of obesity's costs and benefits to be the determinants of obesity.

For our empirical analysis, we employ the quantile regression method, which estimates the effects of a set of covariates on the quantiles of the BMI distribution. The quantile regression method is well suited to the study of obesity. With the adoption of the quantile regression method, we estimate the explanatory variables' effects on the BMI level over the whole distribution.

An alternative method, which can be used to analyze individuals' BMI, is the least squares method. However, this method is not sufficient in the context of obesity analysis. The least squares model concerns with a regressors' effect on the *conditional mean* of the dependent variable. This unfortunately does not provide enough information to make an inference on obesity. This is because there is an optimal range for an individual's BMI, and BMI is not a monotonic indicator of healthiness (too high or too low a BMI level is not ideal for health). To see that, let us consider an example, where the least squares estimation yields a positive coefficient for a certain variable. This positive coefficient may arise from the variable's positive effect on BMI anywhere in the distribution. Yet, different percentiles where the variable takes up a statistically significant effect convey very different implications. For example, if a variable has a positive effect only at the left-half of the BMI distribution (i.e., the lower quantiles), then this variable would not be considered to be conducive to obesity. Such a variable can be considered benign, because it is negatively associated with underweight. On the other hand, if the positive effect appears at locations beyond the median (i.e., the upper quantiles), then this variable can be considered an obesity *risk factor*.

Another alternative would be to define an indicator of obesity using a certain cut-off point and estimate the explanatory variables' effects on this indicator.[1] For example, individuals with a BMI above 25 may be defined as being overweight and above 30 as being obese, as suggested by the World Health Organization (1997). To some extent, the estimation will yield information on a variable's effect on "obesity." The deficiency of this approach is that these cut-off values are only referential rather than definitive, and obesity is more a matter of degree.

In addition, we adopt a two-stage approach to take into account the special features of the health risk knowledge indicators: ordinal, potentially endogenous, and high-dimensional. The first-stage involves the estimation of the health risk knowledge indicators with the ordered probit model, such that the response items are allowed to be ordinal. The first stage estimations produce predicted values, which are continuous measures of the health risk knowledge indicators. Since the residuals (i.e., unobserved individual heterogeneity, whose correlation with the BMI models' residuals leads to endogeneity) are excluded from these predicted values, they are exogenous with respect to the BMI models. Finally, we use factor analysis to reduce the dimension of these predicted indicators, which are found to be sufficiently summarized by only one factor for the male respondents and for the female respondents, respectively.

[1]This is one of the approaches adopted by Chou, Grossman, and Saffer (2002).

The results of this research have significant implications. Firstly, our results demonstrate whether or not individuals' evaluation of the costs and benefits of obesity plays a role in their tendency to be obese/overweight. If obesity risk knowledge is found to have a bearing on the tendency to be obese/overweight, then our contention that one's cost/benefit analysis has an influence on his/her status of being obese/overweight is supported. Secondly, our results are a useful reference for policy makers in designing obesity prevention policies and for medical practitioners, who may supplement regular treatments with obesity risk counseling.

The remaining part of the paper is arranged as follows. Section 2 outlines the current research's background. Section 3 reviews the literature. Section 4 describes the data used in our empirical analysis. Section 5 briefly outlines our empirical methods. Section 6 presents a discussion of the estimation results.

2 Background

Obesity is a worldwide challenge to public health. The prevalence and urgency of the obesity problem led the World Health Organization to declare it a "global epidemic" (see World Health Organization, 1997).

In developed countries, obesity is a major and exacerbating public health problem. For example, based on the Behavioral Risk Factor Surveillance System Survey, 19.8% of U.S. adults in 2000 (20.2% for males and 19.4% for females) are obese (see Mokdad, et al., 2002). Its prevalence rate has also been increasing at an alarming pace, being only 12% in 1991 and rising to 18% in 1998 (see Nestle and Jacobson, 2000), while the prevalence rate and trend in other Western-developed countries are similar to those in the U.S. (see Taubes, 1998). Moreover, it is an emerging problem in developing, transitional, and newly-industrialized countries. For example, Zohoori, et al. (1998) show that the obesity rate among men aged 18–60 has increased dramatically from 1992 to 1996 in Russia. Similar trends are observed in Mauritius (Africa) and Thailand (see Taubes, 1998).

It is well established that obesity is associated with adverse health effects, e.g., gall bladder disease, hypertension, sleep apnea, gout, breast and endometrial cancer, colorectal cancer, and osteoarthritis (see Bray, Bouchard, and James, 1998). While developing, transitional, and newly-industrialized countries are still not alert as to the hazard, in developed countries, enormous efforts have been put on the treatment and prevention of obesity. Various treatment and prevention programs have been implemented in developed countries, for example, surgical treatment (as applied to the extremely overweight), pharmacotherapy, and behavioral modification (e.g., dietary control, exercise, and nutrition education, which could also include treatment or preventive measures against obesity).[2]

It is well recognized that being overweight is a result of an imbalance between energy intake and expenditure. Most obesity treatment programs focus on one or the other side of the energy intake-expenditure equation. Theoretically, any treatments focusing on decreasing one's energy intake or increasing one's energy expenditure should be effective. However, experience shows that for individuals having undergone pharmacotherapy and behavioral modification programs, a weight loss is often followed by a weight rebound (see Kramer, et al., 1989; Jeffery, et al., 1993; and Bray, 1998).

Treatment programs mostly produce short-term effects and their effectiveness dissipates in the long run (see Stunkard, 1996, for a review of the various treatment modalities). It is likely that treatment non-compliance is responsible for the transient effect of obesity treatment programs. At the initial stage after an individual joins a treatment program, because of a correction in the energy intake-expenditure imbalance, the treatment program succeeds in producing weight loss. However, as the individual's self-control or willpower fades, non-perseverance and non-compliances (e.g., absenteeism, failure to follow nutrition guidelines, or dropping out), which involve individual decisions, render these treatment programs ineffective. This suggests that the behavioral and decision making aspects of obesity cannot be

[2]In most cases, surgical treatments yield a substantial and well-maintained weight loss (see Kral, 1998). However, there are serious undesirable side effects.

ignored.

In the public health literature, there are studies that look at the relationship between certain sociodemographic factors and obesity/overweight. They show that the amount of nutrition knowledge that an individual has does not have any statistical association with obesity, while a negative attitude toward obesity is negatively related to obesity (see Harris, 1983; and Gordon-Larsen, 2001). This is another piece of evidence lending support to our contention that individuals' evaluation about the costs of obesity/overweight is an important determinant of obesity and individual decisions are involved.

3 Literature Review

The study of the impacts of health risk knowledge on individual behavior is not new in the economics literature. However, the public health literature has paid less attention to individuals' response to health risk knowledge.

In the economics literature, there are numerous studies which use survey data to evaluate the public's risk perception and examine the impact of this perception on their smoking behavior. Such studies have been pioneered by Viscusi (1990, 1991, 1992, 1995), who found that the higher an individual's subjective risk is from dying from lung cancer, the less likely it is for he/she to smoke. Moreover, most individuals overestimate the risk of dying from lung cancer. Based on data from Taiwan and Spain, Liu and Hsieh (1995) and Viscusi, *et al* (2000) both respectively reach a similar conclusion that health risks from smoking have a negative impact on smoking. It is also found by Liu and Hsieh (1995) and Rovira, *et al* (2000), respectively, that the Taiwanese and Spanish public, in general, overestimate smoking risks.

Also investigating cigarette smoking behavior, Kenkel (1991) adopts an alternative indicator of how much information an individual possess, which is measured by the number of smoking-related diseases that an individual knows. The study finds that the more smoking-related diseases that an individual knows, the less likely he/she is to smoke. Hsieh, *et al* (1996), based on data from Taiwan, and Jones and Kirigia (1999), based on a sample of South African women, show similar findings.

By looking at the relationship between knowledge on health risks and obesity, we implicitly assume that people are rational and the tendency to become obese is, at least to some extent, a matter of choice. This assumption is important to our interpretation of the relationship, because we believe this behavioral assumption is close to the reality. While obesity may not be a deterministic outcome of people's choice or willingness to be obese, people's choice or willingness definitely has some effects on their weight. For example, having some knowledge of the risk of being obese, an individual may implement some preventive or corrective measures, e.g., exercise and/or dietary control. These measures are likely to have at least some effects on weight.

While analysis of individuals' addictive substance consumption (e.g., cigarette) in response to their health risk perception is well researched, people's response to obesity-related risk knowledge has yet to be explored. In the economics literature, the issue of obesity in general is seldom touched upon, with a notable exception being Chou, Grossman, and Shaffer (2002), who look at the determinants of individual obesity and pay special attention to economic factors (regional density of fast-food restaurants and full-service restaurants, and the prices of meals at restaurants, food and cigarettes, etc.). Another economic study of obesity that catches our attention is that by Lakdawalla and Philipson (2002), who argue that the long-run growth in weight is due to the decline in physical activity (at home and on the job) and the lowering of food prices brought about by technological changes.

4 Data

Our empirical work is based on data from the survey *Cardiovascular Disease Risk Factors Two-Township Study* (CVDFACTS) in Taiwan. The CVDFACTS is a longitudinal survey focusing on the relationship between the risk factors of cardiovascular diseases and the development of the diseases (see Yeh, *et al.*, 1994). The survey was conducted in two townships in Taiwan, namely Chu-Dong and Pu-Tzu. In each of these two townships five villages were randomly selected among all villages having either a population of more than 1,000 or a population density of over 200 per square kilometer. All residents in a selected village were mailed an invitation to participate in the survey. The study and its purpose were described in the invitation letter. For those who did not respond, a maximum of three invitation letters were sent.

There are a total of five cycles. In the first cycle (September 1990) of the study, a total of 5106 (2235 males and 2871 females) subjects were recruited. In the second cycle (January 1994), those aged above 20 and hypertension-free, and those who had no missing data in the first cycle were followed. There were 2373 subjects (983 males and 1390 females) and the follow-up rate was 71%. In the third cycle (January 1994–December 1996), all subjects who attended the first and/or second cycles were targeted as potential subjects. The study ended up with 5146 subjects (3153 males and 1993 females), who have finished a set of medical examinations and responded to a questionnaire on health practices and food intakes. The subjects of the fourth cycle (March 1997–November 1998) were limited to those who had attended the third cycle and were above age 35, and only medical examinations were carried out. The present study uses data obtained from the fifth cycle (July 2000–Dec 2001), where a module of questions on obesity risk perceptions were included in the questionnaire. All family members (residing in the same housing unit) of subjects who had attended either the second or third cycle (totaling 5690 individuals) were invited to participate in the fifth cycle. Only 4161 individuals have actually participated in the survey.

In the health risk perception module, subjects were asked whether they think obesity will cause:

(1) apoplexy
(2) hypertension
(3) diabetes
(4) heart disease
(5) gout
(6) breast cancer
(7) ulcer

Possible answers to these questions are:
(A) very likely
(B) possible
(C) not possible and
(D) don't know

By assigning a score of 3 to item (A), 2 to item (B),1 to item (D), and 0 to item (C), we construct a variable from each question measuring a respondent's risk knowledge concerning obesity.

After deleting missing data for the variables that we use in our empirical analysis, there are 3700 individuals in the sample, among them 1726 are males and 1974 are females. In the empirical analysis, we look at males and females separately. The rationale for the stratification of our analysis by gender is that males and females may respond to risk knowledge very differently due to the possibility of very different weights that they put on health, career, social life, and marriage.

The definitions of the variables are detailed in Table 1. The means and standard deviations of the variables used in the empirical analysis are presented for each inter-quantile range in Tables 2 and 3.

To have a closer look at the sample respondents' BMI distribution, we plot it in Figure 1, where the upper graph pertains to males and the lower one to females. In each graph the shaded area is the confidence band and the solid line in the shaded area traces the BMI value at each quantile. The horizontal solid line depicts the BMI's sample median. We can see that there is a steeper increase in the BMI toward the right tail of the distribution and there is also an increase in the variance. The female respondents' BMI distribution exhibits a similar pattern as with the male respondents.

5 Empirical Methods

In this section we present our empirical strategies. We first give a brief illustration of the the quantile regression technique, through which we investigate the impacts of health risk knowledge on BMI at different points of the distribution. This is followed by a presentation of the way we account for the special features of the health risk knowledge indicators in our empirical work.

5.1 The Quantile Regression Technique

To gauge the association between individuals' knowledge on obesity's adverse consequences and their tendency to be overweight, we use the quantile regression model as proposed by Koenker and Bassett (1978). See Buchinsky (1998) and Koenker and Hallock (2001) for a lucid illustration. The purpose of the quantile regression is to estimate conditional quantile functions, where quantiles of a response variable's distribution are specified as functions of observed covariates. The quantile regression is a semi-parametric method, in the sense that while the conditional quantile has a linear form, it involves no assumption on the conditional distribution.

Denoting individual i's BMI as B_i, the quantile regression model pertaining to the θth quantile can be expressed as the following:

$$B_i = \boldsymbol{\beta}'_\theta \boldsymbol{X}_i + \epsilon_{\theta i}, \quad Q_\theta(B_i|\boldsymbol{X}_i) = \boldsymbol{\beta}'_\theta \boldsymbol{X}_i, \tag{1}$$

where $\boldsymbol{\beta}_\theta$ is a vector of coefficients, $\boldsymbol{X}_i$ is a vector of demographic characteristics, $\epsilon_{\theta i}$ is a stochastic term, $Q_\theta(B_i|\boldsymbol{X}_i)$ stands for the conditional quantile of B_i given $\boldsymbol{X}_i$, θ is an index for the quantile, and i is an index for the respondents. The coefficients are estimated by solving

$$\min_{\boldsymbol{\beta}_\theta} \sum_i Q_\theta(B_i - \boldsymbol{\beta}'_\theta \boldsymbol{X}_i | \boldsymbol{X}_i). \tag{2}$$

The θth conditional quantile of B_i given $\boldsymbol{X}_i$ is shown by $Q_\theta(B_i|\boldsymbol{X}_i) = \boldsymbol{\beta}_\theta \boldsymbol{X}_i$. The kth element of vector $\boldsymbol{\beta}_\theta$ represents the marginal effect of the kth covariate,

$$\beta_{\theta k} = \frac{\partial Q_\theta(B_i|\boldsymbol{X}_i)}{\partial X_{ik}}. \tag{3}$$

In other words, $\beta_{\theta k}$ is the marginal change in the θth conditional quantile as a result of a change in X_{ik}.

The most important feature of this framework is that the regressors' marginal effect, $\boldsymbol{\beta}_\theta$, may vary over different quantiles. For a given set of regressors $\boldsymbol{X}_i$, we estimate a set of coefficients $\{\boldsymbol{\beta}_\theta,\ \theta = 0.05,\ 0.01,\ \ldots\ 0.95\}$, pertaining to the nineteen quantiles.

In the quantile regression models, the vector of regressors $\boldsymbol{X}_i$ contains an indicator of a respondent's obesity health risk knowledge (which is elaborated below) and some socioeconomic variables. The socioeconomic variables include a respondent's age and its square (denoted *AGE* and *AGESQ*), marital status (denoted *MARRIED*), degree of satisfaction with one's own health condition (denoted *HEALTH*), years of education (denoted *EDUCATION*), income level and its square (denoted *INCOME* and *INCOMESQ*), hours of work per week (denoted *WORK*), and housework hours per day (denoted *HOUSEWORK*); and whether a respondent has a religious preference or not (denoted *RELIGION*) and whether or not he/she is a vegetarian or not (denoted *VEGETARIAN*). See Table 1 for a detailed description of the variables.

To account for the possibility of heteroskedasticity for the disturbance term $\epsilon_{\theta i}$, we use the bootstrap method to compute the parameters' confidence bands (see Buchinsky, 1995 and 1998). To compute the confidence bands, we draw 1000 bootstrap samples. Each bootstrap sample contains the same number of observations as the original samples (i.e., 1726 for the male sample and 1974 for the female sample).

5.2 Health Risk Knowledge

We have seven indicators for health risk knowledge. These indicators take ordinal integer values, with possible values ranging from 0 to 3, indicating the different likelihood of adverse outcomes. Moreover, these indicators are likely to be correlated with the unobserved individual heterogeneity (i.e., the residual term) in the BMI regression model.

These features of the health risk knowledge indicators create three problems in the empirical work.[3] First of all, given that the health risk knowledge indicators are ordinal, if we use these indicators as regressors in our regressions, then strong restrictions will be imposed on their effects on individuals' BMI (e.g., the effect of "very likely" will have an effect twice as large as that of "possible"). Secondly, the correlation between one's health risk knowledge and his/her BMI leads to the endogeneity problem, which causes biasedness for the coefficient estimates in the BMI regressions. The endogeneity of an individual's knowledge on obesity's health risks may arise from the fact that there are unobserved factors which affect both one's tendency to be overweight and one's risk perception.[4] Finally, if we use all seven indicators simultaneously as regressors in a regression, there is likely to be multicollinearity. This is because these indicators are very likely to be correlated. In this subsection, we describe the way we deal with the special features of the health risk knowledge indicators in order to avoid the problems mentioned above.

Two-Stage Approach and Ordered Probit Model

To take into consideration the first two problems, we adopt a two-stage regression approach, with an ordered probit model used in the first-stage estimation. Denoting a particular health risk knowledge variable for individual i as H_{ki}, where $k = 1, \ldots 7$, the model can be

[3] We thank a referee for pointing them out to us.

[4] An individual's degree of risk aversion is a good example of such unobserved heterogeneity. Knowing that obesity is very likely to be associated with adverse health outcomes, a highly risk averse individual may be less likely to be overweight, because of the prudence that he/she exercises; and a high degree of risk aversion may also prompt one to be more alert about risk information. It may be also that socially-advantaged individuals can afford to have a good diet and have better access to information. The above discussion suggests that the correlation between the health risk knowledge indicators and one's tendency to be obese is negative.

written as:

$$\begin{aligned}
&H_{ki} = j, \quad \text{if} \quad \mu_{kj} < H^*_{ki} \leq \mu_{kj+1}, \quad j = 1, \ldots, 4; && (4)\\
&H^*_{ki} = \boldsymbol{\delta}'_k \boldsymbol{Z}_i + u_{ki}; && (5)\\
&\mu_{k0} = -\infty, \quad \mu_{k4} = \infty; && (6)\\
&u_{ki} \sim N(0,1) \quad \text{(standard normally distributed)}; && (7)
\end{aligned}$$

where μ_{kj} and $\boldsymbol{\delta}_k$ are parameters to be estimated, $\boldsymbol{Z}_i$ is a vector of individual characteristics, the parameter restrictions (6) and distribution assumption (7) are imposed for parameter identification, and the random variable u_{ki} is allowed to be correlated with the residual of the BMI regression model $\epsilon_{\theta i}$, i.e., endogeneity is accounted for. Variable H^*_{ki} stands for a continuous latent measure of individual i's perceived likelihood for the kth adverse health outcome to occur.

Under the ordered probit model, individual i's answer to a health risk knowledge question is determined by his/her value of H^*_{ki}. For example, he/she perceives the likelihood for the kth adverse outcome to be "possible" (i.e., $H_{ki} = 2$) if $\mu_2 < H^*_{ki} \leq \mu_3$. Thus, the ordered probit model allows us to obtain a continuous representation of an ordinal variable.

It is noted that variable H^*_{ki} is unobservable to the econometrician since u_{ki} is unobservable, but this does not pose a problem for us. This is because u_{ki} is to be removed from H^*_{ki} so as to avoid the endogeneity problem anyway.[5] That is, to account for endogeneity we use the predicted variable $\widehat{H}^*_{ki} = \boldsymbol{\delta}'_k \boldsymbol{Z}_i$, instead of the actual latent variable H^*_{ki}, to measure health risk knowledge. See Levin (2001) and Arias, Hallock, and Sosa-Escudero (2001) for similar instrumental variable estimators in the context of quantile regressions, and Amemiya (1982), Powell (1983), and Chen and Portnoy (1996) for the asymptotics of the two-stage quantile regression estimators.

In the presence of endogeneity, we need to use instruments to achieve identification of the health risk knowledge's effects. In general, these instruments need to be correlated with the

[5]The unobservability of u_{ki} causes one problem though. That is, we cannot conduct testing for the existence of endogeneity.

endogenous variable, but uncorrelated with the error term of the model of interest, where the endogenous variables are present as regressors. In the current study, four variables are used as instruments: (1) whether a respondent reads newspapers regularly or not (denoted *NEWSPAPER*); (2) whether a respondent watches TV news broadcasts regularly or not (denoted *TVNEWS*); (3) a respondent's frequency of meeting friends (denoted *FRIENDS*); and (4) whether a respondent participates in community activities or not (denoted *COMMUNITY*). These four variables are all related to a respondent's exposure to information.

The variables *NEWSPAPER* and *TVNEWS* are proxies of the possibility for a respondent's information coming from the media. It is likely that if a respondent reads newspapers or watches news broadcasts regularly, then he/she has more information about the harmful effects of obesity. The other two variables *FRIENDS* and *COMMUNITY* pertain to a respondent's exposure to information through inter-personal interactions. While information from inter-personal interactions is more likely to be imprecise, it is likely to have a greater impact on the receiver, because it is from people he/she trusts or knows. The rationale for using these four variables as instruments is that they are related to a respondent's possible sources of information. There is a greater chance that one's possible information channels are related to the amount of information that he/she has, while they may not directly affect his/her health condition. A more detailed description of these variables is in Table 1.

In addition to the four instruments, the vector of regressors $\boldsymbol{Z}_i$ in the ordered probit models contains all exogenous variables in the BMI model as regressors.

Factor Analysis

The ordered probit model enables us to create exogenous and continuous measures of health risk knowledge $\widehat{H}^*_{ki}$. However, the problem of dimensionality still exists. If we use all of these measures in our regressions, there will be multicollinearity. To reduce the dimension of these measures, we resort to factor analysis. Factor analysis is a statistical technique aiming at finding a small number of orthogonal common factors that linearly summarize a set of original variables. That is,

$$\widehat{H}^*_{ki} = \sum_{f=1}^{C} b_{kf} F_{fi} + e_{ki}, \tag{8}$$

where F_{fi} is the fth common factor, b_{kf} is the fth factor's loading for the kth predicted health risk knowledge, and e_{ki} is the kth predicted health risk knowledge's *unique* factor (analogous to the residual in a regression model). The common factors F_{fi} and the factor loadings b_{kf} are to be estimated. It is noted that, in addition to being orthogonal to each other, these common factors are normalized to have a zero mean.

Factor analysis involves the choice of common factors to be extracted from the original variables. We employ here the *Kaiser criterion*, which is the most widely-used criterion (see Dunteman, 1989, pp22–23). The Kaiser criterion retains factors which have eigenvalues greater than 1.0.[6]

After the performance of factor analysis, we have a set of estimated common factors $\{\widehat{F}_{f1}, \ldots, \widehat{F}_{fC}\}$. These common factors are used as measures of a respondent's health risk knowledge in the BMI quantile regression models. It is noted that the common factors are functions of the predicted values, which are generated variables. In general, when they are used as regressors in a regression model, their coefficients' covariance matrix are complicated analytically. In the current study we avoid the derivation of the covariance matrix analytically by using the bootstrap method to compute the empirical covariance matrix.

Test for Overidentification Restrictions

The reliability of our estimation results hinges on the validity of our instruments (i.e., our exclusion restrictions). To make sure that our instruments are valid, we conduct an overidentification restriction test. Our test is in the spirit of Hausman's (1983, page 433) test of overidentification restriction for linear simultaneous equation models. In the context of a linear simultanous equation model the validity of instruments $\boldsymbol{Z}_i$ implies that the structural

[6] A factor's eigenvalue measures the amount of the original variables' total variance that can be accounted for by that factor.

equation's residual ϵ_i is independent of all the exogenous regressors, i.e., $\mathrm{E}(\epsilon_i|\boldsymbol{Z}_i) = 0$. Under Hausman's (1983) approach a structural equation's predicted residual $\widehat{\epsilon}_i$ is regressed on all the exogenous variables $\boldsymbol{Z}_i$, and the condition $\mathrm{E}(\widehat{\epsilon}_i|\boldsymbol{Z}_i) = 0$, i.e., the sample analog of the orthogonality condition, is tested.

In the context of the quantile regression model the validity of the instruments requires that the residual $\epsilon_{\theta i}$ is orthogonal to all the exognenous variables $\boldsymbol{Z}_i$ at the θth quantile, i.e.,

$$Q_\theta(\epsilon_{\theta i}|\boldsymbol{Z}_i) = 0, \tag{9}$$

which is analogous to the linear simultaneous equation model's orthogonality condition $\mathrm{E}(\epsilon_i|\boldsymbol{Z}_i) = 0$. We test the orthogonality condition (9) by regressing the predicted residual $\widehat{\epsilon}_{\theta i}$ on all the exogenous variables $\boldsymbol{Z}_i$, that is,

$$\widehat{\boldsymbol{b}}_\theta = \operatorname*{Arg\,min}_{\boldsymbol{b}_\theta} \sum_i Q_\theta \left(\widehat{\epsilon}_{\theta i} - \boldsymbol{b}'_\theta \boldsymbol{Z}_i\right), \tag{10}$$

where $\widehat{\epsilon}_{\theta i}$ is obtained from our two-stage instrumental variable quantile regresion at the θth quantile, and $\boldsymbol{Z}_i \equiv \{\boldsymbol{X}_i \ \boldsymbol{Z}_{1i}\}$, with $\boldsymbol{Z}_{1i}$ being the instruments. The validity of the instruments requires $\widehat{\boldsymbol{b}}_\theta = \boldsymbol{0}$, i.e., $\widehat{\epsilon}_{\theta i}$ is orthogonal to $\boldsymbol{Z}_{1i}$.

To test for $\widehat{\boldsymbol{b}}_\theta = \boldsymbol{0}$, we adopt the chi-square test of Koenker and Bassett (1982, page 49). Our null hypothesis is:

$$\mathrm{H}_0 : \widehat{\boldsymbol{b}}_\theta = \boldsymbol{0},$$

and under the null the test statistic is

$$\tau_\theta = \widehat{\boldsymbol{b}}'_\theta \boldsymbol{\Omega}^{-1} \widehat{\boldsymbol{b}}_\theta \sim \chi^2_q, \tag{11}$$

where $\boldsymbol{\Omega}$ is the covariance matrix of $\widehat{\boldsymbol{b}}_\theta$.[7] Under the null, the test statistic τ_θ is chi-square distributed with degree of freedom q, which is equal to the number of instruments minus the number of endogenous variables (that is, $q = 4 - 1$ in our case).

[7] See Koenker and Bassett (1982) or Buchinsky (1998) for the construction the covariance matrix $\boldsymbol{\Omega}$.

6 Empirical Results

The ordered probit estimation results are presented in Tables 4 and 5. These results show that for male respondents the instruments *TVNEWS* and *COMMUNITY* are statistically significant in almost all regressions, while for female respondents *NEWSPAPER* is significant in most regressions. The presence of statistically significant instruments suggests that identification is likely to be achieved. These results also imply that males and females rely on different sources of information.

The factor analysis results are presented in Tables 6–8. The factor loadings for males and females are displayed in Tables 7 and 8. In Table 6, for both males and females there is only one factor with an eigenvalue greater than 1.0. This suggests that only one factor is sufficient to summarize all the seven predicted health risk knowledge variables for the male and the female respondents. Thus, in the quantile regressions of the BMI for both the male and female respondents, we include only one common factor. The two common factors (labeled *RISK* hereafter) identified for males and females are summarized in Table 9.

Before discussing the estimation results, we examine the validity of our overidentification restrictions. The test statistics of the overidentification restrictions test are displayed in Table 10. We accept the null hypothesis that the overidentification restrictions are valid at the θth quantile when the p-value of the test statistic τ_θ is sufficiently above conventional significance levels. We see in Table 10 that at almost all θ's the test statistics' p-values are well above conventional significance levels. This suggests that for almost all of our quantile regression models the overidentification restrictions are valid. An exception is that for the male subsample at $\theta = 0.85$, where the p-value of the test statistic is 0.0615. This p-value is low, although not exceedingly so. This calls for cautions in interpreting the results pertinent to the male subsample at $\theta = 0.85$.[8]

The estimation results are visually summarized in Figures 2–5. Each plot in the figures

[8] We choose not to re-estimate the model for the male subsample at $\theta = 0.85$ with a different set of instruments in order to prevent our overall set of results from being ad hoc.

depicts the coefficient estimates of a given explanatory variable based on the 0.05–0.95 quantile regression models. The solid line, dotted with crosses, in the middle of the shaded area traces the coefficient estimates. The shaded area represents the 90% confidence region of the quantile regression coefficient estimates. The horizontal dotted line (traced by circles) shows the zero-level. For a given quantile, if the confidence interval covers the zero-line, then the coefficient estimate at that quantile is statistically insignificant at the 10% level. To demonstrate the differences between the quantile regression results and the linear regression results, we also plot the linear regression coefficient (i.e., the solid horizontal line) and its confidence bands (i.e., the dashed horizontal line) for each explanatory variable.

Effects of Health Risk Knowledge

The results pertaining to the risk knowledge variable are presented in Figures 2. We first look at the males' results, which are reported in the upper panel of the figure. The graph shows that for quantile regressions at the 0.05–0.65 quantiles, the zero horizontal line is below the confidence region. That is, these coefficient estimates are positive and statistically significant at the 10% level for males. This implies that health risk knowledge is associated with an increase in the BMI for males whose BMI is either around the median or below the median (i.e., below the 0.65 conditional quantiles of the male BMI distribution). It is noted that the 0.65 quantile of the males' marginal BMI distribution is 24.99, meaning that the possession of health risk knowledge is associated with an increase in BMI for male individuals who are not overweight (but nearly so).[9] From the fact that this positive effect occurs at the medium and lower quantiles, we can infer that for males who have more knowledge on the association between obesity and adverse health outcomes, they are less likely to be *underweight*.

The positive effect of health risk knowledge on the BMI's medium to lower quantiles seems not very intuitive. This positive effect may arise from the fact that those who are

[9]By marginal distribution, we refer to the sample distribution, which is not conditional on any explanatory variables.

knowledgeable about the health risk of obesity are more likely to be also well-informed concerning nutrition.

The coefficient of health risk knowledge is statistically insignificant at the upper percentiles of BMI distribution (the 70th–90th), yet, its coefficient monotonically decreases beyond the 70th percentile. At the 95th percentile, the coefficient equals -1.48, which is statistically significant. That is, an increase in health risk knowledge by 1 is associated with a decrease in the BMI by 1.48. This suggests that the relationship between a male individual's BMI and his health risk knowledge is unequivocal at the very right tail of the distribution.[10] The pattern of health risk knowledge's coefficient over the upper quantiles implies that mildly overweight male individuals are not responsive to the risks of obesity. Perhaps they do *not* think that those adverse health outcomes would afflict those who are mildly overweight. However, for males who are close to the conventional definition of being obese, the health risks of obesity are well heeded.

It is worth mentioning that the linear regression coefficient estimate (marked in the figure by a horizontal line) is statistically insignificant (as its confidence interval covers the zero-level horizontal line). If we rely on the linear regression results for inference, then we may incorrectly draw the conclusion that the effect of health risk knowledge is negligible. This is compelling evidence for the study of individuals' BMI to adopt the quantile regression approach.

Effects of Risk Knowledge for Females

Now we turn to the effects of obesity risk knowledge on females' BMI level. The results are plotted in the lower panel of Figure 2, which shows that the results for females are very different from those for males. The health risk knowledge's coefficient fluctuates around zero, and it is statistically insignificant at all percentiles. This implies that for female respondents, the possession of health risk knowledge is not associated with any non-trivial changes in the

[10]The 95th percentile of male's BMI's marginal distribution is 29.41.

BMI at any percentile of the sample distribution.

Effects of Demographic Variables for Males

The results pertaining to the effects of the demographic variables on males' BMI distribution are presented in Figure 4. The results indicate that one's age has a quadratic effect on the BMI level for males, as demonstrated by the results pertaining to the variables *AGE* (which has a positive coefficient at all percentiles) and *AGESQ* (which has a negative coefficient at all percentiles). This quadratic effect is quite consistent across the distribution except for the upper percentiles when both *AGE* and *AGESQ* become insignificant from the 85th percentile onwards. This is consistent with the results of Chou, Grossman, and Saffer (2002), who use linear least squares to estimate American individuals' BMI.

The effect of *MARRIED* is positive at almost all percentiles in the distribution of the male respondents' BMI, but it is statistically insignificant. By contrast, the coefficient of *HEALTH* is negative and it is statistically significant at some upper percentiles. This implies that for a male individual whose BMI is above the median, a decrease in his BMI is associated with an increase in his degree of satisfaction with his own health. It is noted that we do not interpret the relationship between *HEALTH* and the BMI distribution to be one of causality. The rationale for us to include the variable is to hold the health status constant in the regressions.

The years of eduction (denoted *EDUCATION*) have a significantly negative impact on the BMI distribution, except for the 80th–95th percentiles, where the effect is statistically insignificant. By putting income (denoted *INCOME*) and its square (denoted *INCOMESQ*) together in the regression, we intend to capture income's quadratic effect, as found by Chou, Grossman and Saffer (2002). However, the coefficients are statistically insignificant for all percentiles in our estimation.

The coefficient of *RELIGION* (i.e., whether having a religious preference or not) is positive for all percentiles except that for the 95th, and it is positive and statistically significant for some percentiles. That is, having a religious preference is associated with a higher BMI level.[11] As indicated by *VEGETARIAN*'s negative coefficient, male vegetarians have a lower BMI level. This negative association is statistically significant for the 20th–75th percentiles.

The variables *WORK* (denoting amount of work time) and *HOUSEWORK* (denoting amount of housework time) are used to capture an individual's level of daily activity. However, in contrast to Chou, Grossman and Saffer's (2002) linear regression result that *expected* weekly hours have a negative (but tapering off) effect on an individual's BMI, we find that those two variables are statistically insignificant for almost all percentiles.

Effects of Demographic Variables for Females

There are some similarities between the effects of demographic variables on the distribution of the BMI for females and those for males. For example, the effect of age (that pertaining to *AGE* and *AGESQ*) is quadratic, the statistically significant negative effect of education (denoted *EDUCATION*) occurs for individuals at the upper percentiles, and the effect of marital status (denoted *MARRIED*), income (denoted *INCOME* and *INCOMESQ*), work time (denoted *WORK*), and housework time (denoted *HOUSEWORK*) are all statistically insignificant. However, in contrast to males, having a religious preference (i.e., *RELIGION*=1) or being a vegetarian (i.e., *VEGETARIAN*=1) does not show a positive effect and negative effect, respectively, which are found for males. Furthermore, while the satisfaction with one's health (denoted *HEALTH*) has a statistically significant negative coefficient at the upper percentiles of the male BMI distribution, its coefficient is statistically negligible for females.

In sum, the results allude to the fact that it is more difficult to predict females' BMI using their socioeconomic characteristics. Moreover, for variables with statistically significant coefficients for females (i.e., *AGE*, *AGESQ*, and *EDUCATION*), their effects are similar to those for males.

[11]See Ferrero, K.F. (1998) for a similar finding, and Levin (1994) and Koenig, McCullough, and Larson (2001) for a review on the relationship between religion and health.

7 Conclusion

This paper investigates the relationship between individuals' risk knowledge and their tendency to be obese/overweight. We use the quantile regression method to detect the association between individuals' risk knowledge and their BMI level. The technique does not impose any distributional assumption on the regression model. Moreover, with this technique we can examine the relationship between risk knowledge and the BMI at each quantile of the distribution. This is especially useful for analyzing BMI, because the relationship between an individual's health and BMI level is not monotonic and there is an optimal BMI range. By using the quantile regression technique we can show how risk knowledge is associated with BMI, especially for the range of BMI which is considered to be medically unfavorable.

The quantile regression results suggest that for males the relationship between obesity health risk knowledge and BMI is positive and statistically significant below the mid-range of the BMI distribution. It becomes almost negligible around the upper percentiles, and significantly negative at the extreme right tail of the BMI distribution. That is, the negative relationship shows up for individuals who are extremely overweight. The results indicate that, conditional on all other regressors, males around and below the medium of the BMI distribution are less underweight if they possess more health risk knowledge. Actually, this may not be the direct effect of health risk knowledge of obesity, but arises from the positive correlation between health risk knowledge and the nutritional information that one possesses.

The relationship between health risk knowledge and BMI above the mid-range of the BMI distribution suggests that male individuals start to heed the health risks of obesity only when they are extremely overweight. We suspect that male individuals (even those who acknowledge that obesity can lead to harmful health consequences) do not consider it likely that the adverse health outcomes can plague mildly overweight individuals. To examine the empirical relevancy of our speculation, we need further research. One obvious way to investigate this speculation is to conduct a survey asking respondents whether being mildly overweight would lead to any adverse health consequences.

The evidence pertaining to males is useful for health authorities in designing policies. Authorities would be able to reduce the likelihood for an individual to be overweight by implementing programs to enhance the general public's awareness of the harmful effects of obesity. Moreover, medical practitioners could supplement regular treatments of obesity with counseling on obesity's adverse consequences in order to augment treatment effectiveness.

Our results on the effect of health risk knowledge suggest that for males the cost/benefit evaluation plays a role in determining one's obesity status. In contrast, among females, knowledge of obesity's detrimental consequences on health does not have any discernible effect on BMI at all. Furthermore, the results show that it is more difficult to predict females' BMI using their socioeconomic characteristics. These results call for additional efforts and alternative approaches in order to understand the pattern and determinants of females' health behavior.

References

[1] Amemiya, T. (1982), “Two Stage Least Absolute Deviations Estimators,” *Econometrica*, 50, 689–711.

[2] Arias, O., K.F. Hallock and W. Sosa-Escudero (2001), “Individual Heterogeneity in the Return to Schooling: Instrumental Variable Quantile Regression Using Twin Data,” *Empirical Economics,* 26, 7–40.

[3] Bray, G.A. (1998), “Pharmacological Treatment of Obesity,” in G.A. Bray, C. Bouchard and W.P.T James, *Handbook of Obesity* (pp. 953–975). New York: Marcel Dekker.

[4] Bray, G.A, C. Bouchard and W.P.T. James (1998), *Handbook of Obesity.* New York: Marcel Dekker.

[5] Buchinsky, M. (1995), “Estimating the Asymptotic Covariance Matrix for Quantile Regression Models: A Monte Carlo Study,” *Journal of Econometrics,* 68, 303–338.

[6] Buchinsky, M. (1998), “Recent Advances in Quantile Regression Models: A Practical Guide for Empirical Research,” *Journal of Human Resources,* 33, 88–126.

[7] Chen, L. and Portnoy, S. (1996), “Two-Staged Regression Quantiles and Two-Staged Trimmed Least-Squares Estimators for Structural Equation Models,” *Communication in Statistics: Theory and Methods,* 25, 1005–1032.

[8] Chou, S.-Y., M. Grossman and H. Saffer’s (2002), “An Economic Analysis of Adult Obesity: Results from the Behavioral Risk Factor Surveillance System,” *National Bureau of Economic Research* Working Paper Series, No. 9247.

[9] Dunteman, G.H. (1989), *Principal Component Analysis,* Sage University Papers Series: Quantitative Applications in the Social Sciences Number 07–069, Newbury Park: Sage Publication.

[10] Ferrero, K.F. (1998), "Firm Believers? Religion, Body Weight, and Well-Being," *Review of Religious Research,* 39, 224–244.

[11] Gordon-Larsen, P. (2001), "Obesity-Related Knowledge, Attitudes, and Behaviors in Obese and Non-Obese Urban Philadelphia Female Adolescents," *Obesity Research,* 9(2) 112–118.

[12] Harris, M.B. (1983), "Eating Habits, Restraint, Knowledge and Attitude toward Obesity," *International Journal of Obesity,* 7(3), 271–286.

[13] Hausman, J. (1983), "Specification and Estimation of Simultaneous Equation Models," in Z. Griliches and M.D. Intriligator (eds), *Handbook of Econometrics*, Volumn I, Amsterdam: North Holland.

[14] Hsieh, C.-R., L.-L. Yen, J.-T. Liu, C.J. Lin (1996), "Smoking, Health Knowledge, and Anti-smoking Campaigns: An Empirical Study in Taiwan," *Journal of Health Economics,* 15(1), 87–104..

[15] Jeffery, R.W., J.L. Forster, S.A. French, S.H. Kelder, H.A. Lando, P.G. McGovern, D.R. Jacobs and J.E. Baxter (1993), "The Healthy Worker Project: A Work-Site Intervention for Weight Control and Smoking Cessation," *American Journal of Public Health,* 83, 395–401.

[16] Jones, A.M. and J.M Kirigia (1999), "Health Knowledge and Smoking Among African Women," *Health Economics,* 8, 165–169.

[17] Kenkel, D.S. (1991), "Health Behavior, Health Knowledge, and Schooling," *Journal of Political Economy,* 99(2), 287–305.

[18] Koenig, H.G., M.E. McCullough and D.B. Larson (2001), *Handbook of Religion and Health*, New York: Oxford University Press.

[19] Koenker, R. and Bassett (1978), "Regression Quantile," *Econometrica*, 46, 33–50.

[20] Koenker, R. and K.F. Hallock (2001), "Quantile Regression: An Introduction," *Journal of Economic Perspective*, 15, 143–56.

[21] Koenker, R. and G. Bassett (1982), "Robust Tests for Heteroscedasticity Based on Regression Quantiles," *Econometrica*, 50, 43–61.

[22] Kral, J.G. (1998), "Surgical Treatment of Obesity," in G.A. Bray, C. Bouchard and W.P.T James, *Handbook of Obesity* (pp. 977–993). New York: Marcel Dekker.

[23] Kramer, F.M., R.W. Jeffery, J.L. Forster, M.K. Snell (1989). "Long-Term Follow-up of Behavioral Treatment for Obesity: Patterns of Weight Regain among Men and Women," *International Journal of Obesity*, 13, 123–136.

[24] Lakdawalla and Philipson (2002) "The Growth of Obesity and Technological Change: A Theoretical and Empirical Examination," *National Bureau of Economic Research* Working Paper Series, No. 8946.

[25] Levin, J. (2001), "For Whom the Reductions Count: A Quantile Regression Analysis of Class Size and Peer Effects on Scholastic Achievement," *Empirical Economics*, 26, 221–246.

[26] Levin, J.S. (1994), "Religion and Health: Is There an Association: Is It Valid and Is It Causal," *Social Science and Medicine*, 38, 1475–1482.

[27] Liu, J.-T.and C.R. Hsieh (1995), "Risk Perception and Smoking Behavior: Empirical Evidence from Taiwan," *Journal of Risk and Uncertainty*, 11(2), 139–157.

[28] Nestle, Marion and Michael Jacobson (2000), "Halting the Obesity Epidemic: A Public Health Policy Approach," *Public Health Reports*, Vol. 115, 12–24.

[29] Mokdad, A.H., B.A. Bowman, E.S. Ford, F. Vinicor, J.S. Marks, and J.P. Koplan (2002), "The Continuing Epidemics of Obesity and Diabetes in the United States," *Journal of American Medical Association,* Vol 286, No. 10, 1195–1200.

[30] Powell, J. (1983), "The Asymptotic Normality of Two-Stage Least Absolute Deviations Estimators," *Econometrica,* 51, 1569–1576.

[31] Rovira, J., W.K. Viscusi, F. Antoñanzas, J. Costa, W. Hart, I. Carvalho (2000), "Smoking Risks in Spain: Part II–Determinants of Smoking Behavior," *Journal of Risk and Uncertainty,* 21(2-3), 187–212.

[32] Stunkard, A.J. (1996), "Current View on Obesity," *American Journal of Medicine,* 100, 230–236.

[33] Taubes, G. (1998), "As Obesity Rate Rise, Experts Struggle to Explain Why," *Science*, Vol 280, 1367–1368.

[34] Viscusi, W.K., I. Carvalho, F. Antoñanzas, J. Rovira, F. Braa, and F. Portillo (2000), "Smoking Risks in Spain: Part III–Determinants of Smoking Behavior," *Journal of Risk and Uncertainty,* 21(2-3), 213–234.

[35] Viscusi, W.K.(1990), "Do Smokers Underestimate Risks?," *Journal of Political Economy,* 98(6), 1253–1269.

[36] Viscusi, W.K. (1991), "Age Variations in Risk Perceptions and Smoking Decisions," *Review of Economics and Statistics,* 73(4), 577-5-88..

[37] Viscusi, W.K. (1992), *Smoking: Making the Risky Decision,* New York, Oxford, Toronto and Melbourne: Oxford University Press.

[38] Viscusi, W.K. (1995), "Cigarette Taxation and the Social Consequence of Smoking," in J.M. Poterba (ed.) *Tax Policy and the Economy,* Volume 9; Cambridge: MIT Press for the National Bureau of Economic Research, 57–101.

[39] World Health Organization (1997), *Obesity: Preventing and Managing the Global Epidemic.* Geneva: World Health Organization.

[40] Yeh, C.J., W.H. Pan, and C.H. Bai (1994), "Curvilinear Relation Between Age and Hermostatic Parameters in Chinese," *Thromb Haemost*, 72(2), 239–243.

[41] Zohoori, Namvar; Thomas A. Mroz; Barry Popkin; Elena Glinskaya; Michael Lokshin and Dominic Mancini (1998), "Monitoring the Economic Transition in Russian Federation and Its Implications for Demographic Crisis—The Russian Longitudinal Survey," *World Development*, Vol. 26, No. 11, 1977–1993.

Table 1: Definition of Variables

Variable Name	Definition
BMI	A respondent's Body Mass Index; *BMI* $=Weight\ \ in\ \ Kilograms/(Height\ \ in\ \ Meters)^2$.
AGE	A respondent's age.
AGESQ	*AGE* squared.
MARRIED	A respondent's marital status; *MARRIED* =1 if married, *MARRIED* =0 otherwise.
HEALTH	A respondent's degree of satisfaction with own health condition, ranging 0–100.
EDUCATION	A respondent's years of education.
INCOME	A respondent's own income level.
INCOMESQ	*INCOME* squared.
RELIGION	Whether a respondent has a religious preference or not; *RELIGION* =1 if yes, *RELIGION* =0 otherwise.
VEGETARIAN	Whether a respondent is vegetarian or not; *VEGETARIAN* =1 if yes, *VEGETARIAN* =0 otherwise.
WORK	A respondent's hours of work per week.
HOUSEWORK	A respondent's housework hours per day.
NEWSPAPER	Whether a respondent reads newspapers regularly or not; *NEWSPAPER* =1 if yes, *NEWSPAPER* =0 otherwise.
TVNEWS	Whether a respondent watches TV news broadcasts regularly or not; *TVNEWS* =1 if yes, *TVNEWS* =0 otherwise.
FRIENDS	A respondent's frequency of meeting friends; *FRIENDS* =1 if not at all, *FRIENDS* =2 if seldom, *FRIENDS* =3 if once every one or two months, *FRIENDS* =4 if several times per month, *FRIENDS* =5 if once per week, *FRIENDS* =6 if more than two times per week.
COMMUNITY	Whether a respondent participates in community activities or not; *COMMUNITY* =1 if yes, *COMMUNITY* =0 otherwise.

Table 2: Inter-Quantile Means and Standard Deviations for Males.

	Mean (Standard Deviation)									
	0%–10%	10%–20%	20%–30%	30%–40%	40%–50%	50%–60%	60%–70%	70%–80%	80%–90%	90%–100%
BMI	18.61	20.50	21.66	22.53	23.31	24.11	24.92	25.82	27.15	30.37
	(0.93)	(0.39)	(0.27)	(0.22)	(0.24)	(0.23)	(0.24)	(0.30)	(0.50)	(2.84)
AGE	46.86	48.31	51.62	51.01	52.94	54.07	54.61	54.50	54.39	53.23
	(21.34)	(20.12)	(18.38)	(18.21)	(17.10)	(15.63)	(14.52)	(15.22)	(14.58)	(15.17)
AGESQ	2648.26	2736.12	3000.59	2931.22	3093.39	3166.99	3192.02	3200.90	3169.28	3061.95
	(2054.20)	(1925.46)	(1796.12)	(1856.21)	(1759.92)	(1594.79)	(1554.90)	(1587.97)	(1534.62)	(1547.83)
MARRIED	0.60	0.62	0.73	0.73	0.78	0.84	0.88	0.84	0.85	0.84
	(0.49)	(0.49)	(0.45)	(0.45)	(0.41)	(0.37)	(0.33)	(0.37)	(0.36)	(0.37)
HEALTH	71.80	73.35	73.21	74.88	73.25	71.04	72.23	72.62	71.42	70.49
	(12.75)	(11.41)	(12.68)	(12.66)	(12.77)	(11.95)	(12.85)	(13.86)	(12.22)	(13.51)
EDUCATION	11.27	11.28	11.36	11.05	10.93	10.97	10.50	10.68	10.25	9.90
	(3.85)	(3.90)	(3.99)	(4.01)	(4.22)	(3.61)	(4.12)	(3.85)	(3.98)	(3.90)
INCOME	2.82	3.13	3.21	3.45	3.72	3.63	3.70	3.65	3.53	3.18
	(1.90)	(2.04)	(2.27)	(2.28)	(2.19)	(2.13)	(2.21)	(2.34)	(2.33)	(2.12)
INCOMESQ	11.59	13.92	15.42	17.06	18.64	17.69	18.55	18.77	17.82	14.56
	(12.86)	(15.21)	(17.18)	(17.99)	(17.34)	(17.32)	(17.71)	(19.91)	(18.80)	(16.16)
RELIGION	0.76	0.83	0.80	0.83	0.86	0.89	0.87	0.87	0.90	0.87
	(0.43)	(0.38)	(0.40)	(0.38)	(0.35)	(0.31)	(0.34)	(0.34)	(0.30)	(0.34)
VEGETARIAN	0.05	0.09	0.10	0.08	0.09	0.08	0.06	0.07	0.07	0.06
	(0.21)	(0.28)	(0.31)	(0.27)	(0.29)	(0.27)	(0.24)	(0.25)	(0.26)	(0.24)
WORK	21.64	23.56	23.32	24.42	24.34	27.27	25.88	29.27	28.77	28.40
	(26.12)	(26.08)	(25.54)	(27.57)	(26.44)	(27.02)	(27.88)	(27.37)	(28.31)	(28.07)
HOUSEWORK	0.54	0.45	0.40	0.54	0.41	0.50	0.46	0.34	0.44	0.41
	(1.22)	(0.81)	(0.81)	(1.30)	(0.78)	(0.85)	(0.87)	(0.84)	(0.85)	(1.12)
NEWSPAPER	0.55	0.65	0.66	0.65	0.70	0.71	0.68	0.71	0.73	0.61
	(0.50)	(0.48)	(0.48)	(0.48)	(0.46)	(0.46)	(0.47)	(0.45)	(0.44)	(0.49)
TVNEWS	0.88	0.90	0.88	0.89	0.91	0.94	0.95	0.94	0.97	0.90
	(0.33)	(0.30)	(0.33)	(0.32)	(0.28)	(0.24)	(0.23)	(0.24)	(0.17)	(0.30)
FRIENDS	3.47	3.40	3.32	3.61	3.64	3.62	3.74	3.69	3.62	3.78
	(1.64)	(1.55)	(1.54)	(1.58)	(1.58)	(1.59)	(1.62)	(1.60)	(1.65)	(1.65)
COMMUNITY	0.15	0.23	0.25	0.23	0.29	0.24	0.33	0.32	0.29	0.23
	(0.36)	(0.42)	(0.43)	(0.42)	(0.45)	(0.43)	(0.47)	(0.47)	(0.45)	(0.42)
Apoplexy Risk	1.18	1.24	1.27	1.33	1.30	1.26	1.31	1.17	1.29	1.25
	(0.72)	(0.63)	(0.74)	(0.65)	(0.64)	(0.71)	(0.69)	(0.69)	(0.68)	(0.65)
Blood Pressure Risk	1.25	1.30	1.34	1.36	1.30	1.32	1.37	1.21	1.34	1.24
	(0.70)	(0.62)	(0.71)	(0.67)	(0.64)	(0.66)	(0.65)	(0.68)	(0.65)	(0.66)
Heart Disease Risk	1.25	1.29	1.35	1.34	1.31	1.27	1.32	1.24	1.30	1.27
	(0.71)	(0.64)	(0.69)	(0.69)	(0.63)	(0.70)	(0.68)	(0.64)	(0.65)	(0.65)
Diabetes Risk	1.11	1.09	1.20	1.20	1.14	1.09	1.13	1.06	1.18	1.15
	(0.74)	(0.73)	(0.75)	(0.75)	(0.72)	(0.70)	(0.75)	(0.72)	(0.70)	(0.72)
Ulcer Risk	0.46	0.45	0.48	0.52	0.56	0.55	0.58	0.49	0.52	0.47
	(0.70)	(0.70)	(0.70)	(0.72)	(0.73)	(0.70)	(0.74)	(0.68)	(0.72)	(0.68)
Gout Risk	0.74	0.71	0.91	0.85	0.78	0.87	0.92	0.81	0.90	0.87
	(0.77)	(0.73)	(0.82)	(0.77)	(0.77)	(0.79)	(0.77)	(0.75)	(0.77)	(0.76)
Breast Cancer Risk	0.29	0.19	0.30	0.29	0.22	0.30	0.30	0.17	0.22	0.30
	(0.55)	(0.46)	(0.57)	(0.58)	(0.46)	(0.56)	(0.50)	(0.40)	(0.49)	(0.57)

Table 3: Inter-Quantile Means and Standard Deviations for Females.

	Mean (Standard Deviation)									
	0%–10%	10%–20%	20%–30%	30%–40%	40%–50%	50%–60%	60%–70%	70%–80%	80%–90%	90%–100%
BMI	18.09	19.97	20.98	21.95	22.83	23.72	24.59	25.64	27.08	30.54
	(1.00)	(0.34)	(0.27)	(0.27)	(0.25)	(0.27)	(0.25)	(0.33)	(0.55)	(2.56)
AGE	38.13	42.36	47.72	50.74	51.59	54.59	56.45	56.50	56.41	55.22
	(18.23)	(16.47)	(15.50)	(14.96)	(13.55)	(13.19)	(12.33)	(12.73)	(12.92)	(13.35)
AGESQ	1784.17	2064.39	2516.36	2797.69	2844.46	3152.80	3338.33	3353.10	3348.30	3226.34
	(1649.95)	(1533.94)	(1544.46)	(1540.68)	(1407.52)	(1399.11)	(1374.18)	(1383.60)	(1434.27)	(1402.01)
MARRIED	0.47	0.67	0.74	0.75	0.79	0.79	0.82	0.82	0.79	0.75
	(0.50)	(0.47)	(0.44)	(0.43)	(0.41)	(0.41)	(0.39)	(0.38)	(0.41)	(0.43)
HEALTH	71.59	73.83	72.84	70.73	72.05	70.58	70.69	70.94	69.88	69.09
	(14.36)	(13.05)	(11.79)	(12.11)	(12.48)	(13.03)	(12.94)	(11.95)	(14.39)	(13.35)
EDUCATION	11.30	11.06	10.43	9.24	9.00	8.77	7.84	7.88	7.43	7.32
	(4.21)	(4.38)	(4.23)	(4.55)	(4.00)	(4.00)	(3.90)	(4.14)	(4.19)	(4.15)
INCOME	2.80	2.80	2.91	2.66	2.50	2.38	2.47	2.44	2.41	2.18
	(1.61)	(1.93)	(1.88)	(1.77)	(1.80)	(1.86)	(1.67)	(1.76)	(1.64)	(1.57)
INCOMESQ	10.40	11.56	12.02	10.16	9.45	9.13	8.89	9.04	8.46	7.19
	(10.83)	(14.38)	(13.15)	(11.85)	(11.49)	(13.30)	(0.69)	(2.50)	(0.94)	(9.50)
RELIGION	0.79	0.89	0.89	0.88	0.93	0.91	0.91	0.93	0.90	0.90
	(0.41)	(0.32)	(0.31)	(0.33)	(0.26)	(0.29)	(0.28)	(0.25)	(0.30)	(0.30)
VEGETARIAN	0.07	0.15	0.14	0.12	0.14	0.21	0.18	0.18	0.19	0.19
	(0.26)	(0.36)	(0.35)	(0.33)	(0.35)	(0.41)	(0.39)	(0.39)	(0.39)	(0.39)
WORK	24.72	21.49	23.35	18.87	18.62	17.88	18.68	15.11	17.24	17.81
	(26.47)	(25.29)	(25.96)	(23.50)	(24.69)	(25.01)	(26.48)	(22.56)	(25.43)	(27.02)
HOUSEWORK	1.40	1.43	1.45	1.72	1.78	1.87	1.64	1.92	1.51	1.87
	(2.10)	(1.80)	(1.58)	(2.12)	(1.91)	(2.53)	(1.75)	(2.01)	(1.75)	(4.49)
NEWSPAPER	0.58	0.52	0.61	0.50	0.56	0.50	0.51	0.44	0.46	0.42
	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
TVNEWS	0.82	0.87	0.90	0.87	0.90	0.89	0.89	0.89	0.89	0.89
	(0.38)	(0.33)	(0.30)	(0.33)	(0.30)	(0.31)	(0.31)	(0.31)	(0.31)	(0.32)
FRIENDS	3.58	3.16	3.45	3.45	3.39	3.39	3.49	3.24	3.49	3.49
	(1.51)	(1.49)	(1.59)	(1.60)	(1.63)	(1.64)	(1.66)	(1.64)	(1.69)	(1.77)
COMMUNITY	0.19	0.23	0.27	0.28	0.29	0.27	0.27	0.29	0.26	0.28
	(0.40)	(0.42)	(0.44)	(0.45)	(0.46)	(0.45)	(0.44)	(0.45)	(0.44)	(0.45)
Apoplexy Risk	1.30	1.38	1.26	1.26	1.27	1.17	1.24	1.20	1.15	1.06
	(0.67)	(0.65)	(0.70)	(0.67)	(0.66)	(0.75)	(0.66)	(0.72)	(0.71)	(0.71)
Blood Pressure Risk	1.36	1.44	1.33	1.32	1.30	1.25	1.27	1.19	1.15	1.11
	(0.67)	(0.62)	(0.68)	(0.66)	(0.63)	(0.72)	(0.64)	(0.69)	(0.70)	(0.70)
Heart Disease Risk	1.31	1.40	1.33	1.29	1.28	1.28	1.29	1.18	1.16	1.08
	(0.71)	(0.66)	(0.67)	(0.67)	(0.66)	(0.72)	(0.64)	(0.70)	(0.69)	(0.74)
Diabetes Risk	1.18	1.22	1.12	1.09	1.17	1.13	1.09	1.02	0.94	1.01
	(0.76)	(0.72)	(0.74)	(0.75)	(0.69)	(0.75)	(0.73)	(0.75)	(0.77)	(0.77)
Ulcer Risk	0.54	0.51	0.44	0.42	0.47	0.48	0.41	0.45	0.36	0.37
	(0.72)	(0.69)	(0.66)	(0.65)	(0.70)	(0.69)	(0.66)	(0.68)	(0.62)	(0.62)
Gout Risk	0.81	0.91	0.86	0.74	0.81	0.79	0.79	0.82	0.74	0.75
	(0.80)	(0.78)	(0.79)	(0.79)	(0.73)	(0.75)	(0.74)	(0.79)	(0.76)	(0.75)
Breast Cancer Risk	0.34	0.41	0.38	0.36	0.44	0.32	0.32	0.24	0.31	0.32
	(0.58)	(0.62)	(0.62)	(0.59)	(0.63)	(0.55)	(0.55)	(0.51)	(0.54)	(0.60)

Table 4: Ordered Probit of Health Risk Knowledge Regression Results for Males.

	Coefficient (t-statistic)						
	Apoplexy	Blood Pressure	Heart Disease	Diabetes	Ulcer	Gout	Breast Cancer
AGE	-.0172132	-.0305091	-.0161017	-.0217193	-.0020497	.022752	-.0113648
	(-1.355)	(-2.370)	(-1.256)	(-1.747)	(-0.168)	(1.862)	(-0.880)
AGESQ	.0000842	.0001802	.0000725	.0001516	.0000256	-.0002713	.0000735
	(0.694)	(1.470)	(0.592)	(1.274)	(0.219)	(-2.316)	(0.591)
MARRIED	.0890632	.1309239	.1427627	.1309604	-.0389172	-.0168007	.0603145
	(0.953)	(1.383)	(1.511)	(1.430)	(-0.433)	(-0.186)	(0.630)
HEALTH	.0002893	.0014813	.0005482	.001429	.0029562	.0012084	.0047839
	(0.129)	(0.654)	(0.242)	(0.651)	(1.357)	(0.555)	(2.079)
EDUCATION	.0578943	.0514388	.0628949	.0499601	.0313249	.042849	.0364019
	(6.194)	(5.465)	(6.669)	(5.440)	(3.461)	(4.723)	(3.734)
INCOME	-.0206687	-.0339183	-.0670116	-.0341318	-.0008897	-.0123522	.0230605
	(-0.530)	(-0.863)	(-1.701)	(-0.898)	(-0.024)	(-0.332)	(0.582)
INCOMESQ	.0073416	.010064	.0133395	.0080145	.0028529	.003399	.0004052
	(1.461)	(1.981)	(2.616)	(1.645)	(0.607)	(0.717)	(0.081)
RELIGION	-.0396763	.073038	.0023651	.000916	-.121378	-.0134553	.020931
	(-0.488)	(0.895)	(0.029)	(0.012)	(-1.571)	(-0.173)	(0.254)
VEGETARIAN	.1063776	.0954225	.2413067	.144614	-.063054	-.0074496	-.0005791
	(0.996)	(0.883)	(2.203)	(1.384)	(-0.615)	(-0.072)	(-0.005)
WORK	.0026065	.0011757	.0009516	.0009395	.001863	.001391	.0022347
	(2.146)	(0.963)	(0.779)	(0.792)	(1.607)	(1.196)	(1.817)
HOUSEWORK	.0348506	.0525444	.0488894	.060754	.0443528	.1053152	.1052454
	(1.084)	(1.619)	(1.506)	(1.912)	(1.438)	(3.384)	(3.342)
NEWSPAPER	.1874068	.1242194	.1422037	.2232014	.2920351	.1895364	.1256618
	(2.849)	(1.872)	(2.145)	(3.459)	(4.540)	(2.966)	(1.831)
TVNEWS	-.0094078	.0040731	-.0617296	-.0393068	-.0610355	-.0732466	.0924245
	(-0.084)	(0.036)	(-0.549)	(-0.361)	(-0.565)	(-0.678)	(0.798)
FRIENDS	.0191744	.0047381	.0090981	.0148745	-.0095078	-.0036607	.0003634
	(1.090)	(0.268)	(0.514)	(0.864)	(-0.561)	(-0.216)	(0.020)
COMMUNITY	.1226059	.1452368	.1439615	.1518105	.1018316	.1642614	.0297492
	(1.872)	(2.196)	(2.175)	(2.378)	(1.647)	(2.633)	(0.451)
μ_{k1}	-.9726805	-1.399375	-1.044748	-.7350232	.2764937	.4407513	.9441415
	(-2.706)	(-3.841)	(-2.880)	(-2.095)	(0.803)	(1.276)	(2.606)
μ_{k1}	-.7926327	-1.271097	-.9169828	-.5065175	.9386334	.7780901	1.630168
	(-2.206)	(-3.490)	(-2.528)	(-1.444)	(2.721)	(2.250)	(4.486)
μ_{k1}	.6849256	.2739597	.6088759	.7925943	1.821018	1.860257	2.624297
	(1.906)	(0.754)	(1.678)	(2.258)	(5.2648)	(5.361)	(7.145)
Log Likelihood	-1705.6445	-1630.8921	-1636.6751	-1906.2799	-2206.021	-2151.8767	-1818.5346
Observation No.				1726			

Table 5: Ordered Probit of Health Risk Knowledge Regression Results for Females.

	Coefficient (t-statistic)						
	Apoplexy	Blood Pressure	Heart Disease	Diabetes	Ulcer	Gout	Breast Cancer
AGE	.0223396	.0124773	.0285079	.0349072	.0105198	.0324719	.0258471
	(1.849)	(1.019)	(2.335)	(2.933)	(0.886)	(2.754)	(2.092)
AGESQ	-.0003278	-.0002405	-.0003992	-.000431	-.0001565	-.0003777	-.0003305
	(-2.774)	(-2.013)	(-3.343)	(-3.691)	(-1.335)	(-3.253)	(-2.689)
MARRIED	.1837782	.0813562	.1733007	.0315815	.12346	.1599949	.0846633
	(2.547)	(1.121)	(2.390)	(0.446)	(1.723)	(2.258)	(1.143)
HEALTH	.0006721	.0036786	.0017647	.0006163	.00291	.0002467	.0063294
	(0.328)	(1.776)	(0.857)	(0.308)	(1.460)	(0.124)	(3.057)
EDUCATION	.0638382	.0696826	.0722042	.0620775	.0358334	.0516187	.0624993
	(6.994)	(7.576)	(7.849)	(6.943)	(4.019)	(5.803)	(6.683)
INCOME	.1022914	.0947631	.1243936	.0376375	.0757489	.0996272	.1066885
	(2.194)	(2.024)	(2.662)	(0.827)	(1.691)	(2.218)	(2.311)
INCOMESQ	-.0069879	-.0075328	-.0107627	-.0033574	-.0050229	-.0072133	-.0117371
	(-1.007)	(-1.082)	(-1.547)	(-0.499)	(-0.772)	(-1.094)	(-1.760)
RELIGION	.0424421	-.0012598	-.0194641	.0658965	-.0210416	.0934183	-.0499616
	(0.466)	(-0.014)	(-0.211)	(0.747)	(-0.243)	(1.066)	(-0.565)
VEGETARIAN	.1717239	.1526189	.1703423	.1748193	.049865	.1450428	.0558965
	(2.346)	(2.079)	(2.317)	(2.437)	(0.697)	(2.041)	(0.749)
WORK	-.0003628	-.0002834	-.0014394	.0003266	.0003592	-.0003882	-.0001201
	(-0.298)	(-0.232)	(-1.179)	(0.275)	(0.307)	(-0.331)	(-0.100)
HOUSEWORK	.0012234	.0000182	-.0021306	.0099077	-.0052633	-.0081362	.00583
	(0.111)	(0.002)	(-0.191)	(0.921)	(-0.454)	(-0.706)	(0.498)
NEWSPAPER	.1708334	.1358127	.100551	.2055304	.1821569	.2122591	.1883566
	(2.850)	(2.246)	(1.667)	(3.516)	(3.146)	(3.676)	(3.167)
TVNEWS	.001023	.0969894	-.1031385	-.1432288	-.1098708	-.1008011	-.060522
	(0.012)	(1.116)	(-1.185)	(-1.687)	(-1.289)	(-1.194)	(-0.678)
FRIENDS	.02091	.0099089	.0418118	.0195803	.0023525	.0065129	-.0135343
	(1.280)	(0.604)	(2.546)	(1.224)	(0.148)	(0.409)	(-0.818)
COMMUNITY	.020128	.0354176	.0184755	-.0310188	.0857624	.0351971	-.0087815
	(0.335)	(0.585)	(0.306)	(-0.530)	(1.482)	(0.608)	(-0.147)
μ_{k1}	.1151375	-.0919689	.2079563	.4180936	.6436361	.9707314	1.545259
	(0.333)	(-0.262)	(0.595)	(1.231)	(1.912)	(2.883)	(4.407)
μ_{k1}	.2387178	.0195938	.3105507	.6148927	1.301225	1.253566	2.187756
	(0.690)	(5.580e-002)	(0.888)	(1.809)	(3.859)	(3.719)	(6.221)
μ_{k1}	1.716203	1.577563	1.806486	1.865961	2.213812	2.345912	3.26471
	(4.935)	(4.473)	(5.137)	(5.468)	(6.542)	(3.719)	(9.192)
Log Likelihood	-1918.0078	-1844.5166	-1871.2124	-2180.6975	-2412.608	-2385.5542	-2180.6169
Observation No.				1974			

Table 6: Factor Analysis Results: Eigenvalues.

Sample	**Eigenvalue**						
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Males	6.47742	0.20811	0.04053	0.01115	0.00327	-0.01444	-0.02075
Females	6.78261	0.06348	0.04091	0.01039	0.00121	-0.00439	-0.01150

Table 7: Factor Loadings for Males.

Variable	**Factor Loading**				
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Apoplexy Risk	0.98696	-0.09695	-0.01337	0.03958	0.03961
Blood Pressure Risk	0.97004	-0.20469	0.05286	0.04065	-0.01151
Heart Disease Risk	0.97834	-0.16981	-0.05898	-0.05988	0.00684
Diabetes Risk	0.98948	-0.03775	-0.09245	0.00551	-0.03475
Ulcer Risk	0.90704	0.32047	-0.07555	0.02561	0.00563
Gout Risk	0.95014	0.11535	0.06355	-0.05987	0.00865
Breast Cancer Risk	0.94901	0.10268	0.12565	0.00873	-0.01428

Table 8: Factor Loadings for Females.

Variable	**Factor Loading**				
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Apoplexy Risk	0.99659	0.00783	-0.06518	-0.03713	-0.01217
Blood Pressure Risk	0.98634	-0.13442	0.01903	-0.03388	-0.01457
Heart Disease Risk	0.98721	-0.04921	-0.07342	-0.02117	0.02605
Diabetes Risk	0.98062	-0.02600	-0.07301	0.06933	-0.00097
Ulcer Risk	0.97969	0.08259	0.11102	-0.02623	0.01007
Gout Risk	0.97915	0.17893	-0.02850	0.00667	-0.00811
Breast Cancer Risk	0.98073	-0.05839	0.11156	0.04333	-0.00020

Table 9: Common Factor of Health Risk Knowledge—*RISK*.

Sample	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Male	1726	-4.83e-10	.9974748	-2.938905	3.1665
Female	1974	-2.67e-09	2.607548	-9.568942	5.480206

Table 10: Test Statistics of Overidentification Restrictions Test

Quantile	**Test Statistic** τ_θ	
	Male	Female
0.050	0.7800	0.8100
	[0.8542]	[0.8471]
0.100	0.0900	1.3500
	[0.9930]	[0.7173]
0.150	0.2400	1.6500
	[0.9709]	[0.6481]
0.200	0.7800	1.9800
	[0.8542]	[0.5766]
0.250	1.6500	1.6800
	[0.6481]	[0.6414]
0.300	3.2100	1.5300
	[0.3604]	[0.6754]
0.350	1.2300	1.3800
	[0.7458]	[0.7102]
0.400	1.2600	0.5100
	[0.7387]	[0.9167]
0.450	1.5600	1.1100
	[0.6685]	[0.7747]
0.500	1.3500	1.2600
	[0.7173]	[0.7387]
0.550	0.6900	1.0500
	[0.8756]	[0.7892]
0.600	0.9300	1.3500
	[0.8182]	[0.7173]
0.650	0.7500	0.9300
	[0.8614]	[0.8182]
0.700	0.7500	0.9900
	[0.8614]	[0.8037]
0.750	0.8100	1.9200
	[0.8471]	[0.5892]
0.800	3.0300	0.7800
	[0.3870]	[0.8542]
0.850	7.3500	0.3000
	[0.0615]	[0.9600]
0.900	3.3900	0.4800
	[0.3353]	[0.9233]
0.950	4.5000	0.7800
	[0.2123]	[0.8542]

Note: p-value in square parentheses.

Figure 1: Quantiles of BMI for Males and Females.

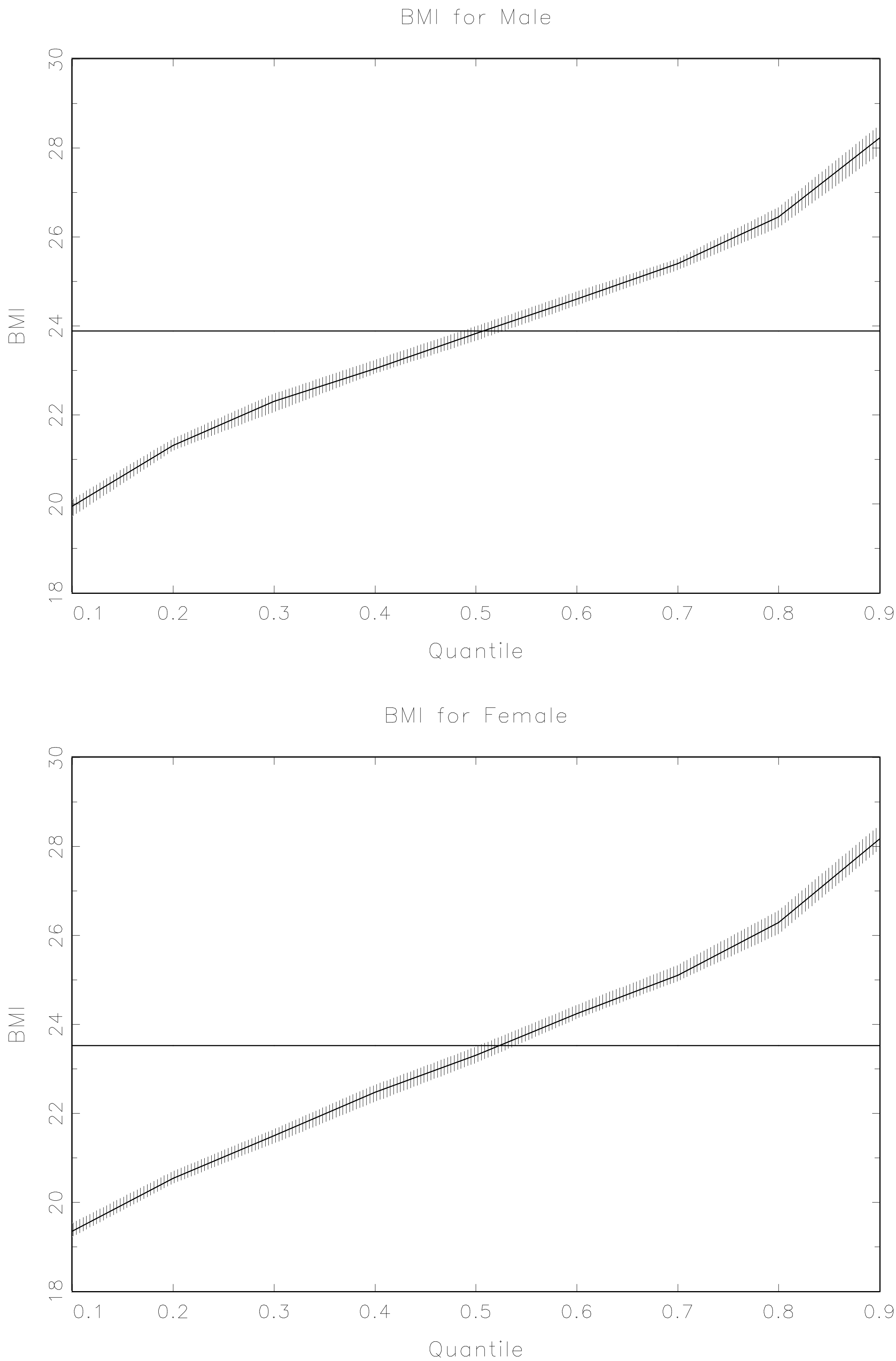


Figure 2: Effects of Health Risk Knowledge on BMI.

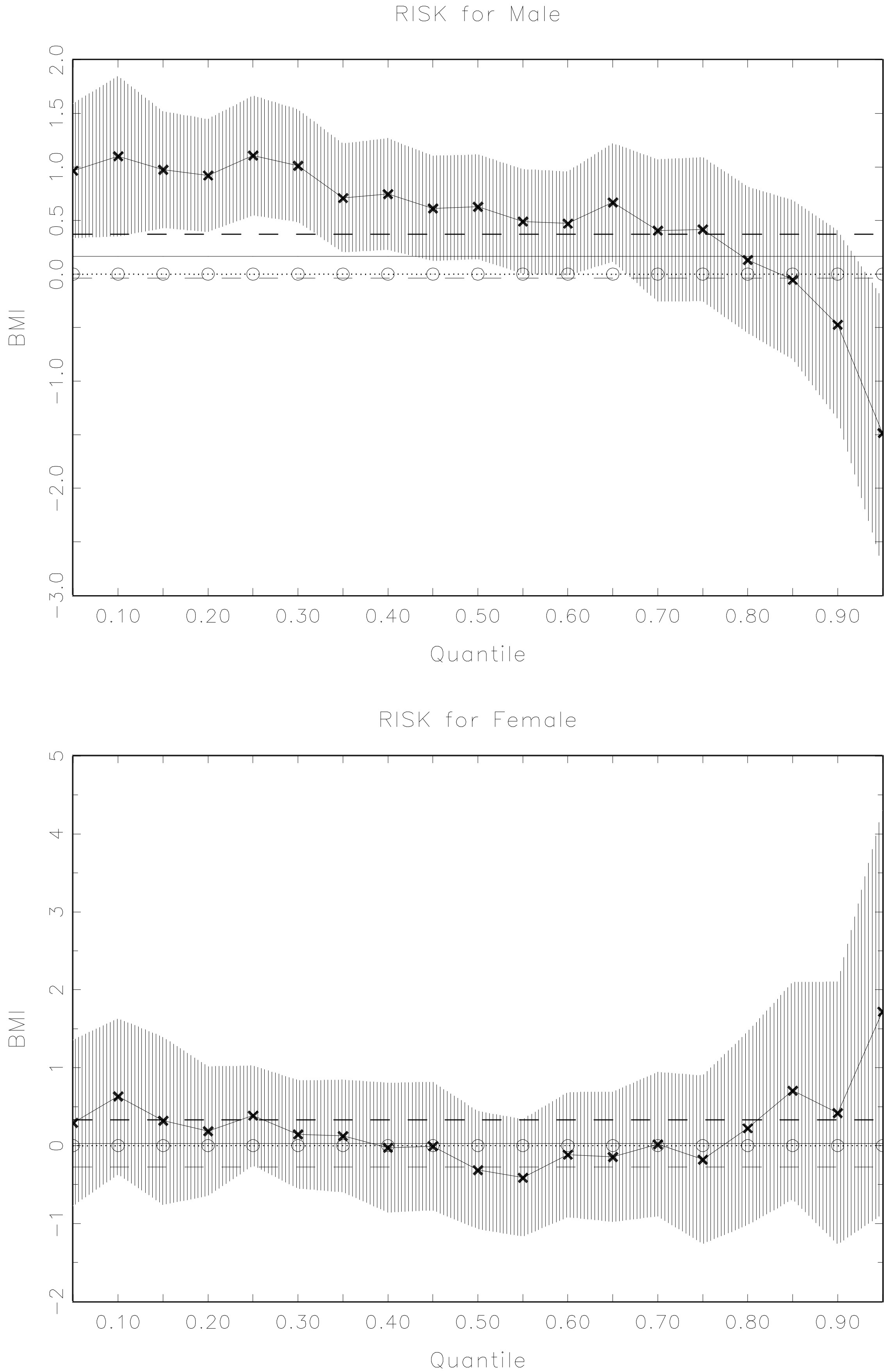


Figure 3: Effects of Socioeconomic Characteristics on BMI for Males.

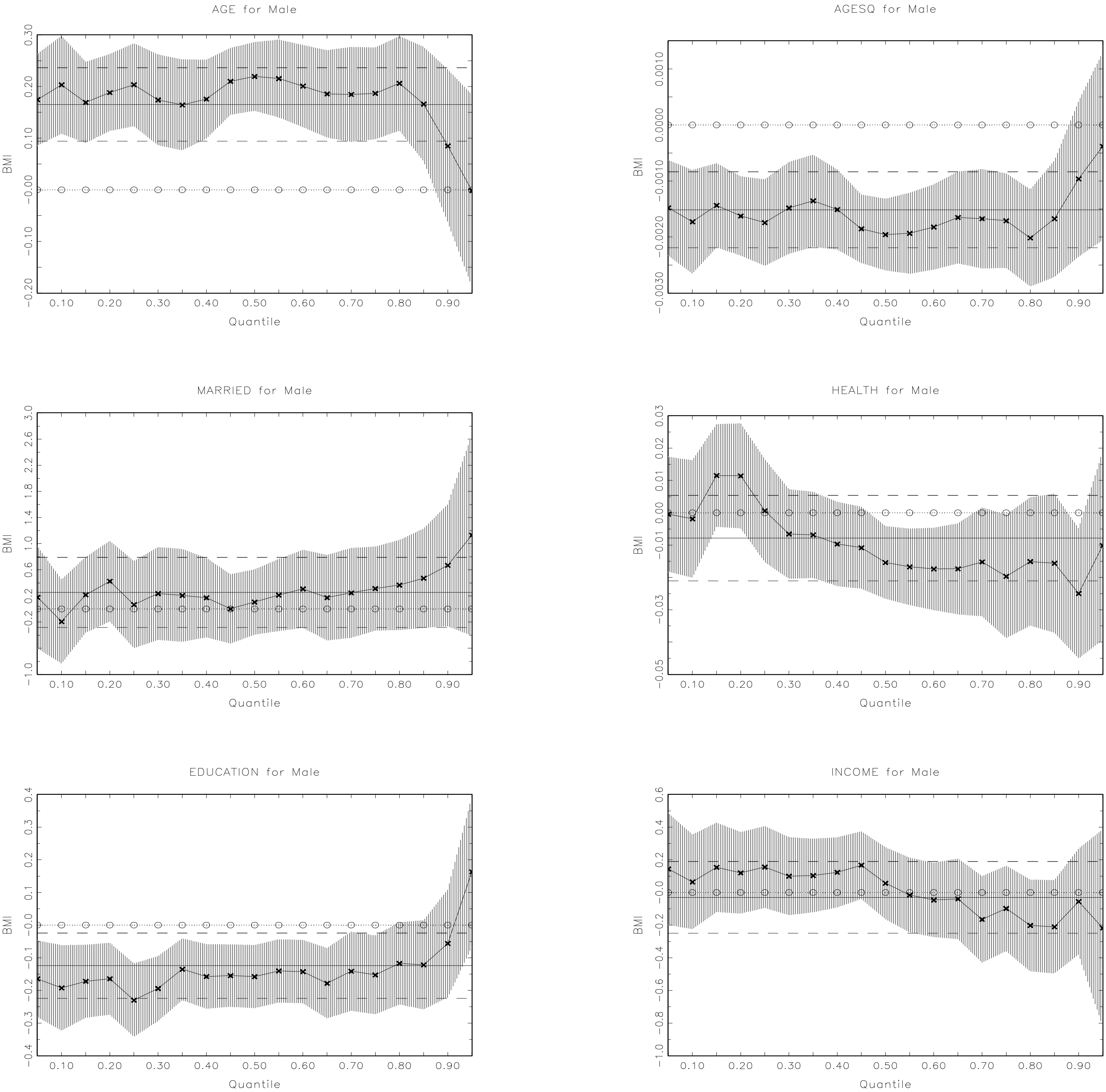


Figure 4: Quantile Regression Results for Males (*continued*).

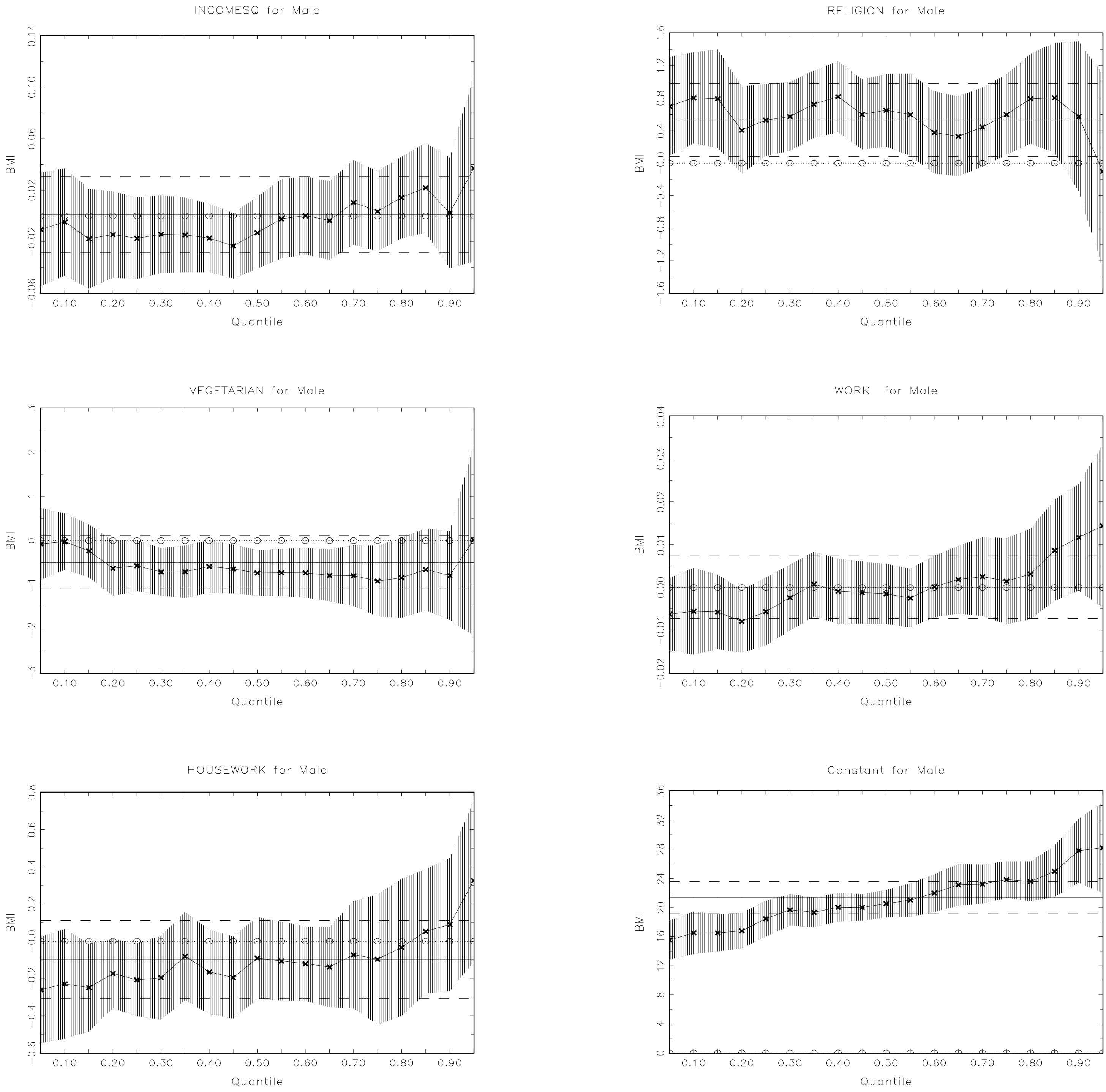


Figure 5: Effects of Socioeconomic Characteristics on BMI for Females.

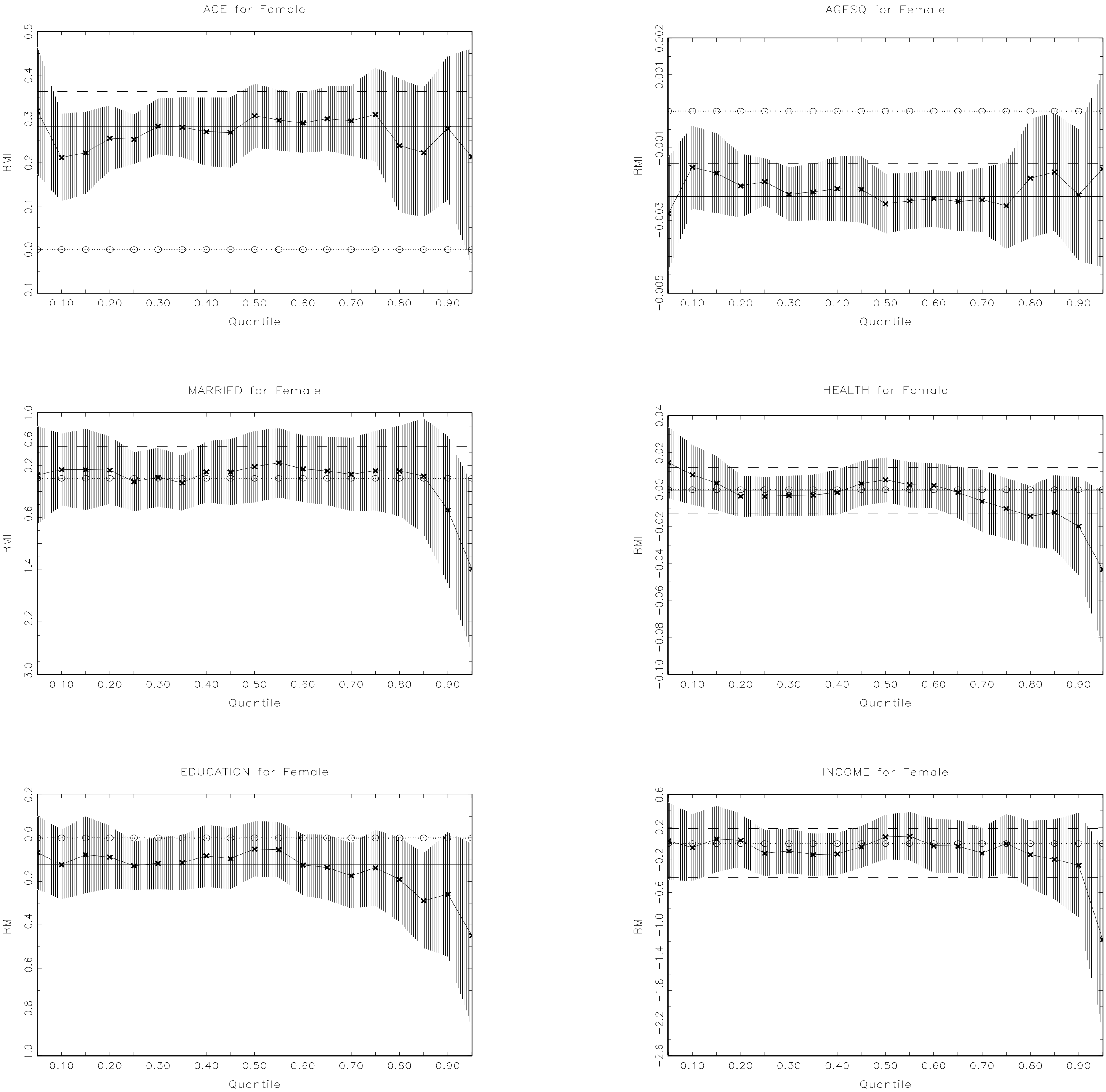
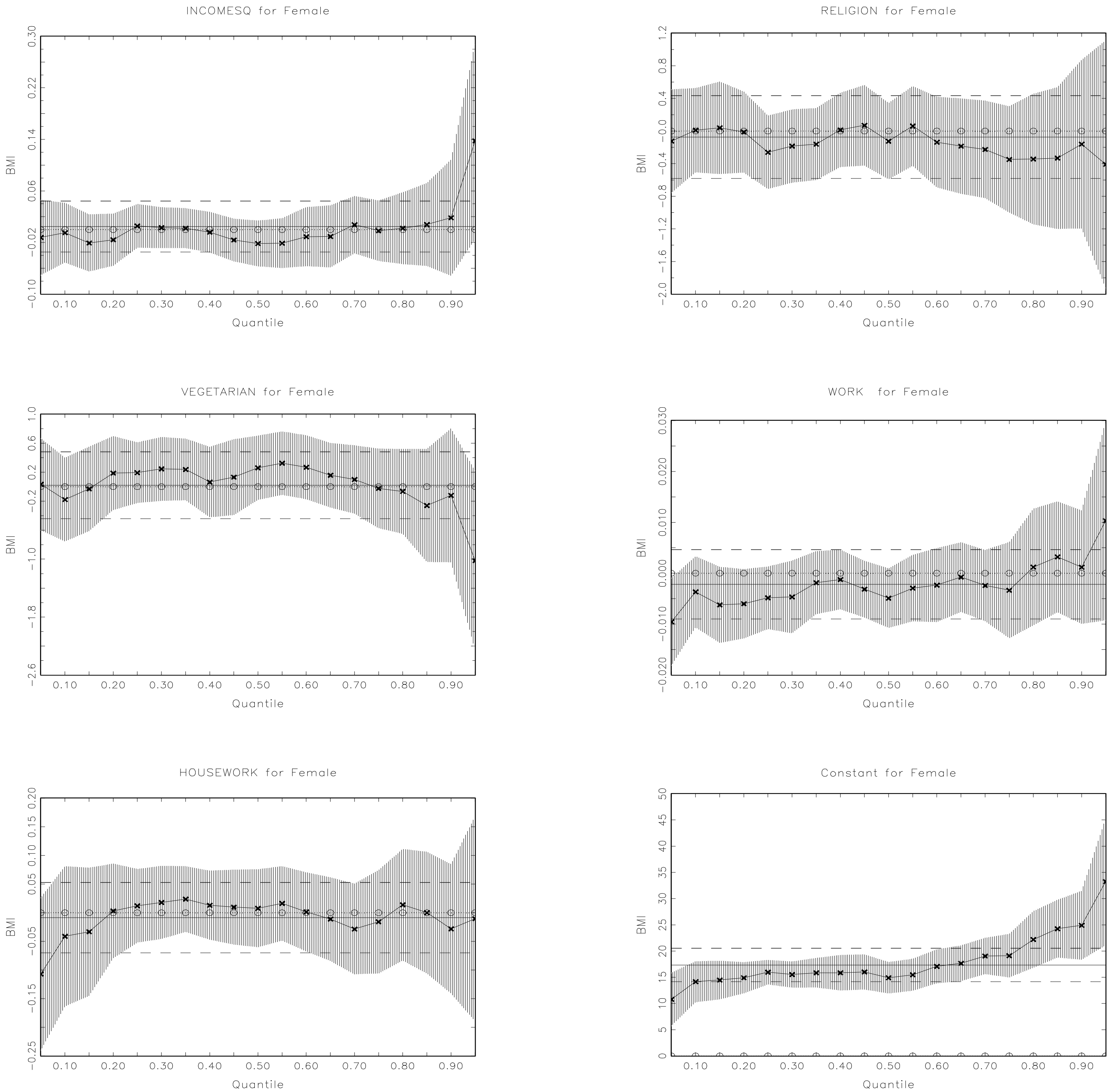


Figure 5: Effects of Socioeconomic Characteristics on BMI for Females (*continued*).



Number	Author(s)	Title	Date
03-A001	Chung-Ming Kuan Wei-Ming Lee	A New Test of the martingale Difference Hypothesis	11/03
03-A002	Chung-Ming Kuan, Yu-Lieh Huang Ruey S. Tsay	A Component-Driven Model for Regime Switching and Its Empirical	11/03
03-A003	Yi-Ting Chen Chung-Ming Kuan	A Generalized Jarque-Bera Test of Concitiional Normality	11/03
03-A004	Kamhon Kan, Sunny Kai-Sun Kwong Charles Ka-Yui Leung	The Dynamics and Volatility of commercial and Residential Property Prices : Theory and Evidence	11/03
03-A005	Kamhon Kan Wei-Der Tsai	Parenting Practices and Children's Education Outcome	11/03
03-A006	Been-Lon Chen	Factor Taxation and Labor Supply In A Dynamic One-Sector Growth Model	12/03
03-A007	Been-Lon Chen	Economic Growth With Optimal Public Spending Compositional	12/03
03-A008	Shin-Kun Peng Ping Wang	Sorting by Foot: Consumable Travel – for Local Public Good and Equilibrium Stratification	12/03
03-A009	Joseph Greenberg Sudheer Gupta Xiao Luo	Towering over Babel: Worlds Apart but Acting Together	12/03
04-A001	Chi-Chung Chen Ching-Cheng Chang	Climate Change and Crop Yield Distribution: Some New Evidence from Panel Data Models	01/04
04-A002	Kamhon Kan Wei-Der Tsai	Obesity and Risk Knowledge	01/04