Semi-parametric Discrete Choice Measures of Willingness to Pay

Ju-Chin Huang*
University of New Hampshire
and
US Environmental Protection Agency

Douglas W. Nychka
National Center for Atmospheric Research

V. Kerry Smith
Arizona State University
and
Resources for the Future

Abstract

A semi-parametric discrete choice method is proposed to recover welfare measures from individual choice data. The estimation procedure and properties of the proposed welfare estimator are discussed. The proposed method is compared with the traditional binary choice models. An application that measures benefits of recreation trips is presented. Our results suggest that the proposed semi-parametric method adds flexibility to the discrete choice modeling and provides a more precise benefit measure than the traditional parametric methods.

Key words: Discrete Choice Methods, Nonparametric Regression, Willingness to Pay, Cubic Smoothing Splines.

JEL: C14, C25, Q20

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* Address correspondence to: Ju-Chin Huang, Department of Economics, University of New Hampshire, Durham, NH 03824, e-mail: jchuang@maple.unh.edu, phone: (603)8623279, fax: (603)8623383. The opinions expressed here are those of the authors, and do not necessarily express the views of the United States Environmental Protection Agency.

1. Introduction

This paper proposes and illustrates a semi-parametric estimator to recover Hicksian welfare measures from individual discrete choice data. Our application is to a discrete response random utility model initially outlined for revealed preference travel cost models by Smith and Kaoru [1986]. However, the findings also have direct relevance for discrete response contingent valuation surveys. Our results indicated that the semi-parametric method does not appear to compromise the precision in benefit estimates as it reduces the restrictions implied by conventional parametric methods for these models (i.e. probit and logit). Our non-parametric method is a cubic smoothing spline function and includes the traditional linear specification as its special case.

This method is not the only flexible approach for estimating binary choice models. However, when non-parametric methods have been evaluated in sampling studies, the results suggest they are usually inferior to a conventional logit, based on the mean squared error and bias in estimates of a model's parameters (see Manski and Thompson [1986] and Horowitz [1992]). Only when there is appreciable heteroscedasticity do the simulation results offer strong support for the non-parametric methods (Klein and Spady [1993] and Li [1996]). These findings seem to be confirmed in a few valuation studies that apply non-parametric or semi-parametric methods to welfare measurement in binary choice models (Chen and Randall [1997], Creel and Loomis [1997], An [2000], Cooper [2002], and Belluzzo [2004]). Thus, the literature suggests there is clear scope for methodological improvements.

2. Semi-Parametric Discrete Choice Welfare Estimators

When binary response models are used to define welfare measures choices are assumed to result from a constrained optimization process. To express this assumption in formal terms, let y_i be the choice variable that y_i=1 if a commodity (or more generally an object of choice) is selected by individual i (with a purchase cost of t_i) and y_i=0 otherwise. t_i defines a lower bound for that individual's WTP. Individual i will purchase the object of choice at price t_i yields greater utility than a situation of no purchase. Thus, the difference in utility associated with the two alternatives, $\Delta v_i = V(1, I_i - t_i; Z_i) - V(0, I_i; Z_i) \geq 0$, where V is the indirect utility function, provides the link between choices and the optimization model. I_i is income, and Z_i is a vector of values of other determinants in the utility function. If we assume Δv_i is a random variable (due to unobserved heterogeneity in preferences), then the probability of y_i=1 (purchase) can be directly related to the induced probability distribution for WTP as follows.

$$
\begin{aligned}
Prob(purchase) &= Prob(y_i = 1) = Prob(\Delta v_i \geq 0) \\
&= Prob(WTP_i \geq t_i) = 1 - G_{WTP}(t_i), \qquad (1)
\end{aligned}
$$

where $G_{WTP}(.)$ is the distribution function for WTP. Conventional practice uses equation (1) with a specification for Δv_i to define the likelihood function. For example, if Δv_i is assumed linear, $\Delta v_i = \alpha - \beta t_i + Z_i'\gamma + e_i$, and the random variable e_i is assumed to follow the logistic (normal) distribution, then the logit (probit) model results. The associated expected WTP has a simple formula, $E(WTP_i)=\frac{\alpha + Z_i'\gamma}{\beta}$, as detailed in Hanemann [1984]. With more complex parametric models the expression E(WTP) depends on the restrictions imposed on $G_{WTP}(.)$ through distributional assumptions or the choice function (Hanemann [1999]).

An important assumption to simplify welfare measurement with this model is a constant marginal utility of income (β). A cubic smoothing spline reduces the restrictions imposed on the modeling structure by focusing on the smoothness of the choice function with respect to the price variable (t_i) and thus can relax this assumption. To consider how this is accomplished, let the nonstochastic component of the utility difference function Δv be *f*(t)+Z′γ, where *f* is a function of t_i and is assumed to belong to the second order Sobolev space, $W_2^2[a,b]$. $W_2^2[a,b]$ is a function space that all functions on [*a,b*] in the space have the first derivative absolutely continuous and the second derivative square integrable. By combining a smoothness criterion and the traditional maximum likelihood criterion, a penalized likelihood function (O'Sullivan et al. [1986]) is formed. With a logistic link function, this penalized likelihood function can be written as equation (2).

$$\max_{\substack{f \in W_2^2[a,b] \\ \gamma \in R}} \sum_{i=1}^{n} (y_i (f_i + Z_i'\gamma) - \log(1 + e^{f_i + Z_i'\gamma})) - \lambda \int_a^b (f''(x))^2 \, dx, \tag{2}$$

The first summation in equation (2) is the usual log-likelihood function for a logit model expressed in terms of the semi-parametric choice function *f*+Z’γ. The integral in the second part of the penalized likelihood function is the roughness function constraining smoothness of *f* in terms of the stated cost, t_i. The smaller the value of this term, the smoother is *f*. *λ* is the smoothing parameter controlling the relative importance of the two terms in (2). As *λ* is allowed to become arbitrarily large, the second term must approach zero. This outcome implies a zero second derivative and a linear fit. Thus, the optimization problem in (2) includes a linear specification as a special case. The penalized likelihood function can be regarded as a generalized ridge regression model.

Equation (2) extends O'Sullivan et al. [1986]. As a result, their findings indicating that, for a given value of *λ*, the solution to a non-parametric logit model (described as (2) without the parametric part of Z′γ) exists and it is a natural cubic smoothing spline function. Thus, *f* is a piecewise cubic polynomial with two continuous derivatives within the data range and a linear function outside the data range. The solution to γ is the typical logit estimator. For a given value of λ, the model can be estimated by the iteratively reweighted least squares (IRLS) method. The optimal value of the smoothing parameter λ can be determined by data driven methods such as generalized cross validation (GCV; Craven and Wahba [1979]). The selection of λ is equivalent to choosing the best spline estimator among a class of alternatives. An IRLS estimation procedure that iteratively estimates f and γ is proposed and the procedure, beginning by estimating f_i with $\gamma = 0$, is outlined as follows.

Step 1. Fit a logistic cubic smoothing spline using the procedure by O'Sullivan et al. (1986); save predicted f_i.[1]

Step 2. Estimate γ given f_i=predicted f_i from step 1; save γ.

Step 3. Repeat step 1 with $Z_i'\gamma$ updated by the estimated γ in step 2; save new predicted f_i.

Step 4. Repeat steps 2 and 3 until the predicted f_i+ $Z_i'\gamma$ converges; save predicted f_i+$Z_i'\gamma$ and optimum λ.

Using the definition for the expected WTP (i.e. E(WTP)=$\int_0^{\infty}(1-G_{WTP}(s))ds-\int_{-\infty}^{0}G_{WTP}(s)ds$) an estimator for WTP can be derived from this model by substituting the estimated logistic probability distribution function into *1-*$G_{WTP}(.)$:

$$W(f)=\int_0^{\infty}\frac{e^{f(x)+Z'\gamma}}{1+e^{f(x)+Z'\gamma}}dx-\int_{-\infty}^{0}\frac{1}{1+e^{f(x)+Z'\gamma}}dx=\int_0^{\infty}\pi(f(x)+Z'\gamma)dx-\int_{-\infty}^{0}[1-\pi(f(x)+Z'\gamma)]dx \quad (3)$$

The estimated expected WTP involves integrating nonlinear function of $f(x)$ using the estimated cubic smoothing spline function. The primary large sample property of this non-parametric WTP estimator can be described as follows:[2]

<u>Theorem 1</u>: Let W(f) be defined as equation (3). Let f_0 *be the true function and* $f_{n\lambda}$ *be the*

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[1] When calculating GCV, the degrees of freedom must be modified to take into account the parametric portion of the model ($Z'\gamma$).

[2] The values of the vector γ can be assumed known or be estimated. Theorem 1 holds in either case.

unique maximizer of (2). If W(f) is finite, then lim Prob(|W($f_{n\lambda}$)-W(f_0)|≤δ)=1, where δ is a small constant.

Theorem 1 ensures the consistency of the WTP estimator derived from the proposed semi-parametric discrete choice method. The proof of the theorem is given in the Appendix A.

An important distinction in the parametric and semi-parametric estimates arises in the computation of estimates for E(WTP). For the former, E(WTP) will generally have a closed form expression, while with semi-parametric estimates it is a numerical integral based on the estimate of $G_{WTP}(.)$. This implies a more complex form for the mean square error (MSE) of WTP estimator. Substituting the expressions for the cubic smoothing spline's estimated WTP and the true WTP into the definition of MSE, we have equation (4), with the subscript *i* omitted for simplicity.

$$MSE = \underset{f_{n\lambda},\hat{\gamma}}{E}\left[\int_a^b \frac{e^{f_{n\lambda}(x)+Z'\hat{\gamma}}}{1+e^{f_{n\lambda}(x)+Z'\hat{\gamma}}}dx - \left(\int_0^\infty \frac{e^{f_0(x)+Z'\gamma}}{1+e^{f_0(x)+Z'\gamma}}dx - \int_{-\infty}^0 \frac{1}{1+e^{f_0(x)+Z'\gamma}}dx\right)\right]^2 \qquad (4)$$

The first part of equation (4) is the estimated expected WTP that is truncated at [*a,b*] and the expression in the parenthesis is the true expected WTP. Equation (4) can be considered an integrated loss function in that it evaluates the overall fit of the probability curve--not the estimator of *f* itself. As a result, the estimates used to generate WTP measures are evaluated by their global performance.

3. Empirical Comparison of Discrete Choice Welfare Measures

To illustrate the method, we used a subset of the data collected in a household survey for a study of recreational site choices in Monongahela River Basin in Pennsylvania (Smith and

Desvousges [1986]). Three binary choice models, logit, probit and our modified cubic smoothing spline, are applied to analyzing the decision to visit the site called The Point at Smithsfield Bridge.[3] In the data, there were 945 visits to recreation sites near Monongahela River and 222 of them were made to The Point. The estimation results of the choice models are given in Appendix B. The average per-trip Hicksian benefit is computed; that is the WTP (as presented in the previous section) in addition to the round-trip costs for a site visit. Empirical distributions of the benefit estimates are constructed using the bootstrap-based method with 500 repetitions. The results are reported in Table 1.

All three models yield similar median benefit estimates. The WTP distributions for logit and probit models are right skewed. The distribution of semi-parametric welfare estimates is less skewed and appears to have a much smaller standard deviation. The 90% confidence intervals for each of the estimators, constructed based on the Efron's percentile method, are also reported. All three binary choice models produce similar welfare measures. The differences are statistically insignificant because of the overlapped confidence intervals. However, the parametric estimates would seem to be less efficient than the estimate from the semi-parametric model. Recall that the semi-parametric model includes the linear logit model as its special case when the smoothing parameter λ approaches infinity. In this case study, the optimum λ value selected by the GCV function tends to be small indicating that the underlying marginal utility of income is not constant. A flexible cubic smoothing spline function to allow heterogeneous marginal utility of income appears to improve the estimation precision of the welfare measures.

Our findings have general implications for the use of discrete response questions in contingent valuation survey. Boyle's [2003] recent comprehensive survey of best practice

[3] Recall that the semi-parametric model is a combination of a cubic smoothing spline function in the price (cost of a trip) variable and a parametric specification for all other variables.

methods in using the contingent valuation concludes that while discrete response questions (and the need for logit and probit estimators to derive WTP estimates) appears to be the *safe approach*, "…it is not absolutely clear that the dichotomous choice questions clearly represent the best approach" (p. 142). His summary suggests this strategy tends to lead to higher estimates for WTP when compared to other stated preference approaches for comparable changes in environmental resources. Our results suggest this may be due to the relative inflexibility of the parametric estimators used to evaluate discrete response surveys. Our bootstrapped sampling distributions suggest the cubic smoothing spline produces a tighter 90% confidence interval with the upper bound estimated WTP that was 62 and 74 percent of the values for the logit and probit estimates, respectively. Our findings conform with the literature that the conventional estimates are not as precise as the non-parametric with heteroscedasticity comparable to what might be expected in the important economic applications where these methods would be applied.

REFERENCES

An, Mark Yuying, 2000, "A Semiparametric Distribution for Willingness to Pay and Statistical Inference with Dichotomous Choice Contingent Valuation Data," *American Journal of Agricultural Economics* 82, 487-500.

Belluzzo, Walter, Jr., 2004, "Semiparametric Approaches to Welfare Evaluations in Binary Response Models, "*Journal of Business & Economic Statistics* 22, 322-330.

Boyle, Kevin J., 2003, “Contingent Valuation in Practice,” in P.A. Champ, K.J. Boyle and T.C. Brown, editors, A Primer on Non-Market Valuation (Dordrecht: Kluwer Academic Publishers).

Chen, Heng Z. and Alan Randall, 1997, "Semi-Nonparametric Estimation of Binary Response Models with an Application to Natural Resource Valuation," *Journal of Econometrics* 76, 323-340.

Cooper, Joseph C., 2002, "Flexible Functional Form Estimation of Willingness to Pay Using Dichotomous Choice Data," *Journal of Environmental Economics and management* 43, 267-279.

Cox, Dennis D., and Finbarr O'Sullivan, 1990, "Asymptotic Analysis of Penalized Likelihood and Related Estimators," *The Annals of Statistics* 18, 1676-1695.

Craven, P., and G. Wahba, 1979, "Smoothing Noisy Data with Spline Functions: Estimating the Correct Degree of Smoothing by the Method of Generalized Cross-validation," *Numerische Mathematik* 31, 377-403.

Creel, Michael, and John Loomis, 1997, "Semi-Nonparametric Distribution-Free Dichotomous Choice Contingent Valuation," *Journal of Environmental Economics and Management* 32, 341-358.

Hanemann, W. Michael, 1984, "Welfare Evaluations in Contingent Valuation Experiments with Discrete Responses," *American Journal of Agricultural Economics*, 66, (August): 332-341.

Hanemann, W. Michael, 1999, “The Economic Theory of WTP and WTA” in I.J. Bateman and K.G. Willis, editors, Valuing Environmental Preferences: Theory and Practice of the Contingent Valuation Method in the US, EU and Developing Countries (Oxford: Oxford University Press).

Horowitz, Joel L., 1992, "A Smoothed Maximum Score Estimator for the Binary Response Model," *Econometrica*, 60 (May): 505-532.

Klein, Roger W. and Richard H. Spady, 1993, "An Efficient Semiparametric Estimator for Binary Response Models," *Econometrica*, 61, 387-421.

Li, C., 1996, "Semiparametric Estimation of the Binary Choice Model for Contingent Valuation," *Land Economics* 72, 462-473.

Manski, Charles F., and T. S. Thompson, 1986, "Operational Characteristics of Maximum Score Estimation," *Journal of Econometrics* 32, 65-108.

O'Sullivan, Finbarr, Brian S. Yandell, and William J. Raynor, Jr., 1986, "Automatic Smoothing of Regression Functions in Generalized Linear Models," *Journal of American Statistical Association* 81, 96-103.

Smith, V. Kerry and William H. Desvousges, 1986, *Measuring Water Quality Benefits*, International Series in Economic Modeling, Kluwer Academic, Norwell, Mass.

Smith, V. Kerry and Yoshiaki Kaoru, 1986, “Modeling Recreation Demand within a Random Utility Framework,” *Economics Letters* 22, 395-399.

Table 1: Benefit Estimates and Bootstrapped Distributions

	Logit	Probit	Semi-parametric
WTP Estimate	2.124	2.033	2.179
Mean[a]	2.418	2.290	2.200
STD	1.354	1.742	0.364
Median	2.107	2.019	2.196
Lower Bound[b]	1.351	1.321	1.593
Upper Bound	4.467	3.705	2.756

[a]It is the mean of the 500 bootstrapped average benefit estimates.
[b]The lower and upper bounds are created based on Efron's percentile method. They form a 90% confidence interval for each of the benefit estimates.

APPENDIX A

As a rule we can appeal to the Slutsky Theorem to establish that any continuous function of a consistent estimator is consistent. The Theorem developed below (due to Cox and O'Sullivan [1990]) describes the specific norm that assures consistency for the penalized likelihood estimators. We summarize their Theorem and the implications below.

<u>Theorem A</u>: *Suppose $m\geq 2$ and $f_0 \in W_2^{mp}$ [0,1], where $3/(2m)<p\leq 1$. If λ_n is a sequence such that $\lambda \to 0$ and for some $\alpha \in (1/(2m),(p-1/(2m))/2]$, $n^{-1}\lambda_n^{-2(\alpha+1/(2m))} \to 0$, then for $0\leq b\leq \alpha$,*

$\lim_{M\to\infty} \liminf_{n\to\infty}$ Prob {a unique maximizer $f_{n\lambda_n}$ of $L_{n\lambda_n}(f)$ satisfies

$$\left\| f_{n\lambda_n} - f_0 \right\|_{W_2^{mb}}^2 \leq M(\lambda_n^{p-b} + n^{-1}\lambda_n^{-(b+1/(2m))})\} = 1$$

where $\|\cdot\|_2 = <\cdot,\cdot>$ is the squared norm of W_2^{mb} with the inner product defined as

$$\begin{aligned} \langle \theta, \varsigma \rangle_{W_2^m} &= \langle \theta, \varsigma \rangle_{L_2} + \langle \theta^{(m)}, \varsigma^{(m)} \rangle_{L_2} \\ &= \int \theta\varsigma dx + \int \theta''\varsigma'' dx \end{aligned} \tag{A1}$$

f_0 is the true function that maximizes $L(f)$, the limiting function of L_n.

$$L(f) = \lim_{n\to\infty} L_n(f) = \int_a^b [\pi(f_0(x))f(x) - \log(1+e^{f(x)})]g(x)dx \tag{A2}$$

According to the theorem, as the smoothing parameter goes to zero and n is large, the distance between the solution to (2) and the true function f_0 is less than a small number with probability one. A heuristic description is as follows. Suppose that $f_{n\lambda}$ is the unique maximizer of (2). The difference between the unique maximizer of L, f_0, and $f_{n\lambda}$ is the estimation error. The estimation error consists of a systematic error and a stochastic error. The two error components represent the bias and the sampling variabilities, respectively, as reflected in the following equation.

$$f_{n\lambda} - f_0 = (f_\lambda - f_0) + (f_{n\lambda} - f_\lambda), \tag{A3}$$

where f_λ is the maximizer of $L(f) - \lambda \int (f'')^2 \, dx$. The difference between f_λ and f_0 is attributable to the addition of the penalty function; hence, it is a systematic error and is independent of the sampling. The difference between $f_{n\lambda}$ and f_λ is a random error due to sampling. Cox and O'Sullivan [1990] analyzed both of these errors and the overall accuracy is the content of Theorem A.

Consistency of the Proposed Welfare Measure

With some additional assumptions, Theorem A can be used to show the consistency of the welfare measure developed from these estimates. Considering the absolute difference between $W(f_{n\lambda})$ and $W(f_0)$,

$$|W(f_{n\lambda}) - W(f_0)| = \left| \int_0^\infty \left(\frac{e^{f_{n\lambda}(x)+Z'\gamma}}{1+e^{f_{n\lambda}(x)+Z'\gamma}} - \frac{e^{f_0(x)+Z'\gamma}}{1+e^{f_0(x)+Z'\gamma}} \right) dx + \int_{-\infty}^0 \left(\frac{1}{1+e^{f_{n\lambda}(x)+Z'\gamma}} - \frac{1}{1+e^{f_0(x)+Z'\gamma}} \right) dx \right| \tag{A4}$$

Formally, the expectation of WTP requires integrating the probability curve from $-\infty$ to ∞. In fact, a welfare measure is usually finite and positive (with rare cases that are negative) in that its distribution is truncated at some finite values. If the welfare measure is assumed to be in a finite range $[-N,M]$ where N and M are positive finite numbers, then the right-hand side of (A4) has finite integrals from $-N$ to zero and zero to M. This is a plausible assumption and it enables us to apply Theorem A.

Since both $e^{f+Z'\gamma}/(1+e^{f+Z'\gamma})$ and $1/(1+e^{f+Z'\gamma})$ are monotonic functions, there exists a function $f^*(x)=\beta f_0(x)+(1-\beta)f_{n\lambda}(x)$, $0 \le \beta \le 1$ and $\beta=\beta(x)$ such that equation (A4) with the assumption of finite range $[-N,M]$ can be rewritten as follows.

$$|W(f_{n\lambda})-W(f_0)|=\left|\int_0^M \frac{e^{f_0+Z'\gamma}}{(1+e^{f_0+Z'\gamma})^2}(f^*-f_0)dx-\int_{-N}^0 \frac{e^{f_0+Z'\gamma}}{(1+e^{f_0+Z'\gamma})^2}(f^*-f_0)dx\right| \tag{A5}$$

Notice that equation (A5) is derived by linearizing the logistic function at f_0 and is not based on the intermediate mean value theorem.

By the Cauchy-Schwartz inequality,

$$|W(f_{n\lambda})-W(f_0)|\le\sqrt{\int_0^M\left(\frac{e^{f_0+Z'\gamma}}{(1+e^{f_0+Z'\gamma})^2}\right)^2dx\int_0^M(f^*-f_0)^2dx}+\sqrt{\int_{-N}^0\left(\frac{e^{f_0+Z'\gamma}}{(1+e^{f_0+Z'\gamma})^2}\right)^2dx\int_{-N}^0(f^*-f_0)^2dx} \tag{A6}$$

If the expected willingness to pay, $W(f_0)$, is finite, $\int\frac{e^{f+Z'\gamma}}{1+e^{f+Z'\gamma}}dx$ will be finite. Hence, $\int\left(\frac{e^{f+Z'\gamma}}{1+e^{f+Z'\gamma}}\right)^2dx$ is finite and can be set to be some constant. It is seen that

$$\begin{aligned}
|W(f_{n\lambda})-W(f_0)| &\le C_1\sqrt{\int_0^M(f^*-f_0)^2dx}+C_2\sqrt{\int_{-N}^0(f^*-f_0)^2dx}\\
&\le C_1\sqrt{\int_{-N}^M(f^*-f_0)^2dx}+C_2\sqrt{\int_{-N}^M(f^*-f_0)^2dx}\\
&= C\sqrt{\int_{-N}^M(f^*-f_0)^2dx}\\
&\le C\sqrt{\int_{-N}^M(f_{n\lambda}-f_0)^2dx}\\
&\qquad \text{(because } f^*=\varphi f_0+(1-\varphi)f_{n\lambda},\ 0\le\varphi\le1)\\
&= C\|f_{n\lambda}-f_0\|_{L_2[-N,M]}\\
&= C\|f_{n\lambda}-f_0\|_{W_2^{bm}[-N,M]} \quad \text{with b=0,}
\end{aligned} \tag{A7}$$

where C_1, C_2, and C are some fixed positive constants. Thus, $|W(f_{n\lambda})-W(f_0)|$ is less than or equal to the norm of $f_{n\lambda}-f_0$. That is, by setting b=0 in Theorem A, when the number of observations is large and the smoothing parameter is very small, $|W(f_{n\lambda})-W(f_0)|$ is less than some small number ε with probability equal to one. The consistency of the welfare measure with finite range derived from the penalized likelihood function is verified.

APPENDIX B. Regression Results of the Choice Models

Dependent Variable = 1 if visited the site = 0 if not	Logit	Probit	Semi-Parametric
Intercept	2.299	1.260	1.519
	(1.543)[a]	(1.527)	(1.072)
Household Income $	$-5.1x10^{-5}$	$-2.7x10^{-5}$	$-3.8x10^{-5}$
	(-3.248)	(-3.019)	(-2.420)
Round Trip Costs $	-0.566	-0.348	-1.592[b]
	(-3.458)	(-3.705)	
Boat Ownership (=1)	0.669	0.369	0.342
	(1.537)	(1.503)	(0.805)
Age	-0.098	-0.055	-0.092
	(-5.160)	(-5.218)	(-4.722)
Years of School Education	0.261	0.149	0.164
	(2.279)	(2.348)	(1.559)
Part Time Worker (=1)	0.210	0.162	0.428
	(0.425)	(0.595)	(0.887)
Retired (=1)	1.701	0.966	1.424
	(2.044)	(1.988)	(1.672)

[a]Numbers in parentheses are the t statistics.
[b]The coefficient of Round Trip Costs is the average of first derivatives of the spline functions.