Semiparametric Analysis of the Effect of Income on the Consumption of Tobacco and Alcohol Products in Turkey

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Abstract

This paper estimates the effect of income on the decision to consume alcohol and tobacco products, and on the corresponding levels of expenditure for households in Turkey using a semiparametric Bayesian approach and data derived from the 2010 Turkish Household Expenditure Survey. We find that unlike alcohol, which remains a normal good, tobacco products become an inferior good at high income levels. However, for smokers and drinkers only, tobacco and alcohol products respectively are normal goods. The results support the claim that taxing tobacco products is likely to keep individuals from smoking for the lower income groups, which include young adults.

1 Introduction

The main research question of this paper is whether consumers view two addictive products, alcohol and tobacco, as normal or inferior goods at different levels of income? This is done by utilizing a special Bayesian estimation method which allows income to enter the conditional mean function semi-parametrically. This research question is investigated in the context of Turkish consumers using a data set derived from the 2010 Turkish Household Expenditure Survey (THES) conducted by the Turkish Statistical Institute (TUIK, 2010).

The findings of this study are not easily generalizable to other countries and likely to be valid only for Turkey, which is a predominately Muslim country where consumption of alcohol is legal. In the constructed data set only 7 percent of the respondents consumes alcohol, however, about 54 percent is smokers. This paper estimates the effect of income on two dependent variables of interest separately. The first variable is a binary choice of being an alcohol and tobacco consumer. The second variable is the level of spending on these addictive products conditional on being a consumer. The adopted semiparametric Bayesian approach is based on Koop and Poirier (2004) and Koop and Tobias (2006). It has been also used by Munkin and Trivedi (2009) to model the effect of income on the decision to purchase dental insurance, Feng and Munkin (2021) to model the effect of BMI on income among rural and urban workers in China and Munkin (2022) to model the effect of social security income on the decision to purchase Medigap insurance.

Tobacco causes around 100,000 deaths in Turkey each year which makes roughly a quarter of all annual deaths. The number of lung cancers has increased 15 times over the last 40 years (Ekuklu et al. 2004). Turkey's per capita consumption of alcohol for people over the age of 15 is relatively small 1.4 L, compared with 9.9 L in Germany and 10.8 L in the United Kingdom (TAPDK, 2012). The World Health Organization (WHO, 2004) reports that 4 million people are alcoholic, and 13 million consume alcoholic products in Turkey. Nearly 20% of health-care expenditure is spent on alcohol-related diseases annually (Ekuklu et al. 2004).

The topic of the paper is a very interesting economics question and at the same time is a very relevant policy issue. The adverse economic and health effects of tobacco and alcohol consumption can be considerable. For developing countries the costs of smoking are most likely high, but it is difficult to estimate. However, reducing smoking and drinking rates is always a desirable objective for any government. A reasonable policy instrument could be imposing taxes on tobacco and alcohol products making them more expensive in the attempt to force price sensitive consumers into quitting. However, given the addictive nature of these goods the extent at which this policy would be successful is not clear. A special consumption tax (SCT) on alcohol and tobacco products was introduced Turkey and first set at 18% in 2002. Then it was increased to 63% in 2009 and 65% in 2011. Subsequently, the government ended the SCT on alcoholic beverages, but lump sum taxes on alcohol were raised to offset the eliminated SCT.

The WHO and the U.S. Centers for Disease Control and Prevention reported that the percentage of smokers 15 years or older in Turkey decreased from 31.3% in 2008 to 27% in 2012. Global Adult Tobacco Survey (GATS, 2010) also reported that smoking rates declined from 47.9% to 41.4% for males and from 15.2% to 13.1% for females during the same period. These decreases in the age categories of 25–34 and 35–44 were from 40.3% and 39.6% in 2008 to 34.9% and 36.2% respectively in 2012. (Bilgic and Yen, 2015). Alcohol consumption, on the other hand, doubled from 500 million liters in 2003 to 1.07 billion liters in 2009 (TUIK, 2010).

The rest of the paper is organized as follows. Section 2 defines the econometric model. Section 3 outlines the estimation procedure. Section 4 describes the data and presents the application.

2 Econometric Model

First we specify the probit model with a non-parametric component. Assume that we have N independent observations for individuals who choose whether to consume a product. In our application the product is either tobacco or alcohol. Let d_i be the binary random variable ($i = 1, ..., N$) representing this choice such that $d_i = 1$ if consuming and $d_i = 0$ otherwise. The latent utility approach defines the binary probit model assuming existence of a latent variable (Z_i) representing the gain in utility received from consuming ($d_i = 1$) relative to the alternative ($d_i = 0$). To allow for income to enter such utility nonparametrically we follow recent work on Bayesian semiparametric techniques by Koop and Poirier (2004) and Koop and Tobias (2006). Let the participation equation be specified as

$$Z_i = f(s_i) + \mathbf{W}_i \boldsymbol{\alpha} + \varepsilon_i, \tag{1}$$

where $\mathbf{W}_i$ is a vector of exogenous regressors, $\boldsymbol{\alpha}$ is a conformable vector of parameters, and the distribution of the error term ε_i is $\mathcal{N}(0, 1)$. Function $f(.)$ is unknown, s_i is income of individual i and parameter $\boldsymbol{\alpha}$ does not include an intercept. The consumption dummy is defined as

$$d_i = I_{[0,+\infty)}\left(Z_i\right), \tag{2}$$

where $I_{[0,+\infty)}$ is the indicator function for the set $[0, +\infty)$.

Values $f(s_i)$ $(i = 1, ..., k_\gamma)$ correspond to k_γ distinct values of income sorted in the increasing order. The nonparametric approach treats all k_γ values of $f(s_i)$ as parameters. The observed income variable takes almost the same number of distinct values as the number of observations. It seems reasonable to assume that the probability of consuming will not change much for small increments in income, and therefore, we round the income variable up to a hundred TL. This produces a smaller number of k_γ relative to the total number of observations N, which reduces the computational burden.

We sort the data by values of s so that s_1 is the lowest level of income and s_N is the largest. The main assumption that we make on function $f(.)$ is that it is smooth such that it is differentiable and its slope does not change too fast (Shiller, 1984).

Stacking (1) over i we obtain

$$\mathbf{Z} = \mathbf{P}\boldsymbol{\gamma} + \mathbf{W}\boldsymbol{\alpha} + \boldsymbol{\varepsilon},$$

where

$$\boldsymbol{\gamma} = \begin{bmatrix} f(s_1) \\ f(s_2) \\ \dots \\ f(s_{k_\gamma}) \end{bmatrix},$$

and $\mathbf{P}$ is an $N \times k_\gamma$ matrix constructed to select the appropriate element of γ for each observation i.

Define an $k_\gamma \times k_\gamma$ matrix $\mathbf{R}$ such that $\boldsymbol{\psi} = \mathbf{R}\boldsymbol{\gamma}$ is a vector of slope changes of function $f(.)$,

$$\psi_j = \frac{\gamma_j - \gamma_{j-1}}{s_j - s_{j-1}} - \frac{\gamma_{j-1} - \gamma_{j-2}}{s_{j-1} - s_{j-2}}, \quad j = 3, ..., k_\gamma,$$

and the first two elements are simply $\psi_1 = f(s_1)$ and $\psi_2 = f(s_2)$. One can think of parameters ψ_j $(j = 3, ..., k_\gamma)$ as numerical approximations to the second order derivatives of function $f(s_j)$, calculated at $k_\gamma - 2$ points corresponding to $j = 3, ..., k_\gamma$. Then

$$\mathbf{Z} = \mathbf{P}\mathbf{R}^{-1}\boldsymbol{\psi} + \mathbf{W}\boldsymbol{\alpha} + \boldsymbol{\varepsilon}.$$

Specifying priors on the numerical second derivatives places priors on the degree of smoothness of $f(.)$. Assume that

$$\psi_j \sim \mathcal{N}(0, \eta), \quad j = 3, ..., k_\gamma.$$

where parameter η follows

$$\eta \sim IG(a, b)$$

with chosen values a and b.

To identify the regression curve $f(.)$ one has to also specify priors on ψ_1 and ψ_2. One can think of the pair ψ_1 and ψ_2 as the initial two points of the regression curve that determines the level of the curve while parameters ψ_j $(j = 3, ..., k_\gamma)$ set its degree of smoothness. We place flat but still proper priors on (ψ_1, ψ_2) as $\mathcal{N}(\mathbf{0}_2, \mathbf{I}_2)$.

Parameters η determines the tightness of the prior for ψ_j. If the prior of η is selected to be too tight, it can result in the regression function to be simply linear. After experimenting with different values a and b we select them such that η is in the interval $[10^{-5}, 10^{-4}]$ producing smooth posteriors. We select proper prior distributions for parameter $\boldsymbol{\alpha}$,

$$\boldsymbol{\alpha} \sim \mathcal{N}(\mathbf{0}, 10\mathbf{I}_k).$$

2.1 The MCMC algorithm

Let $\Delta_i = (\mathbf{W}_i, \boldsymbol{\psi}, \boldsymbol{\alpha})$, and denote $\mathbf{P}_i$ the i^{th} row of matrix $\mathbf{P}$. For each observation i the likelihood is

$$\begin{aligned}\Pr[d_i, Z_i|\Delta_i] &= (2\pi)^{-1/2} \exp\left[-0.5\left(Z_i - \mathbf{P}_i\mathbf{R}^{-1}\boldsymbol{\psi} - \mathbf{W}_i\boldsymbol{\alpha}\right)^2\right] \\ &\quad \times \left[d_i I_{[0,+\infty)}(Z_i) + (1-d_i) I_{(-\infty,0)}(Z_i)\right]\end{aligned}$$

The joint distribution for all observations is the product of such N independent observations over $i = 1, ...N$. The posterior density is proportional to the product of the prior density of the parameters and the joint distribution of observables and included latent variables.

We block the parameter set as Z_i, $[\boldsymbol{\psi}, \boldsymbol{\alpha}]$, η and construct a Gibbs sampler algorithm. The steps of the MCMC algorithm are the following:

1. The latent vectors Z_i $(i = 1, ...N)$ are conditionally independent with bivariate normal distribution $Z_i \overset{iid}{\sim} \mathcal{N}\left[\overline{Z}_i, \overline{H_i}^{-1}\right]$ where

$$\overline{H_i} = 1, \;\; \overline{Z}_i = \mathbf{P}_i \mathbf{R}^{-1} \boldsymbol{\psi} + \mathbf{W}_i \boldsymbol{\alpha}$$

and subject to

$$\begin{aligned} Z_{ji} &\geqslant 0 \text{ if } d_{ji} = 1 \text{ and} \\ Z_{ji} &< 0 \text{ if } d_{ji} = 0. \end{aligned}$$

2. Let the prior distributions of $\boldsymbol{\psi}$ be $\mathcal{N}\left[\underline{\boldsymbol{\psi}}, \underline{\mathbf{H}}_{\psi}^{-1}\right]$ and $\boldsymbol{\alpha}$ be $\mathcal{N}\left[\underline{\boldsymbol{\alpha}}, \underline{\mathbf{H}}_{\alpha}^{-1}\right]$. Denote $\mathbf{G}_i = (\mathbf{P}_i \mathbf{R}^{-1}, \mathbf{W}_i)$, $\boldsymbol{\theta}' = (\boldsymbol{\psi}', \boldsymbol{\alpha})$ with the prior distribution $\mathcal{N}\left[\underline{\boldsymbol{\theta}}, \underline{\mathbf{H}}_{\theta}^{-1}\right]$. Then the full conditional distribution of $\boldsymbol{\theta}$ is $\mathcal{N}\left[\overline{\boldsymbol{\theta}}, \overline{\mathbf{H}}_{\theta}^{-1}\right]$

where

$$\begin{aligned}\overline{\mathbf{H}}_\theta &= \underline{\mathbf{H}}_\theta + \sum_{i=1}^{N} \mathbf{G}_i' \mathbf{G}_i \\ \overline{\boldsymbol{\theta}} &= \overline{\mathbf{H}}_\theta^{-1} [\underline{\mathbf{H}}_\theta \underline{\boldsymbol{\theta}} + \sum_{i=1}^{N} \mathbf{G}_i' Z_i].\end{aligned}$$

3. Finally, given the prior $\eta \sim IG(a, b)$, the full conditional for η is

$$\eta \sim IG\left(\frac{k_\gamma - 2}{2} + a, \left(b^{-1} + \frac{1}{2}\sum_{i=3}^{k_\gamma} \psi_j^2\right)^{-1}\right).$$

This concludes the MCMC algorithm.

2.2 Application

We use data built from the 2010 THES conducted by TUIK. A subset of the data set was previously used by Bilgic and Yen (2015). Households headed by individuals under age 20 are deleted from the sample. Table 1 presents the descriptive statistics.

The THES provides socio-demographic characteristics of the households, including gender, marital and employment status, age categories, education, health insurance coverage, number of automobiles, number of computers, cellphones and TVs, availability of the Internet, properties (shops, grocery stores, lands, apartments, vineyards, orchards), income, home ownership, and presence of children by age categories. Alcohol and tobacco products have their monthly expenditures.

The first column of Table 1 gives means and standard deviations (second raw) of all variables for the full sample of 9822 observations. The second and third columns do it for only those individuals who have positive tobacco and alcohol expenditures respectively. Clearly the smoking and drinking populations are different in many respects of which the differences in income and education are most striking. The drinking population is more educated and more affluent. Drinking individuals are more likely to have a smaller household, live in an urban area and be a male. They are also less likely to have kids of any age.

First we estimate the probit model for the binary indicators of the smoking and drinking status. The model allows income enter the conditional mean semiparametrically. Since income is a continuos variable it takes almost as many distinct values as the number of observations, close to 9822. We round income values up to the nearest increment of 0.04 (400 TL annually). It seems reasonable to assume that the probability of consumption will not change much for such small increments in income. This gives us $k_\gamma = 309$ distinct values of income and that many income parameters to estimate. The results on the estimated posterior means and standard deviations of all parameters except income are presented in Tables 2 and 3 respectively. The estimated income functions are plotted in Figures 1 and 2 for smoking and drinking respectively.

As expected education negatively affects the probability of being a smoker. A higher level of education measured in the number of years of schooling means better understanding the harm caused by smoking. Having kids of all ages, being homeowner and being married have negative impacts on smoking. A possible explanation of this is that having a bigger family makes an individual more concerned about his own health because of the influence from his family members. The excluded age category is 60 years and older which means that being younger than 60 years of age has a positive impact on being a smoker. Surprisingly employment has no statistical effect on smoking.

As a check we estimate a baseline probit model in which income enters the conditional mean linearly and find that it does not have any significant linear effect on the smoking decision. However, Figure 1 shows that the relationship between income and probability of being a smoker is not linear. Although for lower income levels higher income affects the smoking decision in a linear way until it reaches the 25th percentile, after which it flattens indicating that for large enough values of income the decision of smoking perhaps depends on other factors but not on income. For the top 10th percentile the probability of smoking drops substantially, but because there is fewer observations in that range the standard errors become larger. These findings should have direct policy implications. The results support the claim that taxing tobacco products as an instrument to combat smoking is most effective for the lower income individuals. That includes young adults. If making tobacco products more expensive can keep them from smoking that would increase the probability of reducing the number of life-time smokers. In fact this conclusion is consistent with the data from Global Adult Tobacco Survey regarding Turkey in that there was a substantial decrease in the number of smokers in Turkey after all the increases in tobacco consumption taxes in the last decade.

Regarding alcohol, education leads to a higher probability of consumption. Household size, living in an urban area, being a homeowner and married have a negative impact on the probability of drinking. Figure 2 shows that the effect of income is not linear just like in the case of smoking, however, there is a fundamental difference in consumption behavior for the high income group. The inverted S-shaped curve is consistent at the beginning with diminishing marginal returns of income on the probability of drinking. Then a point is reached of a very high income level after which additional income exponentially increases the probability of alcohol consumption. Even though both tobacco and alcohol are addictive goods, drinking is more appealing to the high income group, remaining a normal good while tobacco products becoming inferior. Once again this interpretation is subject to a much smaller number of observations for the high income individuals. However, if taxing alcohol can have any effect on reducing drinking it could be most effective for the low income group.

The semiparametric probit model can be easily modified to allow for a continuous dependent variable. The changes to the MCMC algorithm are minimal: there is no need to draw latent variable Z_i. The full conditional kernel is defined given the observed expenditure Y_i instead of Z_i and the full conditional of the parameters in equation

$$Y_i = f(s_i) + \mathbf{W}_i\boldsymbol{\alpha} + \varepsilon_i$$

is the same as in the probit model with Y_i used instead of Z_i. In fact, we define Y_i as the logarithm of expenditure and estimate the model for positive tobacco and alcohol expenditures respectively with results presented in Tables 4 and 5 and Figures 3 and 4.

After the decision to consume has been made either tobacco or alcohol is considered an addictive good for all individuals in the conditional samples. Therefore, it is expected that there might be different patterns of the effect of income on the level of consumption. It is interesting to see that in both cases the effect of income never flattens, with more income leading to more consumption as expected. The levels of consumption first increase almost linearly with income and then explode for the high income group for both tobacco and alcohol products. For the smokers only sample tobacco products remain a normal good at all income levels.

References

Bilgic, A., and S.T. Yen (2015). Household Alcohol and Tobacco Expenditures in Turkey: A Sample-Selection System Approach. *Contemporary Economic Policy,* 33, 571-85.

Ekuklu, G., S. Deveci, M. Eskiocak, U. Berberoglu, and A. Saltik (2004). Alcoholism Prevalence and Some Related Factors in Edirne, Turkey. *Yonsei Medical Journal*, 45, 207–14.

Feng, L„ and M.K. Munkin (2021). Bayesian semiparametric analysis on the relationship between BMI and income for rural and urban workers in China, *Journal of Applied Statistics*, Forthcoming.

Koop, G. and D.J. Poirier (2004). Bayesian Variants of some Classical Semiparametric Regression Techniques. *Journal of Econometrics*, 123, 259-282.

Koop, G. and J.L. Tobias (2006). Semiparametric Bayesian Inference in Smooth Coefficient Models. *Journal of Econometrics*, 134, 283-315.

Munkin, M.K. and P.K. Trivedi (2009). A Bayesian Analysis of the OPES Model with a Non-parametric Component: Application to Dental Insurance and Dental Care, *Advances in Econometrics.* Volume 23: Bayesian Econometrics.

Munkin, M.K. (2022). Count Roy Model with Finite Mixtures, *Journal of Applied Econometrics*, Forthcoming.

Global Adult Tobacco Survey: Turkey Report 2010 (GATS, 2010), The Ministry of Health of Turkey. Ankara, Türkiye, 2010. Accessed January 30, 2013.

Turkish Inspection Institute for Tobacco and Alcohol Markets (TAPDK, 2012) "Tobacco and Alcohol Market Regulatory Authority. Ankara." 2012. Accessed January 30, 2013.

Turkish Statistical Institute (TUIK, 2010). Accessed March 20, 2012.

WHO (2004). Gender in Lung Cancer and Smoking Research. World Health Organization, Department of Gender, Women, and Health. Geneva: WHO.

Table 1: Summary statistics

		Full sample	If TobcExpd>0	If AlchExpd>0
AlchExpd	alcohol expenditure (TL/month)	3.391	4.814	46.133
		17.579	20.794	47.272
TobcExpd	tobacco expenditure (TL/month)	70.574	130.346	120.047
		92.933	90.333	107.937
Homowner	= 1 if resides in own house	0.623	0.570	0.550
		0.485	0.495	0.498
Numbtech	number of technologies owned	5.799	6.110	7.307
		2.581	2.542	2.674
Numbauto	number of automobiles owned	0.318	0.323	0.494
		0.467	0.469	0.500
NProprty	number of properties owned	1.186	1.073	1.133
		1.033	1.003	1.061
Income	annual income in 10,000 TL	2.297	2.377	3.484
		2.121	2.006	3.499
HSize	size of household	3.772	4.070	3.321
		1.881	1.898	1.346
Urban	= 1 if urban	0.685	0.710	0.749
		0.465	0.454	0.434
Gender	= 1 if male	0.854	0.895	0.920
		0.353	0.307	0.272
Age20-29	= 1 if age is 20-29	0.073	0.080	0.080
		0.260	0.271	0.272
Age30-39	= 1 if age is 30-39	0.234	0.253	0.256
		0.423	0.435	0.437
Age40-49	= 1 if age is 40-49	0.260	0.291	0.278
		0.439	0.454	0.449
Age50-59	= 1 if age is 50-59	0.207	0.219	0.260
		0.405	0.413	0.439
CompHIns	= 1 if has compulsory insurance	0.773	0.744	0.837
		0.419	0.436	0.370
GrnCard	= 1 if receives govt health support	0.123	0.127	0.053
		0.328	0.333	0.223

Table 1 (Continued): Summary statistics

		Full sample	If TobcExpd>0	If AlchExpd>0
Mstatus	= 1 if married	0.855	0.888	0.875
		0.352	0.315	0.331
Employed	=1 if employed	0.677	0.724	0.766
		0.468	0.447	0.424
Educnyrs	Years of education	6.786	6.885	9.238
		4.333	4.010	4.364
Kid0-5	= 1 if kid(s) present: age 0–5	0.274	0.305	0.191
		0.446	0.460	0.393
Kid6-14	= 1 if kid(s) present: age 6–14	0.401	0.434	0.338
		0.490	0.496	0.473
Kid15-19	= 1 if kid(s) present: age 15–19	0.268	0.301	0.258
		0.443	0.459	0.438
dAlch	= 1 if consuming alcohol	0.074	0.104	1.000
		0.261	0.305	0.000
dTobc	= 1 if consuming tobacco	0.541	1.000	0.763
		0.498	0.000	0.425
N	number of observations	9822	5318	722

Table 2: Probit Model for Smoking

EDUCNYRS	-0.027	0.004
NUMBTECH	0.055	0.007
NUMBAUTO	-0.070	0.032
NPROPRTY	-0.101	0.018
GENDER	0.398	0.055
MSTATUS	-0.119	0.054
EMPLOYED	0.033	0.035
Age20-29	0.361	0.066
Age30-39	0.346	0.054
Age40-49	0.368	0.049
Age50-59	0.356	0.043
COMPHINS	-0.346	0.046
GRNCARD	-0.199	0.057
HOMOWNER	-0.199	0.036
Kid0-5	-0.109	0.039
Kid6-14	-0.218	0.037
Kid15-19	-0.109	0.037
HSIZE	0.124	0.012
URBAN	0.036	0.032

Table 3: Probit Model for Alcohol Consumption

EDUCNYRS	0.020	0.006
NUMBTECH	0.075	0.010
NUMBAUTO	0.098	0.047
NPROPRTY	-0.041	0.027
GENDER	0.403	0.091
MSTATUS	-0.222	0.084
EMPLOYED	0.052	0.056
Age20-29	0.152	0.105
Age30-39	0.221	0.087
Age40-49	0.144	0.080
Age50-59	0.247	0.069
COMPHINS	-0.251	0.068
GRNCARD	-0.031	0.099
HOMOWNER	-0.135	0.054
Kid0-5	-0.162	0.064
Kid6-14	-0.033	0.057
Kid15-19	0.050	0.059
HSIZE	-0.123	0.022
URBAN	-0.151	0.050

Table 4: Model for Smoking Expenditure

EDUCNYRS	-0.018	0.004
NUMBTECH	0.023	0.007
NUMBAUTO	0.007	0.033
NPROPRTY	-0.043	0.019
GENDER	0.261	0.063
MSTATUS	-0.093	0.062
EMPLOYED	0.067	0.037
Age20-29	-0.112	0.071
Age30-39	0.028	0.058
Age40-49	0.068	0.053
Age50-59	0.112	0.048
COMPHINS	-0.111	0.044
GRNCARD	-0.285	0.056
HOMOWNER	-0.030	0.037
KID0-5	-0.122	0.040
KID6-14	-0.116	0.037
KID15-19	-0.085	0.037
HSIZE	0.037	0.011
URBAN	-0.044	0.034

Table 5: Model for Alcohol Expenditure

EDUCNYRS	0.005	0.011
NUMBTECH	0.030	0.018
NUMBAUTO	0.077	0.082
NPROPRTY	-0.056	0.049
GENDER	0.419	0.160
MSTATUS	-0.156	0.142
EMPLOYED	-0.031	0.105
Age20-29	-0.649	0.190
Age20-29	-0.576	0.161
Age20-29	-0.206	0.149
Age20-29	-0.089	0.135
COMPHINS	-0.042	0.126
GRNCARD	0.001	0.205
HOMOWNER	-0.010	0.103
KID0-5	-0.031	0.123
KID6-14	-0.007	0.106
KID15-19	-0.152	0.107
HSIZE	-0.041	0.044
URBAN	-0.230	0.096

Figure 1: Effect of Income on the Smoking Probability

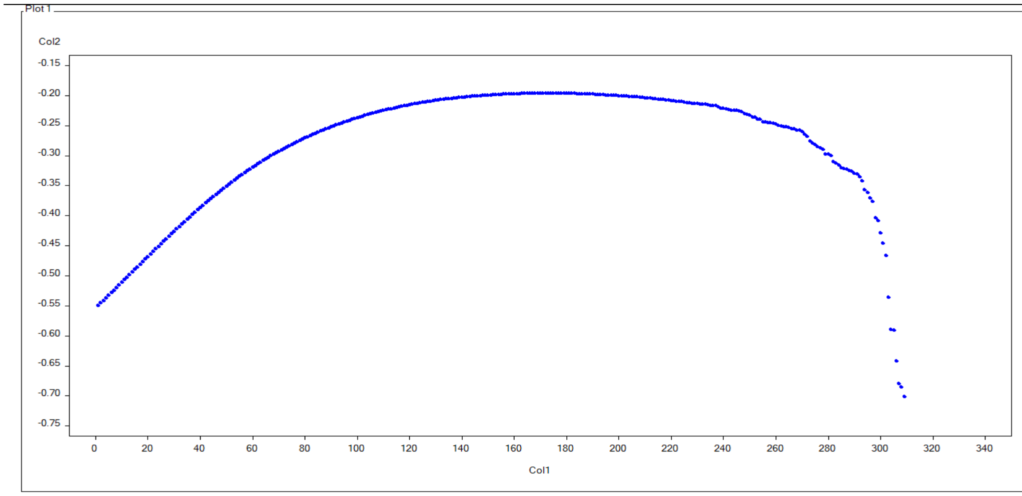

Figure 2: Effect of Income on the Drinking Probability

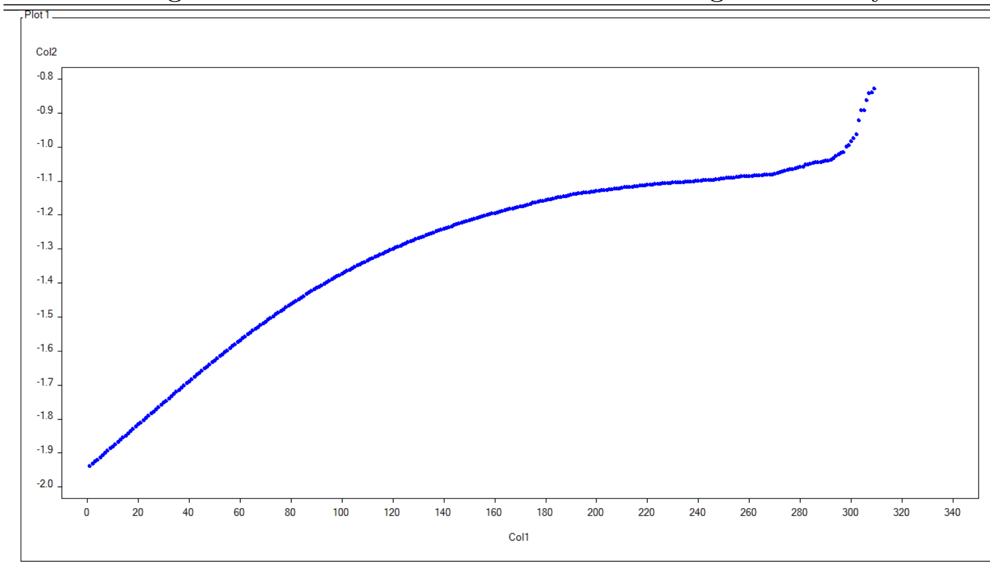

Figure 3: Effect of Income on Smoking Expenditure

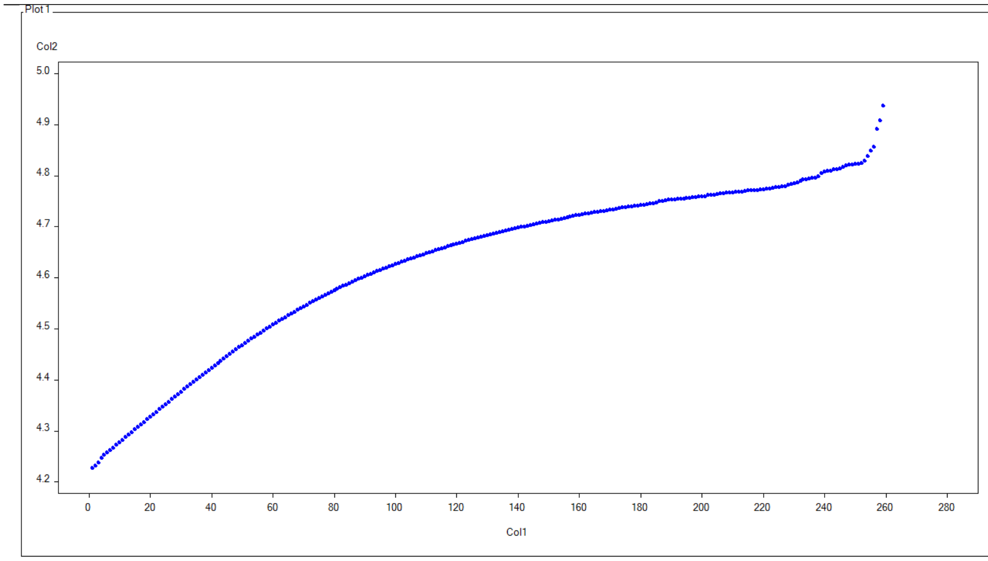

Figure 4: Effect of Income on Drinking Expenditure