Does obesity matter for the Environment? Evidence from Vehicle Choices and Driving

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Abstract

The rising rate of obesity has become a prominent social concern in the U.S. and throughout the world. Several recent literature examines how obesity influences households driving or vehicle choice behavior. While the results in prior studies are compelling, the studies suffer from two shortcomings. First, the researches rely on aggregate data (national or county level), rather than individual level observations, potentially masking important factors determining individual choices on vehicles and driving. Second, while they are able to establish a link between obesity and vehicle choice or driving, linking vehicle choice in turn to overall emissions requires information regarding vehicle miles driven. The objective of this study is to address these two limitations using household observations from the Panel Study of Income Dynamics (PSID), jointly modeling the impact of obesity on the vehicle choice and vehicle miles traveled (VMT). In particular, we investigate the impact of obesity and overweight by employing both reduced-form (linear panel model) and structural model (joint discrete/continuous choice model). Our empirical study suggests that the comprehensive impacts of obesity and overweight on gasoline consumption are little or ambiguous. In other words, the effect of the policy to reduce the rate of obesity and overweight are not as rosy as prior studies expect.

1 Introduction

The rising rate of obesity has become a prominent social concern in the U.S. and through-out the world. A recent report of the National Coalition on Health Care (NCHC) shows that 35.7 percent of U.S. adults are obese in 2009-2010 (NCHS Data Brief 2012). It is a well-known fact that obesity causes public health problems such as high blood pressure, heart disease, and a number of other adverse health conditions. These health problems increase medical costs to society as well. Cawley and Meyerhoefer [5], for example, argue that obesity is associated with $2,741 (in 2005 dollars) per person higher annual medical care costs in the U.S.

Recent interesting studies suggested that the societal impacts of obesity also extend to the environmental arena. They argue that obesity can be an additional indirect factor which makes more gasoline consumption through several different channels. Broadly, the literature focuses on the positive relation between obesity, VMT, and share of light truck which figure 1 shows. Specifically, the literature analyzing how obesity influences households' driving or vehicle choice behavior can be classified into three categories: 1) An approach from engineer's perspective, 2) A relation between miles traveled and obesity, 3) A relation between vehicle choices and obesity.

The first studies focus on the mechanical relation between weight and vehicle fuel efficiency. Jacobson and King [15] show that obesity and overweight increase fuel consumption of non-commercial vehicles by 0.8 percent through placing additional weights in a vehicle. It is associated with approximately one billion gallons of gasoline consumed in the U.S. Similarly, Dannenberg et al. [8] indicate that the weight increase of U.S. passenger accounts for up to 2.4 percent of additional fuel consumption in the U.S. airline industry.

The second group of studies examines how obesity affects vehicle use or reverse effects. Courtemance [6] examines the sequential relation that lower fuel prices cause people use their vehicles more frequently, as a result, it makes people obese. Using cross-sectional individual level data, Behavioral Risk Factor Surveillance System (BRFSS), he finds that 1% increase in gasoline price would contribute to 10% reduction of the rate of obesity and overweight. Jacobson et al. [16] argue that there are positive relation between the number of miles driven by each licensed driver (VMT/LD) and adult obesity with six years time lag. They found that 1 more miles driving per day by all licensed drivers causes 2.2% increase in the adult obesity rate six years later. However, it is likely to be spurious correlation because they do not control other factors such as income which may affect the relation. For example, a video game market has been growing tremendously over the last few decades. Nowadays, both adults and children enjoy the video game rather than physical exercise. Of course, it causes overweight and obesity. Therefore, it can give a wrong conclusion without control these kinds of factors which can affect the rate of overweight and obesity, especially when a study use time-series data.

Last, Li et al. [19] take this argument a step further by suggesting that obese and overweight individual also contribute to emissions through their vehicle choices. They estimate the impact of obesity on vehicle choice by adopting BLP-type aggregate data logit model with county-level annual sales data. They found the new vehicles purchased by individuals who are obese or overweight are, on average, less fuel efficient than those selected by others in the general population. Their simulation results show that 8.6% fuel savings is possible if the rate of overweight and obesity in 2005 has stayed at the 1981 level. However, they implicitly assume that the VMT of overweight and obesity people is equal to those of the other people in the fuel saving simulation.

While the results in earlier works are compelling, the analysis suffers from two shortcomings.[1] First, the researchers rely upon aggregate data (national level time series or county level cross section data), rather than household level observations, which potentially masks important factors determining vehicle choices and VMT. Second, while prior studies investigate a relationship between obesity and either vehicle choices or vehicle miles traveled (VMT), linking vehicle choices in turn to overall gasoline consumption (or emissions) requires information regarding vehicle use. In other

[1] We leave the first category of prior studies, i.e. mechanical relation between fuel efficiency and weight of passengers, as an area of engineers but rather focus on rest of influences.

words, the analysis implicitly assumes that obese individuals drive as much as every other people in the population. However, obesity leads to a more sedentary lifestyle, this could offset the individual's choice of a less fuel vehicle, resulting in no net increase in transportation related emissions. On the contrary, if obese individuals use their vehicle more frequently, the effects are outweighed. It implies that ignoring either one provide an incomplete picture. Moreover, as West [24] pointed out, "... [b]ut, an unobserved household characteristic that affects the utility of miles driven in a particular vehicle bundle is likely to affect both its probability of selection and its intensity of use." (p 740), the demand equation for vehicle purchases or VMT is likely to yields biased estimates. This study investigates the impacts of overweight and obesity on gasoline consumption by filling in the gaps of previous studies. The specific objective of the proposed study is to address two limitations by using individual observations. This study uses the Panel Study of Income Dynamics (PSID) since it is, to our best knowledge, unique micro data including both vehicle information and BMI.

In this paper, we examine two different types of empirical approaches; reduced-form and structural model. First, we employ linear panel fixed effects model as reduced-form approach. In contrast to the data which were used in prior studies, the PSID is longitudinal data which are useful to remove unobserved variable bias through panel data fixed effects model. In reduced-form approach, we estimate the effect of obesity and overweight on VMT, fuel economy, and gasoline consumption, respectively, which allows more comprehensive analysis contrary to prior studies exploring the relation with one of them.

As a structural approach, we adopt joint discrete and continuous econometric model. There are two types of discrete-continuous models used in prior studies. One sets of studies adopt Hausman type two-stage estimator developed by Dubin and McFadden [9]. Train [22] and West [24] estimate the consumer's behavior on vehicle purchases and its utilization by adopting DM's two-stage method. One of main advantages of DM method is relatively easy to implement. However, the DM has inconsistent estimates between discrete and continuous choices although both choices come from the unified behavior. The other follows King type one-step simultaneous estimation. For example, Bento et al. [4] estimate the distributional impact of gasoline tax and Roth [21] examines the equivalence between a simple fuel economy standard and a feebate. Spiller [20] propose a new econometric framework to relax modeling assumptions in previous models. Even though one step estimation gives a theoretically consistent framework and sound policy simulation, it has a difficulty in estimation when the model has a large number of alternatives and non-linear indirect utility function. Bento et al. [4] employ repeated discrete-continuous choice model and Bayesian estimation technique to avoid a large choice set and burden in estimation.

Our findings suggests that the comprehensive impacts of obesity and overweight on gasoline consumption are little or ambiguous. In other words, the effect of the policy to reduce the rate of obesity and overweight are not as rosy as prior studies expect. It is obvious that policy makers make an effort to obtain lower prevalence of obesity, however, our results show that we have to be wary of the exaggerated interpretation.

The rest of the paper is organized as follows. In section 2 we describe the data used and provide summary statistics . Section 3 details the empirical model and estimation strategy, and section 4 presents the empirical results. In section 5 we conclude with the discussion and summary.

2 Data

To assess the impact of obesity on gasoline demand through both vehicle choices and utilization in micro-level, i.e. household level, we collect the data from several sources. As a main source of data, we use the Panel Study of Income Dynamics (PSID). In addition, vehicle characteristics, e.g. fuel economy, wheelbase, and others, come from Ward's Automotive Yearbooks, EPA fuel economy, American Chamber of Commerce Researcher's Association(ACCRA) Cost Of Living Index (COLI), National Automobile Dealers Association (NADA) used car price data and other web sources.

Our data on household characteristics including vehicle ownership, gasoline expenditure and Body Mess Index (BMI) of head and spouse come from the PSID.[2] The PSID is the longest running national panel study in the world after it began in 1968 with a nationally representative sample of households and individual in the United States. The PSID collected information on employment, income, wealth, health, education and numerous other topics annually up to 1997, and after then the survey is conducted every two year. In particular, the PSID has collected details on vehicle-ownership, i.e. manufacturer, model, and model year, as well as gasoline expenditure from 1999.[3] Therefore, our sample periods are recent six surveys, 1999, 2001, 2003, 2005, 2007, and 2009. The reason why we use the PSID is, to the best of our knowledge, the unique household-level data which provide information on vehicle information and BMI.[4]

To construct vehicle attributes, we use Ward's Automotive Yearbook(1982-2009) which include a wide range of vehicle characteristics such as fuel economy, wheelbase, length, width, and horsepower by make, model, and model year. Basically, we use EPA's fuel economy data set, however, it covers from vehicles from 1984. Therefore, we use Ward's data for models older than 1984.

There are two main costs that affect vehicle choices and driving miles, vehicle purchase and driving costs. Even though several different concepts are used in prior studies, we adopt the rental rate and per-mile operating cost suggested by Bento et al. [4]. The rental rate is calculated as $r_{ij} = D_j + \rho P_j + 0.85 I_{ij}^A$ where $(D_j, P_j, I_{ij}^A, \rho)$ denote the depreciation rate, vehicle prices, annual insurance cost, and real interest rate, respectively. The depreciation and vehicle prices calculated using NADA used car guide data.[5] Insurance costs vary with vehicle manufacturer, model, prices, age, region,

[2]Since the PSID does not provide BMI directly, we computed it using information on height and weight and the formula $\frac{\text{weight(lb)}}{\text{height(in)}^2} \times 703$.

[3]The PSID includes the number of vehicles that each household owns or leases and detailed model information on up to three vehicles.

[4]Basically, the PSID is open to public use and widely used for a variety of studies such as labor economics. The PSID provides manufacturer, model year, and types (car, utility, pickup, and van) related to information on vehicle and current state related to address. However, for more precise information, we obtained the data for restricted use which the PSID distributes confidential data through special contracts. Among confidential data, for this study, we have acquired information on specific vehicle model (e.g. Toyota Camry) and geospatial data.

[5]Depreciation is calculated as difference of current and next year real used car prices, and we use MSRP as vehicle prices.

and others. However, there does not exist the data to reflect all factors. Therefore, we use state-level average insurance premium from National Association of Insurance Commissioners (NAIC) and proportion by vehicle make and model computed from *Insurance.com* to obtain insurance premium varying by region and model.[6]

We use yearly average of Daily Treasury Real Long-Term Rates as each year interest rate. To calculate per-mile operating cost, $p_{ij}^M = (p_i^{gas}/MPG_j) + 0.15 I_{ij}^M$, we use CBSA level gasoline prices from the American Chamber of Commerce Researchers Association (ACCRA) data. Since the ACCRA data cover around 300 regions, these give precise variations by regions. Figure 2 shows the distribution of gasoline price by regions and years. Additionally, in contrast to the National Household Travel Survey (NHTS) widely used in prior studies [4, 20, 21]), the PSID do not provide vehicle miles traveled but gasoline expenditure as the Consumer Expenditure Survey (CES) used in other studies [11, 24]. With MPG of vehicles households hold, we compute driving miles as VMT = (Gasoline Expenditure/Gasoline Price × MPG. Therefore, using fairy accurate measure of gasoline prices is important.[7] Table 1 presents summary statistics by survey year after cleaning the data. The observations are gradually increased by year because the PSID adds information on both current PSID households and their children whenever they create new households. The rate of obesity in our sample has steadily increased, reaching 32% in 2009[8].

[6] As Bento et al. reported assigning 85% for rental price and 15% to operating cost is followed by insurance company's suggestion.

[7] The NHTS is the authoritative source of national data on the travel behavior. Recently, it released the data in 2001 and 2009. The NHTS VMT estimates (BESTMILE) are based on odometer reading, self-report annual miles, and model year. Household's average monthly VMT in 2001 and 2009 is 1765.6 and 1654.2 miles. Even though our estimates in 2001 and 2009 are slightly lower than the NHTS estimates, they are close and share same trends to our estimates.

[8] The U.S. national level rate of obesity in 2009 by Centers for Disease Control and Prevention (CDC) is 33.7%. Our sample is very close to the number.

3 Empirical Model

The our goal is to identify the causal effects which obesity affects gasoline consumption through vehicle choices, i.e. fuel efficiency, and driving. In this study, we access the impact of obesity through both ways: 1) reduced-form approach (linear panel data model), and 2) structural model approach (joint discrete and continuous model). In the study of casual inference, one of the most important keys is how to control unobserved time-invariant confounders such as individual potential ability on wage and commuting distance to work in the vehicle choices. For example, Allcott and Wonzy [1] use instrumental variable estimation to control these unobserved individual attributes in studies on causal inferences. However, as Angrist and Pischke [2] note, it is hard to find good instruments. We adopt panel data to control for unobserved variables which may lead to omitted variable bias. In our application, vehicle choices are correlated with miles traveled because both discrete and continuous choices share common characteristics [24]. For example, consumers who purchase vehicles with high fuel efficiency generally drive more because the per-mile operating cost is low.[9] Recent studies employ the joint estimation to control household unobserved characteristics (e.g. Bento et al. [4], Feng et al. [11], Roth [21], Spiller [20], and West [24]).

3.1 Reduced-Form Model

First, we describe a standard fixed effects model we use to assess the impact of obesity that controls for unobserved individual time-invariant heterogeneity through the inclusion of individual fixed effects and time fixed effects. The basic specification for VMT and Gasoline Demand is

$$\ln(Y_{it}) = \alpha_1 D_{it}^{\text{obesity}} + \alpha_2 D_{it}^{\text{overweight}} + \beta_1 \ln(\text{GasPrice}_{it}/\text{MPG}_{it}) + \beta_2 \ln(\text{Income}_{it}) + \mathbf{X}_{it}\beta + \varphi_i + \mathbf{Year}_t + \varepsilon_{it} \tag{1}$$

[9] This behavioral response is called 'rebound effect' or 'take-back effect'.

where Y_{it} is the outcome of interest (i.e. VMT and gasoline consumption) for household i at time t, D_{it}^{obesity} and $D_{it}^{\text{overweight}}$ are indicator variables that set equal to one if a head of household is obese or overweight at time t, $\text{GasPrice}_{it}/\text{MPG}_{it}$ represents per-mile fuel cost, $\mathbf{X}_{it}$ is a vector of household i's characteristics at time t, φ_i is a household specific fixed effects, Year_t is a set of year effects as a parameter to be estimated, and ε_{it} is an error term. The parameters α_1 and α_2 capture the causal effect of interest, i.e. obesity and overweight, on the gasoline consumption or vehicle use. On the contrary, the equation for fuel efficiency, we include the gasoline price when to purchase their vehicles, GasPrice_{it-h_i}.

$$\ln(Y_{it}) = \alpha_1 D_{it}^{\text{obesity}} + \alpha_2 D_{it}^{\text{overweight}} + \beta_1 \ln(\text{GasPrice}_{it-h_i}) + \beta_2 \ln(\text{Income}_{it}) + \mathbf{X}_{it}\beta + \varphi_i + \mathbf{Year}_t + \varepsilon_{it} \tag{2}$$

Above equations (1) and (2) cannot be estimated directly because it contains a lot of parameters, however, alternative deviation form from means makes it possible, as following:

$$Y_{it} - \bar{Y}_i = \alpha_1 (D_{it}^{\text{obesity}} - \overline{D}_i^{\text{obesity}}) + \alpha_2 (D_{it}^{\text{overweight}} - \overline{D}_i^{\text{overweight}}) + (\mathbf{X}_{it} - \overline{\mathbf{X}}_i)\beta + (\mathbf{Year}_t - \overline{\mathbf{Year}}) + (\varepsilon_{it} - \overline{\varepsilon}_i) \tag{3}$$

$$\triangle Y_{it} = \alpha_1 \triangle D_{it}^{\text{obesity}} + \alpha_2 \triangle D_{it}^{\text{overweight}} + \triangle \mathbf{X}_{it}\beta + \triangle \mathbf{Year}_t + \triangle \varepsilon_{it} \tag{4}$$

where the $\triangle$ prefix denotes the change from a year to average. These panel data techniques remove unobserved individual effects which lead biased estimates.

3.2 Structural Model

We next discuss our structural model approach which is based on each household's utility maximization. As we discussed, since the vehicle choices and miles traveled are correlated by unobserved household characteristics, the structural model should capture the relation to avoid bias in estimation. We adopt the model developed by Bento et al. [4] which employ a full-information one-step structural approach. The model assumes that households face T_i choice occasions, i.e. in line with mixed logit with repeated choices. The conditional indirect utility function is defined from the log-linear VMT demand function as following,

$$U_{itj} = \begin{cases} -\frac{1}{\lambda_i}\exp\left(-\lambda_i\left(\frac{y_i}{T_i}\right)\right) + \mathbf{Z}_i^{\varphi}\varphi_i + \mu_i\varepsilon_{it0} & \text{if } j = 0, \\ \\ -\frac{1}{\lambda_i}\exp\left(-\lambda_i\left(\frac{y_i}{T_i} - r_{ij}\right)\right) - \frac{1}{\beta_i}\exp\left(\alpha_i\mathbf{Z}_i^{\alpha}\mathbf{X}_j^{\alpha} + \beta_{ij}p_{ij}^{M}\right) + \tau_i\mathbf{Z}_i^{\tau}\mathbf{X}_j^{\tau} + \mu_i\varepsilon_{itj} & \text{if } j = 1, ..., J \end{cases} \quad (5)$$

$$\text{where} \quad \beta_i = -\exp(\tilde{\beta}_i)$$

$$\lambda_i = \exp(\tilde{\lambda}_i)$$

and where (p_{ij}^M, r_{ij}, y_i) are vehicle per-mile operating cost, rental price, and income of household i's for jth vehicle, $\mathbf{Z}_i^{\alpha}$ is household characteristics, $\mathbf{X}_j$ is vehicle characteristics, and ε_{itj} is an error component capturing unobservable determinants of the households decision, which is assumed to be an *i.i.d.* extreme value random variable.[10]

The other exogenous variables except rental price and per-mile operating cost that may affect the household's choices are included in $\alpha_i\mathbf{Z}_i^{\alpha}\mathbf{X}_j^{\alpha}$. Above all, the key variable of this study, obesity, and interaction with vehicle characteristics are included as

$$\begin{aligned} \alpha_i\mathbf{Z}_i^{\alpha}\mathbf{X}_j^{\alpha} \equiv & \sum_{k=1}^{5}\alpha_{1(k)i}\cdot \text{vintage}_{jk} + \alpha_{2i}\cdot(\text{HP}_j/\text{Weight}_j) + \alpha_{3i}\cdot((\text{HP}_j/\text{Weight}_j)\times \text{Head age}_i) \\ & + \alpha_{4i}\cdot D_i^{\text{obesity}} + \alpha_{5i}\cdot(\text{WB}_j \times D_i^{\text{obesity}}) + \alpha_{6i}\cdot D_i^{\text{overweight}} + \alpha_{7i}\cdot(\text{WB}_j\times D_i^{\text{overweight}}) \\ & + \alpha_{8i}\times(\#\text{ of Adults}) \end{aligned} \quad (6)$$

Following Hausman [13], we derive the VMT demand equation by applying Roys identity.

$$\text{VMT}_{itj} = \exp\left(\alpha_i\mathbf{Z}_i^{\alpha}\mathbf{X}_j^{\alpha} + \beta_i p_{ij}^M + \lambda_i\left(\frac{y_i}{T_i} - r_{ij}\right)\right) + \eta_{itj}, \text{for } j = 1, ..., J \quad (7)$$

[10] For the discrete choices model, we have to define choice sets, i.e. discrete choice alternatives following Bento et al. We divide 10 vehicle classes (compact, luxury compact, midsize, fullsize, luxury mid/full size, small SUV, large SUV, small truck, large truck, and mini van), 5 vintages (new, 1-2 years, 3-6 years, 7-11 years, and 12-18 years), and 7 manufacturers (Ford, Chrysler, GM, Honda, Toyota, Other Asians, and European).

where η_{itj} represents an idiosyncratic error that is assumed to independent across the J alternatives with zero mean and standard deviation $\sigma_i = \exp(\sigma_i^*)$ such that $\eta_{itj} \sim N(0, \sigma_i)$.

Therefore, the combined likelihood function is

$$L_i = \prod_{t=1}^{T_i} \left[\prod_{j=0}^{J} \left(\frac{\exp(V_{ij})}{\sum_k \exp(V_{ik})} \right)^{1_{itj}} \prod_{j=1}^{J} \log \left(\Phi(VMT_{itj}, \sigma_i | j)^{1_{itj}} \right) \right] \tag{8}$$

where 1_{itj} is an indicator function that equals 1 if an household i chooses j at tth choice occasion, and 0 otherwise. We adopt random parameters for all variables to reflect heterogeneous taste and flexible specification. These random parameters and nonlinear specification make estimation via maximum simulated likelihood implausible. As Bento et al. [4] suggested, we employ Bayesian procedure using Markov Chain Monte Carlo (MCMC) technique.[11]

4 Empirical results

4.1 Reduced-Form Model

The results of reduced-form model are presented in table 2. Observations are weighted using the PSID survey weights. For the comparisons, we report the results of OLS estimation as well. It is well-known that the OLS estimation can yield biased estimates, omitted variable bias, when the unobserved household time-invariant variables are correlated with other variables. In our application, if the unobservable variables such as diet, lifestyle, and intensity of physical activity are correlated with obesity variable, the OLS results in inconsistent estimates. In table 2, the 'Overweight (BMI ¿ 25)' variable includes both obese and overweight households, thus, the 'Obesity (BMI ¿ 30)' variable reflects the marginal effect of the obese households. First, the estimates for obesity variable in all equations are not statistically significant. It implies that there is no additional effect

[11] The detailed estimation algorithm is described in appendix of Bento et al. [4] and ch12 of Train [23].

of obesity (BMI > 30)compared to overweight and obesity (BMI > 25). However, the estimates for overweight (BMI > 25) in fixed effects model are significant only in MPG equation while OLS estimates for all equations are significant. In other words, the results show that obese and overweight households tend to own less efficient vehicles, we cannot say that they drive and consume gasoline more. Elasticities of obesity and overweight are reported in the last two rows.[12] The OLS estimates are statistically significant, 0.11 for VMT, -0.02 for MPG, and 0.12 for gasoline demand. On the other hand, the fixed effects model estimates are smaller and insignificant for VMT and gasoline demand. This finding shows that OLS results, i.e. without controlling unobserved variable which may correlated with other variables, lead to biased results, here overestimated. We report the results of various different specifications and different measures of obesity and overweight in table 3 and 4. Panel A of Table 3 presents the model including only obesity dummy variable. As the results in table 2, OLS results show that obesity has significant positive effect for VMT (10% significance level) and gasoline demand and negative effect for MPG. In fixed effects model, signs and magnitudes of obesity variable are similar even though the coefficients for VMT and gasoline demand show significant at 10% level unlike previous results. Panel B of table 3 reports the results of estimation only with overweight (BMI > 25). The results are very close to previous ones. The classification of obesity and overweight is based on body mass index (BMI) which has continuous value. Therefore, obesity and overweight lose the information through the transformation to dummy variables. As alternative measures, we use BMI and weight and height itself. Panel A and B of table 4 report the results from these two different measures of body size. The results in table 4 show that the signs and significance are same as those in table 2. Our estimates show robustness across a variety of specifications and measures of body size. Our results cannot be directly compared with those in prior studies because our study uses household level data and thus dummy variables for obesity and overweight. However, prior studies use aggregate panel or time-series data and therefore they adopt the rate of obesity and overweight. In addition, most studies consider only new sales vehicles rather than currently owned vehicles. Since the effect of

[12] In log-linear model, we can compute the elasticity of dummy variable as $[exp(\alpha) - 1]$. Moreover, our estimates are close to zero, the computed elasticities are very close to coefficients themselves because of $exp(\alpha) - 1 \cong \alpha$.

obesity and overweight is significant only for MPG in fixed effects model, we compare ours with those in Li et al. [19] roughly. They conclude that if the rate of obesity and overweight in 2005, i.e. 67 percent, had stayed at the 1981 level, 47 percent, the average fuel economy for new vehicles demanded in 2005 would be increased from 22.99 to 24.96. However, our result shows only slight increase in MPG, i.e. 23.03 instead of 22.99. They also suggest that approximately 8.6% savings in gasoline consumption can be obtained through the improvement of fuel efficiency by the decrease of the rate of obesity and overweight.[13] However, as we see above, our results show there is no significant decrease in gasoline consumption between two groups.

4.2 Structural Model

Table 5 reports preliminary estimates of joint discrete and continuous model. We separate data-set into 6 each survey year sample because full sample includes too large observation to estimate the model with random parameters and decomposing the sample allows us to understand the change of preferences over time. The results of structural approach show the same direction as our reduced form approach suggests. However, in contract to linear panel model, we cannot evaluate the impact of obesity and overweight variable directly from the coefficients. In future versions of this paper I expect to examine the impact of obesity and overweight through following equations.

$$\frac{\left[\sum_{j=1}^{J} P_{ij}(D_i^{\text{overweight}}=1)\cdot \text{MPG}_j\right] - \left[\sum_{j=1}^{J} P_{ij}(D_i^{\text{overweight}}=1)\cdot \text{MPG}_j\right]}{\left[\sum_{j=1}^{J} P_{ij}(D_i^{\text{overweight}}=1)\cdot \text{MPG}_j\right]} \times 100 \tag{9}$$

$$\frac{\text{VMT}_{ij^*}(D_i^{\text{overweight}}=1) - \text{VMT}_{ij^*}(D_i^{\text{overweight}}=1)}{\text{VMT}_{ij^*}(D_i^{\text{overweight}}=1)} \times 100 \tag{10}$$

$$\frac{\left[\sum_{j=1}^{J} P_{ij}(D_i^{\text{overweight}}=1)\cdot (\text{VMT}_j/\text{MPG}_j)\right] - \left[\sum_{j=1}^{J} P_{ij}(D_i^{\text{overweight}}=1)\cdot (\text{VMT}_j/\text{MPG}_j)\right]}{\left[\sum_{j=1}^{J} P_{ij}(D_i^{\text{overweight}}=1)\cdot (\text{VMT}_j/\text{MPG}_j)\right]} \times 100 \tag{11}$$

[13] They assume that annual VMT is 12,000 miles and constant across normal and obesity and overweight groups.

Above equations (9)-(11) are to compute marginal effects of overweight and obesity.

5 Conclusion

The rising rate of obesity has brought with large social and economic problem over the last several decades in the U.S. and through-out the world. It is well-known that the high prevalence of obesity is accompanied by several negative health problems such as high blood pressure, diabetes, or heart disease. Besides these common negative, recent several studies examine the impact of obesity and overweight on the environment through vehicle emission. There are two channels to increase gasoline consumption, low fuel economy and more vehicle use. There are two main concerns in previous research. First, they cannot control unobserved individual or household characteristics by employing aggregate types of data. Second, prior studies focus on one side of impacts, i.e VMT or fuel economy. Two channels on gasoline consumption may cause conflicting or synergistic action.

The objective of this study is to provide complete picture for the impact of obesity on gasoline consumption by adopting household level observations from the Panel Study of Income Dynamics (PSID). We investigate the impact of obesity by employing both reduced-form (linear panel model) and structural model (joint discrete/continuous choice model). Our empirical study suggests that the comprehensive impacts of obesity and overweight on gasoline consumption are little or ambiguous. In other words, the effect of the policy to reduce the rate of obesity and overweight are not as rosy as prior studies expect.

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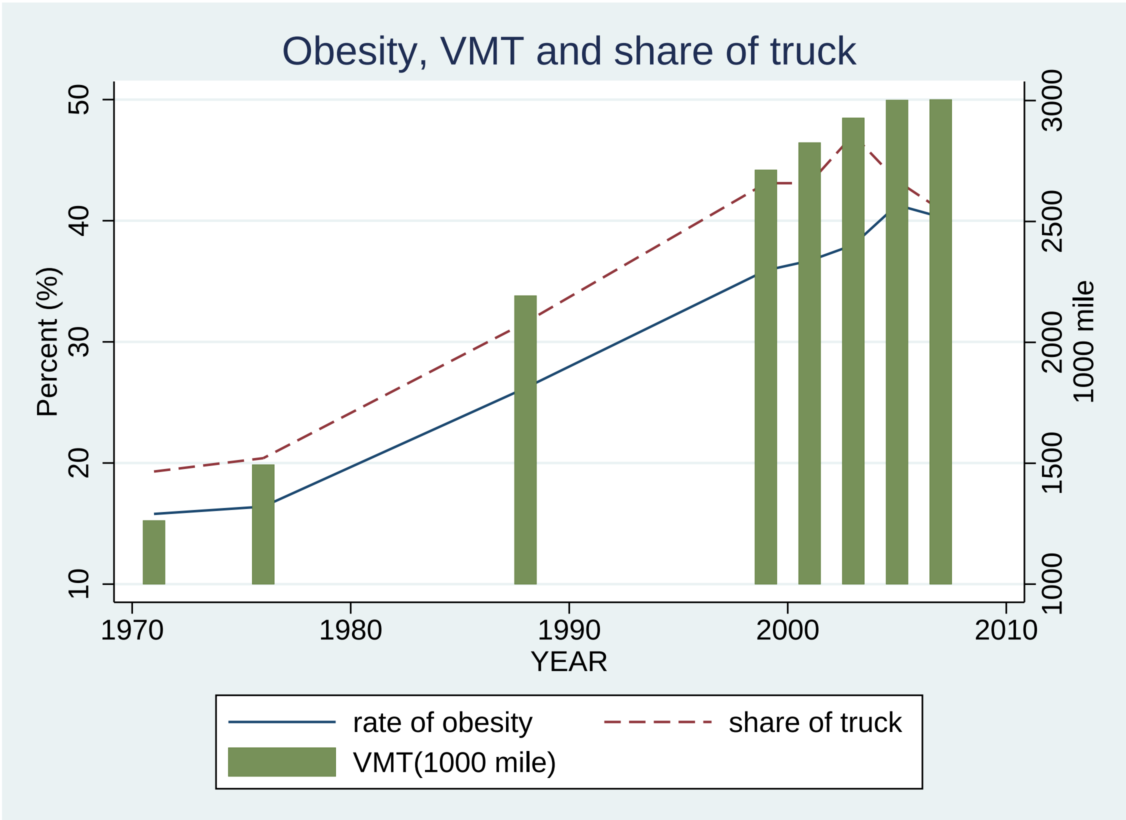

Figure 1: The rate of obesity, Share of Truck, and VMT, Data Source: Behavioral Risk Factor Surveillance System (BRFSS), National Transportation Statistics of Bureau of Transportation Statistics, and EPA Light-duty automotive technology and fuel economy trends: 1975 Through 2012

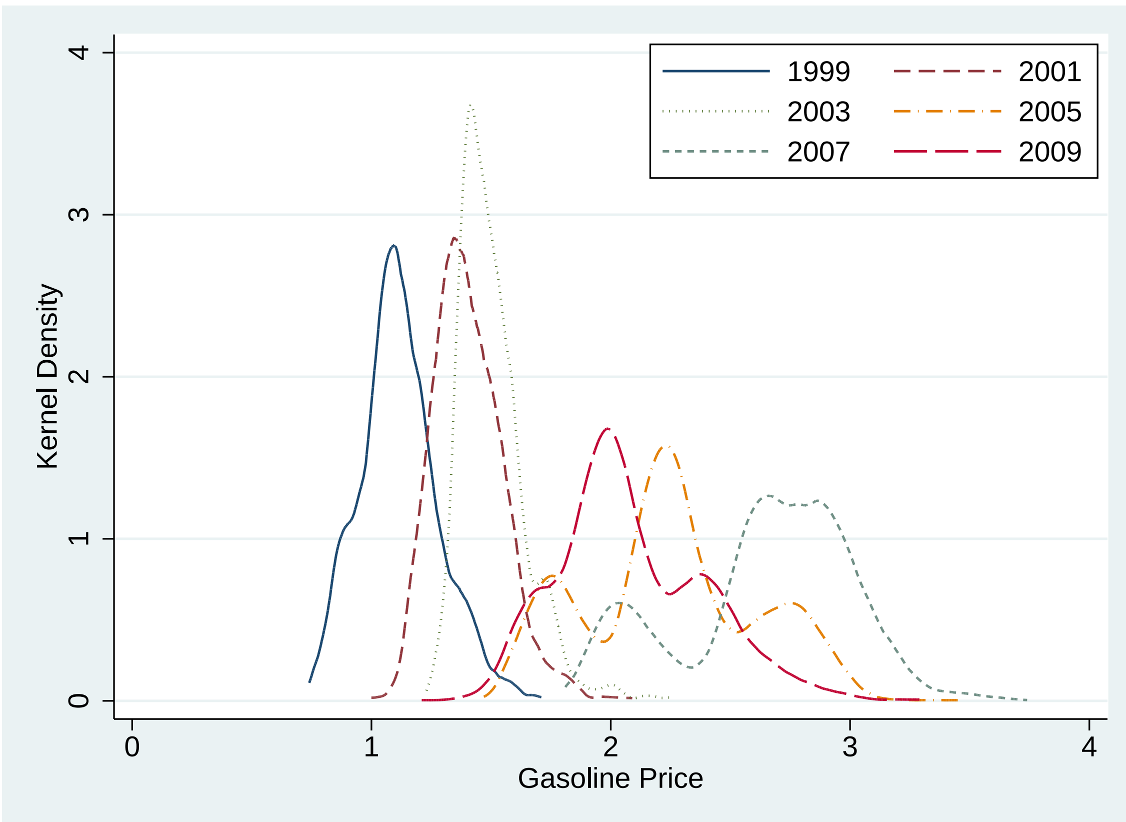

Figure 2: The Distribution of Gasoline Prices: 1999-2009

Table 1: The Summary Statistics by Number of Household Vehicles

	HH with 0 Vehicle	HH with 1 Vehicle	HH with 2 Vehicle	HH with 3 Vehicle
Household Size	2.23	2.19	3.02	3.33
	(1.58)	(1.40)	(1.31)	(1.31)
Number of Adults	1.43	1.45	2.03	2.35
	(0.69)	(0.64)	(0.52)	(0.70)
VMT (1000 miles)	-	12.99	20.84	26.62
	-	(10.89)	(15.74)	(22.06)
Average MPG	-	20.67	19.66	19.53
	-	(4.09)	(3.08)	(2.59)
Rate of Obesity (BMI > 30)	0.31	0.28	0.27	0.28
	(0.46)	(0.45)	(0.45)	(0.45)
Rate of Overweight (BMI 25-30)	0.31	0.36	0.45	0.47
	(0.46)	(0.48)	(0.50)	(0.50)
Age of Head	46.48	43.25	43.69	46.37
	(20.31)	(17.26)	(14.24)	(11.89)
Years of Education (years)	11.40	12.98	13.44	13.35
	(2.81)	(2.59)	(2.56)	(2.54)
Household Income < $30,000	0.73	0.38	0.10	0.05
	(0.44)	(0.49)	(0.29)	(0.23)
Household Income $30,000 - $60,000	0.19	0.38	0.27	0.20
	(0.39)	(0.49)	(0.45)	(0.40)
Household Income $60,000 - $75,000	0.07	0.23	0.63	0.74
	(0.26)	(0.42)	(0.48)	(0.44)
Household Income > $75,000	0.05	0.15	0.48	0.61
	(0.21)	(0.36)	(0.50)	(0.49)
Households (share)	6,697 (0.17)	14,185 (0.35)	14,826 (0.37)	4,690 (0.12)

The standard deviations are reported in the parentheses.

Table 2: The Estimates of Reduced-Form Model

Model	OLS			Fixed Effects Model		
Dependent Variable	ln(VMT)	ln(MPG)	ln(Gas Demand)	ln(VMT)	ln(MPG)	ln(Gas Demand)
Obesity (BMI > 30)	-0.001	-0.002	0.012	0.065	-0.005	0.049
	(0.024)	(0.003)	(0.018)	(0.040)	(0.004)	(0.031)
Overweight (BMI > 25)	0.104***	-0.023***	0.106***	0.021	-0.007**	0.022
	(0.022)	(0.003)	(0.017)	(0.037)	(0.003)	(0.027)
ln(GasPrice/MPG)	-0.361***		0.335***	-0.438***		0.156***
	(0.053)		(0.040)	(0.077)		(0.056)
ln(GasPrice_{t-h})		0.017**			0.006	
		(0.007)			(0.007)	
ln(Income)	0.105***	-0.017***	0.094***	0.040*	-0.003**	0.038**
	(0.019)	(0.002)	(0.014)	(0.022)	(0.001)	(0.016)
Number of Family	0.052***	-0.016***	0.049***	0.029*	-0.016***	0.034***
	(0.008)	(0.001)	(0.006)	(0.015)	(0.002)	(0.012)
Number of Adults	0.137***	0.021***	0.122***	0.095***	0.021***	0.081***
	(0.019)	(0.002)	(0.015)	(0.025)	(0.003)	(0.019)
Number of Vehicles	0.397***	-0.018***	0.377***	0.273***	0.014***	0.247***
	(0.017)	(0.002)	(0.013)	(0.026)	(0.002)	(0.019)
Age of Head	-0.012***	-0.000***	-0.011***	0.001	-0.000	-0.018
	(0.001)	(0.000)	(0.001)	(0.037)	(0.004)	(0.028)
Elasticity Of Obesity	-0.001	-0.002	0.012	0.067	-0.005	0.050
Elasticity of Overweight	0.110	-0.023	0.112	0.021	-0.007	0.022

Note: The standard errors for parameters are robust and * denotes significance at the 10%, ** at the 5%, and *** at the 1%, respectively. Observations are weighted using the PSID survey weights. We use the gasoline price at the time the vehicle was obtained for MPG equation. The OLS regressions include vehicle age group fixed effects, education levels of head fixed effects, city size fixed effects, and year fixed effects. Meanwhile, the fixed effects models includes only time-variant fixed effects, i.e. age group fixed effects, and year fixed effects.

Table 3: The Estimates of Reduced-Form Model: Alternative Specifications

Model	OLS			Fixed Effects Model		
Dependent Variable	ln(VMT)	ln(MPG)	ln(Gas Demand)	ln(VMT)	ln(MPG)	ln(Gas Demand)
			Panel A: Obesity (BMI > 30)			
Obesity (BMI > 30)	0.044*	-0.011***	0.058***	0.067*	-0.005	0.051*
	(0.023)	(0.003)	(0.017)	(0.040)	(0.004)	(0.030)
ln(GasPrice/MPG)	-0.352***		0.345***	-0.438***		0.156***
	(0.053)		(0.040)	(0.077)		(0.056)
ln(GasPrice)		0.018**			0.005	
		(0.007)			(0.007)	
ln(Income)	0.106***	-0.018***	0.095***	0.040*	-0.003**	0.038**
	(0.019)	(0.002)	(0.014)	(0.022)	(0.001)	(0.016)
Number of Family	0.054***	-0.017***	0.051***	0.029*	-0.016***	0.034***
	(0.008)	(0.001)	(0.006)	(0.015)	(0.002)	(0.012)
Number of Adults	0.140***	0.020***	0.125***	0.095***	0.021***	0.081***
	(0.019)	(0.002)	(0.015)	(0.025)	(0.003)	(0.019)
Number of Vehicles	0.401***	-0.019***	0.382***	0.273***	0.014***	0.248***
	(0.017)	(0.002)	(0.013)	(0.026)	(0.002)	(0.019)
Age of Head	-0.012***	-0.000***	-0.011***	0.001	-0.000	-0.018
	(0.001)	(0.000)	(0.001)	(0.037)	(0.004)	(0.028)
Elasticity Of Obesity	0.045	-0.011	0.060	0.069	-0.005	0.052
			Panel B: Overweight (BMI > 25)			
Overweight (BMI > 25)	0.103***	-0.024***	0.111***	0.026	-0.008**	0.026
	(0.021)	(0.003)	(0.016)	(0.036)	(0.003)	(0.027)
ln(GasPrice/MPG)	-0.361***		0.335***	-0.437***		0.157***
	(0.053)		(0.040)	(0.077)		(0.056)
ln(GasPrice)		0.017**			0.006	
		(0.007)			(0.007)	
ln(Income)	0.105***	-0.017***	0.093***	0.040*	-0.003**	0.038**
	(0.019)	(0.002)	(0.014)	(0.022)	(0.001)	(0.016)
Number of Family	0.052***	-0.016***	0.049***	0.030**	-0.016***	0.034***
	(0.008)	(0.001)	(0.006)	(0.015)	(0.002)	(0.012)
Number of Adults	0.137***	0.021***	0.122***	0.094***	0.022***	0.080***
	(0.019)	(0.002)	(0.015)	(0.025)	(0.003)	(0.019)
Number of Vehicles	0.397***	-0.018***	0.377***	0.274***	0.014***	0.248***
	(0.017)	(0.002)	(0.013)	(0.026)	(0.002)	(0.019)
Age of Head	-0.012***	-0.000***	-0.011***	0.000	-0.000	-0.019
	(0.001)	(0.000)	(0.001)	(0.037)	(0.004)	(0.028)
Elasticity Of Overweight	0.108	-0.024	0.117	0.026	-0.008	0.026

The standard errors are reported in parenthesis and * denotes significance at the 10%, ** at the 5%, and *** at the 1%, respectively.

Table 4: The Estimates of Reduced-Form Model: Alternative Measures

Model	OLS			Fixed Effects Model		
Dependent Variable	ln(VMT)	ln(MPG)	ln(Gas Demand)	ln(VMT)	ln(MPG)	ln(Gas Demand)
			Panel A: ln(BMI)			
ln(BMI)	0.122***	-0.027***	0.136***	0.052	-0.011*	0.038
	(0.042)	(0.005)	(0.031)	(0.052)	(0.006)	(0.040)
ln(GasPrice/MPG)	-0.353***		0.343***	-0.437***		0.157***
	(0.053)		(0.040)	(0.077)		(0.057)
ln(GasPrice)		0.017**			0.005	
		(0.007)			(0.007)	
ln(Income)	0.106***	-0.017***	0.095***	0.040*	-0.003**	0.038**
	(0.019)	(0.002)	(0.014)	(0.022)	(0.001)	(0.016)
Number of Family	0.054***	-0.017***	0.051***	0.030**	-0.016***	0.034***
	(0.008)	(0.001)	(0.006)	(0.015)	(0.002)	(0.012)
Number of Adults	0.140***	0.020***	0.124***	0.094***	0.021***	0.080***
	(0.019)	(0.002)	(0.015)	(0.025)	(0.003)	(0.019)
Number of Vehicles	0.401***	-0.019***	0.381***	0.274***	0.014***	0.248***
	(0.017)	(0.002)	(0.013)	(0.026)	(0.002)	(0.019)
Age of Head	-0.012***	-0.000***	-0.011***	-0.000	-0.000	-0.019
	(0.001)	(0.000)	(0.001)	(0.037)	(0.004)	(0.028)
			Panel B: ln(Weight) and ln(Height)			
ln(Weight)	0.199***	-0.057***	0.233***	0.211	-0.036**	0.138
	(0.061)	(0.006)	(0.044)	(0.174)	(0.015)	(0.129)
ln(Height)	-0.128	-0.404***	0.046	-0.289	-0.026	-0.136
	(0.224)	(0.025)	(0.168)	(0.735)	(0.068)	(0.535)
ln(GasPrice/MPG)	-0.366***		0.322***	-0.438***		0.156***
	(0.054)		(0.040)	(0.077)		(0.057)
ln(GasPrice)		0.019**			0.006	
		(0.007)			(0.007)	
ln(Income)	0.104***	-0.014***	0.092***	0.040*	-0.003**	0.037**
	(0.020)	(0.002)	(0.014)	(0.022)	(0.001)	(0.016)
Number of Family	0.054***	-0.018***	0.052***	0.029*	-0.016***	0.034***
	(0.008)	(0.001)	(0.006)	(0.015)	(0.002)	(0.012)
Number of Adults	0.133***	0.030***	0.113***	0.094***	0.021***	0.080***
	(0.019)	(0.002)	(0.015)	(0.025)	(0.003)	(0.019)
Number of Vehicles	0.395***	-0.010***	0.372***	0.273***	0.014***	0.247***
	(0.017)	(0.002)	(0.013)	(0.026)	(0.002)	(0.019)
Age of Head	-0.011***	-0.001***	-0.011***	0.001	-0.000	-0.018
	(0.001)	(0.000)	(0.001)	(0.037)	(0.004)	(0.028)

The standard errors are reported in parenthesis and * denotes significance at the 10%, ** at the 5%, and *** at the 1%, respectively.

Table 5: The Estimates of Structural Model

	1999		2001		2003		2005		2007		2009	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
α parameter												
Vehicle Age #1	2.24	0.02	2.16	0.03	2.20	0.03	2.23	0.03	1.95	0.04	1.92	0.04
Vehicle Age #2	2.28	0.02	2.18	0.03	2.23	0.04	2.20	0.02	1.95	0.04	1.93	0.04
Vehicle Age #3	2.27	0.02	2.18	0.02	2.22	0.03	2.21	0.02	1.97	0.04	1.96	0.04
Vehicle Age #4	2.25	0.02	2.16	0.02	2.21	0.04	2.21	0.02	1.95	0.04	1.95	0.03
Vehicle Age #5	2.22	0.02	2.13	0.02	2.19	0.04	2.19	0.03	1.94	0.04	1.95	0.04
Obesity	0.18	0.03	0.44	0.02	0.36	0.01	0.04	0.02	0.04	0.02	0.29	0.01
Obesity*(WB/100)	-0.09	0.02	-0.32	0.01	-0.25	0.01	0.06	0.01	-0.03	0.01	-0.20	0.01
Overweight	-0.23	0.02	-0.35	0.03	-0.28	0.03	-0.19	0.01	-0.26	0.02	-0.28	0.02
Overweight*(WB/100)	0.21	0.01	0.32	0.02	0.26	0.02	0.20	0.01	0.27	0.01	0.27	0.01
HP/WT	0.15	0.03	-0.20	0.02	0.41	0.03	-0.41	0.02	0.86	0.03	-0.09	0.03
(HP/WT)*(Head Age/100)	0.01	0.06	-0.31	0.02	-1.12	0.05	0.95	0.02	0.30	0.04	0.17	0.03
# of Adults	0.04	0.01	0.06	0.01	-0.01	0.02	0.01	0.01	0.07	0.02	0.12	0.02
β	-0.62	0.06	-0.82	0.08	-0.78	0.06	-1.20	0.08	-1.19	0.06	-1.05	0.04
λ	-7.29	0.13	-6.86	0.13	-7.01	0.08	-7.23	0.08	-6.60	0.06	-7.14	0.09
τ Parameter												
Midsize	-1.81	0.06	-0.49	0.02	-0.44	0.04	0.84	0.03	-0.55	0.04	0.38	0.03
Fullsize	-0.16	0.04	-0.77	0.04	-0.39	0.03	-0.94	0.02	-0.79	0.04	0.23	0.02
Luxury Car	-0.67	0.03	-0.81	0.03	-1.77	0.06	-1.21	0.02	-1.90	0.06	-0.85	0.02
Small SUV	0.24	0.04	0.43	0.03	-0.54	0.02	-0.90	0.05	0.37	0.03	-0.06	0.03
Large SUV	0.74	0.03	-0.23	0.03	-0.33	0.04	0.52	0.06	0.42	0.03	1.18	0.05
Small Truck	-0.32	0.03	-0.81	0.07	-1.93	0.03	-0.37	0.03	-1.94	0.04	0.56	0.03
Large Truck	-0.07	0.03	-0.60	0.06	-0.48	0.05	0.56	0.03	-0.21	0.02	1.13	0.03
Minivan	-0.67	0.03	1.59	0.04	-0.25	0.03	-0.21	0.03	0.24	0.04	0.49	0.03
European	-0.54	0.06	0.78	0.03	1.27	0.04	1.37	0.03	0.09	0.03	-0.37	0.05
Asian (Toyota, Honda, others)	0.08	0.04	-0.88	0.04	1.30	0.05	1.91	0.06	-0.11	0.03	-0.49	0.03
Vehicle Age #1	-1.23	0.03	0.63	0.05	0.76	0.06	0.29	0.03	0.05	0.03	-0.52	0.02
Vehicle Age #2	0.68	0.04	-0.62	0.02	0.48	0.07	-0.29	0.03	0.11	0.06	-1.16	0.05
Vehicle Age #3	-0.55	0.03	-0.31	0.02	-0.18	0.02	0.63	0.03	-0.59	0.05	-0.70	0.02
Vehicle Age #4	0.76	0.03	-0.72	0.02	0.29	0.03	-1.00	0.05	-0.26	0.02	0.03	0.03
WT/100	-2.91	0.03	-4.08	0.02	-4.11	0.03	-3.72	0.03	-3.88	0.05	-4.46	0.04
WB/100	0.74	0.08	-0.22	0.03	-0.87	0.03	0.20	0.05	0.04	0.03	-0.70	0.03
HP/WT	-1.39	0.07	0.56	0.06	0.07	0.05	0.65	0.02	-1.00	0.02	-0.05	0.03
φ parameter	0.12	0.03	-1.28	0.06	-1.75	0.07	0.04	0.02	-0.74	0.06	-1.22	0.07
(Head Age/100)												
College Degree of Head	0.50	0.03	-1.23	0.04	1.15	0.03	-0.38	0.03	1.06	0.03	-1.01	0.05
250k $\leq$ MSA $<$ 1m	-0.13	0.03	0.44	0.02	0.58	0.02	-0.58	0.03	0.59	0.02	0.10	0.03
MSA $<$ 250k	-0.74	0.05	-0.35	0.03	1.02	0.02	0.90	0.03	0.14	0.03	-0.76	0.03
Non-MSA $>$ 20k	0.08	0.04	-0.29	0.03	0.02	0.02	-0.77	0.03	0.10	0.03	1.30	0.05
Non-MAS $<$ 20k	-0.52	0.03	-0.11	0.03	-1.22	0.05	0.63	0.02	-0.49	0.02	-0.69	0.04
Rural	-1.39	0.03	0.75	0.03	0.28	0.03	0.37	0.03	-0.68	0.03		