Determinants of Smoking Cessation: A Panel Data Analysis Using HRS

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Abstract

Using longitudinal data of HRS from, this paper analyzes older smokers' participation decision and cigarettes consumption decisions using two-part and hurdle models with correlated random effects. This study extends the existing literature by incorporating both cigarette prices and health shocks in one unified framework. Our estimates indicate that raising cigarette price plays an effective role in both reducing participation and amount of consumption of cigarettes. Simultaneously, health shocks like diagnosed heart diseases and cancers are found to raise the probability to quit smoking substantially, which verifies the curative aspect of quitting behavior in the elderly. However, if the smoker does not quit even after a health shock, the shock shows a weak effect in reducing smoking intensity. By a decomposition analysis, we show that whereas both health shocks and cigarette prices explain the reduction in smoking prevalence, increases in cigarette prices are main reasons for the drop in smoking intensity over the period of 1992-2010.

Keywords: Smoking cessation; Health shocks; Hurdle model; Correlated random effects; Self-selection bias; HRS; Price elasticity

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1. Introduction

Smoking is considered as one of the greatest causes of preventable mortality. Not surprisingly, a lot of attention has been devoted to the study of smoking cessation and cigarette consumption. Especially, policy makers consider cigarette taxes as an effective way to reduce the tobacco consumption and a huge literature tried to corroborate the significance of its effect and estimate the magnitude. However, the health risk and concerns for smoking can also have substantial effect on reducing or quitting smoking. Some studies have shown that people who possess information on health effects of smoking have the tendency to change their addictive habits - called preventive quitting. Also, many elderly smokers quit after they were diagnosed with some diseases - called curative quitting. However, most previous studies only focus on one side of the story. No one has incorporated both these two reasons - curative and preventative – aspects of quitting into one framework. Our paper incorporates those two aspects into one framework using a longitudinal data from Health and Retirement Study (HRS). Besides this, we propose a hurdle model to estimate the smoking participation and conditional demand comprehensively as our baseline estimation.

Section 2 reviews existing literature on the impact of health and price/taxes on smoking and on modeling selectivity in nonrandom samples. Section 3 discusses our empirical strategies, and descriptions of data follow in Section 4. Section 5 is dedicated to the interpretation of results in the light of models of smoking participation and consumption, and then the paper is concluded in section 6 with discussions.

2. Literature

2.1Previous research on older adults smoking behavior

Since the classic health demand model by Grossman (1972) and rational addiction model by Becker and Murphy (1988), there are huge literatures about smoking behavior, most of which have focused attentions on youths and their price elasticities, while few papers provide evidence on smoking behavior of older adults, let alone considering their special health conditions, albeit indirectly or as part of examining the demographic characteristics that include age.

In one of the earliest studies on elderly smoking behavior, Lewit and Coate (1982) found little evidence that taxes reduce the smoking participation or consumption of adults aged 35 and older, after controlled simple three-category health status, from whom they estimate a price participation elasticity of -0.15 and demand price elasticity of -0.15 which are not significant at all conventional levels. More recent studies consistently found no systematic evidence that price reduces smoking prevalence among older adults, like Evans and Farrelly (1998), Farrelly et al. (2001) which defined an older adult as an individual at least 40 years old, while Evans and Farrelly (1998) did found significant price elasticity on conditional demand model at -0.498. More recently, DeCicca and McLeod (2008) estimated the elasticity of demand of cigarette for old smokers with the cross-sectional data from BRFSS, in which price participation elasticities is estimated to be about -0.3 for the group aged from 45 to 59 and 0.2 for the group aged from 45 to 64. Adda and Cornaglia (2013), however, found no significant tax elasticity for age group of 45 and over using data of NHANES 1988-2006. There are also several studies which did estimate price effect for adults smoking, but not on older people specifically. Tauras (2006), using the sample aged 46 on average, found a small price participation elasticity at -0.126 and price demand elasticity of -0.07, and DeCicca, Kenkel and Mathios (2008)'s estimates indicated that higher taxes have no significant effect on young adults' cessation decision and participation decision overall when anti-smoking sentiment is controlled. Liu (2010) found that for the elders aged 45 and over, only the group 45-64 has significant participation elasticity of 0.159, while the elders, on average, have cessation elasticity ranged from 19% to 60% which are not consistently significant. A recent study, DeCicca and Kenkel (2015) found that over-estimated price elasticity of demand is very common to see, as "the mean price elasticity across the 86 studies is -0.48", while from 1995 to 2010, cigarettes price increased by more than 100%, the observed average number of cigarettes per day only decreased by less than 25%.

Although for older smokers, health status, especially smoking-related diseases are important for decision making of participation and consumption, a few paper provide evidence on how smokers adjust smoking behaviors based on their health information. Jones (1993) found that doctor advice cannot effectively increase the probability of (successful) quitting. Sundmacher (2012) investigated the effect of health shocks on smoking and obesity, and confirmed that the contemporary health shocks had a significant positive impact on the probability of quitting smoking in the panel data context.

Being a smoker, non-smoker or ever-smoker is not randomly assigned by nature, hence, a self-selection bias need to be taken care of especially in participation decisions. Heckman (1979) suggested a two-stage estimator to correct the selection bias. However, the covariance matrix generated by OLS estimation of the second stage is inconsistent. Lahiri and Song (2000) estimated a two-step probit method using the Heckman-Lee two-step correction for initiation and cessation decisions. To model selectivity in count data models, Ophem (2000) suggested an estimable model by transforming the underlying processes to the bivariate normal distribution, in the case of the switching-regression model in which two regimes are distinguished with potentially different data generating processes. Min and Agresti (2005) proposed the so called two-part hurdle model with correlated random effects, which comprehensively handles the zero observations and the positive counts, and takes the correlation between measurements upon the same subject at different occasions into account. Under the context of smoking, on the one hand, the two-regime framework is modeled to allow for the relapse after quitting. On the other hand, the self-selection underlying the sequential decisions is corrected by using two correlated random effects.

2.2 The impact of smoking cessation on health

The 1990 U.S. Surgeon General is the first comprehensive study of the health benefits of smoking cession and concluded that smoking cessation improves immediate, long term health and increase longevity, and it benefits at all ages, even for those who already suffer from smoking-related illness. For instance, among persons with diagnosed CHD, smoking cessation markedly reduces the risk of recurrent heart attack and cardiovascular death. In many studies, this reduction in risk has been 50 percent or more. As for mortality, Taylor et al. (2002) found that individuals who quit enjoy prolonged life spans, relative to those who continue to smoke. Although the gain in longevity is largest at young ages, it remains substantial at older ones. Ostbye and Taylor (2004) further found that smoking cessation leads not only to increases in years of life, but also in years of healthy life (YHL) by reducing smoking-related illness.

3. Empirical Methods

This study employs two approaches to estimate participation and consumption decisions. Section 3.1 uses two parts model including Probit model with random effect to analyze smoking participation decision, in which selectivity is addressed by Heckman-Lee two-step correction, and zero-truncated count model for conditional demand, and then Section 3.2 proposed a two-part hurdle model with correlated random effects to analyze these two decisions comprehensively, while addressing the selectivity problem sticking in both decisions. Comparing with random effect, the fixed-effect models would drastically reduce the number of observations which lead to the potential to cause massive distortions and will almost make the sample unrepresentative of the population. And one more practical reason is that, given our data with only 8 waves, recently proposed methods[1] for the fixed effect in probit model cannot reduce the bias caused by the incidental parameter problem to be negligible, based on the results from simulation.

3.1 Two-part model of Probit with Heckman-Lee two step correction and zero-truncated negative binomial regression

The smoking participation decisions, both initiation and cessation, are modeled as outcomes of utility maximization using a random utility model. This model is derived from Heckman (1979) and Lahiri and Song (2000) (also see Evans and Farrelly (1998)), and based on the following fundamental premise:

[1] See Carro (2007), Arellano and Hahn (2006), Fernadez-Val (2009), Bester and Hansen (2009), Hahn and Kuerstainer (2011), and etc.

the baseline and induced risk factors of cigarette smoking are not always equal for all individual. After perceiving the risk information from health shock (as defined in section 4) and retail price each period, smokers determine their behaviors based on their updated subjective belief concerning health deterioration and monetary cost.

Most individuals make their initiation decision when they are young, based on his own subjective judgment of the costs and the benefits of the alternatives. Let I_i be the indicator of whether individual i initiated, and let I_i^* be the latent variable such that

$$\begin{aligned} I_i &= 1 \text{ if } I_i^* > 0 \\ &= 0 \text{ if } I_i^* \le 0 \end{aligned} \tag{1}$$

where $I_i^* = z_i'\gamma + v_i = G_i$, z_i is $K_0 \times 1$ vector, controlling for some demographic variables that are relevant to smoking initiation when they were deciding whether to initiate, and γ is a $K_0 \times 1$ parameter vector.

For each period in our observation window, an older faces a decision to make between two alternatives: to smoke or not. Let y_{it} be the binary variable which indicates the response to the question “Do you smoke cigarettes now?” for individual i at time t. If the answer is yes, then $y_{it} = 1$, otherwise, $y_{it} = 0$. With the latent variable y_{it}^*, we could construct the following Probit model as the participation decision:

$$\begin{aligned} y_{it} &= 1 \quad \text{if } y_{it}^* > 0 \\ &= 0 \quad \text{if } y_{it}^* \le 0 \end{aligned} \tag{2}$$

where

$$y_{it}^* = x_{it}^T \beta_X + P_{it}\beta_p + H_{it}^T \beta_H + \mu_i + u_{it} \tag{3}$$

x_{it} is a $K_1 \times 1$ vector, including individual characteristics; P_{it} is retail price of cigarettes per pack for individual i at time t; H_{it} is a $K_2 \times 1$ vector which include a set of measures of health (including health shocks) for individual i at time t. β_X, β_P and β_H are $K_1 \times 1$, 1×1 and $K_2 \times 1$ parameter vectors to be estimated.

Random effect μ_i is used to address the correlation cross time and meet the following standard assumption

$$\mu_i \sim IIN(0, \sigma_\mu^2)$$

which is independent with u_{it} and (x_{it}, H_{it}).

If v_i is correlated with error term in (3), then selectivity will prevail. Without the prejudice to the generalization, this selectivity is assumed to be captured only in the correlation between v_i and u_{it} with:

$$\operatorname{cov}(v_i, u_{it}) = \sigma_{12}^s \tag{4}$$

For an individual, the expected value of the latent variable conditional on initiation decision is

$$E(y_{it}^* \mid I_i) = x_{it}'\beta_X + P_{it}\beta_p + H_{it}\beta_H + \mu_i + E(u_{it} \mid I_i) = G_{it} + \mu_i + \sigma_{12}^s mills_i \tag{5}$$

where inverse Mills ratio $mills_i$ is defined as

$$mills_i = \begin{cases} \dfrac{\phi(G_i)}{\Phi(G_i)} & \text{if} \quad I_i = 1 \\ \dfrac{-\phi(G_i)}{1-\Phi(G_i)} & \text{if} \quad I_i = 0 \end{cases} \tag{6}$$

$$G_{it} = x_{it}'\beta_X + P_{it}\beta_p + H_{it}\beta_H$$

where $\phi(.)$, $\Phi(.)$ are density and cumulative density function of standard normal distribution respectively. σ_{12}^s is defined at (4).

Therefore, we could rewrite (3) as

$$\begin{aligned} y_{it}^* &= x_{it}'\beta_X + P_{it}\beta_p + H_{it}\beta_H + \mu_i + u_{it} \\ &= x_{it}'\beta_X + P_{it}\beta_p + H_{it}\beta_H + \sigma_{12}^s mills_i + \mu_i + \varepsilon_{it} \end{aligned} \tag{6}$$

where $\varepsilon_{it} \sim IIN(0,1)$, and $E(\varepsilon_{it} \mid I_i) = 0$.

We fit this model via maximizing log-likelihood of the random-effect model. The conditional probability of smoking, $y_{it} = 1$, is

$$\begin{aligned} &\Pr(y_{it} = 1 \mid I_i, x_{it}, P_{it}, H_{it}, \mu_i) \\ &= \Pr(\varepsilon_{it} > -(x_{it}'\beta_X + P_{it}\beta_p + H_{it}\beta_H + \mu_i + \sigma_{12}^s mills_i) \mid I_i, x_{it}, P_{it}, H_{it}, \mu_i) \\ &= \Phi(x_{it}'\beta_X + P_{it}\beta_p + H_{it}\beta_H + \mu_i + \sigma_{12}^s mills_i) \end{aligned}$$

Then the panel-level (marginal) likelihood L_i is given by

$$L_i(B,\sigma_{12}^s,\sigma_\mu)=\int_{-\infty}^{\infty}\prod_{t=1}^{T}\left[\Pr(y_{it}=1\,|\,I_i,x_{it},P_{it},H_{it},\mu_i)^{y_{it}}\Pr(y_{it}=0\,|\,I_i,x_{it},P_{it},H_{it},\mu_i)^{(1-y_{it})}\right]f(\mu_i)d\mu_i$$

where $f(\cdot)$ is density function of μ_i defined above and $B=(\beta_X^T,\beta_P,\beta_H^T)^T$.

The integral is approximated by Adaptive Gaussian quadrature, and the number of quadrature point we used is 20. Then the likelihood function could be wrote as

$$L(B,\sigma_{12}^s,\sigma_\mu)=\prod_{i=1}^{N}L_i(B,\sigma_{12}^s,\sigma_\mu)$$

A sequential question that "how many cigarettes do you smoke per day?" will be asked only if the individual is a (daily) smoker and the response to which is a positive integer. In specifying the conditional demand function, we employ (truncated) count model due to the discrete nature of number of cigarettes[2]. Poisson distribution and negative binomial distribution are commonly used approaches for count data and the later one is preferred because it allows for more heterogeneity.

Specifically, y_{it} here is the number of cigarettes smoked per day for individuals who self-reported as smokers, then the function is

$$P(y_{it}\,|V_{it},\mu_i,Smoking=Yes)=\frac{g(y_{it};\lambda_{it}(\mu_i))}{[1-g(0;\lambda_{it}(\mu_i))]},$$

where μ_i, a typical random effect, is included again to allow for correlation cross time and defined as above; V_{it} is the covariates vector including $\{x_{it},H_{it},P_{it}\}$. The conditional mean of dependent variable, $\lambda_{it}(\mu_i)$, is parameterized as

$$\lambda_{it}(\mu_i)=\exp(x_{it}^T\zeta_x+P_{it}\zeta_p+H_{it}^T\zeta_H+\mu_i)$$

in the negative binomial distribution with probability density function as

$$g(y_{it};\lambda_{it}(\mu_i))==\frac{\Gamma\left(\alpha^{-1}+y_{it}\right)}{\Gamma\left(\alpha^{-1}\right)\Gamma\left(y_{it}+1\right)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda_{it}(\mu_i)}\right)^{-\alpha}\left(\frac{\lambda_{it}(\mu_i)}{\alpha^{-1}+\lambda_{it}(\mu_i)}\right)^{y_{it}}.$$

MLE is used in estimation with likelihood function of

$$L(\zeta_x,\zeta_p,\zeta_H,\sigma^2,\alpha)=\int\prod_{i=1}^{N}\prod_{t=1}^{T}\frac{g(y_{it};\lambda_{it}(\mu_i))}{[1-g(0;\lambda_{it}(\mu_i))]}f(\mu_i)d\mu_i.$$

[2] Although linear regressions are usually used by previous studies, our comparison shows that count model could notably outperform linear regression using our sample. Detailed results are available upon request.

Similarly to Probit model, the integral is approximated by Adaptive Gaussian quadrature, and the number of quadrature point we used is 20.

3.2 Hurdle model with correlated random effects

Our second specification, hurdle model, is first proposed in Min and Agresti (2005). Under the context of smoking, we prefer hurdle model over two parts model because of two reasons. One is that the demand could be analyzed jointly with participation decision by considering smoker's previous smoking trajectory. The other reason is more practical that the previous intensity of smoking is proved to affect the probability of smoking or quitting, while including lagged smoking intensity in the participation model makes the optimization process problematic since lagged smoking intensity almost predetermined the dependent variable. With hurdle model, the estimate of propensity to smoke could utilize the information of smoking intensity using correlated random effects and avoid the problematic optimization. To our best knowledge, no study has ever analyzed participation of smoking and cigarettes consumption jointly while taking care of self-selection in two switching regimes.

Implicitly, there are two different data generating processes for zero and positive value separately. The Probit is used to model the data generating process (DGP) for dichotomous variable indicating whether the individual is a smoker; and a zero-truncated negative binomial distribution is used to model the probability of each possible positive value. Selectivity prevails if the observations are distributed across the regimes by some endogenous selection rule. Since it's reasonable to believe that the propensity to smoke and addiction to nicotine are different for non-smokers, smoking quitters and persistent smokers, initiation is an endogenous decision and this selectivity is possibly related to both regimes. Ophem (2000) showed that the endogenous selectivity could be modeled in two regimes of switching-count model by allowing error terms from two components following a bivariate normal distribution, which simplified our framework to a hurdle model with correlated random effects in two regimes.

Similarly, the first regime is formulated using Probit with random effect μ_{1i}, except that the inverse Mills ratio is removed; and a zero-truncated negative binomial distribution with random effect μ_{2i} conditional on smoking could be used to model the data generating process of positive value.

The (conditional) hurdle model is, then, formulated as

$$P(y_{it} \mid V_{it}, \mu_{1i}, \mu_{2i}) = \begin{cases} (1 - P_{it}(\mu_{1i})) & \text{if } y_{it} = 0 \\ P_{it}(\mu_{1i}) \dfrac{g(y_{it}; \lambda_{it}(\mu_{2i}))}{[1 - g(0; \lambda_{it}(\mu_{2i}))]} & \text{if } y_{it} > 0 \end{cases}$$

where

$$V_{it} = \{x_{it}, H_{it}, P_{it}\}$$

$$\text{probit}\, P_{it}(\mu_{1i}) = x_{it}^T \beta_x + P_{it}\beta_p + H_{it}^T \beta_H + \mu_{1i} \tag{9}$$

$$g(y_{it};\lambda_{it}(\mu_{2i})) = \frac{\Gamma\left(\alpha^{-1} + y_{it}\right)}{\Gamma\left(\alpha^{-1}\right)\Gamma\left(y_{it}+1\right)} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda_{it}(\mu_{2i})}\right)^{-\alpha} \left(\frac{\lambda_{it}(\mu_{2i})}{\alpha^{-1} + \lambda_{it}(\mu_{2i})}\right)^{y_{it}} \tag{10}$$

x_{it}, P_{it}, and H_{it} are defined as section 3.1, with their corresponding coefficient vectors ζ_X, ζ_P and ζ_H. μ_{1i} is the random effect in the first regime.

To parameterize the mean and/or variance in the second regime,

$$\lambda_{it}(\mu_{2i}) = \exp(x_{it}^T \zeta_x + P_{it}\zeta_p + H_{it}^T \zeta_H + \mu_{2i}) \tag{11}$$

where μ_{2i} is the random effect in the second regime.

Those two regimes of the model could be tied together by assuming that the random effects are jointly normal and possibly correlated,

$$(\mu_{1i}, \mu_{2i}) \sim Normal(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}) \tag{12}$$

Let B be the vector of all parameters to estimate, $(\beta_X^T, \beta_P, \beta_H^T, \zeta_X^T, \zeta_P, \zeta_H^T, \sigma_1^2, \sigma_2^2, \sigma_{12}, \alpha)$, then the marginal likelihood function for this hurdle model is:

$$L(\mathrm{B}) = \prod_{i=1}^{N} L_i(\mathrm{B})$$

where

$$L_i(\mathrm{B}) = \int \prod_{t=1}^{T} [1 - P_{it}(\mu_{1i})]^{I_{y_{it}=0}} \prod_{t=1}^{T} \left\{ P_{it}(\mu_{1i}) \frac{g(y_{it};\lambda_{it}(\mu_{2i}))}{[1 - g(0;\lambda_{it}(\mu_{2i}))]} \right\}^{I_{y_{it}>0}} \phi(\mu_{1i}, \mu_{2i}) d(\mu_{1i}, \mu_{2i})$$

$$= \prod_{t=1}^{T} [1 - P_{it}]^{I_{y_{it}=0}} \prod_{t=1}^{T} \left\{ P_{it} \frac{g(y_{it};\lambda_{it})}{[1 - g(0;\lambda_{it})]} \right\}^{I_{y_{it}>0}}$$

and $\phi(\mu_{1i}, \mu_{2i})$ is the joint density function of (μ_{1i}, μ_{2i}) defined at (12).

The procedure NLMIXED in SAS enables us to do the estimation as it fits nonlinear mixed models by maximizing an approximation to the likelihood integrated over the random effects. Different integral approximations and optimization techniques are available in this procedure, and we use adaptive Gaussian quadrature for the integration and Quasi-Newton algorithm for the likelihood maximization.

4. Data

The Health and Retirement Study (HRS) is a longitudinal household survey data set for the study of retirement and health among the elderly in the United States. The study interviews 22,000 Americans age over 50 and their spouse every two years on subjects like health care, housing, assets, pensions, employment and disability. Furthermore, the RAND Center for the Study of Aging, with funding and support from the National Institute on Aging (NIA) and Social Security Administration (SSA), created the RAND (L version) HRS data files. The RAND HRS is a concise subset of the HRS, over ten waves (1992, 1993/1994, 1995/1996, 1998, 2000, 2002, 2004, 2006, 2008, and 2010). This study uses the main body of RAND (L version) with administrative data of state identifier from HRS.

Since some respondents deceased especially after severe health shocks, our panel is not strictly balanced. Also, some health measures, like new diagnosed heart disease, are obtained by differencing two consecutive responses to the interview question, "have you ever been told by a doctor that you have heart disease?", therefore, the actual number of waves of our panel is nine (maximum possible number of observations for each respondent is nine). Due to these above factors and missing data, the final sample contains 18,177 respondents and 98,941 observations.

4.1 Variables in the initiation equation

People generally make initiation decisions when they're young. Unfortunately, the timing of initiation is not complete in HRS since the relevant question was not asked for several waves. To avoid the potential problems of retrospect, in the initiation equations, included covariates are time-invariant and being consistent over individual's whole life, such as cohort, religions, gender, race, parent's education, born area, personality and life styles. Since we can't observe their adolescent behaviors, some related variables are used as proxies of their life style and personality. For instance, the schooling year is relevant to patience; the reported job with the longest tenure could reflect their living environment and social nature or requirement, and so on. The detailed explanations for those time-invariant variables are listed in appendix, Table 1, Panel A.

4.2 Cigarette price and smoke-free air laws

In the participation and consumption estimations, the same covariates are included, except the inverse Mills ratio in Probit of two part model (Section 3.1). We merge information on cigarette price from the Tax Burden on Tobacco (Orzechowski and Walker 2011) which report taxes and retail price by state and year, with administrative data of state identifier of respondents. In practice, the results are very similar whether use price or tax. Here we choose price (including federal and state taxes) because it's what smokers mainly concern in decision-making process. We deflate the variable using the national consumer price index. Since the timing of data collection for HRS is across the whole year, while Tax Burden on Tobacco report the retail price of cigarettes as of November every year, we use last year retail price in our models. Figure 1 displays the cigarette price per pack between 1991 and 2011 by state, adjusted for inflation. Cross-sectional variation takes 29.28% toward total variation, while most of the variation is the variation over time.

Both models also add controls for the state-level smoke-free air laws. One of the measures is a dichotomous variable which is equal to one if there is effective state-level smoking ban on one of locations including restaurants, private worksites and bars. The other measure comes from the TUS-CPS (Tobacco Use Supplement to the Current Population Survey[3]), from which we use the percentage of respondent who think smoking should not be allowed anywhere in bars as a measure of state-level anti-smoking sentiment.

4.3 Health shocks and other health measures

In general, two types of health information are controlled. One type captures the shock that individual experienced recently (within two years), like the heath shocks defined in Smith et al. (2001) and Sundmacher (2012). Specifically, if the individual stayed in a hospital overnight, visited doctors more than five times, or lower self-rated health by at least two grades, then a health shock (HS) is regarded to occur on this individual. Besides that, if there is a newly diagnosed heart disease, cancer, or high blood pressure during last two years and has no history of that disease before, the health shock is also identified. To be a health shock, for example, if the respondent reported in wave 5 a heart disease that occurred after the survey of wave 4, and reported no history of heart disease before wave 4, this is recorded as a health shock. This measure is applied on heart disease, cancer and high blood pressure. In summary, first type is formed by newly perceived health information.

The other type of health information is health condition that individual ever had before (HC) which includes previously diagnosed heart diseases, cancers and hypertension. We control both HS and HC since it's reasonable to assume that people might have different reaction to the newly diagnosed disease and relapse of old illness.

[3] The Tobacco Use Supplement to the Current Population Survey (TUS-CPS) is a national survey of tobacco use as part of the US Census Bureau's Current Population Survey in 1992-1993, 1995-1996, 1998-1999, 2000, 2001-2002, 2003, 2006-2007, and 2010-2011.

4.4 Summary statistics

The smoking prevalence has been steadily decreasing especially after the release of Surgeon General (1964). This aggregate trend is shown in Figure 1. During our observation window, approximately, the average cigarettes consumption per capita decreased from 100 packs (1991) to 50 packs (2011) per year. While the (deflated) total tax collection including federal and states tax increased gradually after 1991 and aggressively after 2008.

There is no clear border line between nonsmokers and smokers, because the transition between ever-smokers and current smokers are common in our sample. Table 2 compares the demographic of observations between current smokers with full sample, and table 3 compares the sample of ever-smoked individuals with full non-smokers group.

From the perspective of observations, current smokers are significantly younger, have a higher self-assessed health and a lower number of schooling years, which indicate evident self-selection. At the same time, current smokers are more likely to be married and retired, and more smokers are divorced or widowed. When we compare the sample of ever-smoked individual with non-smokers, these two samples do not have significantly different age, while the non-smokers have a higher schooling year, are less likely to be a male, and more likely to be a protestant. As for the prevalence of health shocks, less health shocks are observed from current smokers, this phenomenon is caused by the corresponding behavior change after health shocks and could be explained by table 3, from which the group of smokers and former smokers have a significantly higher prevalence of health shocks than that of non-smokers, including hospitalization, doctor visits, and newly diagnosed heart diseases and cancers.

5. Results

5.1 Selectivity

As stated above, the selectivity equation includes the variables that remain the same across the life span to make sure that no reverse causality would present. Our estimates (Table 3) demonstrated that people who were born since the great depression to the Second World War are more likely to start smoking and less likely to initiate for the cohort after 1948 which, in some extent, reflects the evolution of common knowledge about smoking. Also, being Catholic and Protestant reduced the probability of initiation by 7.15% and 14.95% respectively. Besides that, consistent with previous studies, more educated people are less likely to initiate smoking; however, parental education has a positive effect on offspring’s initiation, after we excluded parental education’s effect on children’s educational achievement and occupation. The underlying reason might be that highly educated parents are related to higher income. In 1950s, and before, when our respondents were young, in America cigarette smoking was the epitome of cool and glamour, instead linked with the deterioration of health which is widely accepted as common knowledge, and cigarettes were even originally sold as expensive handmade luxury goods for the urban elite[4]. Under that background, highly educated parents, coupled with better economic condition, have a positive correlation with offspring's smoking initiation.

Comparing with other ethnics, Caucasian and African-American are more likely to start smoking and their probability to initiate are higher by 4.96% and 6.66% respectively; male's probability to initiate is significantly higher than female by 21.58%, and military service would increase this probability by 18.86%. Besides that, initiation is also related to personality, for which, we used the longest reported-job and schooling year as proxies. It's reasonable to assume that occupations choice are relevant to personality, and then, living environment and social requirement. As showed in Table 3, service, technology and finance related jobs are negatively related to smoking initiation's probability, while jobs of blue collar tend to induce smoking. Last but not least, relatively to people born in Midwest states, people who born in Northeast states have higher probabilities to initiate significantly.

With the estimates of initiation equation, the inverse Mill's ratio in Probit model is then constructed as (6), and its coefficient in participation model is the covariance between the error terms of initiation equation and participation equation, σ_{12}^{s}. By rejecting the hypothesis that $\sigma_{12}^{s} = 0$, our estimate verifies that the selectivity does exist in the decision making of smoking, and its positive sign is reasonable as the individual characteristics that induced people to initiate would also increase the propensity to continue smoking in elderly age.

5.2 Main Estimates

Our baseline estimates cross different models are summarized in Table 4 through 7. Left panel represents estimates from models where the dependent variable equals one if the individual is reported as daily smoker and right penal represents estimates from models of cigarettes consumption intensity. In both panels, left and right, we present the estimates of the effect of cigarette price from two specifications which correspond to the columns of Table 4. The specifications reported in columns are Probit model with random effect and Heckman-Lee two-step correction, Probit part from hurdle model, zero-truncated negative binomial regression, and count part from hurdle model. With the same structure, Table 5 and 6 show the estimates of effects of health shocks on two smoking decisions.

As showed in Table 4, we find evidence that higher cigarette price reduce daily smoking prevalence in our preferred specification. In particular, our estimate implies that a $1 increase in cigarette price will reduce the probability to smoke by nearly 3.6% over average. Relative to a base of 16.6%, this translates to 21.7% reduction in probability and -0.557 participation elasticity which is large relative

[4] It was not in the United States until mass-production methods coupled with aggressive marketing that the industry began to see off traditional pipe-smoking and tobacco-chewing habits.

to general consensus and previous studies (reviewed in section 2.1). Furthermore, in cigarette demand part, we find consistent and significant evidence that higher cigarette price reduce the amount smoked. Specifically, a $1 increase in cigarette price could reduce the average number of cigarette per day by nearly 0.8 in hurdle model and 1 in ZTNB model, which are, equivalently, about 4.6% and 5.7% of average intensive margin, and implies a price elasticity of -11.5% and -14.3%. The elasticities reported in this article are considered "short-run" elasticities, since cigarette consumption is not modeled as addictive good. Previous studies, like Becker and Murphy (1998), showed that the "long-run" elasticities from rational addiction models lead to a greater price responsiveness.

Estimates for the effect of health shocks are found significant and consistent in participation (Table 5). A health shock as hospitalization and high frequency of doctor visits, on average, could reduce the probability to smoke by 52% and 26% respectively, while by hurdle model, a downgrade of self-assessed health does not have significant effect on smoking participation. Unlike participation, only hospital staying shows an effective reduction effect on cigarette consumption, which is about 7% or 1.2 cigarettes. When it comes to specific disease diagnoses (Table 6), results have the similar pattern with general health shocks. A newly diagnosed heart disease, cancer and hypertension could effectively reduce the participation probability by, respectively, -0.121, -0.103 and -0.064, which implies -72.7%, -61.9% and -37.9% relative to the average probability of smoking. Of heart diseases, cancers and hypertensions diagnosed at least two years ago, effects are similar, but slightly smaller in magnitude, suggesting decaying effect over time. Relatively, heart diseases and cancers demonstrate very strong effect on quitting, while high blood pressure shows a smaller but still persistent impact. These findings provide sound evidence for the theories about curative quitting. The difference between the newly diagnosed diseases with previously diagnosed diseases reflects the extra incentive to quit for new health information or, in other word, decayed effect of old illness. According to our results, there is no effect of "curative reduced consumption", since once the smoker decides to continue smoking after a health shock, the number of cigarettes does not tend to decrease unless he or she stay in hospital which is probably caused by close surveillance.

As the leading causes of death in U.S., cancer and heart diseases possess the most evident warning effect, as indicated in our results, due to their immediate deterioration on health and relative low cure rate; while the hypertension are chronic and hence generate relatively less immediate incentive to quit smoking.

We find no evidence that State-level smoking free air law and anti-smoking sentiment would effectively reduce the smoking prevalence for elderly, while there is evidence that the state-level anti-smoking sentiment is associated with lower average smoking intensity (Table 7).

From the perspective of model selection, estimates for conditional demand of these two models are consistent in both significance level and magnitude of coefficients. The main difference between the two parts model with hurdle model lies in the estimation of participation, which is reasonable as the estimations of probability to smoke is likely to be different for with and without the smoking intensity information.

If we contribute the drop of smoking participation and cigarette consumption to the following four main factors: cigarette price, health problems, aggregate trend and state-level smoking bans, our estimates show that the main factors that affect participation and conditional demand are different.

Over the period of 1994-2010, smoking prevalence of our sample dropped from 23.60% to 12.03%, by 11.57%, and the participation elasticity of -0.557 implies 6.01% of reduction as average price facing our sample increase from 1.66 to 3.60 in 1992 dollar. In other words, about 50% observed reduction of prevalence is explained by increased price (see Figure 2). As for the rest of the quitting behavior, on the one hand, aggregate trend and state-level smoking bans show hardly any significant effect on individual level participation behavior. On the other hand, coefficients before health problems are substantial both statistically and economically. Therefore, it's natural to contribute the other half of observed smoking prevalence drop in our sample to occurrence of health problems.

Conditional on smoking, the number of cigarettes smoked per day decreased from 19.77 to 13.85, as shown in Figure 3, over the period from 1994 to 2010. As price facing smokers increased from 1.66 to 3.58 in 1992 dollars, 2.65 cigarettes reduction is implied by the price elasticity of demand, 0.115, which is about 45% of total decrease in smoking intensity, and interestingly, 3.23 cigarettes drop is due to aggregate trend, i.e. 54% of total reduction. Health problems, unlike in participation decision, have barely any effect on conditional demand. Hence, the main factors for smoking intensity drop are cigarette price and aggregate trend.

To summarize the decomposed effect on two smoking decisions, higher price tends to reduce both participation and demand of smoking considerably, health problems, including health shocks and existing health problems mainly induce smokers to quit, and aggregate trend seems affect mainly on conditional demand, other than smoking participation.

5.3 Heterogeneity

Given our main estimates, it's natural to ask the next question: is there relevant heterogeneity in the response to cigarette price and health information? Table 8 presents our estimates of responses to price and health information change for subgroups, so that the price elasticities and response to health shocks is allowed to vary by gender, ethnics, education and age. We find the evidence that low-educated individuals, defined as those with less than 12 schooling years, are much more price-sensitive than their more-educated counterparts. In particular, $1 increase in cigarette price will decrease the fraction of smokers we label as low-educated by over 20%, and for smokers who don't quit, the number of cigarettes is predicted to reduce by about 0.6, while the participation and demand elasticities for more-educated smokers are not significant at any conventional level. The significance of participation elasticities are diluted when we divide the sample by gender and age group, as none of these subgroups has significant marginal effect. However, there is an interesting finding that smokers aged over 65-year tend to reduce much more cigarettes consumption as price goes up. Among all subgroups, male smokers shows the strongest response to price as $1 increase in price could reduce over 1.6 cigarettes per day on average, and white sample has the highest participation elasticity, which is implied by that over 26% of white smokers would quit when price goes up by $1.

Part Ⅱ of Table 8 presents the individual's response to health shocks of subgroups. Two findings are worthy to mention. One is that male tend to be more responsive to health shocks in both participation behavior and conditional demand behavior. The other one lies in different age groups, although both age groups exhibit curative quitting consistently. Relative younger group (age from 45 to 64 years) has a higher probability to quit with a newly diagnosed disease, like heart attack, while older group (age over 65) will reduce more cigarettes conditional on smoking after health shock of hospitalization.

6. Discussion

6.1 Rounding effect

In our data, the number of cigarettes shows a common problem of self-reported survey data which is the rounding effect. For instance, there are 47.6% of reported numbers that are multiples of 20, and 84.6% that are multiples of 5. To deal with this issue, different units for the number of cigarettes are used in estimation of conditional demand models. Our results (Table 9) show that estimate of price elasticity is robust to the different measures of smoking intensity (number of quarter pack per week, number of pack per week, number of quarter pack per month and number of pack per month), and it ranges from -12.3% to -14.3%, which is transferred to the marginal effect from -0.83 to -0.96.

6.2 Bootlegging Effect

The problem of bootlegging may exist in the cigarette industry, which lead to an underestimate if it's not properly addressed. Briefly speaking, since the prices are different across states, consumers in one state might be tempted to buy cigarette from lower price/tax state. Baltagi and Levin (1986) used the minimum real price of neighboring states to capture the cross-border effects whereas Keeler, et al. (1993) had the average real price of neighboring states. To take the cross-border bootlegging effect into consideration, the effects of minimum and average cigarette price of neighboring states are estimated in our conditional demand models.

Our results indicate a significant smuggling effect for elders. In the specification with minimum price of neighboring states (column 2 in Table 10), the coefficient is -0.0844, which translates to an elasticity of -18.9%, while with the average price of neighboring states (column 3 in Table 10), the elasticity is -28.5% which is much higher than the elasticity of price in baseline model. The estimates for price in their own state decrease tremendously after we add the minimum or average price of neighboring states, which is possibly caused by the high correlation among these prices, which can reach up to 92%. However, if there is no bootlegging effect for elders, then the sum of these two price elasticities are not supposed to change much, and the more than doubled price elasticity in column 3 implies that the smuggling effect does exist for our elderly smokers, although this effect cannot be accurately estimated with our current models.

While the results are not reliable because of the deterioration of multilinearity, the changes of price elasticity after the smuggling effect is added also shed a light on the question, that is, for the true price smokers have, which measure is more representative.

7. Conclusion

This study analyzes the effect of price, health information and other factors on the smoking participation and consumption behavior. Specifically, participation and cigarettes demand are estimated both separately and jointly by using two-part and hurdle models with correlated random effects. Our panel data set is unbalanced because the respondents of HRS are old and many are deceased before our last available interview.

We found evidence that a higher cigarette price reduce the smoking prevalence and intensity for elders, which shed some light on possible policy implications. Specifically, our estimated participation elasticity are large relative to the general consensus for elders and to the estimates reviewed earlier in this paper, which is ranged from -21% to -56%. Although smaller than the elasticities associated with smoking participation, our results present consistently significant and precise price elasticities of demand which ranged from -0.12 to -0.14. In one word, the higher cigarette price explained 52% drop in smoking participation and 45% drop in smoking intensity.

When we compare the effect of price to that of health shocks, later one has a much stronger effect on continuation than demand conditional on smoking. A general health shock has the marginal effect on probability to smoke from -11% to -52%, whereas heart diseases, cancers and hypertension could reduce the probability of participation ranging from 38% to 73%, depending on which disease is diagnosed. On the contrary, health shocks shows little impact on the smoking intensity of hard-core smokers who continue to smoke even after health shocks, as only hospitalization reduces the smoking intensity slightly.

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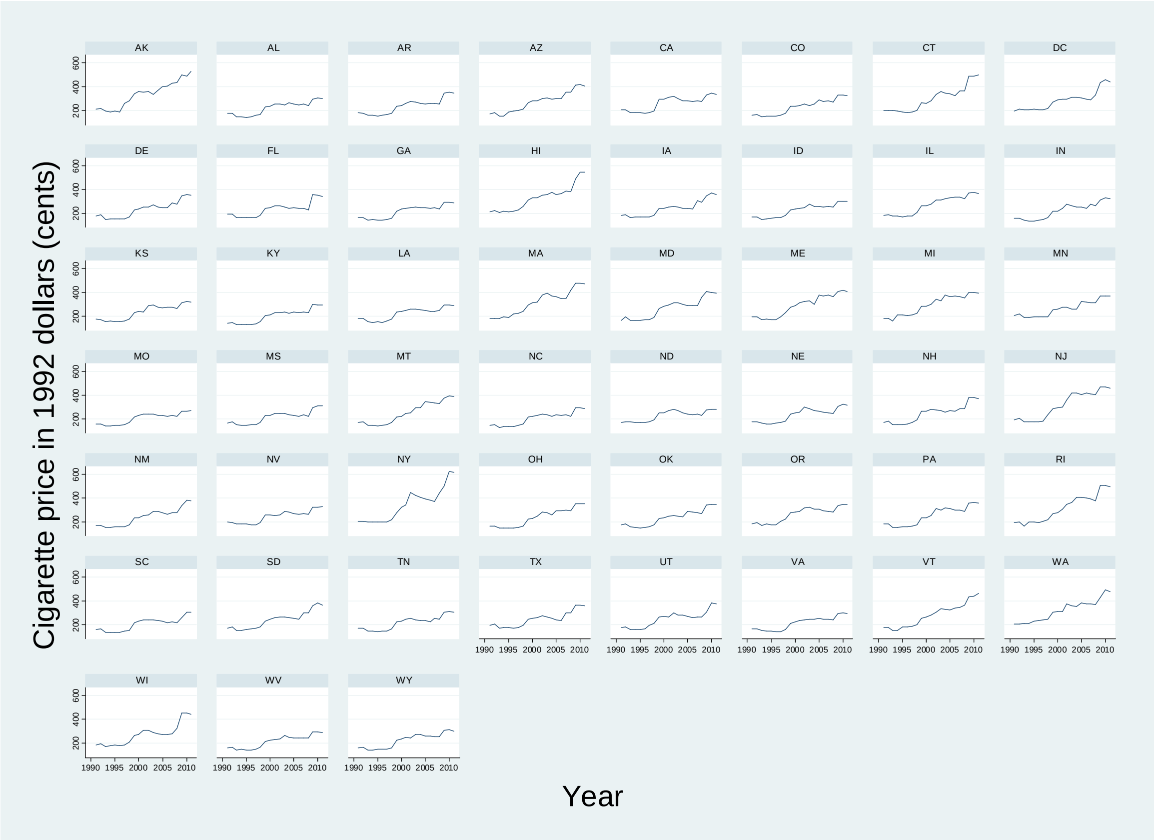
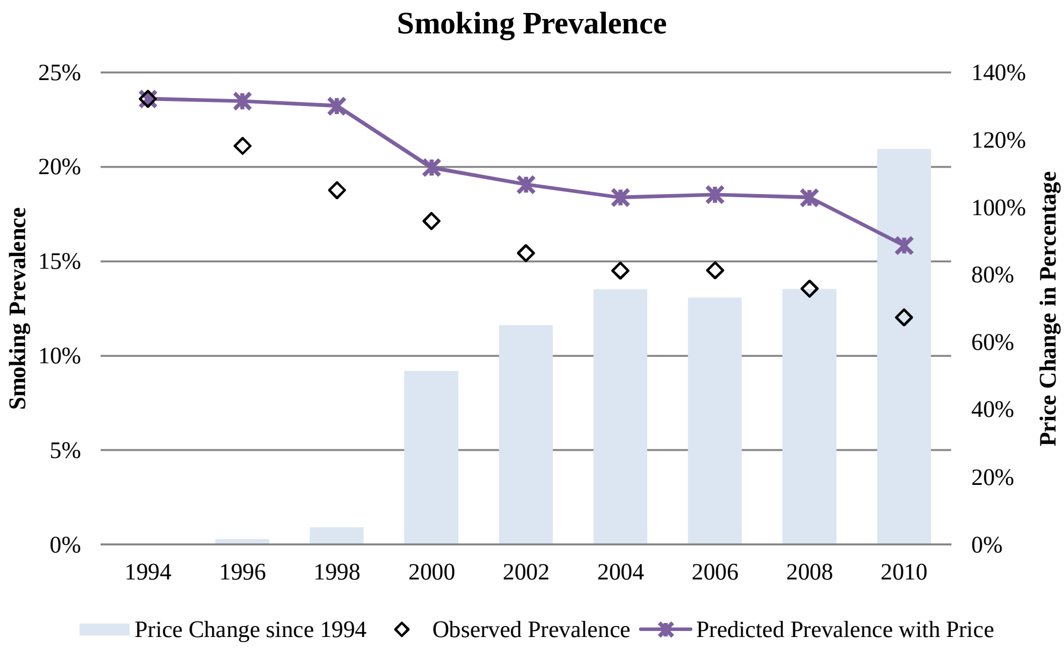
9. Appendix

Figure 1- Cigarette price by state from 1991 to 2011



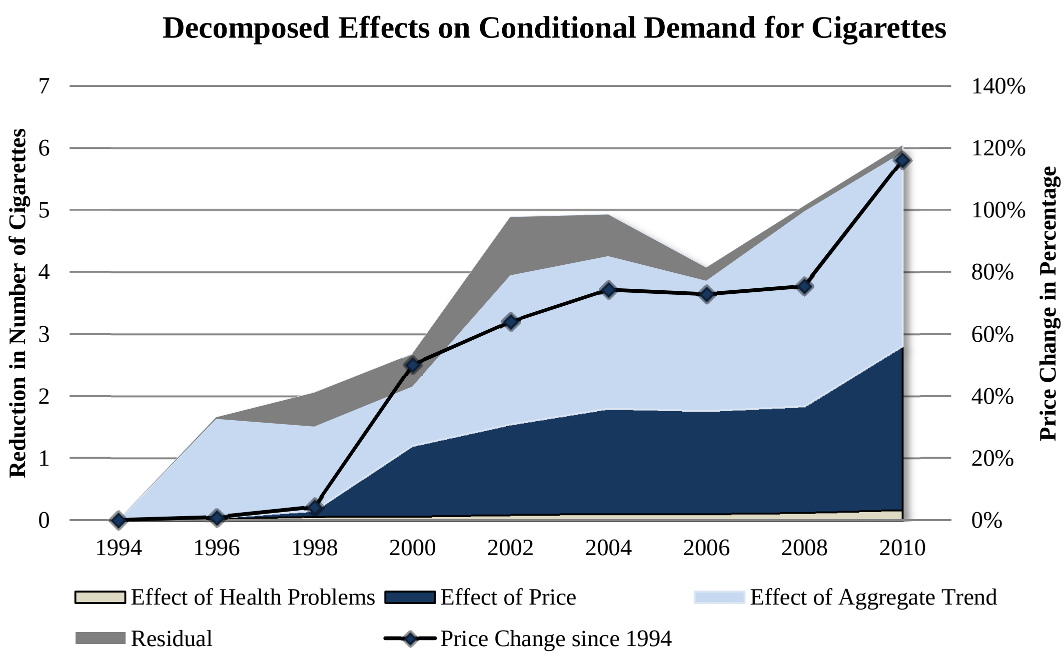
Source: The Tax Burden on Tobacco (2012), 2012

Figure 2- Predicted smoking prevalence by price change only



Source: The Tax Burden on Tobacco (2012) and authors' calculation

Figure 3- Decomposed effects on conditional demand for cigarettes



Source: The Tax Burden on Tobacco (2012) and authors' calculation

Table 1- Description of Variables

Variables	Description
Time-invariant variables (Demographics) panel A	
Cohort: AHEAD	Born before 1924
Cohort: CODA	Born during depression, 1924-1930
Cohort: HRS	Born during 1931-1941
Cohort: WB	Born during war, 1942-1947
Cohort: EBB	Born during Early baby boomers, 1948-1953
Catholic	Religious preference, Catholic
Protestant	Religious preference, Protestant
Black	Binary indicator for Africa-American
White	Binary indicator for Caucasian
Hispanic	Binary indicator for Hispanic
Male	Binary indicator for male
Foreign born	Not born in the U.S.
South born	Born in southern states
Western born	Born in western states
North born	Born in northeast states
BMI	Body Mass Index, normalized by sample mean
BMI^2	Squared BMI
Exercise	Vigorous physical activity at least three times per week
Veteran	Ever been in military service
Service	The industry associated with the longest–held job is service (business/repair service/personal services and entertainment)
Sale	The industry associated with the longest–held job is sale (wholesale/retail)
Technology	The industry associated with the longest–held job is technology (Transportation/ professional/related service)
Finance	The industry associated with the longest–held job is Finance (finance/ insurance/real estate)
Blue collar	The industry associated with the longest–held job is blue collar (mining and construction/manufacture)
Income	Household income divided by the size of family
Short-sighted	Financial planning horizon is next few month or shorter
Schooling year	Years of schooling normalized by sample mean
Schooling year^2	Squared schooling year
Father Educated	Binary indicator for schooling year of father>=12
Mother Educated	Binary indicator for schooling year of mother>=12

Variables	Description
Time-variant variables (Demographics) Panel B	
Age	Age when interviewed
Age^2	Squared age
Married	Binary indicator if respondent is married when interviewed
Spouse smoking	Binary indicator if married and spouse is smoking when interviewed
Retired	Binary indicator if respondent is retired when interviewed
IRA	Binary indicator if value of IRA/Keogh account is positive
Wave dummies	Binary indicator if interview year=1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010
Time-variant variables (Health measure dummies) Panel C	
HC: heart disease	Binary indicator: Respondent was ever told by a doctor that she/he had a heart problems[5]
HC: cancer	Binary indicator: Respondent was ever told by a doctor that she/he has cancer[6] or a malignant tumor
HC: hypertension	Binary indicator: Respondent was ever told by a doctor that she/he has hypertension/high blood pressure
HC: SAH	Self-assessed health from level 1 (excellent) to level 5 (poor)
HS: hospitalization	Binary indicator: at least 1 day stay in hospital during last two years or since last interview
HS: doctor visits	Binary indicator: visited doctors at least 5 times during last two years or since last interview
HS: SAH	Binary indicator: Self-assessed health is decreased by at least 2 levels during last two years or since last interview
HS: heart disease	Binary indicator for a newly diagnosed heart disease after last interview and *HC: heart disease* is 0 before this wave
HS: cancer	Binary indicator for a newly diagnosed cancer after last interview and *HC: cancer* is 0 before this wave
HS: hypertension	Binary indicator for a newly diagnosed hypertension after last interview and *HC: hypertension* is 0 before this wave
Time-variant variables (Smoking related) Panel D	
Smoke ever	Binary indicator if ever initiate smoking, dependent variable in initiation stage
Smoke now	Binary indicator if smoking now, dependent variable in participation model
Smoke intensity	Number of cigarettes smoked per day if smoking, dependent variable in conditional demand model
Cigarette price	Weighted average price per package (20 cigarettes) including federal and state taxes
ASS	Anti-smoking sentiment, measured by the percentage of respondent who think smoking shouldn't be allowed anywhere in bars in state level, from TUS-CPS
Smoking bans	Binary indicator if there is effective state-level smoking ban on one of locations including restaurants, private worksites and bars

[5] Including a heart attack, coronary heart disease, angina, congestive heart failure, or others

[6] Excluding minor skin cancer

Table 2- Summary statistics –by observation and individual

	By Observation		By Individual	
	Current-smokers	**Quitter and Non-smokers**	**Smokers and Former smokers**	**Non-Smokers**
Panel A---- Socio-demographics				
N	16375	82395	11328	6784
Age	60.92***	65.00***	53.09	52.14
Schooling year	11.85***	12.71***	12.35**	12.89**
Catholic	26.64%	26.49%	27.24%**	25.27%**
Protestant	62.97%***	65.03%***	62.10%***	66.56%***
Male	45.38%*	44.36%*	53.10%***	33.21%***
Household size	2.33***	2.27***		
Married	58.49%***	70.19%***		
Divorced/widowed	32.50%***	23.90%***		
Retired	45.29%***	55.80%***		
Panel B---- Health variables				
HS: hospital	20.24%***	23.04%***	60.13%***	56.50%***
HS: doctor	48.85%***	58.72%***	83.83%	84.71%
HS: SAH	5.40%***	4.74%***	23.90%***	21.33%***
HS: heart disease	2.56%***	3.26%***	18.04%***	15.63%***
HS: cancer	1.61%***	2.20%***	12.19%***	10.30%***
HS: hypertension	4.89%	4.55%	24.76%	25.74%
HC: heart disease	20.81%***	24.56%***		
HC: cancer	10.72%***	13.40%***		
HC: hypertension	47.95%***	56.38%***		
SAH	2.96***	2.68***		

Note:

1. *P-value for the test* $H_0 : P_1 = P_2$ or $\mu_1 = \mu_2$ *versus* $H_1 : P_1 \neq P_2$ or $\mu_1 \neq \mu_2$;
2. * *p-value < 0.05,* ** *p-value < 0.01,* *** *p-value < 0.001;*

Table 3- Initiation equation

Dependent variable: $I_i = 1$ if ever iniated smoking			
	Estimates	**Marginal effect**	**Std. Err.**
Cohort: CODA	0.0549^{***}	0.020	0.01
Cohort: HRS	0.208^{***}	0.076	0.00
Cohort: WB	0.0965^{***}	0.035	0.01
Cohort: EBB	0.0028	0.001	0.01
Catholic	-0.114^{***}	-0.042	0.00
Protestant	-0.242^{***}	-0.087	0.00
Foreign born	-0.265^{***}	-0.098	0.00
Male	0.339^{***}	0.126	0.00
Veteran	0.301^{***}	0.109	0.00
Service	-0.0679^{***}	-0.025	0.00
Technology	-0.0682^{***}	-0.025	0.00
Finance	-0.0552^{***}	-0.020	0.01
Blue collar	0.0436^{***}	0.016	0.00
Black	0.108^{***}	0.039	0.01
White	0.0791^{***}	0.029	0.01
Hispanic	-0.202^{***}	-0.074	0.01
Schooling year	-0.167^{***}	-0.061	0.00
Father Educated	0.0672^{***}	0.024	0.00
Mother Educated	0.0599^{***}	0.022	0.00
South born	-0.0112	-0.004	0.00
Western born	0.00972	0.004	0.00
North born	0.103^{***}	0.037	0.00
Dep. Mean	0.583		
N	173,460		

Note:

1. * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

Table 4- Estimated Effect of Cigarette Price on Smoking

Full Sample	Probability of Daily Smoking		Average Number of Cig. per day	
	(1) Probit with RE	(2) Hurdle Model-Regime 1	(3) ZTNB with RE	(4) Hurdle Model-Regime 2
Real Price	-0.054	-0.145*	-0.059***	-0.047***
	(0.0568)	(0.0570)	(0.017)	(0.017)
	[-0.013]	[-0.036]	[-0.987]	[-0.794]
Elasticity	-0.213	-0.557*	-0.143***	-0.115***
Dep. Mean	0.157	0.166	16.821	16.821
Mean price	2.574	2.579	2.424	2.424
N	83594	98770	16221	16221

Note:

1. Standard error in parentheses.
2. Marginal effect is in brackets.
3. * P-value < 0.05, ** P-value < 0.01, *** P-value < 0.001.
4. For Probit model and zero-truncated negative binomial model (ZTNB), the random effects are estimated using empirical Bayes.
5. The marginal effects in regime 1 of hurdle models are calculated as $\hat{\beta} \cdot \phi(z)$, where $z = \Phi^{-1}(p)$ and p is the sample mean of the indicator variable for daily smoking, $\hat{\beta}$ is the estimated coefficient, $\phi(\cdot)$ is the standard normal probability density function, and $\Phi^{-1}(\cdot)$ is the inverse of the standard normal cumulative density function.
6. The marginal effect in regime 2 of hurdle model is $\hat{\beta} \cdot \bar{Y}$, and the elasticity is $\hat{\beta} \cdot \bar{X}$, where $\bar{Y}$ and $\bar{X}$ are sample mean of dependent variable and cigarette price respectively.
7. Standard errors of marginal effects and elasticities are calculated using Delta-Method.

Table 5- Estimated Effect of Health Shocks on Smoking

	Probability of Daily Smoking		Average Number of Cig. per day	
Full Sample	**(1) Probit with RE**	**(2) Hurdle Model-Regime 1**	**(3) ZTNB with RE**	**(4) Hurdle Model-Regime 2**
HS: Hospitalization	-0.379***	-0.442***	-0.072***	-0.074***
	(0.0379)	(0.0377)	(0.0126)	(0.0127)
	[-0.074]	[-0.086]	[-1.16]	[-1.20]
HS: Doctor Visits	-0.224***	-0.194***	0.007	-0.001
	0.0345	0.0336	0.0110	0.0110
	[-0.048]	[-0.043]	[0.115]	[-0.012]
HS: SAH	-0.225**	-0.081	-0.023	-0.016
	(0.065)	(0.063)	(0.021)	(0.021)
	[-0.048]	[-0.019]	[-0.391]	[-0.269]
Dep. Mean	0.157	0.166	16.821	16.821
N	83594	98770	16221	16221

Note:

1. Standard error in parentheses.
2. Marginal effect is in brackets.
3. * P-value < 0.05, ** P-value < 0.01, *** P-value < 0.001.
4. For Probit model and zero-truncated negative binomial model (ZTNB), the random effects are estimated using empirical Bayes, and marginal effects are calculated at individual level.
5. The marginal effect in regime 1 of hurdle model is calculated as $\Phi(z+\hat{\beta})-p$, where $z=\Phi^{-1}(p)$ and p is the sample mean of the indicator variable for daily smoking, $\hat{\beta}$ is the estimated coefficient.
6. The marginal effect in regime 2 of hurdle model is $(\exp(\hat{\beta})-1)\cdot\bar{Y}$, where $\bar{Y}$ is the sample mean of dependent variable.
7. Standard errors of marginal effects are calculated using Delta-Method.

Table 6- Estimated Effect of Health Shocks on Smoking

Full Sample	Probability of Daily Smoking (1) Probit with RE	(2) Hurdle Model-Regime 1	Average Number of Cig. per day (3) ZTNB with RE	(4) Hurdle Model-Regime 2
HS:	-0.588^{***}	-0.731^{***}	-0.085	-0.039
Heart Disease	[-0.101]	[-0.121]	[-0.509]	[-0.639]
	{-64.34%}	{-72.69%}	{-3.03%}	{-3.80%}
Previously diagnosed	-0.372^{***}	-0.451^{***}	-0.008	-0.014
heart disease	[-0.072]	[-0.088]	[-0.133]	[-0.228]
	{-46.25%}	{-52.81%}	{-0.79%}	{-1.36%}
HS:	-0.490^{***}	-0.565^{***}	0.002	0.013
Cancers	[-0.089]	[-0.103]	[0.031]	[0.228]
	{-56.9%}	{-61.9%}	{0.18%}	{1.35%}
Previously diagnosed	-0.384^{***}	-0.455^{***}	-0.027	-0.028
cancer	[-0.074]	[-0.088]	[-0.443]	[-0.468]
	{-47.4%}	{-53.2%}	{-2.63%}	{-2.78%}
HS:	-0.249^{***}	-0.303^{***}	0.001	-0.002
Hypertension	[-0.052]	[-0.064]	[0.016]	[-0.038]
	{-33.2%}	{-38.6%}	{0.10%}	{-0.22%}
Previously diagnosed	-0.317^{***}	-0.297^{***}	-0.019	-0.019
hypertension	[-0.064]	[-0.063]	[-0.322]	[-0.317]
	{-40.7%}	{-37.9%}	{-1.92%}	{-1.88%}
Dep. Mean	0.157	0.165	16.821	16.821
N	83594	98770	16221	16221

Note:

1. Marginal effect is in brackets.
2. Marginal effect in percentage in braces.
3. Diseases with prefix HS are newly diagnosed.
4. * P-value < 0.05, ** P-value < 0.01, *** P-value < 0.001.
5. Marginal effects and elasticities are calculated as Table 5.
6. Standard errors of marginal effects are calculated using Delta-Method.

Table 7- Estimates of other parameters

Full Sample	Probability of Daily Smoking		Average Number of Cig. per day	
	(1) Probit with RE	(2) Hurdle Model-Regime 1	(3) ZTNB with RE	(4) Hurdle Model-Regime 2
SAH	0.08411***	-0.01989	0.01279*	0.008879
	(0.02051)	(0.01993)	(0.006165)	(0.006158)
Exercise	-0.1876***	-0.0947**	-0.00964	0.001235
	(0.0352)	(0.03412)	(0.01134)	(0.01134)
Age	0.06021*	0.05444*	0.03348***	0.02078**
	(0.02739)	(0.02633)	(0.00788)	(0.007832)
Age^2	-0.00138***	-0.00111***	-0.00033***	-0.00022***
	(0.000214)	(0.000217)	(0.000064)	(0.000064)
Married	-1.0242***	-0.7491***	-0.1127***	-0.1205***
	(0.05878)	(0.05694)	(0.01685)	(0.01682)
Spouse smoking	1.5266***	1.0731***	0.1375***	0.1412***
	(0.06588)	(0.06088)	(0.01768)	(0.01763)
Retired	-0.08146*	-0.1576***	0.01098	0.01996
	(0.03919)	(0.03879)	(0.01212)	0.01213)
Income	-0.03773	-0.02924	-0.00556	-0.00282
	(0.02254)	(0.02424)	(0.008784)	(0.008824)
IRA	-0.2697***	-0.0119	-0.01174	-0.01441
	(0.0438)	(0.04297)	0.0137)	(0.01368)
Short-sighted	0.6402***	0.4242***	(0.01524	0.01271
	(0.113)	(0.1049)	(0.02209)	(0.0221)
Schooling year	-1.0831***	-0.366***	-0.05564***	-0.06723***
	(0.06487)	(0.05825)	(0.01322)	(0.01329)
Schooling year^2	-0.175***	0.03449	-0.029***	-0.02692***
	(0.03618)	(0.03422)	(0.007736)	(0.007711)
Veteran	0.8516***	0.5611***	0.002907	0.01773
	(0.1278)	(0.1202)	(0.02644)	(0.02657)
Male	0.708***	0.2364*	0.2092***	0.2115***
	(0.1167)	(0.1073)	(0.02395)	(0.02398)
Africa-American	0.4039	0.1035	-0.3204***	-0.3189***
	(0.2558)	(0.266)	(0.05224)	(0.05244)
White	0.3088	0.1995	0.2266***	0.218***
	(0.2287)	(0.2495)	(0.04785)	(0.04798)
Hispanic	-1.5117***	-1.4728***	-0.5144***	-0.5612***
	(0.1919)	(0.2779)	(0.03987)	(0.04115)
ASS	-0.2914	-0.3188	-0.03207	-0.1946*
	(0.3253)	(0.3262)	(0.09791)	(0.09772)
Smoking bans	0.07875	0.02084	0.01264	0.005605
	(0.05496)	(0.05463)	(0.01763)	(0.01762)
N	83594	98770	16221	16221

Note:

1. Standard error in parentheses.
2. * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001;
3. All models also contain the industries associated with the longest–held job and wave dummies.

Table 8- Heterogeneity Analysis- Part Ⅰ

Panel A: Participation	Gender		Education		Ethnics		Age	
	Men	Women	Low	High	White	Black	Age<65	Age≥65
Real Price	-0.079	0.005	-0.170*	-0.156	-0.179**	0.093	-0.114	0.025
	(-0.90)	(0.07)	(-2.41)	(-1.60)	(-2.73)	(0.70)	(-1.37)	(0.29)
Marginal effect	-0.020	0.001	-0.047*	-0.031	-0.043**	0.025	-0.033	0.005
Elasticity	-0.304	0.021	-0.610*	-0.680	-0.703**	0.333	-0.371	0.121
Dep. Mean	0.167	0.162	0.196	0.122	0.160	0.193	0.210	0.107
Mean price	2.567	2.588	2.538	2.634	2.583	2.515	2.373	2.825
N	43983	54787	56548	42222	80956	13800	52639	45128

Panel B: Demand	Gender		Education		Ethnics		Age	
	Men	Women	Low	High	White	Black	Age<65	Age≥65
Real Price	-0.092***	-0.046*	-0.035^{+}	0.001	-0.047*	-0.071	-0.050*	-0.080**
	(-3.51)	(-2.05)	(-1.70)	(0.04)	(-2.52)	(-1.61)	(-2.25)	(-2.84)
Marginal effect	-1.629***	-0.693*	-0.583^{+}	0.019	-0.840*	-0.776	-0.843*	-1.186**
Elasticity	-0.223***	-0.113*	-0.085^{+}	0.003	-0.115*	-0.173	-0.115*	-0.220**
Dep. Mean.	18.531	15.400	16.961	16.521	18.145	11.287	17.414	15.373
Mean price	2.419	2.462	2.417	2.497	2.436	2.436	2.317	2.743
N	7365	8856	11073	5148	12917	2657	11075	4816

Note:

1. *t*-statistics in parentheses.
2. $^{+}$ p-value < 0.10, * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001;
3. All models also contain other covariates which are the same with the baseline specification;
4. Marginal effects are calculated as Table 4, Hurdle model.

Table 8- Heterogeneity Analysis- Part Ⅱ

Panel A: Participation	Gender		Education		Ethnics		Age	
	Men	Women	Low	High	White	Black	Age<65	Age≥65
HS: Hospital	-0.596***	-0.386***	-0.424***	-0.474***	-0.427***	-0.504***	-0.431***	-0.499***
	[-0.108]	[-0.077]	[-0.096]	[-0.071]	[-0.082]	[-0.108]	[-0.102]	[-0.066]
HS: Doctor Visits	-0.298***	-0.188***	-0.203***	-0.195***	-0.225***	-0.147	-0.212***	-0.321***
	[-0.064]	[-0.042]	[-0.051]	[-0.035]	[-0.049]	[-0.038]	[-0.056	[-0.048
HS: SAH	-0.173	-0.185*	-0.088	-0.082	-0.112	-0.108	-0.215*	-0.171
	[-0.040]	[-0.041]	[-0.023]	[-0.016]	[-0.026]	[-0.028]	[-0.056]	[-0.028]
HS: Heart Disease	-0.915***	-0.561***	-0.722***	-0.708***	-0.746***	-0.659*	-0.751***	-0.618**
	[-0.137]	[-0.101]	[-0.139]	[-0.091]	[-0.119]	[-0.129]	[-0.151]	[-0.075]
HS: Cancers	-0.580***	-0.495**	-0.566***	-0.558**	-0.546***	-0.586	-0.726**	-0.302*
	[-0.106]	[-0.093]	[-0.118]	[-0.080]	[-0.098]	[-0.120]	[-0.148]	[-0.046]
HS: Hypertension	-0.396***	-0.025***	-0.256***	-0.281**	-0.279***	-0.323*	-0.346***	-0.201***
	[-0.081]	[-0.006]	[-0.063	[-0.048]	[-0.058]	[-0.076]	[-0.086]	[-0.032]
Dep. Mean	0.167	0.162	0.196	0.122	0.160	0.193	0.210	0.107
N	43983	54787	56548	42222	80956	13800	52639	45128

Panel B: Demand	Gender		Education		Ethnics		Age	
	Men	Women	Low	High	White	Black	Age<65	Age≥65
HS: Hospital	-0.078***	-0.064***	-0.080***	-0.058*	-0.078***	-0.050	-0.066***	-0.088***
	[-1.389]	[-0.948]	[-1.312]	[-0.938]	[-1.364]	[-0.546]	[-1.105]	[-1.298]
HS: Doctor Visits	-0.003	0.013	0.012	0.001	0.011	0.019	0.015	-0.002
	[-0.053]	[0.207]	[0.207]	[0.013]	[0.194]	[0.213]	[0.257]	[-0.024]
HS: SAH	0.004	-0.058*	-0.050*	0.023	-0.012	-0.081	-0.028	-0.057
	[0.067]	-0.869]	[-0.834]	0.388]	[-0.219]	[-0.878]	[-0.488]	[-0.845]
HS: Heart Disease	-0.162***	0.035	-0.039	-0.035	-0.062	0.071	-0.072	-0.002
	[-2.775]	[0.556]	[-0.652]	[-0.566]	[-1.093]	[0.825]	[-1.203]	[-0.025]
HS: Cancer	0.008	-0.024	-0.081	-0.017	-0.001	0.146*	-0.041	0.101*
	[0.141]	[-0.361]	[-1.325]	[-0.278]	[-0.009]	[1.771]	[-0.705]	[1.636]
HS: Hypertension	0.042	-0.036	-0.013	0.024	0.012	0.056	0.003	0.032
	[0.787]	[-0.546]	[-0.219]	[0.404]	[0.228]	[0.650]	[0.061]	[0.492]
Dep. Mean	18.531	15.400	16.961	16.521	18.145	11.287	17.414	15.373
N	7365	8856	11073	5148	12917	2657	11075	4816

Note:

1. Marginal effect is in brackets.
2. * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001;
3. All models also contain other covariates which are the same with the baseline specification;
4. Marginal effects are calculated as Table 5, Hurdle model.

Table 9- Rounding effect

Conditional Demand	(1) Baseline: # of cig. /d.	(2) # of quarter pack /wk.	(3) # of quarter pack /mo.	(4) # of pack /wk.	(5) # of pack /mo.
Real Price	-0.059**	-0.052**	-0.053**	-0.052**	-0.050**
	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)
Elasticity	-0.143**	-0.127**	-0.130**	-0.127**	-0.123**
ME1[4]	-0.958	-1.191	-5.235	-0.303	-1.243
ME2[5]	-0.958	-0.851	-0.872	-0.865	-0.829
Mean of dep. Variable	16.821	23.532	100.927	5.993	25.331
Mean price (in 1992 $s)	2.442	2.442	2.442	2.442	2.442
N	16221	16221	16221	16221	16221

Note:

1. Standard error in parentheses.
2. * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001;
3. All models also contain other covariates which are the same with the baseline specification;
4. Marginal effect has the same unit with dependent variables;
5. Marginal effect is converted to the unit of dependent variable in the baseline specification, number of cigarettes per day.

Table 10- Bootlegging effect

Conditional Demand	(1) Baseline	(2) Bootlegging (MIN.)	(3) Bootlegging (AVE.)
Price	-0.0587***	-0.0313*	-0.00959
	(-0.0185)	(0.0179)	(0.0192)
Minimum price of neighboring states		-0.0884**	
		(-0.0364)	
Average price of neighboring states			-0.121***
			(-0.0306)
ASS	-0.327***	-0.259***	-0.260***
	(0.0901)	(0.942)	(0.0915)
Smoking bans	0.0286*	0.0249	0.0262
	(0.0168)	(0.169)	(0.0168)
Mean price[4] (in 1992 $s)	2.442	2.142	2.358
Corr. With *price*	1.00	0.8993	0.9155
N	16221	16221	16221

Note:

1. Standard error in parentheses.
2. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01 for two-sided tests;
3. All models also contain other covariates which are the same with the baseline specification;
4. Mean of retail price, minimum price of neighboring states and average price of neighboring states, respectively.