How Health Insurance Affects Health Care Demand – A Structural Analysis of Behavioral Moral Hazard and Adverse Selection*

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Abstract

Individuals with health insurance use more health care. One reason is that health care is cheaper for the insured. Additionally, having insurance can encourage unhealthy behavior via moral hazard. Previous work studying the effect of health insurance on medical utilization has mostly ignored behavioral changes due to having health insurance, and how that in turn affects medical utilization. This paper investigates the structural causal relationships among health insurance status, health behavior, and medical utilization theoretically and empirically, and separates price effects from behavioral moral hazard effects. Also distinguished are the extensive vs. intensive margins of insurance effects on behavior

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1 Introduction

There is a large literature examining the effect of health insurance on health care. This literature generally shows that health insurance is associated with an increased use of health care, though the direction of causality and the ultimate effects of health insurance on health are questionable.

Traditionally, researchers focus on two issues: First, individuals buying health insurance are likely to be those who anticipate greater need of health care, **due to, e.g., their greater health risk**. This is frequently referred to as adverse selection. **Recent literature switches from this traditional view and explores potential advantageous selection effects of health insurance (see, e.g., Finkelstein and McGarry, 2006, Fang et al., 2008, Doiron et al., 2008, and references therein). That is, the insured tend to be those with observed (e.g. higher education) and unobserved (e.g. greater health-consciousness) characteristics that are correlated with lower health risk. In either case,** statistically**,** this means that insured individuals are a non-randomly selected sample of the population. They have observed and possibly unobserved characteristics that are correlated with demand for medical care. Second, health insurance reduces the effective price of health care, so other things equal, the insured tend to use more health care. For example, individuals who are just indifferent between using and not using a certain medical service at uninsured rates will tend to use it if they have insurance. This is a direct price effect.

There is a third less well recognized indirect connection between insurance and health care: due to moral hazard, individuals once insured may become less cautious about their unhealthy or risky behaviors, which could lead to more health problems, requiring more health care. That is, individuals may respond to their insurance status and change behaviors, and thereby need more health care. **The impact of health insurance on health behavior tends to be separately examined from that on medical**

utilization in the existing literature. More detail will be provided in the next section.

This paper jointly considers the insurance decision, health behavior, and medical utilization, and investigates the direct and indirect insurance effects on medical utilization, controlling for the selection effect. The selection effect is a causal relationship running from health care utilization to health insurance; whereas both the direct price effect and the indirect insurance effect that discourage healthy behavior are causalities running from health insurance to medical utilization. The latter two effects cannot be separated without looking at the simultaneous relationships among health insurance, behavior, and health care utilization, even if the adverse selection is accounted for by econometric techniques or experimental designs.

Research and findings about moral hazard in the context of health insurance are relatively scanty; however, moral hazard is well documented in other insurance contexts that involve adverse health consequences. For example, Dave and Kaestner (2006) note an increase in car accidents when car insurance is more generous, and an increase in workplace injuries associated with increases in workers' injury compensation. Intuitively, health insurance may encourage individuals to engage in less healthy behavior because it provides a safety net and lowers the monetary and emotional cost of the resulting negative health consequences. For example, individuals with chronic diseases are more likely to rely on medication instead of behavioral improvement once medication becomes cheaper. This is especially true when the impacts of behavioral improvement show up gradually and in a less perceptible way than medication.

In this paper the disincentive effect of health insurance on individuals' healthy behavior is referred to as "behavioral moral hazard." In contrast, "direct effect" is defined as health insurance lowering the price of medical care and hence inducing individuals to use more care *ceteris paribus*.[1] **That is, the direct effect measures the direct price effect if individuals did not respond to their insurance status and changed health behavior.** Although both may lead to increased health care utilization, their ultimate effects on health are different.

The increased use of health care resulting from behavioral moral hazard may not result in better health, because it is only intended to compensate for increased unhealthy behavior. In contrast, increases in health care utilization caused by the direct effect of lower costs is more likely to improve health.

A policy implication is that mandating insurance coverage to improve a targeted population's health status may not be fully efficient. The efficiency in part depends on how much individuals substitute medication for behavioral improvement. For example, Klick and Stratmann (2006) examine the effect of mandates in some states that required health insurance providers to cover diabetes treatment without increasing premiums. Their study shows that these mandates generate strong disincentives for individuals' behavioral prevention and systematically increase the diabetics' BMI in the affected states, which is taken as a result of engaging in worse diet and exercise practice. Therefore, distinguishing between the two effects may further uncover policy relevant parameters.

Distinguishing the two effects may also improve our understanding of a puzzle in the literature: while a great deal of research shows that health insurance results in increased use of health care, there is little evidence that having heath insurance leads to improved health (Haas et al., 1993a, b, Perry and Rosen, 2001). Findings from the RAND Health

[1] These two terms are related to but not the same as the existing *ex ante* and *ex post* moral hazard concepts in health economics. *Ex ante* moral hazard refers to the moral hazard that takes place before a sickness episode, which is further classified into self-insurance (demand for preventive care) and self-protection (exercising, abstention from smoking etc). *Ex post* moral hazard refers to moral hazard that takes place after a sickness episode, i.e., using more health care when one gets sick. Here the focus is on distinguishing two different ways that health insurance may cause increased demand of health care and exploring their relative roles. The direct price effect is a rational economic behavior, i.e., individuals' natural response to decreased prices of health care. It can be predicted *ex ante* by examining the price elasticity of care.

Insurance Experiment (Newhouse, 1993) show that those for whom health care was free used about 40% more health services than those who had some cost sharing, but this resulted in "little or no measurable effect on health status for the average adult."

The difficulty in identifying the causal impact of health insurance on health behavior and that on medical utilization is to control for possible advantageous or adverse selection effects. For example, if more health-conscious or more risk-averse individuals self-select into the insured group, or if the insurer successfully picks up the group of people who have healthier habits through, e.g., their price discrimination, then we will observe that the insured have healthier behavior. This will lead to a downward bias in the estimated insurance effect on unhealthy behavior. Similarly, if the insured have observed or unobserved characteristics that are positively or negatively correlated with medical utilization, then estimates of the insurance impacts on medical utilization will be biased.

In a simple and fully tractable utility maximization framework, this paper derives the structural relationships among the decision to buy health insurance, health behavior, and medical utilization. I show that medical utilization is a function of endogenous health insurance and health behavior, and health behavior is a function of the endogenous insurance decision. **The health insurance equation, which is a reduced-form, characterizes selection effects, where past health behavior and lagged health status capture health consciousness and in part high or low health risk types.** I also show that exogenous changes in the price (or availability) of health insurance can identify the insurance effects while past behavior and the price of unhealthy behavior, such as the price of alcohol, can help identify the impact of current unhealthy behavior, like unhealthy drinking, on medical utilization when conditioning on health.

This paper's empirical analysis draws on a sample of male non-retirees from the US

Health and Retirement Study (HRS). **The empirical analysis focuses on heavy drinking behavior, because in the HRS data set, smoking is a dummy variable, which in only informative about the extensive margin, but not the intensive margin of health insurance effects. Since heavy drinking tends to be highly correlated with other unhealthy behavior, such as smoking, focusing on heavy drinking at least sheds light on the behavioral moral hazard. I also conduct a sensitivity analysis examining the effect of health insurance on the probability of smoking.**

The HRS is a panel data set, so one can control for last period health, past average income, as well as past drinking behavior. The latter is crucial because of state dependence and the addictiveness of unhealthy behaviors. The HRS data are augmented with the monthly alcohol price index based on the date an individual was interviewed on and where the individual was living when interviewed. Two supply-side factors that can exogenously affect insurance availability are reaching age 65, the Medicare eligibility age, and having a spouse working full time, which provides an additional source of health insurance coverage.

In the empirical analysis, drinking behavior is specified as a generalized Tobit or sample selection model, in which log transformation is applied to the positive level of unhealthy drinking. Health insurance shows up as an endogenous dummy in both the participation (selection) equation and the quantity of unhealthy drinking equation in the Tobit specification. The generalized Tobit for unhealthy drinking separately accounts for the extensive margin (changes in the percentage of individuals who participate in unhealthy behavior) and the intensive margin (changes in the quantity of unhealthy behavior by participants) of the insurance effect, which turns out to be empirically important. The estimated log medical utilization equation is a linear regression that include unhealthy drinking and health insurance as endogenous regressors.

The empirical results show that the effects of health insurance are different at the two margins, and the effect at the intensive margin is more consistent across samples than that at the extensive margin. Health insurance does not seem to make a non-drinker or healthy drinker become an unhealthy drinker, whereas it is likely that health insurance encourages relatively heavy drinkers to drink even more. The effect of increased unhealthy drinking on medical utilization in the short run however is likely to be small.

The rest of the paper proceeds as follows. Section 2 reviews the literature. Section 3 sets up the theoretical model. Section 4 discuss empirical specifications, data, and identification issues. Section 5 presents the empirical results. Concluding remarks are provided in Section 6.

2 Literature Review

Most existing studies on health insurance effects examine the reduced-form effect of health insurance effect on medical utilization (See **Savage and Wright, 2003 for a discussion and the references therein, as well as** Zweifel and Manning, 2000 and Buchmueller et al, 2005 for surveys of this literature). These studies do not consider the impact of having health insurance on individuals' health behaviors, and how that might affect their medical utilization. Below is an illustration of the focus of this literature compared with the focus here.

Among the studies that examine the *ex ante* moral hazard of health insurance, some focus on the impact of insurance coverage on the receipt of preventative care, such as mammography or prostate or cholesterol screening. These studies include Roddy et al. (1986), Lillard et al. (1986), Keeler and Rolph (1988), Cherkin et al. (1990), McWilliams et al. (2003), and Decker (2005). The rest examine the effect of health insurance on binary health behavior indicators, such whether one smokes or exercises or

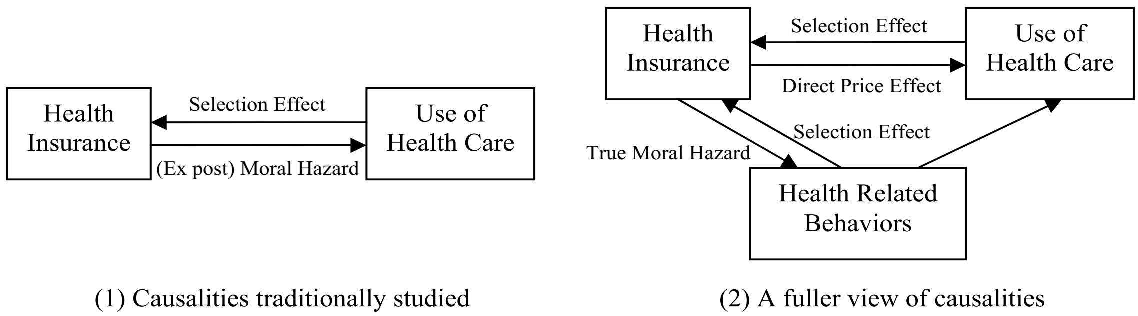

Figure 1: Focuses of the existing literature and those of this paper

note. For example, Courbage and Coulon (2004) examine whether purchasing private health insurance (in addition to the universally provided public insurance) modifies the probability of exercising, smoking and undergoing regular check-ups in the UK. Using Probit and instrumental variable estimation, they find that having additional private insurance may lead to healthier choices.

In addition, Kenkel (2000) examines the effect of health insurance on a series of unhealthy behavior indicators as well as on the use of preventive care. Based on standard logit model estimation, Kenkel's study suggests that people with private health insurance are more likely to engage in health promoting behavior than those without insurance. However, the author points out that these results may be biased if insurance status is endogenous to health practices. **Since it is generally believed that one's health insurance status is endogenous, the finding that healthy behavior is positively correlated with health insurance may reflect advantageous selection effects of health insurance instead of causal effects.**

Card et al. (2008) examine the effect of Medicare eligibility on a large range of mostly discrete outcomes: usage of medical procedures and whether one smokes or exercises, as well as self-reported health, obesity, and mortality rates. Their study exploits the exogenous increase in health insurance coverage at age 65, the Medicare eligibility age. They show that eligibility for Medicare has a significant impact on health care utilization and a discernable effect on self-reported health, though reaching age 65 has no systematic effect on mortality rates and on probabilities of smoking, exercising, or being obese.

Khwaja (2002, 2006) looks at individuals' health insurance decisions, health habits, and care utilization simultaneously in a dynamic discrete choice model framework. In particular, based on a dynamic programming approach, Khwaja (2002) shows that insurance coverage causes insignificant moral hazard in probabilities of having habits like smoking and drinking, and significant moral hazard in the probability of seeking medical treatment. Khwaja (2006) limits the analysis to Medicare only and finds that Medicare generates a low level of moral hazard in the probabilities of alcohol consumption, smoking and exercise among the elderly.

To summarize, most existing studies consider the insurance effect either on medical utilization or on health behavior, but do not look at the simultaneous structural relationships among health insurance, behavior and health care utilization. A couple of studies that do consider all three focus on discrete outcomes, i.e., they examine the insurance effect on the probability of having an unhealthy habit rather than the quantity. These studies find that health insurance does not have a significant effect on the probability of participating in unhealthy behavior (extensive margin); however, it is reasonable to believe that, given participation, health insurance may have a nonnegligible effect on the quantity of unhealthy behavior (intensive margin). For example, health insurance may not induce a non-smoker to become a smoker, but it is more likely to affect how much a smoker smokes. Looking at discrete outcomes fails to identify the empirically important intensive margin of the insurance effect, which may lead to misleading conclusions about the behavioral moral hazard effect.

In contrast to the previous literature, this paper adopts a fully tractable continuous choice model and derives the structural relationships among the decision to buy health insurance, health behavior, and health care utilization. The resulting structural equations show the identification of the effects of endogenous health insurance and behavior on medical utilization. Using quantitative instead of just qualitative data, this paper is able to examine both the extensive and intensive margins of insurance effects. Distinguishing the direct and indirect effects of health insurance on medical utilization as well as the extensive and intensive margins of behavioral moral hazard provide more policy relevant implications. For example, if health insurance makes people who already indulge in drinking drink even more, but does not cause people to take up unhealthy drinking, then policies for improving behavior should primarily target current heavy drinkers.

3 Theoretical Model

Assume a typical individual makes choices to maximize his expected utility, given his initial health condition, habits, and preferences. This section sets up a simple theoretical model of utility maximization, and derives explicitly the structural relationships among health behaviors, medical care utilization, and the decision to buy health insurance. The resulting model also shows the source of identification for the structural parameters of interest.

3.1 The Basic Theoretical Model

As Grossman (1972) and many others have noted, consumers value health. Better health may improve the efficiency of consumption of other goods, whereas health care is merely a means to producing health or slowing its decline. Therefore, this paper assumes that a typical individual draws utility from his health, unhealthy behavior (such as unhealthy drinking, but the model easily extends to a vector of unhealthy behaviors), and consumption of a composite good. Unhealthy behavior is addictive, so how much one enjoys the unhealthy consumption depends on one's habit stock. Engaging in unhealthy behavior generates utility, but it also produces disutility through its harmful effects on health.

Here health is viewed as a durable consumption good with value that depreciates with age. An individual may invest in health using medical care and health related behavior. The individual is also subject to health shocks, so an individual's health evolves according to[2]

$$H_1 = \delta H_0 + qM_1 + rB_1 + s_1 \tag{1}$$

where the subscript 1 is used for the current period and 0 for the previous period. So H_1 = current health; H_0 = initial (previous) health status; $1-\delta$ = health depreciation rate; M_1 = medical care; B_1 = health related behavior; s_1 = health shock, such as a heart attack, or injury, or more generally including any other individual heterogeneity that affects current health.

The potential addictiveness of unhealthy behavior implies that the marginal utility of current unhealthy behavior B_1 depends on past behavior B_0 (Becker and Murphy, 1988; Becker, Grossman and Murphy, 1994), so both B_1 and B_0 enter the current utility function. Current health H_1 and habits B_1 could depend on health and behavior for many previous periods, but for simplicity, the model here assumes that all previous periods are subsumed into period zero. However, one could instead include multiple lags explicitly if desired.

For computational tractability and simplicity, assume that utility is given by

$$U = -\left(v + hH_0 - H_1\right)^2/2 - a\left(\tau + bB_0 - B_1\right)^2/2 + cH_1B_1 + C_1, \tag{2}$$

which is maximized subject to the budget constraint

[2]For convenience of notation, an individual subscript is dropped from all the equations.

$$C_1 + p_{B_1} B_1 + p_{I_0} I_0 + (1 - dI_0)\, M_1 = W \tag{3}$$

where B_1, H_1, and M_1 are defined as in equation (1); C_1 = composite goods consumption, which is taken to be the numeraire; W = wealth; I_0 = insurance dummy; p_{I_0} = insurance premium; p_{B_1} = the price of B_1 (e.g., alcohol price); d = insurer co-payment rate, with $d \in (0, 1]$. Also τ and v are taste parameters that characterize bliss points for health and behavior, respectively, and h, a, b, and c are constant utility parameters.

In equation (2) the coefficient for the first quadratic health term is normalized to be one for convenience. Health is only ordinally observed, so this normalization is without loss of generality. The term $v + hH_0$ in the quadratic health component of utility says that the utility of current period health H_1 depends on a bliss point that is determined by the individual's taste for health v and last period health H_0. The utility of health therefore depends on both the change in health and the current level, e.g., a decrease from last period's health creates disutility even if the current level of health is high. Similarly, the term $\tau + bB_0$ makes the utility of current period unhealthy behavior B_1 depend on both the bliss point determined by the individual's taste for the behavior τ and the past level of unhealthy behavior B_0, thereby embodying the effects of addiction or habits. The interaction term between H_1 and B_1 captures the fact that the enjoyment (i.e., the marginal utility) of unhealthy behavior generally depends on one's health condition. A constant term in the utility function is omitted, since it is irrelevant for utility maximization.

The utility function, equation (2), is assumed to be quasi-linear in consumption, which causes wealth effects to drop out.[3] **How wealth is determined has no impact, and so is not explicitly modeled here. For example, given this model, having W be a function of current behavior, health, and**

[3]**This is an assumption that greatly simplifies solving the model while still provides the main causal relationships and identification, i.e. exclusion restrictions in the equations of health insurance and health behavior.**

hence medical care M_1, in general would not change the ultimate functional forms of all choice variables and hence identification. One may concern that in a more general setup, past behavior could affect W, and thereby affect all the choice variables here. However, it could only do so through past incomes, so as long as one controls for past income in the eventual behavior and medical utilization equations, the identification results that follow from this quasi-linear utility should still hold. The later empirical specifications of behavior and medical utilization control for past average income (representing permanent income) as one dimension of individual characteristics.

The subscript 0 is used for insurance, because it is assumed that the individual purchases health insurance for period 1 at the end of period zero. Individuals are assumed to be rational and forward looking, and in particular will choose whether to buy insurance in period zero based on expected period 1 utility.

Begin by substituting C_1 from the budget constraint (3) into equation (2). Utility maximization then yields the first order condition (FOC) for M_1

$$\frac{\partial H_1}{\partial M_1}(v + hH_0 - H_1) + \frac{\partial H_1}{\partial M_1} cB_1 - (1 - dI_0) = 0,$$

that is,

$$-q^2 M_1 + q\,(c - r)\,B_1 + q(h - \delta)H_0 - (1 - dI_0) + q(v - s_1) = 0.$$

Solving for M_1 gives

$$M_1 = -\frac{1}{q^2} + \frac{c - r}{q} B_1 + \frac{(h - \delta)H_0}{q} + \frac{d}{q^2} I_0 + \frac{v - s_1}{q}. \tag{4}$$

The above first order condition describes how an individual chooses medical care to maximize utility, so it is the structural equation for medical utilization. This equation shows that an individual's medical utilization M_1 depends on both his health behavior B_1 and his health insurance status I_0, conditional on his initial health status H_0. We will next show that the individual's health behavior B_1 further depends on his health insurance status I_0. Therefore, this simple theoretical model shows that health insurance can have both direct and indirect (through behavior) effects on medical utilization.

The FOC for B_1 is

$$\frac{\partial H_1}{\partial B_1}(v + hH_0 - H_1) + cB_1\frac{\partial H_1}{\partial B_1} + cH_1 + a(\tau + bB_0 - B_1) - p_B = 0$$

The individual is rational, so to maximize utility the FOC for both M_1 and B_1 must hold. Substituting M_1 specified by equation (4) into equation (1), and substituting the resulting expression for H_1 into the FOC for B_1 gives

$$\left(c^2 - a\right)B_1 + chH_0 - (c - r)(1 - dI_0)/q + abB_0 + cv + a\tau - p_B = 0$$

Behaviorally, this equation means that when the individual chooses B_1, he takes into account not only how B_1 affects health, but also how health will be affected by his chosen level of M_1 (which itself depends on his insurance status). Solving the resulting FOC for B_1 then gives

$$B_1 = \frac{r - c}{a - c^2}\frac{(1 - dI_0)}{q} + \frac{chH_0 + abB_0 - p_B + cv + a\tau}{a - c^2} \tag{5}$$

This derivation assumes that the resulting B_1 is non-negative or unconstrained by sign, for example, B_1 may be the logged quantity of unhealthy consumption and so can be negative or positive. This simplifying assumption allows us to focus on the identification of the structural model first, by identifying which variables appear in each equation. Imposing the constraint that B_1 is non-negative would, by Kuhn-Tucker, yield a standard

Tobit for B_1. The next section provides a more general model that separates the decision to participate (whether to set $B_1 = 0$ or not) from the above expression for the quantity to consume if participating.

For identification, note also that conditional on health status H_0, past behavior B_0 and price p_{B_1} appear only in the equation for B_1 and not in the structural M_1 equation, so B_0 and p_{B_1} provide exclusion restrictions that can be used to identify the effect of endogenous health behavior on medical utilization. Intuitively, the price of health behavior affects the quantity demanded, B_1, directly while it could only affect medical utilization through the budget constraint. This is a second-order effect which is formally zero in our quasi-linear utility function, and which I assume is small enough to be ignored in practice. After conditioning on both initial health and current behavior, past behavior B_0 has no direct effect on medical utilization M_1. That is, B_0 affects M_1 only through its impact on B_1 and H_0, and the two measures sufficiently summarize one's past behavior.[4]

Now consider the insurance decision. In period 0, the individual decides whether or not to buy health insurance for period 1, depending on which choice gives higher expected utility in period 1. Therefore, for both $I_0 = 1$ and $I_0 = 0$, substitute into the utility function the corresponding optimal choices of M_1 and B_1. The resulting utility function with either value of I_0 is stochastic, because the health shock is not realized until period 1. Conditional on the individual's information set $F^0 = \{B_0, H_0, v, \tau\}$, he compares the expected utility in the two cases, and buys insurance if and only if the expected utility of buying health insurance exceeds that of not buying.

Plugging the equations (4) and (5) in the utility function yields

$$U \quad = \quad \frac{1}{2(a-c^2)} \left[(r-c)\,\Delta + chH_0 + abB_0 + cv + a\tau - p_B \right]^2$$

[4]More generally, past health behavior affects current medical utilization only through its effect on health, so conditioning on health leads to an opportunity to identification. Also, the impacts of past behavior on health manifest gradually, so it is assumed that past behavior is unlikely affect current medical utilization directly without showing any impacts on lagged health status.

$$+W - p_{I_0} I_0 - \Delta \left(hH_0 - \delta H_0 + v - s_1 \right) + \Delta^2/2,$$

where $\Delta = \left(1 - dI_0\right)/q$. Denote U when $I_0 = 1$ as U^1, and U when $I_0 = 0$ as U^0. Then

$$I_0 = I\left[E(U_1^1 - U_1^0 \mid F^0) \geq 0\right],$$

where $I[\cdot]$ is an indicator function that equals one when the bracketed term is true, and zero otherwise. Assume that the health shock s_1 has mean zero, though more generally s_1 can be allowed to depend upon B_0 and H_0. Then

$$I_0 = I[r\left(\kappa_1 - \kappa_2\right) \frac{d-2}{2q^2} - \left(\kappa_2 h + \delta\right) H_0 - ab\kappa_1 B_0 + \kappa_1 p_B - \kappa_2 v - a\kappa_1 \tau - \frac{q}{d} p_{I_0} \geq 0], \quad (6)$$

where $\kappa_1 = \frac{r-c}{a-c^2}$, and $\kappa_2 = \frac{rc-a}{a-c^2}$. Let

$$p_{I_0}^* = \frac{d}{q}\left(r\left(\kappa_1 - \kappa_2\right) \frac{d-2}{2q^2} - \left(\kappa_2 h + \delta\right) H_0 - ab\kappa_1 B_0 + \kappa_1 p_B - \kappa_2 v - a\kappa_1 \tau\right),$$

which is the price at which the individual is just indifferent between buying and not buying health insurance, i.e., $p_{I_0}^*$ is the individual's willingness-to-pay or reservation price for insurance. Equation (6) then says that the individual buys health insurance if and only if his willingness-to-pay for insurance is higher than p_{I_0}, the actual price he needs to pay.

These steps together produce the following system of equations:

$$M_1 = -\frac{1}{q^2} + \frac{(c-r)}{q} B_1 + \frac{d}{q^2} I_0 + \frac{(h-\delta)}{q} H_0 + \frac{v - s_1}{q}$$

$$B_1 = \kappa_1 \frac{(1 - dI_0)}{q} + \frac{chH_0 + abB_0 - p_B + cv + a\tau}{a - c^2}$$

$$I_0 = I\left[r\left(\kappa_1 - \kappa_2\right) \frac{d-2}{2q^2} - \left(\kappa_2 h + \delta\right) H_0 - ab\kappa_1 B_0 + \kappa_1 p_B - \frac{q}{d} p_{I_0} - \kappa_2 v - \kappa_1 a\tau > 0\right]$$

We can write this system more simply as

$$M_1 = \gamma_0 + \gamma_1 B_1 + \gamma_2 I_0 + \gamma_3 H_0 + e_M \tag{7}$$

$$B_1 = \beta_0 + \beta_1 I_0 + \beta_2 H_0 + \beta_3 B_0 + \beta_4 p_{B_1} + e_B \tag{8}$$

$$I_0 = I\left[\lambda_0 + \lambda_1 H_0 + \lambda_2 B_0 + \lambda_3 p_{B_1} - p_{I_0} + e_I \geq 0\right] \tag{9}$$

where the γ, β, and λ terms are coefficients, while the e terms are the departures from means of linear combinations of the random utility parameters v, τ, and s_1, and these e errors are correlated across equations.

Notice that this system is triangular, in that B_1 depends on I_0, and M_1 depends on both B_1 and I_0. Note also that p_{I_0} shows up only in the insurance equation. Therefore, one can use variables that can exogenously affect the price of health insurance, e.g., some supply-side factors, as instruments to identify the effects of health insurance. Also, as noted earlier, p_{B_1} and B_0, appear in the equation for B_1 but not M_1, so these can be used as instruments for B_1 in the M_1 equation, and so the structural M_1 equation can be identified.

Equation (9) is the individual's demand function for insurance, which depends on the insurance price that is endogenously determined by both supply and demand. The price an individual must pay depends in part on characteristics of the individual. Rather than build a formal model of the supply side of the insurance market, I will assume that the combination of supply and demand produces a reduced form expression for an individual's insurance price p_{I_0} that is a function of the individuals' age, health condition H_0, behavior B_0 (consistent with the practice of insurers determining premiums based on pre-existing conditions and health habits) and other characteristics as well as observed and unobserved supply side factors.

In particular, there is a big exogenous supply-side price change at age 65

in the US – since almost all individuals can enroll in Medicare either free or at a low cost at 65, the effective insurance price available to individuals at this age is close to zero. Therefore, an age dummy indicating age 65 or above provides one source of exogenous variation in the insurance price. It hence enters the reduced-form health insurance equation as an exclusion restriction. Another potential source of variation is insurance choices through one's spouse. In particular, if a spouse works full time, then an individual may often be able to obtain health insurance though his spouse's coverage.

Taken together, the system of equations (7), (8), and (9) show that the price of unhealthy behavior and lagged behavior can identify the impact of current behavior on medical utilization, conditional on health status, while factors that exogenously affect the availability and hence the price of health insurance, such as reaching age 65, can identify the effect of health insurance on health behavior as well as on medical utilization.

3.2 Modeling Participation of Unhealthy Behavior

The previous section mainly considers the consumption decision of unhealthy behavior, and derives the structural relationship among health insurance, quantity of unhealthy behavior, and medical utilization. Since the derivation assumes participation, the resulting model only applies to unhealthy behavior participants. This section extends the model by allowing for a participation decision separate from the quantity of consumption decision.

In the literature on alcohol drinking or cigarette smoking, the participation decision is generally considered to be a different decision-making process than the consumption decision, and hence is modeled separately (see, e.g., Yen and Jones, 1996). A variety of empirical models have been used in the literature to separately account for participation and consumption. These include two-part models, standard Tobit, generalized (Type

II) Tobit, and some variants of generalized Tobit models.

Two-part models assume that the participation and the consumption decisions are determined independently and hence have equations for each that can be estimated separately. In contrast, the standard Tobit assumes that zero outcomes and non-zero outcomes are generated by the same underlying process. As mentioned in the previous section, the standard Tobit can be obtained by imposing a non-negativity constraint on the quantity choice variable in utility maximization. Since it imposes the same data generating process (DGP) and hence the same coefficients in the participation and the level of consumption equations, it imposes implausible restrictions in this paper's context. For example, the standard Tobit method of just imposing a nonnegativity constraint on B_1 when maximizing equation (2) would imply that the effect of health insurance on the probability of unhealthy drinking (extensive margin) is the same as that on the amount of drinking among unhealthy drinkers (intensive margin).

Generalized Tobit models allow participation and consumption to be two different but correlated decisions. The generalized Tobit model can be derived from a two-stage decision making process. In the first stage the individual decides whether or not to participate in unhealthy behavior, which may depend on factors that are distinct from the decision of how much to consume once participating. For example, one could decide not to consume alcohol for religious reasons, or decide to drink alcohol just under peer pressure. Kenkel (1990) applies a generalized Tobit model to estimating the effect of consumer health information on health care use. Fry and Pashardes (1994) use Logit instead of Probit for participation and then a linear regression for positive expenditures to estimate UK household tobacco demand. Yen and Jones (1996) apply a generalized Tobit with a Box-Cox transformation on the continuous dependent variable to modeling cigarette consumption in the UK.

Since the standard Tobit imposes implausible restrictions in this paper's context, the model of the previous section will now be extended to allow for a generalized Tobit specification of drinking behavior. This generalized Tobit nests two-part models and standard Tobits as special cases, and having separate participation and consumption equations will allow us to distinguish between the extensive and intensive margins of the health insurance effect on health behavior.

Let D be an indicator for unhealthy behavior, with $D = 1$ if participating in unhealthy behavior, and $D = 0$ otherwise. Let U be the utility function specified in equation (2), and let U^* be the utility losses or gains associated with abstaining from unhealthy behavior, which may embody social or religious attitudes, and may also depend on the optimal quantity of unhealthy behavior if one were to participate. The utility for all individuals can then be written as

$$\widetilde{U} = U - (1 - D)U^*. \tag{10}$$

One chooses to participate if and only if U^* is positive, which means $D = I\left(U^* \geq 0\right)$. Given D, the observed quantity of unhealthy consumption for any individual can then be written as $D \cdot B_1$, where the level of consumption B_1 is given by equation (8). That is, we observe B_1 if and only if one participates, i.e., $D = 1$. Note that the structural equation for M_1 is simply given by its FOC. Under general assumptions about U^*, for example, U^* is linear in M_1, the FOC and hence the structural equation for M_1 will have the same expression as before. For simplicity, the insurance I_0 index function is also assumed to remain linear in this case.

Further assume that a reduced-form expression for U^* is given by $U^* = X'\omega + e_D$, where X includes 1, I_0, H_0, B_0, and p_{B_1}, and e_D is a random utility parameter that could depend on or be correlated with other random utility parameters, in particular ν and τ. Then bringing all these results together gives the system of equations to be estimated

$$I_0 = I\left(\lambda_0 + \lambda_1 H_0 + \lambda_2 B_0 + \lambda_3 p_{B_1} - p_{I_0} + e_I \geq 0\right) \tag{11}$$

$$D = I[\alpha_0 + \alpha_1 I_0 + \alpha_2 H_0 + \alpha_3 B_0 + \alpha_4 p_{B_1} + e_D \geq 0] \tag{12}$$

$$B_1 = D\left(\beta_0 + \beta_1 I_0 + \beta_2 H_0 + \beta_3 B_0 + \beta_4 p_{B_1} + e_B\right) \tag{13}$$

$$M_1 = \gamma_0 + \gamma_1 B_1 + \gamma_2 I_0 + \gamma_3 H_0 + e_M \tag{14}$$

In this system, equations (12) and (13) together comprise the generalized Tobit model for unhealthy behavior, with the selection equation (12) determining the probability of participating in unhealthy behavior and equation (13) determining the quantity of unhealthy behavior. Both equations include health insurance as a dummy endogenous regressor. The coefficients of the insurance dummy in the probability and quantity equations give the extensive and intensive margins of the insurance effect on unhealthy behavior, respectively.

It is well known that data on unhealthy behavior, such as alcohol drinking or cigarette smoking, are typically characterized by a nontrivial fraction of zero outcomes and a skewed distribution of the positive outcomes (Manning and Mullahy, 2001). Equation (12) deals with zero outcomes, and in the empirical analysis the quantity measure B_1 is taken to be logged number of alcoholic drinks consumed. Since a log transformation can correct for the skewed distribution, I will then be able to assume normal errors in this system of equations. In the empirical analysis, I will also parameterize tastes ν and τ in the above equations by individual characteristics, including an income measure.

Medical utilization has relatively a small proportion of zero values. Given a long enough time period, we should observe everyone has positive medical utilization, so zero medical utilization represents "infrequent purchase" instead of non-participation in this case. Therefore, the medical utilization equation is modeled as a linear regression for simplicity.

4 Empirical Analysis

4.1 Empirical Specification

The previous section models an individual's decisions on whether to participate in unhealthy behavior and the quantity of unhealthy behavior if participating, so the resulting model for unhealthy behavior is a generalized Tobit or sample selection model. In the case of alcohol drinking, a low level of drinking is generally considered healthy (Dufour, 1996). For this paper's purpose, it is reasonable to distinguish between healthy drinking (including zero drinking) and unhealthy drinking. Therefore, the generalized Tobit in this paper's empirical analysis has a participation equation that determines self-selection into unhealthy drinking and a regression equation that determines the amount of unhealthy drinking. This particular specification allows investigating whether health insurance encourages unhealthy drinking and hence evidence of moral hazard.

In the literature, there is no consensus regarding what counts as a healthy level of drinking. Summarizing the results of many studies, Kloner and Rezkalla (2010) note, "Numerous studies have used a J-shaped or U-shaped curve to describe the relationship between alcohol use and total mortality. The nadir of the curves based on recent meta-analysis suggested optimal benefit at approximately half a drink per day."[5] This paper therefore defines unhealthy drinkers as those consuming more than half a drink a day (3.5 per week) on average. This paper assumes that this is the range for which increases in drinking are medically associated with decreases in health. A higher cutoff level such as 7 or 14 drinks per week could have been used, but doing so would dramatically cut

[5]The US National Institute on Alcohol Abuse and Alcoholism says that "up to two drinks per day for men and one drink per day for women and older people" is a "safe" level of drinking for people without certain medical conditions (see, e.g., http://www.niaaa.nih.gov/FAQs/General-English/default.htm#safe_level). But safe is not the same as healthy.

the size of the estimation sample. In addition, male's and female's drinking may be determined completely differently, so the empirical analysis uses males' data only.

Individual tastes υ and τ are parameterized as a function of individual characteristics. This is because this paper's model already has lagged behavior as a covariate, and without sufficiently long panel data it is impossible to distinguish between individual heterogeneity and state dependence, i.e., current period behavior depending on last period behavior (Heckman, 1981).[6] These characteristics will be discussed in the next section.

Finally, given the highly skewed distribution of alcohol consumption and medical utilization, a log transformation is applied to the positive level of alcohol consumption and medical utilization. Unlike drinking, medical utilization is specified as a linear regression, so one has to deal with transforming zeros. Zero is still transformed as zero here, and then at the right-hand side a dummy indicating zero medical utilization is included as a covariate. This is numerically equivalent to transforming zero into some unknown negative number (i.e., the log of the true average visits by infrequent users), as the coefficient of the included dummy would capture this mean value.[7]

4.2 Sample Description

This study's empirical analysis uses data from the US Health and Retirement Study (HRS) made available by the RAND Center for the Study of Aging. The HRS is a national panel survey of individuals over age 50 and their spouses in the US. It has extensive information on demographics, income, health, health insurance, and health care utilization etc. Data have been collected every two years since 1992. Seven waves

[6]Due to the lagged dependent and independent variables, to have a panel of two time periods, all the key variables have to be available for individuals for at least three consecutive waves of survey. The HRS is a very unbalanced panel for the variables required by this paper's empirical analysis.

[7]For the lagged zero alcohol consumption, I also transform it into zero and then include a dummy indicating last period not drinking.

of data have been released so far. Early waves do not have quantitative information on alcohol drinking. This paper first draws a sample from the 5th wave (year 2000) of HRS along with lagged variables from the 3rd and 4th waves. A further analysis is based on the pooled 5th, 6th, and 7th waves (years 2000, 2002, and 2004) of HRS, along with lagged information from the 3rd and 4th waves.

I focus on male non-retirees who are no older than 70 to avoid the impact of retirement and the potential outlier influence due to the inclusion of end-stage patients. Individuals who are on Medicaid or long-term care are not included. Further removing observations with missing values yields a sample of 2,907 observations, including 2,670 insured and 237 uninsured individuals. The quantity of drinking is measured by the number of alcoholic drinks consumed per week and medical utilization measured by the total number of doctor and hospital visits in the last two years (i.e., since last survey). Health insurance is a dummy indicating if an individual has any type of insurance, including both private and government insurance.[8] The five categories of self-reported health are recoded as three dummy variables representing excellent health, very good or good health, and fair or poor health (the default) respectively. Physician diagnosed diseases include hypertension, diabetes, heart disease, cancer, stroke, lung disease, arthritis, and psychiatric disease.

Individual characteristics controlled for include age, race (white and Hispanic dummies), education, and income. Education are in three categories, college or above, high school or GED, and less than high school education (the default). Income is given by the logarithm of the average lagged household income adjusted by family size, i.e., the average household income in the last two waves divided by family size squared. The

[8] **For simplicity, the structural model is developed with a binary health insurance variable (i.e., choosing either to be insured or not). The underlying assumption is that the insurance decision depends on prices only, but not insurance types. Therefore, here health insurance is a dummy indicating being covered by any health insurance. Under general conditions, the estimated insurance effect in this case can be interpreted as the average effect of the two types of health insurance. Later a sensitivity analysis separates these two types of health insurance.**

reason to use lagged income instead of current income is to avoid the impact of current health and hence current alcohol drinking and medical utilization on income. Summary statistics of the sample by insurance status are reported in Table 1.

Table 1 to be placed here.

As shown by Table 1, the insured individuals on average have 7.1 visits of a doctor/hospital in two years, in contrast to 5 visits among the uninsured. In addition, 29.1% of insured individuals currently drink more than half a drink per day (or 3.5 drinks per week) in contrast to 35.4% for the uninsured. The insured on average have 3.6 alcoholic drinks per week, while the uninsured on average have 6.1 alcoholic drinks. Therefore, the uninsured group consists of a larger fraction of relatively heavy drinkers and they drink more on average. **In addition, 32.5% of the uninsured are current smokers, in contrast to only 18.1% of the insured.**

It appears that health insurance is associated with healthier behavior on average. However, these simple correlations may reflect advantageous selection effects rather than causal effects of health insurance. First, similar differences exist in past heavy drinking and smoking behavior between the insured and the uninsured, so the insured individuals may have a healthier lifestyle *ex ante*. Second, the insured are on average about 1.5 years older than the uninsured. Age differences may partly explain their difference in alcohol drinking, because a lot of unhealthy behavior, such as heavy drinking, tends to decline with age among the elderly (Card et al. 2008). Associated with older age, the insured are also more likely to have certain diagnosed diseases, such as cancer and heart disease, though the insured tend to report better health than the uninsured for the last period. Therefore, the physical condition of the insured may limit their probability and amount of heavy drinking. Finally, the insured on average have higher education and higher household income, which are associated with better health knowledge and higher health consciousness, and so they may demand more health and healthier behavior.

Among the insured, 18.1% are 65 or older, while only 3.8% among the uninsured. Also, 37.9% of the insured have a spouse who was working full time, in contrast to 21.1% of the uninsured. Therefore, both the age dummy indicating 65 or older and spouse working full time are strongly positively correlated with having health insurance in the sample. Whereas the alcohol price index does not seem to be correlated with health insurance status.

4.3 Identification and Estimation

Both insurance status I_0 and alcohol consumption B_1 in the structural medical utilization equation are endogenous. The theoretical model in section 3 shows that variables that can exogenously affect the insurance price p_{I_0} but not alcohol consumption and medical utilization can serve as instrumental variables for health insurance. One such variable is the age dummy indicating age 65 or above, and the other is a dummy indicating spouse working full time. Both are discussed in the following.

As discussed, at age 65 the availability of Medicare makes the effective price of available insurance almost zero, which results in a significant increase in the insurance coverage rate. The age dummy can serve as a valid instrument for health insurance, since it is related to a supply-side price change. Card et al. (2008) use this exogenous change in a regression discontinuity estimation of the impact of Medicare eligibility on discrete measures of medical utilization and health behavior. The assumption is that medical care utilization and health behavior would evolve smoothly with age if there were no discrete change in insurance coverage at age 65. A detailed discussion about the validity of this assumption can be found in their study.

In the data used here, the insurance coverage rate for individuals aged just above 65, i.e., 65 - 66 is 96%, in contrast to 89% for individuals just under 65, i.e., 64-65. Figure 2 below shows the age profile of health insurance coverage rates generated by a nonparametric regression of health insurance on age, holding other covariates at their sample means. The figure shows clearly a discrete jump in the insurance holding probability at age 65. To capture this discrete jump, the empirical insurance equation includes the age dummy as a covariate. Age, age squared, and interaction terms between these two terms and the age dummy are included in all equations to capture the smooth age profile of the dependent variables before and after 65. These interaction terms allow the first and second derivatives of the dependent variables with respect to age to change at 65, but still maintains that there is no jump at this age. Tentatively including the age dummy in the behavior and care utilization equations does not yield significant coefficients. Therefore, similar to Card et al. (2008), the age dummy is plausibly excluded from these quantity equations.

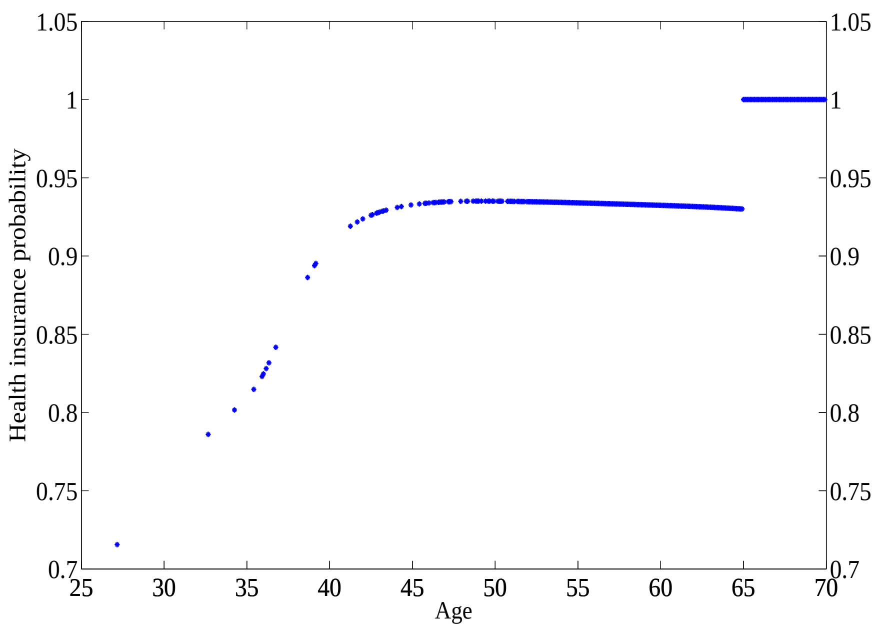

Figure 2 Nonparametric age profile of health insurance holding probability

An individual may have health insurance coverage through his spouse's job if the spouse is working full time. So spouse working full time should intuitively be positively correlated with health insurance. After controlling for all the relevant individual characteristics, including age, income, health, and past drinking behavior, spouse working full time is not expected to directly affect one's medical utilization and alcohol consumption and hence is excluded from these equations. To check the instrumental variable validity, several over-identification tests are performed. None of them rejects the exogeneity of the age dummy and spouse working full time to drinking and medical utilization.[9]

Recall that the two instrumental variables for alcohol consumption in the medical utilization equation are alcohol prices and past alcohol consumption. Past alcohol consumption is available in the HRS, but alcohol prices are not. Two alcohol consumption questions asked in HRS are "in the last three months, on average, how many days per week have you had any alcohol to drink?" and "in the last three months, on the days you drink, about how many drinks do you have?" The HRS also has data on which census region an individual was living in and on what date an individual was interviewed on. Since the interview dates spread over a year or longer, it is possible to investigate both time and regional variation in the alcohol price that different individuals face.[10] For each individual I derive the monthly average alcohol price index for his region for the time period he was asked about alcohol consumption. The alcohol price index data are from the Bureau of Labor Statistics (BLS).

Given that the unhealthy drinking model is a generalized Tobit with an endogenous health insurance dummy in both the probability and level equations of the Tobit specification, the model is estimated using a two-step procedure. First, the unhealthy drinking probability equation (12) along with the health insurance equation

[9]The validity of the exclusion restrictions is examined using Sargan's and Basmann's over-identification tests in the linear instrumental variable regression setting and Hansen's J test in a two-step efficient general method of moments (GMM) setting. For the alcohol consumption, the P-values of the three tests are 0.596, 0.597 and 0.622 respectively. For the medical care utilization, the P-values are 0.192, 0.193, and 0.182, respectively.

[10]For example, the 1998 HRS survey started interviewing in January 1998 and ended in March 1999.

(11) is jointly estimated as a bivariate probit. Then, based on the estimated parameters in this first step, I include in the level of drinking equation (13) control functions that deal with sample selection and the endogeneity of health insurance in this equation. The control function (expressed as lambda terms in Tables 3-6) equals the conditional mean of the regression error in the level of drinking equation conditioning on all the covariates in this equation. Let ρ be the correlation coefficient between the two latent errors in the bivariate probit and $\phi(\cdot)$ and $\Phi(\cdot)$ be the standard normal pdf and cdf, respectively. $\Phi(a, b, \rho)$ is a standard bivariate normal cdf with correlation coefficient ρ evaluated at a and b. Also for notational convenience, let $X_I b_I$ be the linear index function for the health insurance equation and $X_D b_D$ be that for the unhealthy drinking choice equation. The bias correction terms can then be written as $I\frac{\phi(X_I b_I)\Phi(X_D b_D - \rho X_I b_I)/\sqrt{1-\rho^2}}{\Phi(X_I b_I, X_D b_D; \rho)} - (1-I)\frac{\phi(X_I b_I)\Phi(X_D b_D - \rho X_I b_I)/\sqrt{1-\rho^2}}{\Phi(-X_I b_I, X_D b_D; -\rho)}$ and $I\frac{\phi(X_D b_D)\Phi(X_I b_I - \rho X_D b_D)/\sqrt{1-\rho^2}}{\Phi(X_I b_I, X_D b_D; \rho)} + (1-I)\frac{\phi(X_D b_D)\Phi(-X_I b_I + \rho X_D b_D)/\sqrt{1-\rho^2}}{\Phi(-X_I b_I, X_D b_D; -\rho)}$. A more general form of the control function that allows for a correlated random coefficient on health insurance can be found in Kim (2006).[11]

The medical utilization equation (14) has two endogenous variables, unhealthy drinking and health insurance. I use as instrumental variables the fitted values from the estimated unhealthy drinking and health insurance (probit) equations and implement instrumental variable estimation for the medical utilization equation.

5 Empirical Results

This section reports the basic estimation results and considers alternatives aimed at reducing standard errors and increasing the precision of estimates.

[11]Estimation in this paper is coded in Stata 11 and the code is available upon request.

5.1 Basic Estimation Results

In all tables, estimation results based on the 5th wave of HRS are reported in column (1) and those based on the pooled 5th, 6th, and 7th waves of data are presented in column (2). The latter will be discussed in the next section. The first two columns in Table 2 presents the marginal effects of covariates and associated standard errors in the health insurance equation. In this equation, the effect of the age dummy indicating age 65 or above ($Age \geq 65$) is given by coefficients on the age dummy and on the two interaction terms between age, age squared and the age dummy. The one-time shift in the insurance probability implied by these estimated coefficients is 3.7%, which is statistically significant. Not surprisingly, spouse working full time is also significantly positively correlated with having health insurance. **More drinking last period is associated with a smaller probability of having health insurance, which is consistent with the sample descriptive statistics and implies advantageous selection on behavior of health insurance, i.e., health insurance picks out a sample of individuals who have healthier behavior *per se*.** Note that this could be due to either self-selection or screening from the insurance companies.

As expected, higher household income in the past and higher education is associated with higher probabilities of having health insurance. Having a diagnosed disease in the previous period does not significantly affect the probability of having insurance, except for having psychiatric diseases. Individuals who report having good to excellent health are more likely to have health insurance than those reporting poor or fair health, though the difference is not significant.

Table 2 to be placed here.

Columns (1) and (2) present estimated marginal effects of covariates and associated standard errors in the participation of unhealthy drinking equation. Table 3 presents coefficient estimates in the quantity of unhealthy drinking equation. Column (1) in Table 2 shows that health insurance decreases the probability of unhealthy drinking by 10.8%, though the estimate is not statistically significant, whereas Column (1) in Table 3 shows that health insurance increases the quality of drinking among those relatively heavy drinkers by an insignificant 8.4%. Bootstrapped standard errors are reported in Table 3, since the estimation involves two steps. Recall that in the raw data health insurance is strongly negatively correlated with both the probability and the quantity of unhealthy drinking. After taking into account the endogeneity of health insurance, the negative correlation between health insurance and the quantity of unhealthy drinking disappears. As expected, last period drinking is significantly correlated with both the probability and the quantity of current unhealthy drinking. Individuals who have less than high school education drink much more on average than those who have higher education. Also, better health last period is associated with higher drinking in the current period. Whites on average drink less than non-whites.

Table 3 to be placed here.

Table 4 reports the estimated medical utilization equation. Column (1)-a presents the estimated structural medical utilization equation (14), for which bootstrapped standard errors are reported. (1)-b presents estimates of a semi-reduced form medical utilization equation, in which alcohol consumption is substituted out and only health insurance remains as an endogenous regressor. So it can be estimated easily by one-step standard maximum likelihood. Both estimates are based on the 5th wave of HRS data. Column (1)-a shows that health insurance increases unhealthy drinkers' doctor/hospital visits by 32.1% when controlling for their alcohol consumption. Although plausible in magnitude, it is not statistically significant. Also, a 10% increase in alcohol consumption among unhealthy drinkers increases their doctor/hospital visits by 0.74%. Excellent health is associated with significantly fewer doctor/hosptital visits. Almost all physician diagnosed diseases are associated with positive and significant increases in doctor/hosptital visits except for heart diseases.

Column (1)-b in Table 4 shows that health insurance increases doctor/hospital visits by a significant 55.9%. This effect is a reduced-form effect, which captures both the direct and indirect effects of health insurance on medical utilization, since alcohol consumption have been substituted out in this equation.

Table 4 to be placed here.

Using a Tobit specification instead of a linear model for doctor/hospital visits yields similar estimates. This may be due to the small proportion of zeros, and hence an ignorable sample selection effect in the doctor/hospital visit equation. Estimating the Tobit specification shows that health insurance increases both the probability of visiting a doctor/hospital and the number of visits. But the increase in the probability is small and statistically insignificant, while the increase in the number of visits is similar to what was reported above.

5.2 Reducing Standard Errors of Estimation

The previous section shows that health insurance decreases the probability of unhealthy drinking by 10.8% and increases the amount of unhealthy drinking by 8.4%. Also the direct effect of health insurance on doctor/hospital visits among unhealthy drinkers is 32.1%. Although these estimated insurance effects are considerable in size, they are not statistically significant except in specification (1)-b of Table 4 where a semi-reduced form medical utilization equation is estimated. In addition, a 10% increase in unhealthy drinking is estimated to increase unhealthy drinkers' doctor/hospital visits by 0.74%. This small and insignificant impact is plausible considering that it represents the immediate effect instead of the long-run accumulated effect of unhealthy drinking on medical utilization.

The large standard errors and hence insignificance of many of these estimates could be due to the relatively small sample size. For example, in the total of 2,907 observations only 862 are unhealthy drinkers. In this section, I re-estimate equations (12), (13), and (14) using the pooled 5th, 6th, and 7th waves of HRS data. The pooled data has 7,180 observations, among which 2,154 are unhealthy drinkers. One may be concerned about the serial correlation in the model errors due to the panel nature of HRS data. Surprisingly, there is almost no overlap between the three waves of data in the final sample, so the pooled data can be essentially treated as pooled cross-sections. However, this raises the concern that the samples from each wave may not be equally representative of the same population, due to either sampling or cohort effects. It is worth emphasizing that the purpose of this further analysis is mainly to investigate whether a larger sample can reduce standard errors and hence yield more significant estimates, and whether the estimated parameters of interest would change dramatically.

Comparing column (1) based on the smaller sample and (2) based on the larger pooled data in Table 2, one can see that the estimated insurance effect on the probability of unhealthy drinking changes from -10.8% to -4.1%. In contrast, in Table 3, the estimated insurance effects on the amount of unhealthy drinking remain similar for both samples, 8.4% vs. 9.9%, while the standard error in this case shrinks about one third from 0.311 to 0.199. Columns (1) and (2) in Table 4 show that the estimated direct effects of health insurance on doctor/hospital visits are also very similar across the two samples, 32.1% vs. 31.3%, whereas the standard error goes down from 0.485 to 0.299. The estimated increases in doctor/hospital visits due to increased unhealthy drinking are small using either sample, 0.74% vs. 0.30% given a 10% increase in alcohol drinking.

Increasing the sample size raises the risk of bias from pooling across possibly different populations. However, the above analysis indicates that pooling across the data waves reduces the standard errors of estimation, without substantially changing the point estimates of the parameters of primary interest: the health insurance effects on unhealthy drinking and on medical utilization. Overall, it appears that the health insurance effects on the probability of unhealthy drinking and on the quantity of drinking by unhealthy drinkers are different. Unlike the extensive margin, the insurance effect at the intensive margin (effect on the quantity of unhealthy drinking) is positive and remains similar across different samples. However, the immediate effect of increased unhealthy drinking on doctor/hospital visits is negligible in the medical utilization equation. In contrast, the direct effect of health insurance on doctor/hospital visits is considerable and consistent across samples.

5.3 Further Discussions

This section discusses various issues associated with the previous empirical analysis and presents results of some sensitivity analyses or robustness checks. Estimates from these sensitivity analyses are summarized in Table 5.

First of all, this paper uses heavy drinking as the proxy of unhealthy behavior due to data limitations. One may wonder whether the results depend on which unhealthy behavior is used. In particular, smoking may better represent unhealthy behavior, because smoking is non-controversially unhealthy and so one does not have to draw an arbitrary line between the healthy and unhealthy quantities. Given the available binary measure of smoking, I examine the effect of health insurance on the probability of smoking.[12] The estimated effect is -0.035, and it is not statistically significant. So consistent

[12] Unlike the data on drinking, quantity data on smoking is not available in the HRS, so insurance effects on the intensive margin of smoking cannot be estimated.

with the result for the probability of drinking, health insurance does not seem to be able to change a non-smoker to a smoker. Note that this is in sharp contrast to the simple comparison between the insured and the uninsured – the insured are much less likely to be a smoker, 18.1% vs. 32.5%.

Second of all, the previous empirical analysis treats light drinkers essentially the same as nondrinkers. To check whether separating drinkers from non-drinkers would systematically change the estimates, I now distinguish between drinkers and non-drinkers and estimate the insurance effect on the decision of being a drinker first. Health insurance is not found to have a significant effect on the probability of participating in drinking (the estimated effect is -0.129, with a standard error 0.198).

Then conditional on being a drinker, I distinguish between light drinkers and heavy drinkers and re-estimate the Tobit model for heavy drinking among drinkers, which consists of a binary choice equation for participation in heavy drinking and a regression equation for the quantity of heavy drinking, both having health insurance as a binary endogenous variable. This is equivalent to specifying a two-part model for the decision of being a drinker or not and then a Tobit (sample selection) model for heavy drinking among drinkers. The estimated health insurance effects on heavy drinking are quantitatively almost identical to those by the previous specification at both the extensive margin (-0.100 compared to -0.108 before) and the intensive margin (both are 0.084).

Another issue is that for simplicity, the structural model is developed with a binary health insurance variable (i.e., choosing either to be insured or not). The assumption is that the decision to buy health insurance depends on prices only, but not insurance types. In the previous empirical analysis, health insurance is therefore a dummy indicating covered by any health insurance, including both private insurance and government insurance. However, the decision for buying these two types of health insurance might be different, so I re-estimate the model using only individuals who are younger than 65 and covered by the private insurance.

Since most insured individuals (about 90%) have private insurance in this paper's sample, focusing on private insurance yields results that are largely consistent with the previous estimates. These estimated insurance effects are within one standard error of the previous estimates. The extensive margin of the insurance effect on heavy drinking is small, negative and insignificant (-0.036 with a standard error 0.127), whereas the intensive margin is positive (0.045 with a standard error 0.323). Both the insurance effect on the quantity of heavy drinking and that on medical utilization are still positive with larger standard errors, which could be due to the smaller sample used and weaker identification, since this estimation does not utilize the exogenous change in the insurance rate induced by Medicare eligibility at age 65.

Table 5 to be placed here

Lastly, from a theoretical point of view, it is important to separate curative and preventative visits. Unlike doctor visits, hospital utilization is more likely to be curative. Therefore as a robustness check, I use hospital stays (the total number of nights stayed in a hospital since last survey) as a measure of medical utilization and re-estimate the model. In this case, both health insurance and heavy drinking are still found to have positive effects on medical utilization. But the estimated effect of health insurance on utilization is close to zero and insignificant. This is plausible, considering

that hospital stays tend to be associated with relatively serious health problems (and hence may be less affected by one's insurance status) and that the decision to stay in a hospital and how long to stay is mainly a physician's decision. Overall, it seems that health insurance mostly affects doctor visits, but not necessarily hospital stays.

6 Conclusions

This paper investigates the direct and indirect effects of health insurance that can lead to increased use of health care. A simple theoretical model is used to derive the structural causal relationships among the decision to buy health insurance, health behavior, and medical utilization. The resulting equations show that medical utilization is a function of health insurance and health behavior, and that health behavior is further a function of health insurance. These equations also show that past health behavior and the price of behavior can identify the effect of endogenous health behavior on medical utilization, while variables that exogenously affect the price of health insurance, such as Medicare eligibility at age 65 and spouse working full time, can identify the effects of endogenous health insurance.

Drawing on samples of male non-retirees from the HRS, this study's empirical analysis estimates medical utilization measured by doctor/hospital visits, unhealthy behavior represented by unhealthy drinking (defined as more than half a drink per day, or more than 3.5 drinks per week), and health insurance equations. The unhealthy drinking is specified as a generalized Tobit, where both the binary participation equation and the level of unhealthy drinking equation has health insurance as an endogenous regressor. The model is estimated by a two-step procedure, where the first step is a bivariate probit estimation of the binary participation and the health insurance equations. The second step is ordinary least square (OLS) estimation, after plugging in unhealthy drinking equation control functions, i.e., bias correction terms that correct for sample selection and the endogeneity of health insurance in this equation. The medical utilization equation is specified as a linear regression with both unhealthy drinking and health insurance as endogenous regressors. This equation is estimated by IV estimation using as instrumental variables the fitted value from the unhealthy drinking model and the health insurance probit estimation.

The empirical estimation based on the 5th wave of HRS shows that having health insurance decreases the probability of unhealthy drinking by 10.8% while increases the quantity of unhealthy drinking among unhealthy drinkers by 8.4%. It is also shown that health insurance increases doctor/hospital visits by 32.1% when controlling for unhealthy drinking. In the full structural model these effects are not statistically significant, perhaps because of the complexity of the model relative to the size of the available sample. However, estimation of a semi-reduced form medical utilization equation using the same sample, in which unhealthy drinking is substituted out and only health insurance remains as an endogenous regressor, yields a significant effect of health insurance (55.9%) on doctor/hospital visits. This effect can be interpreted as a reduced-form effect, which captures both the direct and indirect effects of health insurance on medical utilization. Further, using a larger sample from the pooled 5th, 6th, and 7th waves of HRS, this paper finds that the point estimates of health insurance effects on the quantity of unhealthy drinking and doctor/hospital visits remain similar, while the standard errors decrease by over a third. The former point estimate is 9.9%, while the latter is 31.3%. The estimated insurance effect on the probability of adopting unhealthy drinking decreases to -4.1% from -10.8%. The estimated increases in doctor/hospital visits given a 10% increase in unhealthy drinking are 0.74% and 0.30% for these two samples.

Several sensitivity analyses are conducted to investigate some of the issues

pertaining to this paper's main empirical analysis. These include investigating the effect of health insurance on smoking, distinguishing between private insurance and government insurance, distinguishing between drinkers and non-drinkers and then between light drinkers and heavy drinkers among drinkers, as well as using alternative measures of medical utilization. Estimates based on these alternative specifications and samples are largely consistent with those of the main analysis.

Overall, it appears that the effect of health insurance on the probability of participating in unhealthy behavior and that on the quantity of unhealthy behavior are different. For example, health insurance does not seem to cause non-drinkers or healthy drinkers to become unhealthy drinkers (**or to cause non-smokers to become smokers**; the impact at the extensive margin is negative or insignificant at most); however, it is likely that health insurance encourages unhealthy drinkers to drink even more (the effect at the intensive margin is positive and comparable across samples). Effective policy design may take this difference into account. For example, in July 2006, three West Virginia counties adopted a pilot Medicaid program. Members could sign an agreement valid for a year that required them to engage in positive health behaviors, such as maintaining healthy weight, exercising, quitting tobacco use. Those who signed and adhered to the agreement were then rewarded with additional benefits (Tworek and Horn, 2007). Considering the empirical results here, such a program would be most beneficial if it targeted people who currently actively engage in unhealthy behavior, because these people's behaviors are likely to be affected most by health insurance.

This paper's analysis suggests several related issues that would be useful topics for future research. First, the empirical analysis here draws on samples from the HRS, which means a relatively older cohort of individuals are focused on. It would be interesting to conduct similar analysis using panel data on relatively younger individuals. **Second,**

this paper mainly uses heavy drinking as the proxy of unhealthy behavior due to data limitations. Estimation of the structural model requires panel data that track individuals' health behavior over time, along with permanent income, last period health, current health insurance and health care utilization information. To my best knowledge, such a data set is not readily available anywhere else. Later work might be done on other unhealthy behavior if higher quality data become available. In addition, doctor or hospital visits here include both visits for curative purposes and those for preventive purposes; it would be useful to investigate whether health insurance affects the two types of visits differently. Addressing this question also requires more information than what is available in the current data set. Lastly, it would also be useful to look at some cross-country comparisons, particularly comparisons with places like Canada and some European countries that have universal health care coverage.

Table 1 Summary statistics of the sample by health insurance status

	The insured (n=2,670)		The uninsured (n=237)	
	Mean	Std. Dev.	Mean	Std. Dev.
Doctor/hospital visits in two years	7.079	11.21	5.046	9.422
More than half a drink per day	0.291	0.454	0.354	0.479
Alcoholic drinks per week	3.607	7.117	6.143	13.48
Alcoholic drinks per week last period	3.998	8.143	6.527	13.37
smoking	0.181	0.385	0.325	0.469
smoking last period	0.203	0.402	0.325	0.469
Log past average household income	9.335	1.111	8.616	1.455
Education:				
High school or GED	0.330	0.470	0.304	0.461
College or above	0.521	0.500	0.270	0.445
White	0.851	0.356	0.793	0.406
Hispanic	0.067	0.249	0.283	0.451
Age	59.93	5.163	58.52	5.708
Age$\geq$65	0.181	0.385	0.038	0.192
Last period health:				
Good/ Very good health	0.642	0.479	0.549	0.499
Excellent health	0.193	0.395	0.165	0.372
Hypertension	0.350	0.477	0.350	0.478
Diabetes	0.106	0.308	0.110	0.313
Cancer	0.045	0.207	0.017	0.129
Heart diseases	0.125	0.331	0.089	0.285
Stroke	0.025	0.155	0.021	0.144
Lunge diseases	0.036	0.186	0.042	0.201
Psychiatric diseases	0.059	0.235	0.093	0.291
Arthritis	0.325	0.468	0.342	0.475
Spouse working full time	0.379	0.485	0.211	0.409
Alcohol price index	1.011	0.019	1.009	0.019

Table 2: Health insurance and probability of unhealthy drinking

	Health Insurance		Unhealthy Drinking			
			(1)		(2)	
Health insurance			-0.108	(0.099)	-0.041	(0.065)
Age≥65	0.037	(0.006)***				
Spouse working full time	0.042	(0.008)***				
Education:						
High school or GED	0.039	(0.009)***	-0.039	(0.033)	0.003	(0.021)
College or above	0.063	(0.012)***	0.001	(0.033)	0.016	(0.021)
White	-0.002	(0.010)	-0.038	(0.027)	-0.018	(0.018)
Hispanic	-0.054	(0.022)***	0.098	(0.037)***	0.020	(0.024)
Age	0.030	(0.009)***	0.005	(0.029)	0.005	(0.019)
Age^2	-0.027	(0.008)***	-0.002	(0.026)	-0.004	(0.017)
(Age≥65)*Age	2.771	(1.119)**	0.008	(0.017)	0.002	(0.010)
(Age≥65)*Age^2	-2.044	(0.831)**	-0.013	(0.026)	-0.003	(0.015)
Log past average household income	0.013	(0.003)***	0.014	(0.009)	0.011	(0.006)*
Last period health:						
Good/ Very good health	0.014	(0.011)	0.046	(0.030)	0.033	(0.019)*
Excellent health	0.011	(0.012)	0.050	(0.036)	0.058	(0.024)**
Hypertension	-0.004	(0.009)	-0.007	(0.021)	-0.004	(0.013)
Diabetes	0.003	(0.012)	-0.011	(0.035)	-0.045	(0.021)**
Cancer	0.026	(0.015)*	0.058	(0.047)	0.028	(0.028)
Heart diseases	0.018	(0.010)*	-0.016	(0.032)	-0.009	(0.019)
Stroke	0.016	(0.019)	0.014	(0.070)	0.029	(0.042)
Lunge diseases	0.005	(0.019)	0.017	(0.053)	0.000	(0.033)
Psychiatric diseases	-0.035	(0.021)	-0.033	(0.045)	-0.008	(0.025)
Arthritis	0.000	(0.009)	-0.002	(0.021)	0.004	(0.013)
Log last period quantity of drinking	-0.015	(0.006)***	0.218	(0.008)***	0.218	(0.005)***
Last period not drinking	-0.020	(0.013)	-0.209	(0.033)***	-0.208	(0.020)***
Log alcohol price index	0.066	(0.210)	0.076	(0.504)	-0.122	(0.372)
Alcohol price missing	-0.089	(0.080)	-0.024	(0.133)	0.014	(0.014)

Note: Marginal effects of covariates at the sample mean are reported, except for those on Age and Age^2 before and after 65. Those are the scaled coefficients, i.e., coefficients multiplied by the standard normal density at the sample mean. (1) is based on the 5^{th} wave of HRS, and (2) is based on the pooled 5^{th}, 6^{th}, and 7^{th} waves of HRS. Standard errors are in the parentheses; * significant at the 10% level; ** significant at the 5% level; ***significant at the 1% level.

Table 3: Quantity of unhealthy drinking

	Log(alcoholic drinks per week)			
	(1)		(2)	
Health insurance	0.084	(0.311)	0.099	(0.199)
Education:				
High school or GED	-0.333	(0.113)***	-0.093	(0.103)
College or above	-0.178	(0.083)**	-0.107	(0.090)
White	-0.168	(0.072)**	-0.071	(0.055)
Hispanic	0.116	(0.129)	-0.005	(0.094)
Age	-0.086	(0.087)	-0.001	(0.060)
Age^2	0.083	(0.080)	0.002	(0.054)
(Age≥65)*Age	-0.004	(0.054)	0.011	(0.028)
(Age≥65)*Age^2	0.001	(0.082)	-0.018	(0.042)
Log past average household income	0.028	(0.031)	0.019	(0.018)
Last period health:				
Good/Very good health	0.204	(0.098)**	0.138	(0.069)**
Excellent health	0.224	(0.114)*	0.234	(0.084)***
Hypertension	0.051	(0.039)	0.040	(0.037)
Diabetes	0.074	(0.114)	-0.160	(0.076)**
Cancer	0.143	(0.131)	0.108	(0.089)
Heart diseases	0.031	(0.140)	0.031	(0.058)
Stroke	-0.205	(0.199)	-0.040	(0.138)
Lunge diseases	0.244	(0.161)	0.144	(0.104)
Psychiatric diseases	-0.040	(0.129)	-0.083	(0.067)
Arthritis	0.009	(0.045)	0.035	(0.052)
Log last period quantity of drinking	0.970	(0.114)***	1.062	(0.101)***
Last period not drinking	-0.543	(0.323)*	-0.787	(0.275)***
Log alcohol price index	-1.205	(1.578)	-0.527	(1.487)
Alcohol price missing	-0.213	(0.439)	0.082	(0.042)**
Lambda1	-0.121	(0.150)	-0.160	(0.090)*
Lambda2	1.424	(0.354)***	1.775	(0.289)***
Constant	1.448	(2.353)	-1.140	(1.597)

Note: (1) is based on the 5^{th} wave of HRS, and (2) is based on the pooled 5^{th}, 6^{th}, and 7^{th} waves of HRS. Bootstrapped standard errors are in the parentheses; * significant at the 10% level; ** significant at the 5% level; ***significant at the 1% level.

Table 4: Medical utilization

	Log(doctor/hospital visits every two years)					
	(1)-a		(1)-b		(2)	
Health insurance	0.321	(0.485)	0.559	(0.254)**	0.313	(0.299)
log # of alcoholic drinks per week	0.074	(0.099)			0.030	(0.039)
Education:						
High school or GED	-0.055	(0.123)	-0.098	(0.101)	-0.048	(0.069)
College or above	0.121	(0.134)	0.055	(0.105)	0.094	(0.078)
White	-0.052	(0.102)	-0.037	(0.086)	-0.147	(0.065)**
Hispanic	-0.112	(0.128)	-0.072	(0.111)	-0.151	(0.079)*
Age	-0.002	(0.107)	0.000	(0.078)	0.068	(0.048)
Age^2	0.013	(0.097)	0.013	(0.071)	-0.053	(0.044)
(Age≥65)*Age	-0.010	(0.053)	-0.022	(0.050)	-0.034	(0.032)
(Age≥65)*Age^2	0.015	(0.080)	0.032	(0.076)	0.053	(0.048)
Log past average household income	0.000	(0.036)	-0.002	(0.026)	0.009	(0.021)
Last period health:						
Good/Very good health	-0.148	(0.081)*	-0.140	(0.094)	-0.113	(0.066)**
Excellent health	-0.245	(0.116)**	-0.220	(0.110)**	-0.242	(0.055)***
Hypertension	0.307	(0.050)***	0.294	(0.061)***	0.267	(0.035)***
Diabetes	0.329	(0.110)***	0.310	(0.117)***	0.346	(0.048)***
Cancer	0.307	(0.147)**	0.316	(0.142)**	0.304	(0.055)***
Heart diseases	0.107	(0.104)	0.111	(0.097)	0.215	(0.048)***
Stroke	0.443	(0.272)*	0.404	(0.207)**	0.285	(0.150)*
Lunge diseases	0.254	(0.155)*	0.341	(0.146)**	0.211	(0.108)*
Psychiatric diseases	0.248	(0.142)*	0.300	(0.138)**	0.214	(0.073)***
Arthritis	0.205	(0.052)***	0.213	(0.063)***	0.134	(0.030)***
Zero doctor/hospital visits	1.345	(0.061)***	1.302	(0.088)***	1.360	(0.031)***
Log last period quantity of drinking			0.024	(0.034)		
Last period not drinking			0.127	(0.127)		
Log alcohol price index			-1.207	(1.467)		
Alcohol price missing			-0.233	(0.367)		
Constant	0.584	(3.036)	0.415	(2.178)	-1.090	(1.260)

Note: (1)-a, b are based on the 5^{th} wave of HRS, and (2) is based on the pooled 5^{th}, 6^{th}, and 7^{th} waves of HRS. For (1)-a and (2), bootstrapped standard errors are in the parentheses; * significant at the 10% level; ** significant at the 5% level; ***significant at the 1%level.

Table 5: Health insurance effects based on alternative samples or specifications

Sample/Dependent variable	Probability of behavior	Quantity of behavior	Medical utilization
1. Private insurance and under 65 only	-0.036 (0.127)	0.045 (0.323)	0.764 (0.562)
2(a). Whether a drinker/nondrinker	-0.129 (0.198)		
2(b). Among drinkers, whether a heavy drinker	-0.100 (0.100)	0.084 (0.304)	
3. Whether a smoker/nonsmoker	-0.035 (9.496)		
4. Measuring medical utilization by hospital utilization			0.012 (0.243)

Note: Estimates are based on the 5th wave of the HRS; Standard errors are in the parentheses.

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